JMIR Nursing

Virtualizing care from hospital to community: Mobile health, telehealth, and digital patient care
Volume 8 (2025) ISSN 2562-7600 Editor in Chief: Elizabeth Borycki, RN, PhD, FIAHIS, FACMI, FCAHS, Social Dimensions of Health Program Director, Health and Society Program Director, Office of Interdisciplinary Studies; Professor, School of Health Information Science, University of Victoria, Canada

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Nurses' Intention to Integrate AI Into Their Practice: Survey Study in Canada

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Abstract

Background: The integration of artificial intelligence (AI) into health care is set to revolutionize the sector, offering opportunities to enhance diagnostic accuracy, personalize treatment, and improve patient outcomes. However, little is known about nurses' readiness to integrate AI into their professional practice.

Objective: This study aimed to identify the key factors influencing nurses' intention to integrate AI into their practice.

Methods: An online survey was distributed to 3000 members of the professional order of nurses in Quebec, Canada. A total of 312 nurses participated, with 307 completing the full questionnaire. Data were analyzed using descriptive statistics and partial least squares structural equation modeling.

Results: Nurses' beliefs about the role of AI and trust in AI were found to predict intention to integrate AI significantly. Facilitating conditions influenced beliefs and familiarity with AI, which in turn shaped perceptions of AI's impact. The model explained 65% of the variance in behavioral intention.

Conclusions: The findings highlight the importance of enhancing nurses' familiarity with AI and fostering positive beliefs and attitudes to promote effective integration. Educational strategies targeting these beliefs can facilitate AI adoption in nursing.

(JMIR Nursing 2025;8:e76795) doi:10.2196/76795

KEYWORDS

artificial intelligence; nurses; intention; facilitating conditions; familiarity with AI; beliefs about AI; attitudes toward AI; online survey; mobile phone

Introduction

Background

The integration of artificial intelligence (AI) into health care is poised to transform the sector by offering unprecedented opportunities to enhance diagnostic accuracy, personalize treatment plans, and improve patient outcomes [1-3]. AI technologies can rapidly and accurately process vast amounts of data, uncovering patterns and generating predictions that may elude human practitioners. These capabilities not only support more accurate diagnoses but also facilitate the development of individualized treatment strategies tailored to each patient's unique profile, thereby advancing the quality and precision of care delivery.

Beyond reshaping diagnostic and therapeutic processes, AI holds substantial promise for a broad spectrum of health care professionals. For nurses in particular, AI can enhance patient monitoring, reduce workload, and support clinical decision-making in high-stakes tasks such as triage [4]. AI-powered systems can synthesize data from wearable devices, detect early signs of clinical deterioration, and alert nurses in real time, enabling timely and proactive interventions [5,6]. Furthermore, predictive analytics tools can assist with workforce planning by optimizing shift scheduling and staffing levels, helping ensure that nursing resources are allocated efficiently and per patient acuity [7].

AI also opens new avenues for enhancing mental health nursing. For instance, chatbot-based applications and virtual therapists can provide real-time support, extending the reach of mental health services [8]. These tools can analyze linguistic cues in speech and text to detect indicators of depression, anxiety, and other conditions, thereby facilitating earlier identification and intervention by nursing staff [9]. In orthopedic care, AI-driven technologies offer similarly transformative potential. Tools that personalize rehabilitation plans and monitor patient adherence can deliver real-time feedback, promoting the correct execution of exercises and enabling continuous progress tracking [10].

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Moreover, AI-enabled robotic assistants and exoskeletons can play a pivotal role in physical rehabilitation by supporting mobility training and functional recovery in patients with musculoskeletal impairments [11].

As health care systems increasingly implement AI technologies [12], it becomes essential to understand the factors that influence nurses' intentions to integrate these tools into their clinical practice. Although AI holds considerable promise for improving patient care, much of the existing research on AI adoption in health care has focused on physicians and medical students [13,14], leaving the perspectives of other professional groups, particularly nurses, underexplored. This study seeks to address this gap by examining the determinants of nurses' intention to adopt AI in their practice. Specifically, we investigate the following research question: What factors influence nurses' intention to integrate AI into their clinical practice? A deeper understanding of these factors will help inform the design of targeted interventions aimed at supporting nurses in the adoption of AI-enabled technologies, thereby enhancing the safety, quality, and efficiency of the health care services they deliver.

The remainder of the paper is structured as follows. We begin by presenting the theoretical foundations that guided the development of our research model and hypotheses. This is followed by a detailed description of the survey design, measurement instruments, and analytical procedures used. We then report the main findings and discuss their implications for nursing education and clinical practice. The paper concludes by outlining the study's limitations and identifying directions for future research.

Theoretical Modeling

To address the above-mentioned research question, we first developed a theoretical model grounded in 2 complementary behavioral theories. The first theoretical foundation is the theory of interpersonal behavior (TIB) by Triandis [15], which posits that individuals' behavioral intentions are shaped by their beliefs about a behavior. In this framework, *beliefs* are understood as cognitive judgments—assessments of what an individual thinks is true or likely regarding a given object, technology, or behavior. These judgments are based on personal perceptions and may or may not reflect objective reality. For example, one may hold the belief that scientific advancements generally contribute to societal well-being. In our study, nurses' beliefs refer to their perceptions of the role that AI technologies can play in their own professional practice and broader nursing profession, as well as their trust in the reliability and utility of AI-based health technologies. Consistent with prior studies [13,16-19], we argue that more positive beliefs, reflected in stronger perceptions of AI's professional relevance and greater trust in its outputs, are associated with a higher intention to integrate AI into practice (hypothesis 1 [H1]).

Our second theoretical foundation is the theory of reasoned action (TRA), which emphasizes the role of attitudes as immediate antecedents of behavioral intention [20]. In contrast to beliefs, which are cognitive in nature, attitudes are affective or evaluative responses—feelings of favor or disfavor—toward an object, technology, or behavior. In this study, we operationalize attitudes through 2 constructs: perceived impactfulness of AI (positive) and anxiety toward AI (negative). Perceived impactfulness refers to the extent to which nurses feel that AI-enabled tools can enhance their performance, while AI-related anxiety captures the discomfort, fear, or apprehension experienced when thinking about or interacting with AI-based systems. Prior research suggests that favorable attitudes, such as high perceived usefulness and low anxiety, can promote AI adoption, whereas negative emotional responses may deter it [21-26]. Hence, we posit that nurses with more favorable attitudes toward AI will exhibit a stronger intention to integrate AI into their professional practice (H2).

Both the TIB and TRA highlight that beliefs serve as cognitive precursors to attitudes. That is, individuals form emotional evaluations (ie, attitudes) based on their underlying beliefs about a behavior. For example, Schnall et al [27] found that health care providers' trust-based beliefs about mobile health technologies influenced their perceived usefulness, an attitudinal judgment. Applying this logic to our model, we hypothesize that nurses with stronger positive beliefs about the role of AI and greater trust in its capabilities will be more likely to develop favorable attitudes toward using AI in their clinical practice (H3).

The third theoretical component of our model centers on "facilitating conditions" as a key determinant of nurses' behavioral intention to adopt AI technologies. This construct, grounded in the technology acceptance model (TAM)—a foundational framework for examining technology adoption [28]—captures the external factors that influence an individual's perceived ease of performing a task, such as using AI in clinical settings. In this study, we conceptualize facilitating conditions through two indicators: (1) nurses' general digital literacy, reflected in their familiarity with consumer technologies such as laptops and mobile phones; and (2) their prior exposure to AI tools, including chatbots and machine learning applications. Building on recent empirical findings by Qaladi et al [29], we posit that greater familiarity with AI fosters a more nuanced understanding of both its capabilities and limitations, which in turn supports more favorable attitudes and intentions toward its adoption in nursing practice.

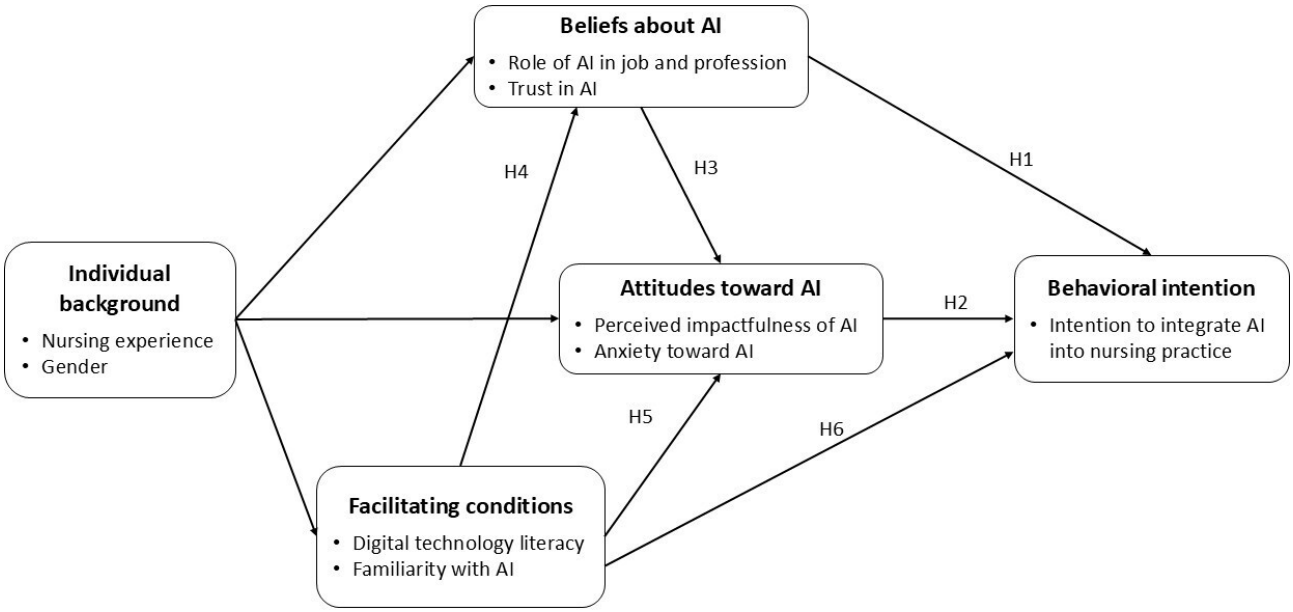
Prior research suggests that facilitating conditions exert both direct and indirect effects on individuals' intention to adopt AI technologies. Drawing from the TAM, which posits that external conditions shape beliefs, attitudes, and ultimately behavioral intentions, we hypothesize a similar set of relationships in the context of nursing practice. Specifically, we propose that more favorable facilitating conditions will lead to more positive beliefs about AI among nurses (H4), more favorable attitudes toward AI (H5), and a stronger intention to integrate AI-powered tools into clinical practice (H6).

Additionally, informed by prior studies on digital health training [13,30] and recent applications of the TAM in health care contexts [31,32], we incorporate a fourth construct—individual background—into our research model. This construct is operationalized as a composite of 2 demographic characteristics: gender and years of nursing experience. Given the exploratory nature of this study, we do not posit specific directional hypotheses but rather suggest that individual background may

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influence nurses' perceptions of facilitating conditions, their beliefs about AI, and their overall attitudes toward its use. The theoretical model tested in this study is presented in Figure 1.

Figure 1. Theoretical model. AI: artificial intelligence.



Methods

Study Design and Study Population

This study used a cross-sectional web-based survey design and adhered to the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines [33] to ensure methodological rigor and transparency. To obtain a representative sample, we partnered with the professional order of nurses in Québec, Canada. The order randomly selected 3000 active members from its registry of over 82,000 nurses and distributed an invitation letter on our behalf. Eligibility was limited to currently active members, thereby ensuring that respondents were engaged in professional nursing practice. The survey was accessible from the middle of October 2023 to early February 2024, with a follow-up reminder sent 3 weeks after the initial invitation. Participation was voluntary and uncompensated. Respondents accessed the survey via a secure Qualtrics link; the platform complies with relevant data privacy laws and regulations in Canada.

Questionnaire Development

The operationalization of several research variables included in our model was based on the extant literature. Indeed, given the maturity of the research stream, this approach benefits from previous empirical validations and, thus, ensures the validity and reliability of the selected measurement items. The measures for the dependent variable (behavioral intention) and the role of AI in jobs and professions were adapted from Wagner et al [13], while the measure for trust in AI was adapted from Ouimet et al [34], and the measure for AI anxiety was informed by the work of Wang and Wang [35]. We were unable to locate any pre-existing questionnaire that assessed the perceived impactfulness of AI; hence, we decided to develop our own measure for this construct. Before data collection, we pre-tested the questionnaire with a panel of 4 nursing professionals. Only minor adjustments were made following this validation phase. The measurement items are reported in Multimedia Appendix 1.

Statistical Analysis

The data were first analyzed through descriptive statistics, using the IBM SPSS software (version 28). Component-based partial least squares structural equation modeling (PLS-SEM) was then used to test the research model (Figure 1), as implemented in the *SEMinR* package (version 2.3.2).

Ethical Considerations

Ethics approval was obtained from the relevant institutional review board, the HEC Montréal Research Ethics Committee, on August 10, 2023, ensuring that all study procedures adhere to ethical guidelines and standards (#2024 - 5512). Before beginning the survey, all participants provided informed consent electronically, having been presented with a comprehensive overview of the study's objectives, procedures, potential risks, and anticipated benefits. Throughout this study, participant privacy and data integrity were rigorously protected in line with established research ethics guidelines and applicable data protection regulations. No financial incentives or compensation were offered to participants.

Results

Overview

A total of 312 nurses responded to the online survey, yielding a response rate of 10%. Of these, 307 respondents completed the full questionnaire and were retained for analysis. As shown in Table 1, the sample included 280 nurses who reported not using AI in their practice (nonusers) and 27 who identified as current users. The respondents were predominantly female, 84.3% (n=236) among nonusers and 74% (n=20) among users, with male respondents comprising 13.6% (38/280) and 22%

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(6/20), respectively. Regarding professional experience, 55% (154/280) of nonusers and 56% (15/27) of users reported having 16 years or more of nursing experience. Concerning facilitating conditions, AI nonusers reported significantly lower familiarity with AI technologies (mean 3.8, SD 1.9) compared to AI users (mean 5.0, SD 2.1), suggesting that familiarity may play a role in shaping adoption behavior.

Table . Profile of the respondents.

Nurses' individual background and facilitating conditions for AI[a] (VIF)[b]	AI nonusers (n=280)	AI users (n=27)	*t* test; 2-tailed (*df*)	*P* value
Nursing experience (VIF: 1.02; years), n (%)			−0.61 (305)	.55
1: 0-5	35 (12.5)	3 (11.1)		
2: 6 - 10	51 (18.2)	5 (18.5)		
3: 11 - 15	39 (13.9)	4 (14.8)		
4: 16 - 20	45 (16.1)	4 (14.8)		
5: 21 - 30	70 (25)	3 (11.1)		
6: 30 or more	39 (13.9)	8 (29.6)		
Prefer not to respond	1 (0.4)	0 (0)		
Gender (VIF: 1.02), n (%)			1.03 (29)	.31
1: Female	236 (84.3)	20 (74.1)		
0: Male	38 (13.6)	6 (22.2)		
Prefer not to respond	6 (2.1)	1 (3.7)		
Digital technology literacy (VIF: 1.07)			−0.46 (305)	.64
Mean (SD)	3.7 (0.9)	3.8 (0.8)		
Minimum	1	3		
Maximum	5	5		
Familiarity with AI (VIF: 1.07)			−3.01 (305)	.003
Mean (SD)	3.8 (1.9)	5.0 (2.1)		
Minimum	1	1		
Maximum	10	10		

[a]AI: artificial intelligence.

[b]VIF: variance inflation factor.

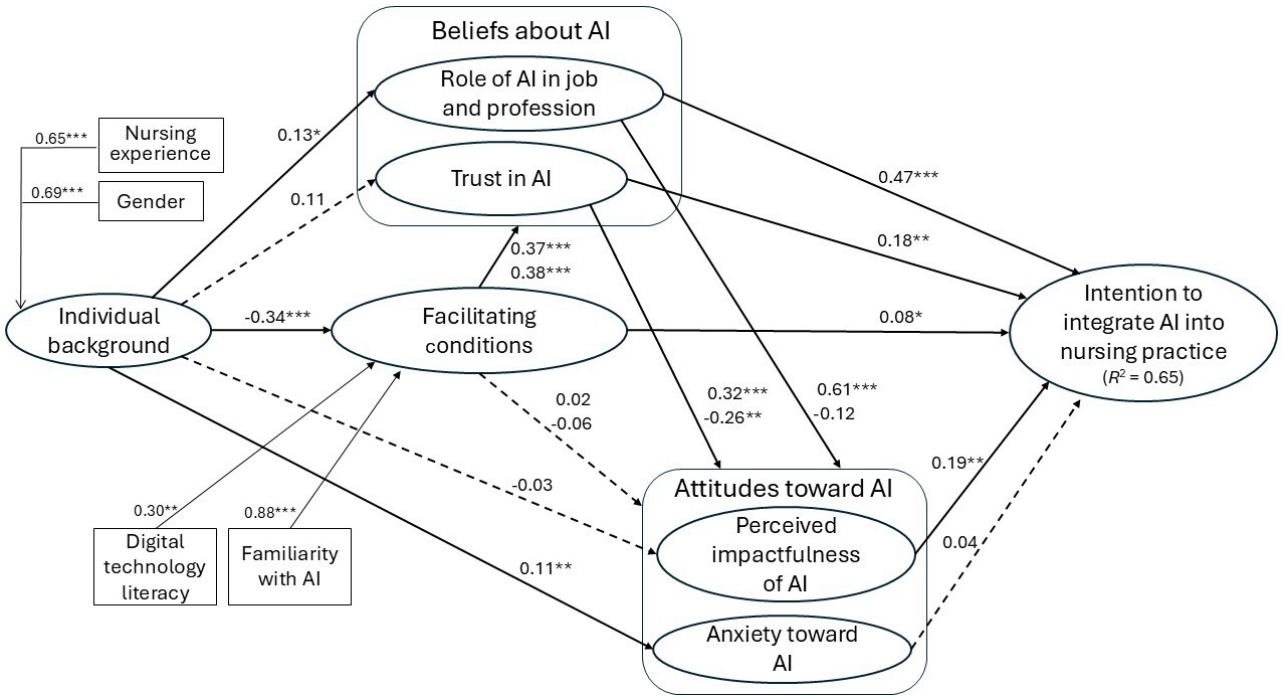
Given the PLS-SEM model to be tested, an a priori power analysis was conducted using G*Power (version 3.1.9.7; Heinrich-Heine-Universität Düsseldorf) [36] to determine the minimum sample size required to detect an R^2 of 0.10 with 80% power and a 5% significance level. Based on this analysis, a minimum of 122 respondents was required [37]. Although response rates of 10% to 15% are common in online social science surveys [38], such rates may introduce the risk of nonresponse bias [39]. To assess this possibility, we first compared the responses of the 61 "late" respondents (ie, the final 20% of participants) with those of the 246 earlier respondents, following the procedure recommended by Hikmet and Chen [40]. No statistically significant differences were found between the 2 groups concerning key variables, including facilitating conditions, beliefs, attitudes, and behavioral intention toward AI. As a second step, we compared the demographic characteristics of our sample with those of the broader population of nurses in Québec. The sample was found to be representative in terms of age, gender, and years of professional experience. Taken together, these 2 assessments suggest that nonresponse bias is unlikely and that our sample reasonably reflects the characteristics of the target population.

Measurement Model Analysis

To address missing data, mean substitution was applied to the research variables included in the analysis. In our model, 2 constructs—individual background and facilitating conditions for AI—are specified as formative, reflecting their composite and multidimensional nature (Figure 2). The remaining 5 constructs are modeled as reflective. The analysis was conducted using the *SEMinR* package for PLS-SEM, which allows for the simultaneous estimation of the measurement and structural models. Accordingly, the psychometric properties of the 7 constructs were assessed within the context of the full research model.

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Figure 2. PLS-SEM results (n=280). Gender (0: male; 1: female); * *P*<.10, ** *P*<.05, *** *P*<.001. AI: artificial intelligence; PLS-SEM: partial least squares structural equation modeling.



The first step in evaluating the reflective constructs involves assessing their internal consistency and unidimensionality. As shown in Table 2, all Cronbach α values exceeded the recommended threshold of 0.70, indicating satisfactory internal consistency. Unidimensionality was assessed by examining the standardized item (indicator) loadings for each construct. For exploratory research, a loading of at least 0.60 is typically considered acceptable, while a threshold of 0.40 may be tolerated for newly developed scales [37]. The indicator loadings for all reflective constructs met or exceeded these thresholds, thus supporting their unidimensionality.

Table . Unidimensionality and internal consistency of the research constructs.

Research construct (number of items)	α[a]	Item loadings							
		λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8
Role of AI[b] in jobs and professions (8)	0.89	0.82	0.82	0.87	0.64	0.79	0.61	0.59	0.43
Trust in AI (3)	0.76	0.90	0.82	0.43	N/A[c]	N/A	N/A	N/A	N/A
Perceived impactfulness of AI (6)	0.83	0.85	0.90	0.74	0.90	0.82	0.72	N/A	N/A
Anxiety toward AI[d]	1.00	1.00	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Intention to integrate AI into practice (3)	0.86	0.70	0.95	0.81	N/A	N/A	N/A	N/A	N/A

[a]Cronbach α coefficient of reliability.

[b]AI: artificial intelligence.

[c]N/A: not applicable.

[d]Index (as opposed to scale) measure.

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Next, because the standard reliability and validity criteria used for reflective constructs do not apply to formative constructs, it is essential to assess the absence of multicollinearity among the indicators of each formative construct. This is typically evaluated using the variance inflation factor, with values below 3.3 indicating acceptable levels of collinearity [41]. In our analysis, variance inflation factor values for the 6 formative indicators ranged from 1.01 to 1.29, well within acceptable limits, thereby confirming the absence of problematic multicollinearity.

Once the formative constructs have been validated, we proceeded to assess the reliability, convergent validity, and discriminant validity of the 5 reflective constructs. As shown in Table 3, all composite reliability coefficients exceeded the recommended threshold of 0.70, supporting the internal consistency of these constructs. Evidence of convergent validity is provided by the average variance extracted values, all of which were above the 0.50 threshold, indicating that each construct explains more than half of the variance in its indicators.

Table . Reliability and validity of the research constructs.

Research construct	cr[a]	AVE[b]	HTMT[c] matrix						
			1	2	3	4	5	6	7
Individual background	N/A[d]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Facilitating conditions for AI[e]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Role of AI in jobs and professions	0.89	0.50	0.27	0.39	N/A	N/A	N/A	N/A	N/A
Trust in AI	0.78	0.56	0.25	0.35	0.76	N/A	N/A	N/A	N/A
Perceived impactfulness of AI	0.93	0.68	0.14	0.31	0.85	0.78	N/A	N/A	N/A
Anxiety toward AI[f]	1.00	1.00	0.29	0.29	0.34	0.37	0.32	N/A	N/A
Intention to integrate AI into practice	0.86	0.68	0.27	0.34	0.77	0.69	0.74	0.26	N/A

[a]Composite reliability of a reflective construct = $(\Sigma\lambda_i)^2/((\Sigma\lambda_i)^2+\Sigma(1-\lambda_i^2))$.

[b]AVE: average variance extracted (by a construct from its reflective indicators) = $\Sigma\lambda_i^2/n$.

[c]HTMT: heterotrait-monotrait ratio of correlations.

[d]N/A: not applicable.

[e]AI: artificial intelligence.

[f]Index (as opposed to scale) measure.

The final step involved verifying discriminant validity, which ensures that each construct is empirically distinct from the others. For the 2 formative constructs, discriminant validity is supported by the fact that each shares less than 50% of its variance with any other construct (ie, interconstruct correlations remain below 0.71). For the 5 reflective constructs, discriminant validity was assessed using the heterotrait-monotrait ratio of correlations. As indicated in Table 3, all heterotrait-monotrait ratio of correlations values fell below the 0.90 threshold [42], thus confirming satisfactory discriminant validity.

The use of a self-administered questionnaire with a single respondent per case introduces the potential for common method bias (CMB), which can inflate observed relationships among constructs. To mitigate this risk, we implemented procedural remedies, including the use of varied question formats and response scale types. Additionally, we conducted statistical checks to assess the presence of CMB. First, we examined the correlation matrix among the 5 reflective constructs. According to prior recommendations, interconstruct correlations exceeding 0.90 may indicate problematic common method variance [43]. In our data, the highest observed correlation—between role of AI in jobs and professions and perceived impactfulness of AI—was 0.78, suggesting that CMB is unlikely to be a significant concern.

To further assess CMB, we conducted the Harman single-factor test, which involves an exploratory factor analysis of all reflective items without rotation [44]. The results revealed the emergence of multiple factors, with no single factor accounting for the majority of the variance (ie, less than 50% of the total covariance). Taken together, these findings provide reasonable assurance that CMB does not pose a significant threat to the validity of our results.

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Path Analysis

The research model was tested by evaluating the path coefficients (β) that link the constructs in the research model, as shown in Figure 2.

- H1 (confirmed): results from the PLS-SEM analysis indicate a positive effect of nurses' beliefs about AI on their behavioral intention to adopt it. Specifically, nurses who perceive AI as playing an important role in their jobs and professions report a stronger intention to integrate AI into their practice (β=.47, *P*<.001). Additionally, trust in AI also exerts a significant, though smaller, positive effect on behavioral intention (β=.18, *P*=.0389).
- H2 (partly confirmed): this hypothesis posited a positive relationship between nurses' attitudes toward AI and their intention to adopt it. This relationship is partially supported by the data. Nurses' perceptions of AI's impactfulness are significantly associated with their behavioral intention (β=.19, *P*=.0357). However, their feelings of anxiety toward AI do not significantly influence intention (β=.04, *P*=0.1615).
- H3 (partly confirmed): the expected positive relationship between nurses' beliefs about the role of AI in their jobs and professions and their attitude toward AI was partly confirmed. A significant positive effect is observed between nurses' perceptions of AI's role in their job and their views of its impactfulness (β=.61, *P*<.001), but no significant relationship is found between these beliefs and anxiety about AI (β=−.12, *P*=.1715). In contrast, nurses' trust in AI significantly influences both dimensions of attitude: positively with perceived impactfulness (β=.32, *P*<.001) and negatively with anxiety (β=−.26, *P*=.0114).
- H4 (confirmed): the analysis reveals that facilitating conditions exert a positive and statistically significant influence on both components of nurses' beliefs about AI. Specifically, facilitating conditions are positively associated with nurses' perceptions of AI's role in their jobs and professions (β=.37, *P*<.001), as well as with their trust in AI (β=.38, *P*<.001). As shown in Figure 2, the most influential explanatory element within the facilitating conditions construct is familiarity with AI, highlighting it as a critical enabler of positive beliefs regarding AI adoption in nursing practice.
- H5 (unconfirmed): contrary to expectations, facilitating conditions—particularly nurses' familiarity with AI—were not found to significantly influence attitudes toward AI. Specifically, no significant relationship was observed between facilitating conditions and perceptions of AI's impactfulness (β=.02, *P*=.3194), nor between facilitating conditions and feelings of anxiety related to AI (β=−.06, *P*=.1792). These findings suggest that while facilitating conditions shape beliefs, they do not directly affect attitudes, and thus their influence on behavioral intention is indirect, operating through beliefs rather than attitudes.
- H6 (confirmed): as hypothesized, a statistically significant, though modest, direct effect was found between facilitating conditions and nurses' behavioral intention to adopt AI (β=.08, *P*=.0599). More importantly, facilitating conditions also exert an indirect effect on intention, mediated through nurses' beliefs about AI. This finding underscores the importance of ensuring adequate support structures and familiarity with AI to foster both belief formation and intention to adopt AI tools in nursing practice.

Regarding the influence of individual background characteristics, the results indicate that experienced female nurses reported lower levels of familiarity with AI, stronger beliefs about AI's role in their jobs and professions, and higher levels of anxiety toward AI when compared to inexperienced male nurses. Taken together, nurses' familiarity with AI, their beliefs about its relevance, and their attitudes toward its use explained 65% of the variance (R^2) in their intention to integrate AI into clinical practice. This substantial explanatory power provides strong empirical support for the overall validity of the research model tested in this study.

Discussion

Principal Findings

This study aimed to identify the key factors influencing nurses' intention to integrate AI into their clinical practice. Our findings offer several important insights into the relationships among nurses' familiarity with AI, their cognitive beliefs about AI, their affective attitudes toward AI, and their behavioral intentions regarding its integration in nursing practice.

Our study found that nurses' beliefs, specifically their perceptions of AI's relevance to their role and their trust in AI technologies, were significant predictors of their intention to integrate AI into clinical practice. Nurses who recognized the meaningful contribution of AI to the nursing profession and trusted its outputs were more inclined to adopt AI tools. These results are consistent with the TIB [15] and prior research [13,16,17], which emphasize the role of beliefs as cognitive antecedents to behavioral intention.

These findings are further supported by a recent scoping review on AI in health care [45], which identified trust in AI systems and perceived clinical relevance as 2 of the most frequently reported facilitators of adoption among health care professionals. In line with this broader evidence base, our study reinforces the centrality of belief-related factors in shaping adoption intentions. Importantly, the review also highlights a persistent gap in nursing-specific empirical studies, a gap our study addresses by focusing exclusively on nurses and providing actionable recommendations for strengthening both educational and organizational readiness for AI adoption and integration.

Second, while attitudes also played a role, their influence was more modest. Nurses' perceptions of AI's impactfulness, representing a positive evaluative attitude, were positively associated with intention, although the effect size was weaker than that of beliefs. In contrast, AI-related anxiety, a negative affective attitude, did not significantly predict behavioral intention. This lack of association may be explained in part by the relatively low levels of anxiety reported by participants (mean 0.9, SD 1.3 on a 0 - 4 scale). These findings suggest that although attitudes matter, they may be secondary to beliefs in predicting the intention to adopt AI. This pattern aligns with prior evidence in behavioral science, where cognitive beliefs

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often explain more variance in intention than affective evaluations alone [46,47].

Third, our results also highlight the importance of facilitating conditions, particularly familiarity with AI, in shaping beliefs. Nurses with greater exposure to and understanding of AI technologies were more likely to hold positive beliefs about AI's professional relevance and to trust AI-based tools. However, these conditions did not significantly shape nurses' attitudes, either in terms of perceived impactfulness or anxiety. This suggests that familiarity with AI serves as a foundational enabler of belief formation, which in turn influences attitudes and, ultimately, intention.

Finally, consistent with the TRA [20], we found that beliefs not only had a direct effect on intention but also indirectly influenced intention through their effect on attitudes. This mediating role reinforces the sequential logic of our model, wherein facilitating conditions act as antecedents to beliefs, beliefs act as antecedents to attitudes, and both beliefs and attitudes contribute to the formation of behavioral intention with regard to integrating AI into nursing practice.

Study Implications

Our study contributes to the growing body of literature on AI integration in nursing by providing empirical evidence on the factors influencing nurses' intentions to adopt AI. As health care services and systems evolve from physician-centric models toward greater interdisciplinarity [47,48], our findings help fill an important gap by focusing on the beliefs, attitudes, and intentions of nursing professionals, an understudied group in AI adoption research.

Our results have 3 main implications for nursing education, professional development, and institutional policy. First, the strong influence of familiarity with AI on both beliefs and behavioral intentions underscores the importance of targeted efforts to build AI literacy. It is important to distinguish here between general digital technology literacy, defined in our study as familiarity with everyday consumer technologies (eg, smartphones and mobile apps), and nursing informatics (NI) competencies, which encompass more advanced skills such as data interpretation, digital communication, and decision-making support using AI.

In Canada, recent updates to the national NI competency framework reflect this shift by explicitly including AI-related competencies that nursing students and professionals are expected to develop. These include understanding AI applications in clinical contexts, recognizing their limitations, and collaborating with AI-driven decision support systems. Raising awareness of these updated expectations is essential, particularly among nurse educators, curriculum designers, and clinical leaders. As noted by Lattuca et al [48], the novelty and rapid evolution of AI in health care mean that many educators and practitioners are still unfamiliar with how to prepare nurses to engage with these technologies.

To address this gap, we recommend that undergraduate and graduate nursing curricula incorporate dedicated AI literacy modules. These modules should go beyond technical content to include ethical considerations, human-AI collaboration scenarios, and critical appraisal of AI-driven decision support systems. Case-based learning and interdisciplinary projects could further support students in developing both conceptual understanding and practical readiness.

Second, for nurses currently in practice, continuing professional development programs should integrate hands-on demonstrations and simulation-based training with real or prototype AI-enabled tools. Providing opportunities to interact with AI in low-risk environments can enhance understanding, reduce anxiety, and strengthen trust. These interventions are especially important for nurses with less direct exposure to AI and can be aligned with evolving national competency frameworks and accreditation standards.

Third, health care institutions have a role to play in fostering and facilitating conditions for AI integration. This includes providing time and resources for training, supporting access to AI-enabled tools, and designating clinical champions who can help guide and mentor peers in adopting these technologies. Creating such conditions not only supports individual readiness but also helps build organizational capacity for responsible and effective AI deployment in nursing care.

Study Limitations and Future Research

This study has several limitations that should be acknowledged. First, the cross-sectional design of this study limits our ability to draw causal inferences. While our model is grounded in established behavioral theories, we cannot ascertain the temporal ordering of the observed relationships. Future research should consider longitudinal designs that track changes in nurses' beliefs, attitudes, and behavioral intentions over time. For instance, studies could follow nurses before and after targeted AI training programs or throughout AI implementation in clinical settings. This would allow researchers to assess whether increased exposure to AI technologies results in durable shifts in intention and eventual adoption. Longitudinal studies would also enable examination of organizational learning mechanisms and help identify critical windows for intervention.

Second, although our sample was shown to be demographically representative of the broader population of nurses in Québec, the response rate of 10% remains a potential limit. While this rate is consistent with prior online survey research targeting health care professionals [38], it may still introduce concerns regarding nonresponse bias. Despite conducting 2 standard tests, we acknowledge that our sample may underrepresent nurses with lower interest in or exposure to AI. Consequently, the relationships observed in our model (eg, between familiarity with AI and intention to integrate AI) may be somewhat inflated due to self-selection bias. Future studies using complementary methods (eg, follow-up interviews, alternative sampling frames) could help confirm the robustness and generalizability of these findings.

Third, a further limitation lies in our operationalization of familiarity with AI, which was measured using a single self-assessment item. While this approach offers a simple and scalable indicator, its breadth may result in variability in interpretation. Future studies could enhance content and construct validity by including behavioral indicators (eg, prior

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use of AI tools such as predictive analytics, chatbots, or clinical decision support systems) or by asking respondents to provide examples of specific AI applications they have encountered. Open-ended questions or mixed-method designs could also enrich understanding of the depth and context of nurses' familiarity with AI.

Fourth, this study was conducted in a country with an advanced national health system, Canada, which may limit the generalizability of the findings to other national contexts. Future studies could replicate this research in different countries and health care systems to compare results and enhance generalizability.

Fifth, further research is needed to explore other potential factors influencing AI adoption, such as organizational support, peer influence, and regulatory environments. Understanding these factors could provide a more comprehensive picture of the drivers and barriers to AI integration in nursing care.

Conclusions

Our study highlights the critical role of nurses' familiarity with AI, beliefs about AI, and attitudes toward AI in shaping their intentions to integrate AI into their practice. By addressing these factors through targeted educational programs and initiatives, health care organizations can promote the adoption of AI-based health technologies, ultimately enhancing the safety, quality, and efficiency of nursing care delivery. NI researchers should continue to investigate the complex interplay of factors influencing AI adoption to inform effective strategies for integrating AI into nursing practice.

Acknowledgments

We would like to thank the participating professional association for its valuable assistance with data collection. Funding for this research was provided by the Research Chair in Digital Health at HEC Montréal. The guarantor is GP.

Authors' Contributions

GP and FAES contributed equally to the conception and design of this study. GP performed the literature review. FAES was responsible for data collection. LR performed the data analyses. All authors contributed to the writing of this paper.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Questionnaire survey items.
[DOCX File, 19 KB - nursing_v8i1e76795_app1.docx]

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Abbreviations

AI: artificial intelligence
CMB: common method bias
NI: nursing informatics
PLS-SEM: partial least squares structural equation modeling
STROBE: Strengthening the Reporting of Observational Studies in Epidemiology
TAM: technology acceptance model
TIB: theory of interpersonal behavior
TRA: theory of reasoned action

Edited by E Borycki; submitted 30.04.25; peer-reviewed by M Kleib, M Shaban; revised version received 09.06.25; accepted 09.07.25; published 05.09.25.

Please cite as:
Pare G, Raymond L, Etindele Sosso FA
Nurses' Intention to Integrate AI Into Their Practice: Survey Study in Canada
JMIR Nursing 2025;8:e76795
URL: https://nursing.jmir.org/2025/1/e76795
doi:10.2196/76795

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Applications of Artificial Intelligence in the Control of Infectious Diseases in the Post-COVID Era: Scoping Review

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Abstract

Background: The COVID-19 pandemic exposed systemic vulnerabilities in public health infrastructure, underscoring the urgency for innovation in disease surveillance and emergency response. Artificial intelligence (AI) has emerged as a promising tool to enhance the accuracy, efficiency, and scalability of public health interventions. Yet, there remains a limited understanding of how AI has been applied in real-world infectious disease control and who is contributing to its development and implementation.

Objective: This scoping review aimed to map current applications of AI in public health practice for infectious disease control since 2020. Specifically, it examined (1) the types of AI tools in use, (2) their purposes and implementation contexts, and (3) the professional and institutional actors leading these efforts, including the role of nurses.

Methods: Using the Joanna Briggs Institute's population, concept, and context framework, a structured search in Ovid MEDLINE was conducted, which was guided by the "5Cs" framework for health emergency preparedness from the World Health Organization (WHO). The search focused on English-language, peer-reviewed studies from 2020 that used AI tools for infectious disease control within real-world public health practice. Nonoriginal articles, simulation-only studies, and studies that lacked real-world implementation were excluded.

Results: Out of 600 screened studies in Ovid MEDLINE, 10 met the inclusion criteria. Two major AI types were identified: machine learning (ML) algorithms and language-based tools such as chatbots and large language models. ML tools supported outbreak detection, risk stratification, and resource allocation, while language-based tools promoted health communication, particularly around immunization and HIV prevention. Studies were conducted in a diverse range of countries, including several low- and middle-income countries, and used national datasets or surveillance systems. Despite nurses comprising half of the global health workforce, no nursing-affiliated authors were found among first or corresponding authors, and no nurses were represented in the broader authorship of the included studies.

Conclusions: AI technologies are being increasingly applied to support public health responses to infectious diseases, with applications ranging from predictive analytics to real-time public engagement. However, adoption remains limited in scale, scope, and professional diversity. The near-total absence of nursing participation in AI-related public health research is particularly striking and represents a missed opportunity for inclusive innovation. Strengthening implementation research and advancing informatics education among nursing professionals are critical next steps to ensure that AI tools reflect the realities of public health practice and promote equitable outcomes.

(JMIR Nursing 2025;8:e84242) doi:10.2196/84242

KEYWORDS

artificial intelligence; infectious disease control; public health practice; machine learning; large language models; health communication; nursing representation; implementation science

Introduction

According to the World Health Organization (WHO), approximately 7.1 million deaths due to COVID-19 have been reported as of July 2025 [1]. This pandemic exposed the vulnerabilities and systemic shortcomings of global public health infrastructure, underscoring the urgent need for structural reforms [2]. COVID-19 clearly highlighted the limited and uncoordinated pandemic preparedness, leaving health systems unprepared and overwhelmed during a rapidly spreading outbreak [3].

It is evident that public health, like other facets of modern life, needs comprehensive modernization to ensure resilience and effectiveness in the face of future global health crises [4]. The

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potential of artificial intelligence (AI) has emerged as a powerful engine of transformation. While there is currently no universally accepted definition of AI in the field of public health [5], the WHO has described it as "the performance by computer programs of tasks that are commonly associated with intelligent beings" [6]. The application of AI to public health has started to reshape how agencies and the practitioners of health manage disease surveillance and health services, as well as how they predict, prevent, and optimize health outcomes at the population level [7]. Predictive modeling, real-time analytics, natural language processing (NLP), and automated support systems for decisions are some areas in which AI has shown great potential for enhancing accuracy, efficiency, and scalability [7-9]. In clinical and medical research, AI has been applied across diverse areas of health care, including disease diagnostics, infectious disease forecasting, medical imaging interpretation, and drug discovery [7,10,11]. However, in public health, it is still unclear which AI tools are being used in practice and to what extent.

As AI continues to revolutionize how data are collected, interpreted, and used for the control of infectious diseases, understanding how AI augments the practice of public health becomes critical. Mapping the landscape of AI applications to the control of infectious diseases provides a clear picture of the use of these technologies. This understanding is also relevant to the frontline workers of the public health workforce and the interprofessional teams of nurses, data scientists, epidemiologists, and public health practitioners, who are responsible for developing and delivering AI-based interventions. Interprofessional collaboration promotes the development of innovation, closing the gap between research and the frontline application of solving real-world health challenges [12].

Given their frontline roles, nurses need to be an integral part of interprofessional teams in AI development and implementation in health care and public health. Despite their vital role in health care delivery systems, nurses are often underrepresented in public health [13]. Nurses comprise approximately 50% of the global health workforce and have historically not only contributed to clinical care but also supported entire public health systems [14]. Nonetheless, the limited focus on nurses in public health underscores the need to incorporate nursing leadership and nursing expertise as integral components of equitable and sustainable systems [13].

In response to these challenges, this review aims to explore how AI has been used to support the control of infectious diseases in public health and how it strengthens responses to such challenges, particularly by examining the contributors in this emerging field. Specifically, it outlines the current landscape of AI applications in three key areas: (1) identifying the types of AI tools currently used for infectious disease control; (2) examining the specific infectious disease strategies where these tools are applied; and (3) analyzing who is leading and contributing to these AI-driven efforts, across countries, institutions, and professional fields, including nursing.

Methods

Structuring the Review Using the Population, Concept, and Context Framework

As the review's objective was to map the landscape of AI applications in infectious disease control, the population, concept, and context (PCC) framework recommended by the Joanna Briggs Institute (JBI) was adopted. The PCC framework is most suitable for reviews intended to clarify major concepts, identify areas of knowledge gaps, and summarize how research is conducted regarding a focus topic [15]. The review focuses on the actors involved in the control of infectious diseases (population), the use of AI tools for the control of infectious diseases (concept), and the postpandemic era of the practice of public health since the year 2020 (context).

Using the PCC framework, the following research questions were articulated:

1. What types of AI tools are currently being used to address infectious disease problems in public health?
2. How are these AI tools being applied across different stages and settings of infectious disease control?
3. Who is leading and participating in these AI-enabled efforts—specifically, to what extent are nursing professionals represented in the published literature?

Key Concept Definitions

To achieve conceptual clarity and provide consistent analysis, this review defined its 3 central concepts: AI, infectious diseases, and public health interventions.

AI is defined as the use of computational techniques that enable machines to perform tasks that typically require human intelligence [16]. This includes, but is not limited to, machine learning (ML), deep learning, NLP, neural networks, and large language models (LLMs) [16,17]. As the WHO pointed out, AI is now an integral part of how health systems operate [6].

Infectious diseases are illnesses caused by pathogenic organisms or their toxic byproducts, transmitted to susceptible hosts through contact with infected individuals, animals, or contaminated surfaces or objects [18]. Due to the possibility of rapid spread among populations and across borders, infectious diseases pose a constant and high-priority threat to global health systems [19]. The urgency of timely detection, decision-making, and coordinated responses in managing infectious disease outbreaks has made this domain a natural candidate for the application of advanced technologies such as AI [20].

Public health interventions refer to coordinated strategies implemented to achieve targeted outcomes related to disease prevention and population health improvement [21]. Infectious diseases, more than others, frequently need swift, orderly responses, which can be targeted at either the infecting source (the isolation or elimination of infectious material) or vulnerable persons (through quarantine, risk communication, or immunization) [22,23].

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WHO's 5Cs Framework for Health Emergency Preparedness and Response

For identifying studies that address all 3 core concepts (AI, infectious diseases, and public health interventions), a comprehensive search strategy was required. Although choosing keywords for AI and infectious diseases is relatively straightforward, the concept of public health interventions is more expansive and diverse. To address this complexity, the WHO's "5Cs" framework for health emergency preparedness and response was adopted as a conceptual guide [24]. The framework organizes intervention efforts into 5 domains: Emergency Coordination, Community Protection, Collaborative Surveillance, Safe and Scalable Care, and Access to Countermeasures. These elements capture the practical requirements of real-world infectious disease response and, as such, represent a suitable resource for informing this review.

Each of the domains was then related to applicable infectious disease control concepts and subsequently linked to Medical Subject Headings (MeSH) (Table 1). For example, the domain of Collaborative Surveillance was linked to terms such as "Population Surveillance," "Contact Tracing," and "Early Diagnosis." Some of the terms were applicable in more than one domain, like "Emergency Medical Services" and "Diagnostic Tests, Routine," as they span multiple areas of public health response rather than being limited to a single function.

Table . Mapping of the domains of the World Health Organization's 5Cs strategy to infectious disease concepts and MeSH[a] terms.

5Cs strategy domains	Infectious disease concepts	Related MeSH terms
Emergency Coordination	• Emergency preparedness • Outbreak response • Incident management	• Disaster Planning • Emergency Medical Services • Disease Outbreaks • Public Health Administration
Community Protection	• Vaccination • Risk communication • Health education • Community engagement	• Vaccination • Immunization Programs • Health Education • Health Communication • Community Participation
Collaborative Surveillance	• Surveillance • Contact tracing • Screening • Early detection	• Population Surveillance • Contact Tracing • Diagnostic Tests, Routine • Mass Screening • Early Diagnosis
Safe and Scalable Care	• Infection control • Health system capacity • Workforce protection	• Infection Control • Health Services • Delivery of Health Care • Emergency Medical Services
Access to Countermeasures	• Diagnostics • Therapeutics • Supply chains • Resource allocation	• Diagnostic Tests, Routine • Pharmaceutical Services • Pharmaceutical Preparations • Drug Delivery Systems • Resource Allocation

[a]MeSH: Medical Subject Headings.

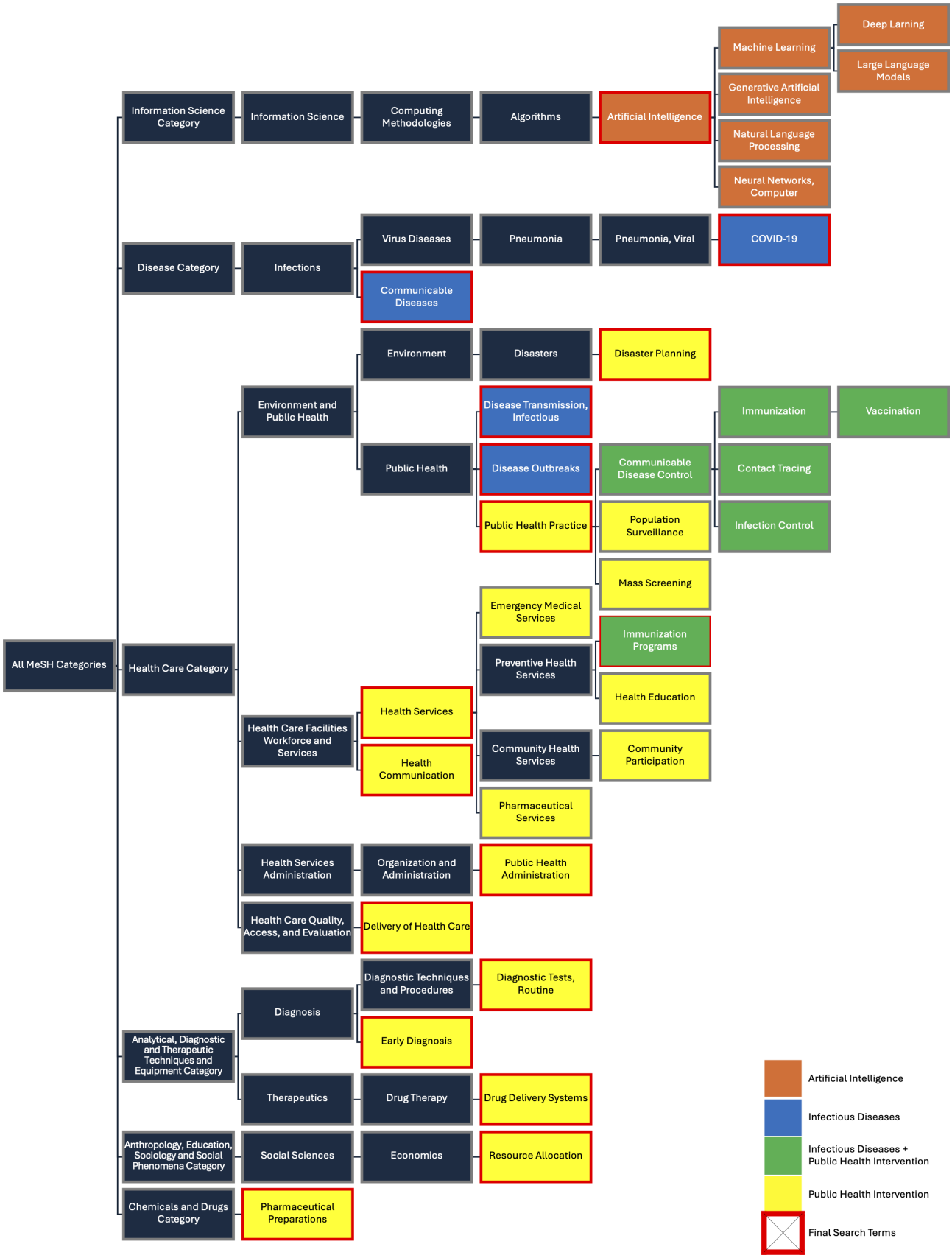
Search Strategy

To enhance the comprehensiveness of the search and minimize the risk of omitting relevant literature, the MeSH terms identified in relation to each WHO 5Cs domain were further examined in terms of their hierarchical structure. Wherever possible, broader parent terms were included in the search strategy to ensure that conceptually related subheadings were not excluded. For example, "Population Surveillance" and "Mass Screening" are nested under "Public Health Practice," and in this case, "Public Health Practice" was included. The search strategy is presented in Multimedia Appendix 1.

Figure 1 visualizes the final set of MeSH terms considered for inclusion, mapped onto their official hierarchical structure. Colors indicate conceptual categories: orange for AI terms, blue for infectious disease terms, yellow for public health intervention terms, and green for terms relevant to both infectious diseases and public health interventions. Terms in red boxes were ultimately selected for inclusion in the final search strategy.

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Figure 1. Hierarchical structure of reviewed and selected Medical Subject Headings (MeSH) for the final search strategy.



These finalized MeSH terms were combined to construct a conceptually aligned search strategy in Ovid MEDLINE, to reflect the 3 core domains of this review—AI, infectious diseases, and public health interventions. The explosion function enabled the incorporation of studies that included only narrower terms in the search results. For example, since "Public Health Practice" was included in the search strategy with the explosion function enabled, studies with keywords, such as "Mass

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Screening" or "Population Surveillance," which are nested under "Public Health Practice," were also captured in the search results.

For the concept of AI, the search strategy included the MeSH term "Artificial Intelligence" with the explosion function enabled. To ensure that AI was a central focus of investigation, the search was limited to studies that explicitly mentioned AI-related terms in the article title, including "Artificial Intelligence," "AI," "Large Language Model*," "Machine Learning," "Deep Learning," "Natural Language Processing," "Neural Network*," "Generative Artificial Intelligence," "ChatGPT*," and "Chatbot*."

For the second core concept, infectious diseases, the search strategy incorporated MeSH terms such as "*Disease Transmission, Infectious," "*Infectious Diseases," "*Disease Outbreaks," and "*COVID-19."

Lastly, to identify relevant studies involving public health interventions, MeSH terms selected based on the WHO's 5Cs framework were included: "*Disaster Planning," "*Public Health Practice," "*Health Services," "*Health Communication," "*Public Health Administration," "*Delivery of Health Care," "*Diagnostic Tests, Routine," "*Early Diagnosis," "*Pharmaceutical Preparations," "*Drug Delivery Systems," and "*Resource Allocation."

However, some terms, such as "Communicable Disease Control" and "Immunization Programs," inherently encompass the concepts of infectious diseases and public health interventions. To account for this overlap, search results for these combined terms were integrated with results from the separate concepts of infectious diseases and public health interventions using an OR operator, and the final set was combined with AI-related terms using an AND operator.

Finally, the search was limited to English-language, human-subject studies published from 2020 onward to reflect the post–COVID-19 landscape. Nonoriginal publications, such as case reports, commentaries, editorials, letters, meta-analyses, news articles, and review studies, were excluded from the search results.

Inclusion and Exclusion Criteria

The PCC framework was subsequently reapplied to guide the screening process and determine study eligibility. For the *population* element, the first step in screening was to determine whether the studies were concerned with infectious diseases affecting humans. Studies focusing on nonhuman pathogens (eg, infectious waste disposal) or environmental contamination were excluded.

Next, in line with the *concept* element, an assessment was conducted to determine whether the tools used in public health interventions were genuinely based on AI. Studies that involved only basic digitalization or mechanization, without integrating AI functionalities, were not considered eligible.

The *context* of the review focused on public health practice after the pandemic. In applying this criterion, particular attention was paid to whether each study explicitly addressed a public health domain. For example, if the study covered the AI tools that were used to support clinical decision-making in emergency department triage or to optimize resource allocation within health care facilities, the study was excluded, as these applications fall outside the scope of public health practice as defined in this review.

Another key element related to the context was the practical implementation of AI. Studies were excluded if the AI tools were not applied to real populations, did not utilize official public health data, or lacked real-world implementation. This included studies limited to development or analysis only, such as simulation or predictive modeling. However, studies were deemed eligible if they had a clear practical application to public health. For example, studies that used authorized public health systems or infrastructure for data, such as national surveillance platforms or electronic health records, were included, as they demonstrated direct relevance to and integration within existing public health practice.

Data Extraction

The initial screening was performed using Rayyan, a freely accessible web-based tool designed to support literature reviews [25]. Retrieved references were added to the software for the purpose of duplicate checking as well as title and abstract screening. Duplicates identified by the software were removed. The identified studies were evaluated in full text for the purpose of final inclusion.

Data extraction was conducted on all the studies identified for full-text screening. To ensure consistency and comprehensiveness, a standardized data extraction template was created using Microsoft Excel. The data involved general information about each study, including authorship, year of publication, country of origin, study objectives, study design, study setting, and study results.

Aside from the overall study features, additional data elements were extracted to answer each of the 3 research questions. To answer the first research question on the types of AI tools, information was collected on the specific AI technologies applied in the studies (eg, neural networks, ML, and NLP).

For the second research question on the application of AI tools in infectious disease control, data were extracted regarding their use or purpose (eg, prediction, prevention, surveillance, and response to outbreak), the degree of implementation (eg, local, national, and regional), and the specific type of infectious disease being targeted.

Finally, to address the third research question on leadership and participation in AI-enabled public health initiatives, affiliation data of the authors were obtained, including the type of institution (eg, university, government, or company), academic or professional discipline (eg, medicine, nursing, technology, or informatics), and authorship (eg, first author or corresponding author), with particular attention to the inclusion of nursing professionals.

A critical appraisal of study quality was not considered according to the updated methodological JBI guidelines for scoping reviews [15].

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Ethical Considerations

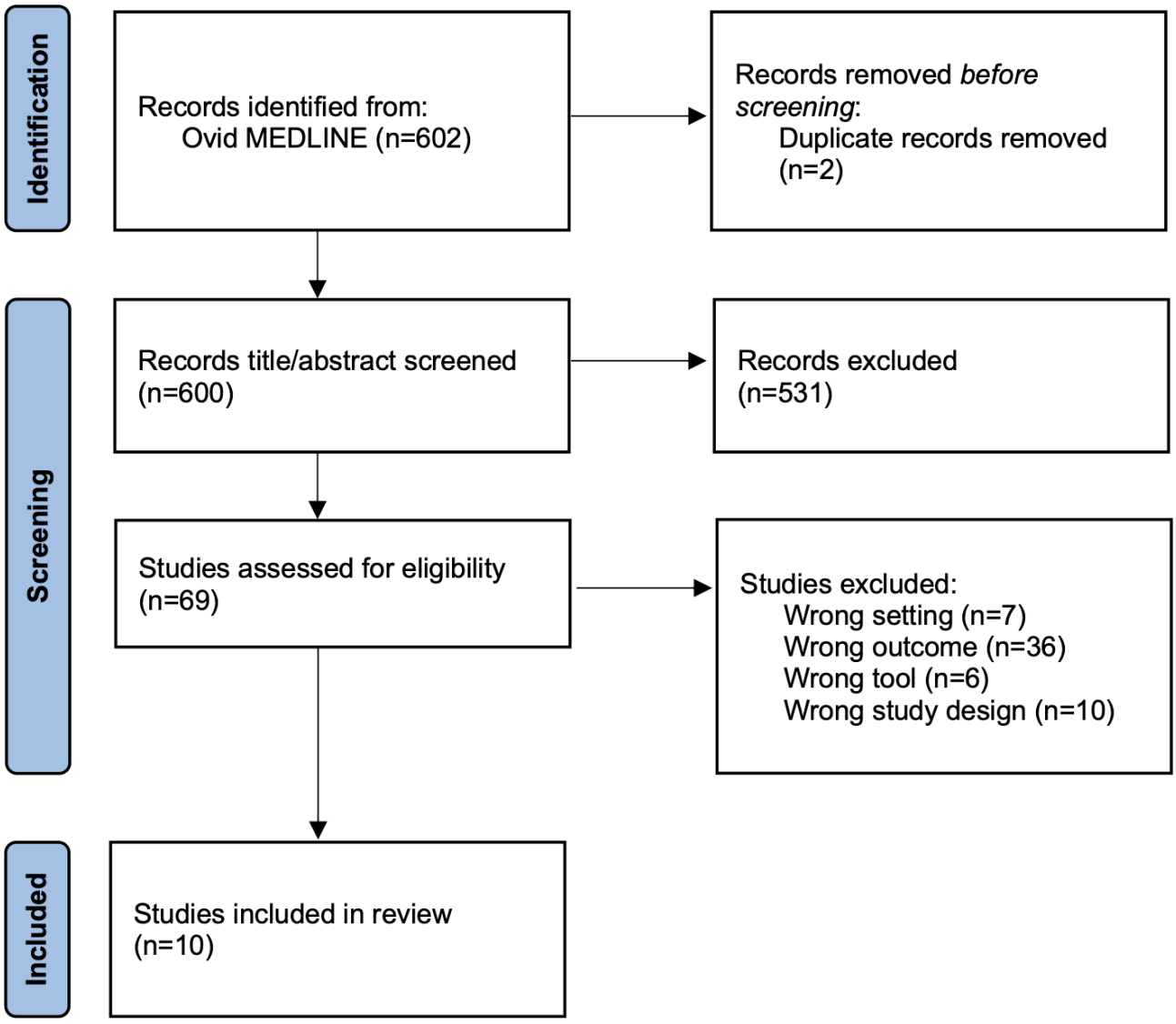
Ethics approval was not sought, as this review did not involve human subjects in any form (no collection of primary data from human participants or no use of secondary data).

Results

Article Selection

The initial search in Ovid MEDLINE identified 602 records on June 13, 2025. After removing 2 duplicate records, 600 unique articles remained for screening. During title and abstract screening, 531 articles were eliminated primarily because they did not involve infectious diseases affecting humans. Of the remaining 69 studies, 59 were screened out at the full-text level for reasons such as nonpublic health focus (eg, clinic- or hospital-based studies), inappropriate study design (eg, protocols or editorials), irrelevant intervention (eg, tools not based on AI), or lack of real-world application (eg, studies limited to model development or simulation rather than implementation) (Figure 2). As a result, 10 studies were ultimately included in the final review. The PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist is presented in Checklist 1.

Figure 2. Article selection process.



General Characteristics of the Included Studies

Table 2 provides an overview of the key characteristics of the 10 articles that were selected for this review. These studies reflected a wide geographic distribution and covered several countries, including the United States (n=1), Brazil (n=2), Pakistan (n=1), Italy (n=2), China (n=1), Kenya (n=1), and Tanzania (n=1), with 1 study covering multiple countries in Africa (Burundi, Ethiopia, Madagascar, Uganda, Rwanda, and Zambia).

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Table . Summary of key findings from the included studies.

Study	Country	Level of implementation	Target disease	Purpose of AI[a]
Asnake et al [26], 2025	Tanzania	National	VPDs[b]	Surveillance, vaccination
Cosma et al [27], 2025	Italy	Local	VPDs	Health communication
Friedman et al [28], 2025	Kenya	National	HIV	Screening
Gianquintieri et al [29], 2022	Italy	Local	COVID-19	Outbreak identification
Massa et al [30], 2023	Brazil	Local	HIV	Health education
Siddiqi et al [31], 2024	Pakistan	Local	VPDs	Vaccination, health education
de Souza Filho et al [32], 2023	Brazil	National	COVID-19	Screening
Tadese et al [33], 2024	Africa	Regional	VPDs	Surveillance, vaccination
Xiao et al [34], 2024	United States	Local	COVID-19	Resource allocation
Zhang et al [35], 2021	China	National	Foodborne diseases	Outbreak identification

[a]AI: artificial intelligence.

[b]VPDs: vaccine-preventable diseases.

In terms of scope, 5 studies used AI tools at the local level, targeting specific cities or subnational regions. Four studies were classified as national-level studies, including those that developed open-access web-based platforms without specifying a particular locality. The remaining study examined the regional usage of an AI tool and involved multiple African countries as mentioned above.

The target diseases of the included studies differed. Of the 10 studies, 3 addressed COVID-19, 4 addressed vaccine-preventable diseases, 2 focused on HIV, and 1 addressed foodborne diseases.

Research Question 1: Types of AI Tools

The first research question examined what types of AI tools have been used to support the management of infectious diseases for public health. ML was the most utilized approach, and it appeared in 7 of the 10 studies. The remaining 3 studies utilized language-based AI technologies, including LLMs and NLP (Table 3).

Table . Summary of machine learning and language-based artificial intelligence studies.

Study	Software	Performance evaluation
Machine learning studies		
Asnake et al [26], 2025	Jupyter Notebook	Accuracy, precision, recall, F_1-score, AUC[a]
Friedman et al [28], 2025	Likely implemented in R software	AUPRC[b]
Gianquintieri et al [29], 2022	Not specified	AUC
de Souza Filho et al [32], 2023	Not specified	Sensitivity, specificity, accuracy, AUC
Tadese et al [33], 2024	Jupyter Notebook	Accuracy, recall, F_1-score, precision, AUC
Xiao et al [34], 2024	Likely implemented in R software	Reduction in hospitalization
Zhang et al [35], 2021	Python	Recall rate, F_1-score
Language-based artificial intelligence studies		
Cosma et al [27], 2025	ChatGPT	—[c]
Massa et al [30], 2023	Dialogflow	—
Siddiqi et al [31], 2024	Python	—

[a]AUC: area under the curve.

[b]AUPRC: area under the precision-recall curve.

[c]Not applicable.

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Language-Based AI: LLMs and NLP

Studies using language-based AI differed from those using ML in both applications of AI and data collection and analysis. These studies typically released chatbots or conversational platforms in real-world settings. One example is the study by Massa et al [30], which involved the development of "Amanda Selfie," a gender-affirming chatbot that attempted to raise pre-exposure prophylaxis (PrEP) awareness among adolescents in Brazil. It was programmed to work on Facebook Messenger and used Dialogflow (Google LLC/Alphabet Inc), an NLP framework that allows the system to understand user messages as well as respond accordingly [36]. Dialogflow acts as the chatbot's brain, determining user intent as well as managing conversation flow. Programming languages for the chatbot were Perl (Larry Wall/The Perl Foundation) and JavaScript (Brendan Eich/Oracle Corporation). Frameworks, such as Bottender, Catalyst, and Mojo, were used to ease and streamline the development process.

In another study, Siddiqi et al [31] developed "Bablibot," a chatbot for caregivers of children who are eligible for immunization in Pakistan. Built with Python and the Django framework, it used NLP, ML, and a human-in-the-loop system combining AI automation with human oversight to provide real-time support in Roman Urdu via SMS text messages and WhatsApp messages. Bablibot was interoperable with the provincial immunization registry, providing customized responses, and could work without an internet connection, which made the project suitable for use in low-resource, low-literacy environments.

Another project used the readily available NLP-based AI model, ChatGPT, for generating and standardizing vaccination consent forms to be used in Italy [27]. In this study, the AI tool was used to provide customized information or recommendations depending on user needs. As a result, data for evaluating the effects of the AI tool were collected after deployment, based on actual user interactions.

ML Algorithms

Several studies employed ML to control infectious diseases from structured sets of data using supervised models of learning. As observed in studies by Tadese et al [33] and Asnake et al [26], model development began with data collection from large-scale, representative datasets, such as Demographic and Health Surveys (DHS), from which relevant features were extracted based on sociodemographic, maternal, and health care–related variables. In the study by Friedman et al [28], open-source geospatial datasets (eg, from WorldPop, Meta, or IHME) were also integrated to enrich individual-level medical data.

If needed, these datasets can be preprocessed through imputation of missing values; balancing techniques, such as SMOTE (Synthetic Minority Oversampling Technique); and normalization, so that ML models can learn properly scaled data [26,33]. However, if the ML model adopts the extreme gradient boosting (XGBoost) algorithm, which includes a built-in method called sparsity aware split finding, imputation is unnecessary because it enables handling missing values internally without prior imputation [28].

Building on this prepared data, model training is the follow-up step of tool development commonly mentioned in these studies, to enable accurate prediction or classification for a specified public health endpoint, for example, classifying children who are probable to have incomplete immunization or predicting zero-dose status [26,33]. In this step, various ML algorithms are commonly considered, for example, logistic regression, random forest (RF), support vector machine (SVM), XGBoost, and ensemble methodologies such as adaptive boosting. Tuning of hyperparameters is typically done as necessary for model performance optimization [26,28,33].

Common measures of evaluation included accuracy, precision, recall, and F_1-score [33,26], as well as area under the curve (AUC) [35,32]. Additionally, Friedman et al [28] used area under the precision-recall curve, which is of particular significance under drastic class imbalance. The selection of measures normally conformed to the nature of the set and the intention of prediction. These measures were used to gauge the quality and strength of trained models for performing special public health tasks of prediction. They indicate how effectively the models identify, predict, or classify public health events in practice. For example, a higher AUC reflects stronger discriminatory ability to distinguish between at-risk and not-at-risk populations, while a higher F_1-score suggests balanced model performance between sensitivity and precision, which is particularly valuable in public health decision-making.

Model interpretability is also a recurring focus. Tadese et al [33] and Zhang et al [35] used Shapley Additive Explanations (SHAP) values to quantify the input feature–specific contribution individually to model predictions, for use in supporting clinical or programmatic decision-making. In the study by Zhang et al [35], for instance, SHAP was used alongside tree-based models to identify salient risk factors for foodborne disease outbreaks from a national surveillance system across China. Additionally, Tadese et al [33] used SHAP for the interpretation of XGBoost predictors of incomplete immunization among children under the age of 5 years across East Africa. This assisted in distinguishing features that were common across underimmunized children. In each instance, the use of SHAP allowed for not only accurate but also interpretable prediction of modifiable risk factors and hence supported relevant public health responses.

Programming environments were stated explicitly, facilitating easier identification of development tools. Asnake et al [26] and Tadese et al [33] applied Jupyter Notebook, implying the use of Python. Zhang et al [35] also used Python, running their outbreak detection models with scikit-learn for model training and evaluation, XGBoost for boosting-based tree modeling, and fuzzywuzzy for string-based feature extraction.

In other cases, although the environment of programming itself was not mentioned, methodological information available suggests the likely selection of software. Xiao et al [34] likely ran their policy learning framework in R, as they closely followed the approach proposed by Athey and Wager, including

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the use of tree-based policy classes and doubly robust estimation [37]. Given that Athey and Wager provided R packages, such as policytree and grf, to support these procedures [37] and the model components of a similar nature (eg, finite-depth decision trees and generalized RFs) are also noted, the computational process of Xiao et al [34] strongly suggests an R-based implementation. Similarly, Friedman et al [28] did not indicate the use of software, but reference to the use of the mice package [38], an R package for handling multivariate imputation, suggests that R software was most likely used in their study.

Research Question 2: AI Application Purposes in Infectious Disease Control

The type of AI (whether language- or ML-based) played an important role in the type of infectious disease control activities supported. This review found that studies that applied language-based models were primarily designed to support health communication and health education, while studies that involved ML-based models covered large-scale analysis of structured data tasks, such as surveillance, case identification, outbreak prediction, and resource mobilization, which have traditionally required more time and human labor (Table 2).

Health Communication and Health Education

Both Massa et al [30] and Siddiqi et al [31] described language-based AI technologies that were implemented to enhance health communication. The chatbots actively involved people, using individually tailored communication to prevent infectious diseases. Specifically, the Amanda Selfie chatbot provided more culturally appropriate messages for adolescent men who have sex with men and adolescent transgender women to promote awareness and use of HIV PrEP. Amanda Selfie adopted the language used by these adolescents. Interestingly, 61.1% of adolescents were reached through Amanda Selfie, higher than what would be achieved on Instagram or WhatsApp. This tool was especially effective among transgender adolescent girls and young people. Although its sole impact on the uptake of PrEP was modest, Amanda Selfie showed increased uptake when accompanied by professional support.

Similarly, Bablibot promoted vaccination by providing essential information for caregivers [31]. By addressing common vaccine schedule worries, adverse events, and service delivery, the tool helped reduce caregivers' concerns regarding vaccination and promoted informed decisions. Its integration into the local immunization registry also supported customized communication based on children's immunization history. This helped Bablibot reduce missed vaccinations and increase caregiver confidence regarding immunization programs, where traditional one-to-one counseling remained limited.

Cosma et al [27] used ChatGPT for improving the usability and readability of vaccination consent forms as an alternative health communication. ChatGPT revised medical technical terms and abbreviated formal forms for ease of reading for patients and family members. These forms were subsequently evaluated by health care professionals in the vaccination unit, showing improved usability and readability. The AI tool served as an assistant for reducing the workload of manually preparing user-friendly health papers.

Identifying At-Risk Individuals or Populations

One of the significant strengths of ML is its ability to process large-scale data and extract complex patterns that would otherwise be unavailable using traditional statistical methods [39]. This makes ML an ideal candidate for identifying individuals or subgroups most vulnerable and those needing special consideration. For instance, Asnake et al [26] and Tadese et al [33] used supervised learning models, including XGBoost and RF, to analyze DHS data and predict incomplete or zero-dose vaccination status among children in East Africa. By identifying risk profiles, including maternal education, household income, antenatal care visits, and geographic location, the models presented actionable suggestions about subgroups that require the most attention for immunization outreach.

Friedman et al [28] demonstrated a similar approach for the scenario of HIV screening in Kenya. Based on routinely and officially collected electronic medical record data, they trained multiple supervised learning algorithms to identify individuals likely to test positive for HIV. Their model had remarkable predictive accuracy and was constructed for implementation into real-time clinical practice, with high suitability for resource-challenged settings. Hence, the system makes the most of the efficiency of the tests, optimizes service prioritization, and minimizes missed diagnoses.

One of the studies adopted probable case identification of COVID-19 using a digital screening platform [32]. The online platform used an ML algorithm to estimate the likelihood of COVID-19 based on user-reported symptoms and sociodemographic characteristics. Integrated into a telemedicine service, the platform helped reduce unnecessary hospital referrals by classifying patients requiring further evaluation. Deployed in Brazil during the early stages of the pandemic, it served as both a triage support system and an early warning mechanism for local outbreak control.

Early Warning of Disease Outbreaks

ML's capacity to process large and complex data is useful in various types of disease surveillance, including early warning of disease outbreaks. Zhang et al [35] developed a high-performance algorithm to overcome the large number of false positives of suspected outbreaks reported by China's national Foodborne Disease Monitoring and Reporting System. Among various ML algorithms that they explored, the XGBoost model achieved the highest performance, showing an excellent capability of distinguishing between true outbreaks and false alarms. Notably, the model output included not only binary classifications but also probability scores, enabling fine-grained alert levels.

Meanwhile, Gianquintieri et al [29] applied ML for emergency medical service records to create high-resolution territorial notifications for COVID-19 across Lombardy, Italy. The supervised learning algorithm (RF) reached approximately 80% sensitivity for identifying active transmission and provided daily, municipality-scale notifications capable of preceding official outbreak patterns. This approach facilitated more proactive public health responses and effective prioritization of

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testing and health care resources, particularly for initial or resurging pandemic waves.

Resource Allocation

Xiao et al [34] showed that the ML algorithm is also applicable for optimized resource allocation in a public health crisis. They developed a policy learning tree (PLT) model using retrospective electronic health record data to improve the distribution of monoclonal antibodies for COVID-19 treatment in the United States. The PLT model was trained to focus treatment on patients who would most benefit from treatment and minimize hospitalization. By comparison, the ML-based approach had higher accuracy and efficiency than traditional point-based strategies, and it has the potential to inform real-time clinical decision-making for public health emergencies.

Research Question 3: Leadership and Participation in AI-Enabled Public Health Efforts

To examine who is leading and participating in AI-enabled public health interventions, the institutional affiliations, disciplinary backgrounds, and authorships of the 10 selected studies were analyzed.

A total of 77 authors contributed to the 10 studies included in this review. Among them, 3 individuals held dual affiliations, resulting in 80 total institutional affiliations. As shown in Table 4, academic institutions accounted for the largest share (47/80, 59%), followed by government agencies (14/80, 18%), private companies (7/80, 9%), nongovernmental organizations (NGOs) (7/80, 9%), clinics (3/80, 4%), and independent research institutes (2/80, 3%).

Table . Institutional affiliations of authors contributing to artificial intelligence–enabled public health interventions.

Type of institution	Value (N=80[a]), n (%)
University	47 (59)
Government	14 (18)
Company	7 (9)
NGO[b]	7 (9)
Clinic	3 (4)
Research institute	2 (3)

[a]Three authors had dual affiliations; therefore, the total number of institutional affiliations (N=80) exceeds the total number of authors (N=77).

[b]NGO: nongovernmental organization.

The disciplinary classification of each author's affiliation was then analyzed. Of the 78 disciplinary designations identified among the 77 authors (accounting for dual affiliations), the most common area was public health, accounting for 34 out of 78 cases (44%). This was followed by informatics (17 affiliations, 22%) and medicine (15 affiliations, 19%). Technology-related disciplines accounted for only 5 affiliations (6%), while 7 affiliations (9%) fell into the "other" category (Table 5).

Table . Disciplinary classification of authors' affiliations.

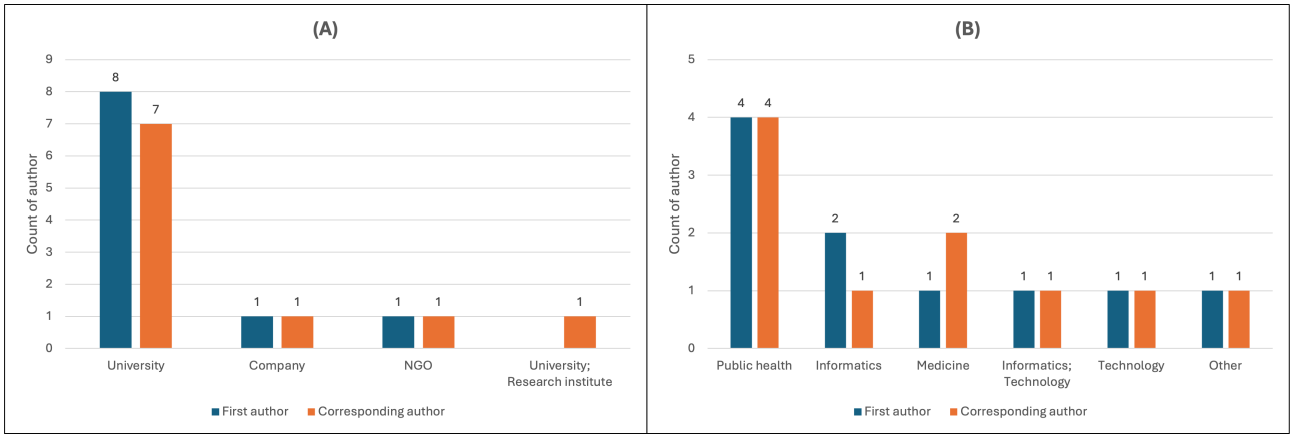
Disciplinary field	Value (N=78[a]), n (%)
Public health	34 (44)
Informatics	17 (22)
Medicine	15 (19)
Technology	5 (6)
Other	7 (9)

[a]Dual affiliations in different disciplinary fields resulted in a total of 78 disciplinary designations, although there were 77 authors in total.

Authorship roles were also explored to examine how leadership in AI-enabled public health interventions is distributed. Universities again comprised most first and corresponding author affiliations. Among the 10 studies, 8 had first authors from universities and 7 had corresponding authors from universities, followed by NGOs and an independent research institute (Figure 3A). Disciplinary affiliations also showed that public health was the most frequently represented field across both roles (Figure 3B). Informatics-related departments were more frequent for first authors, whereas medical departments were more likely for corresponding authors. There were no nursing-affiliated authors as first authors or corresponding authors, and the analysis of all co-authors did not indicate their presence.

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Figure 3. Author role distribution by institution type (A) and discipline (B) in artificial intelligence–enabled infectious disease control studies. NGO: nongovernmental organization.



Discussion

Principal Findings

This review aimed to map the use of AI for infectious disease control within public health settings in the post–COVID-19 era. It focused on identifying cases of actual implementation in real-world contexts. By synthesizing evidence from 10 studies across diverse global settings, it highlighted the types of AI tools used, their applications in infectious disease control, and the profiles of the experts leading these efforts.

AI for Infectious Disease Control: Language Models Versus ML

One valuable finding was the clear division of AI applications into 2 major categories: ML-based modeling and language-based communication tools. This distinction reflects broader structural dynamics in public health, where back-end analytics for decision-making and front-line community engagement for health communication often function as separate operational domains. ML tools like RF, SVM, and XGBoost, were frequently applied to structured datasets to perform classification, prediction, and risk stratification. These approaches facilitated the timely detection of populations at increased risk [26,28,33], outbreak forecasting [29,35], and data-driven resource allocation [34].

By contrast, language-based systems, such as chatbots and LLMs, were used primarily to enhance communication, education, and user engagement. These tools often operated on popular platforms like Facebook Messenger or WhatsApp, allowing real-time interaction in local languages and formats tailored to specific populations [30,31]. Their deployment was evident in interventions focused on vaccine promotion or HIV prevention, where timely and culturally responsive communication is essential [30,31].

Notably, these 2 categories vary in terms of not only function but also technological accessibility. AI implementation typically demands considerable technological infrastructure and expertise, including programming expertise, statistical modeling familiarity, and the ability to work with large-scale health data [40]. This might in part account for the fact that these tools were largely created within research institutes or universities. Conversely, language-based tools lend themselves more easily to implementation using available chatbot frameworks, application programming interface–based services, and commercial applications like ChatGPT. These systems usually demand no or little programming expertise and are thus more accessible for public health practitioners with limited technological capability [41]. As such, the lower barrier to entry for language-based AI might have made it easier to broadly adopt these technologies in real-world public health contexts.

However, the studies included in this review largely concerned text- and data-based modalities. While different forms of multimodal AI, including visual, behavioral, and biometric instruments, are becoming increasingly available [42], no multimodal AI studies were identified that involved application in practice within real-world public health, implying a limited technological scope within practice at present.

Some experimental research was found during the initial screening, which indicates potential directions. For instance, a study created an AI system to track people's social distancing in low-light situations and presented a possible solution for pandemic real-time behavioral tracking [43]. Other innovations included automated drone-based mosquito release systems [44] and mobile instruments for determining the species of mosquitoes based on sound recordings [45]. Although these studies were excluded from the final analysis due to limited real-world implementation, these examples show upcoming prospects for expanding AI use beyond text and data.

Two Functions of AI in Infectious Disease Control: Communication and Analysis

Another important finding of this review was that the functional applications of AI in the prevention and control of infectious diseases broadly fall into two main categories: (1) health communication and education, and (2) data-driven analysis and decision support. These functions were closely aligned with the type of AI technology employed.

Health communication and education emerged as prominent areas where AI was applied. Language-based tools, such as chatbots and LLMs, were commonly used to facilitate real-time messaging, disseminate accurate information, and encourage behavior change. These tools often operated on popular platforms like Facebook Messenger or WhatsApp [30,31].

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Cosma et al [27] further demonstrated that tools, like ChatGPT, can be not only effective but also easily implemented even by users with minimal technical expertise.

Meanwhile, ML was used to process large-scale datasets and inform decision-making and strategic planning. ML models were frequently used to analyze data from national surveillance systems, medical records, and health surveys. These models supported outbreak detection [29,35], identification of at-risk populations [26,28,32,33], and allocation of resources [34].

This functional divide suggests that the roles of AI in public health are shaped by not only technical capabilities but also the specific demands of the intervention context. Language-based AI excels in fostering user engagement and information exchange, whereas ML algorithms are better suited for handling complexity and scale in backend decision-making. While the former typically interfaces with the public, the latter primarily supports health professionals behind the scenes.

These findings are well aligned with the WHO's 5Cs framework, which was initially used to delineate the scope of public health interventions in this review. Language-based AI primarily supports community protection through communication and education, while ML contributes to collaborative surveillance, emergency coordination, and access to countermeasures by enabling data-driven prediction, response, and resource management across public health systems. Although safe and scalable care was not directly addressed in the reviewed studies, it remains an important domain for future AI applications in clinical and workforce settings.

Leadership Without Nurses? Participation Patterns in AI-Based Interventions

The authorship analysis revealed clear patterns regarding who is leading and participating in AI-enabled public health interventions. Academic institutions dominated authorship roles, accounting for the majority of both first and corresponding authors. Disciplines, such as public health, informatics, and medicine, were most represented, with technical and analytical expertise concentrated among first authors, and medical leadership more often reflected among corresponding authors.

However, one of the most striking findings was the complete absence of nursing professionals in primary authorship positions or among the broader group of co-authors affiliated with schools, colleges, or departments of nursing across the 10 final studies. This is surprising given the central role nurses play in health systems globally, particularly in frontline service delivery, community health engagement, and population-level care coordination [14].

Importantly, this absence does not appear to be limited to public health alone. A broader body of literature indicates that nurses are frequently absent from the design and decision-making structures for digital health technologies in other areas, such as clinical decision support, predictive analytics, and patient-facing AI [46,47]. As Bakken and Dreisbach argue [48], the incorporation of nursing insights is essential for creating more holistic health information systems.

As noted earlier, nurses comprise approximately 50% of the global health workforce, and there are an estimated 29 million nurses worldwide [14]. The limited involvement of nurses in the development and implementation of AI and other digital health technologies is an important issue that needs to be addressed. This underrepresentation may be partly explained by structural challenges like the unavailability of AI education or data infrastructure in nursing curricula or by further isolation of nursing expertise from technological innovation areas [48]. The American Association of Colleges of Nursing and the Alliance for Nursing Informatics are advocating for informatics/AI competencies in nursing education and advancing nursing informatics leadership, including AI projects, but gaps remain due to the need for training, curriculum revisions, and limited funding opportunities. The current gaps highlight an urgent need for more intentional inclusion of nursing voices within interprofessional teams developing and using AI-based technologies for public health and health science.

Recommendations to Address Gaps in Implementation and Representation

Gaps

Despite encouraging innovations, this review highlights several notable gaps. First, this review identified only 10 studies that implemented AI tools in real-world public health practice—a number vastly lower than anticipated, considering the number of AI research articles that get published at present. Second, the applications of AI were not evenly spread across regions and disease conditions. The majority were concerned with COVID-19 or vaccine-preventable infections, while other infectious diseases like tuberculosis and malaria still carry a large burden across the world, primarily in low- and middle-income countries [49,50]. Further, scaling up at national or international levels was less frequent, and this indicates low scalability for most tools beyond pilot scaling at local levels.

Strengthen Implementation Research on AI in Public Health Practice

The relative absence of implementation studies in public health indicates that most AI innovations exist at the pilot or proof-of-concept phase, with few attaining system-level implementation. To get a complete view of the feasibility, sustainability, and public health effects of AI-enabled interventions, more implementation research is needed. This involves exploring how AI tools get implemented, adapted, and scaled within the framework of the existing health system. Strengthening this body of work is essential to bridge the gap between AI-based tool development and the public health improvement desired, and to ensure that technological innovations translate into measurable improvements in disease prevention and control.

Next, and most importantly, there was no representation of nursing professionals as authors within the analyzed literature. Considering the important contributions of nurses to the health system, this omission is an important oversight. This oversight could affect the practicality and fairness of AI-enabled interventions in the real world. The complete absence of professionals affiliated with nursing programs or

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nursing-focused organizations in authorship roles, despite nurses' central roles in frontline health protection, is a significant finding for additional action.

Advance Informatics Education to Support Nursing Participation in AI

While educational background could not be assessed directly, this absence may underscore the need for formal informatics education and AI training in nursing, which includes foundational data literacy, ethics of AI, and basic principles of human-AI interaction. Future research must examine what the most ideal type of educational intervention, curricular revision, or continuing education is for equipping nurses with the baseline skills needed for contribution back into AI development and application. Empowering nurses with the ability to meaningfully interact with AI is not only a matter of workforce development but also a strategic imperative for ensuring that emerging technologies are grounded in the realities of care delivery and aligned with the values of person-centered, equitable public health.

Limitations

This review has several limitations. First, the search was limited to a single database (Ovid MEDLINE) and excluded studies indexed in other bibliographic databases (eg, Scopus, Web of Science, and IEEE Xplore). Hence, the results and subsequent interpretations are based on studies indexed in MEDLINE, which limits the comprehensiveness of the review, likely missing relevant studies in computer science or broader multidisciplinary databases. Although this strategy assisted in increasing the specificity of the search, it decreased the generalizability of the findings.

Second, the inclusion criterion was the use of AI tools in practical public health situations. Therefore, many simulation- or model-based studies were excluded. However, they could be helpful for future implementation in epidemic forecasting, as explained by Kraemer et al [51]. While the eligibility criterion in this study helped prioritize studies with demonstrated practical application, it may have narrowed the scope of technologies captured in the review.

Third, the disciplinary categorization of authors aligned with institutional affiliation and not with individual professional education. Therefore, the lack of nursing professionals could be an indication of the lack of metadata available and not the absolute absence of nursing engagement. In this way, the results for professional representation must be interpreted with care because the results could be affected by how disciplinary affiliation is reported and documented.

Conclusion

AI technologies are increasingly being applied to support public health responses to infectious diseases, with applications ranging from predictive analytics to real-time public engagement. However, adoption remains limited in scale, scope, and professional diversity. The near-total absence of nursing participation in AI-related public health research is particularly striking and represents a missed opportunity for inclusive innovation. Strengthening implementation research and advancing informatics education among nursing professionals are critical next steps to ensure that AI tools are equitable, reflect the realities of public health practice, and promote equitable outcomes.

Acknowledgments

The study authors thank Liz Weinfurter (health sciences librarian) for her guidance in the search strategy.

Funding

This study received funding from a rapid response grant of the Data Science Institute (DSI), Research and Innovation Office, University of Minnesota. The study principal investigator (SR) and first author (CK), who received research support from the grant as a student, are grateful to DSI for the funding.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Search strategy.
[DOCX File, 19 KB - nursing_v8i1e84242_app1.docx]

Checklist 1
PRISMA-ScR checklist.
[PDF File, 250 KB - nursing_v8i1e84242_app2.pdf]

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Abbreviations

AI: artificial intelligence
AUC: area under the curve
DHS: Demographic and Health Surveys
JBI: Joanna Briggs Institute
LLM: large language model
MeSH: Medical Subject Headings
ML: machine learning
NGO: nongovernmental organization
NLP: natural language processing
PCC: population, concept, and context
PLT: policy learning tree
PrEP: pre-exposure prophylaxis
RF: random forest
SHAP: Shapley Additive Explanations
SVM: support vector machine
WHO: World Health Organization
XGBoost: extreme gradient boosting

Edited by E Borycki; submitted 16.09.25; peer-reviewed by A Girma, T Ricks; revised version received 20.10.25; accepted 20.10.25; published 17.11.25.

Please cite as:
Kim C, Austin R, Wurtz R, Delaney CW, Rajamani S
Applications of Artificial Intelligence in the Control of Infectious Diseases in the Post-COVID Era: Scoping Review
JMIR Nursing 2025;8:e84242
URL: https://nursing.jmir.org/2025/1/e84242
doi:10.2196/84242

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Large Language Models in Nursing Education: Concept Analysis

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Abstract

Background: Large language models (LLMs) are increasingly used in nursing education, yet their conceptual foundations remain abstract and underexplored. This concept analysis addresses the need for clarity by examining the relevance, meaning, contextual applications, and defining attributes of LLMs in nursing education, using Rodgers' evolutionary method.

Objective: This paper aims to explore the evolutionary concept of LLMs in nursing education by providing a concept analysis through a comprehensive review of the existing published literature.

Methods: Rodgers' evolutionary concept analysis method was used. PubMed, CINAHL, PsycINFO, Scopus, and Google Scholar were used to search for relevant publications. A total of 41 papers were included based on inclusion criteria that focused on studies published in English within the last 5 years to ensure relevance to the current use of LLMs exclusively in nursing education. Studies were excluded if they focused on clinical nursing applications, were not available in English, lacked full-text accessibility, or examined other artificial intelligence (AI) technologies unrelated to LLMs (eg, robotics).

Results: As a result of this analysis, a proposed definition of LLMs in nursing education has been developed, describing them as accessible, personalized, innovative, and interactive tools that create revolutionary learning experiences, often leading to enhanced cognitive and skill development and improvement in learning and teaching quality.

Conclusions: This concept analysis highlights LLMs' transformative potential to enhance access to resources, support individualized learning, and augment nursing education. While promising, careful attention must be given to their limitations and ethical implications, ensuring their integration aligns with the values and goals of nursing education, particularly in specialized areas such as graduate nursing programs.

(JMIR Nursing 2025;8:e77948) doi:10.2196/77948

KEYWORDS

large language models; artificial intelligence; nursing education; undergraduate nursing education; graduate nursing education; concept analysis

Introduction

Over the last 5 years, there has been significant interest in the advancement of artificial intelligence (AI) in nursing education [1,2]. This includes a growing focus on AI-derived tools such as chatbots, adaptive learning systems, and AI-based patient simulations that offer opportunities to increase student engagement and motivation, improve learning outcomes, and support educators in their teaching efforts [3,4]. Recent discourse in nursing education has explored various intersections related to both educator and student engagement with AI, as related to aspects of the learning process [2,5], personalized instruction [6-8], interactive learning experiences [6,8,9], and enhanced access to diverse educational resources [6,9,10]. In addition to general discussion of AI in the learning process, the emergence of large language models (LLMs) has more recently gained popularity in the nursing education literature. LLMs are advanced types of AI systems trained on large volumes of text data to understand, generate, analyze, summarize, and predict additional content, simulating human-like interactions [11-13]. LLMs use deep learning, particularly transformer-based architectures, to process and produce coherent text responses based on user input [14].

The most widely known LLM is OpenAI's Generative Pre-Trained Transformer, or ChatGPT. ChatGPT was launched in November of 2022 and quickly became a groundbreaking application, obtaining 1 million users within 5 days, and over 200 million active users worldwide [11,13,15,16]. As of spring 2025, ChatGPT appears to be the most widely used and studied LLM in nursing education [16]; regardless, other models such as Google Gemini and Microsoft Bing are also considered LLMs and belong to this category [11]. Following the release of ChatGPT, concerns arose within the academic community regarding academic integrity, academic dishonesty, and excessive use of technology by students, prompting the New York Department of Education to abruptly restrict access to the LLM over fears of academic integrity breaches [9,17-19]. While these concerns are valid, LLMs continue to be applied in nursing

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education to enhance clinical simulation scenarios, provide personalized support for assignments, assist students and educators in developing study materials, and improve learning by promoting interactive discussions, problem-solving, and critical thinking [2,5,6,12,16,19-21]. Despite the increasing usage of AI-powered tools in higher education [1,3], the concept of LLMs in nursing education remains conceptually abstract. This lack of clarity is due in part to inconsistent terminology across the literature, with terms like "chatbot," "GenAI," and "LLMs" often used interchangeably without a clear distinction. Furthermore, there is a scarcity of formal definitions that delineate the role and scope of LLMs within nursing pedagogy. This conceptual ambiguity is further compounded by the evolving nature of the AI-powered technology itself and the variability in how learning outcomes are defined and assessed across educational settings [22]. Subsequently, the purpose of this paper is to explore and clarify the concept of LLMs in nursing education using Rodgers' [23] evolutionary concept analysis method. The analysis will examine and present the surrogate terms, defining attributes, antecedents, consequences, empirical referents, and a model case to further situate LLMs within the broader educational and technological landscape. As a result of this concept analysis, a definition of LLMs in nursing education will be developed and presented. Due to the limited clarity related to the theoretical foundations or practical applications of LLMs in nursing education, this concept analysis is important toward advancing understanding and guiding future research and practice of this emerging concept.

Methods

Design

Rodgers' [23] evolutionary method of concept analysis was chosen to analyze LLMs in nursing education because it accommodates the dynamic, context-dependent nature of emerging technologies, enabling an exploration of how the concept evolves over time and its significance in education [23]. Conducting a concept analysis using the Rodgers [23] method involves identifying the concept, its surrogate terms, and selecting suitable data collection methods; gathering data to determine attributes, antecedents, and consequences; and illustrating the concept with examples while identifying areas for further development [24]. Rodgers' [23] evolutionary concept analysis consists of several phases that are flexible and iterative, rather than following steps in a linear progression. The methodology outlined by Duffy et al [24] in their concept analysis of relational connection in telehealth practice was used to guide the methods of this analysis, as it offers a clear and systematic approach to examining evolving concepts within nursing practice in the context of emerging technologies.

Data Collection

A comprehensive search was conducted by the lead author between January and March 2025 across 5 databases: PubMed, CINAHL, PsycINFO, Scopus, and Google Scholar. Keywords included "large language models," "LLMs," "language model," "genAI," "conversational AI," "ChatGPT," "chatbot," "artificial intelligence," "AI," "nurs* education," "undergraduate nurs* education," and "graduate nurs* education." Boolean operators and truncation were used to optimize search sensitivity. Inclusion criteria focused on studies published in English in the last 5 years to ensure relevancy of the use of LLMs exclusively in nursing education. Exclusion criteria eliminated studies that focused on LLMs in clinical nursing settings, studies not published in English, studies lacking full-text accessibility, and studies that focused on other forms of AI technology unrelated to LLMs (eg, robotics). Antecedents of the concept were identified primarily from included articles; however, supplemental literature outside the inclusion criteria was also referenced. This approach was necessary, as not all included articles explicitly discussed antecedents of LLMs in nursing education. Titles were screened for relevance by the lead author, followed by abstract reviews for eligibility. Articles meeting the inclusion criteria were read in their entirety, and those that did not address the concept of LLMs in nursing education were excluded from the analysis. Reference lists of included articles were used to locate additional sources. In total, 41 articles were included; 36 met inclusion criteria directly, and 5 additional sources were included to support the discussion of antecedents. While the Elo and Kyngäs [25] method of inductive content analysis was not formally adopted, the thematic analysis conducted in this study closely aligns with its principles, including category development and abstraction to identify key attributes, antecedents, and consequences of LLMs in nursing education [25]. A total of 9 studies used qualitative methodology [9,12,17,26-31], 11 used quantitative designs [6,7,32-40], 1 used a mixed methods approach [41], 2 were educational evaluations or frameworks [16,42], 6 were narrative or discussion papers [11,19,43-46], and 7 were systematic, literature, scoping, or rapid reviews [2,5,8,18,20,47,48]. Among the 5 articles included for the discussion of antecedents, 1 was a policy report [49], 1 a professional standards document [50], 1 a conceptual framework [51], 1 a discussion paper [52], and one a literature review [53].

Results

The second step in Rodgers' [23] method of analysis involves identifying surrogate terms of the concept [20]. Currently, the nursing education literature uses a variety of definitions or terms to describe the concept of LLMs. Terms used to refer to the concept of LLMs in nursing education included AI-based LLMs [42]; AI model [31]; AI tool, system, or platform [6,9,31,38,42]; AI application [6,7,17,28,42]; technological support for learning [42]; generative AI [5-7,17,28,31,32,35,38,41,46]; large language technology [33]; text-generated language models [6]; natural language processing model or program [8,28]; ChatGPT chatbot [33]; generative pretrained transformers [7]; AI-powered chatbot [2,5,27,34,41]; automated conversational agents [2]; conversational AI [20]; software [31]; educational tool [7]; and learning assistance tool [39]. The included papers were reviewed to determine the attributes, antecedents, and consequences of LLMs in nursing education. Table 1 demonstrates a summary of the relationship between the antecedents, attributes, and consequences of the concept.

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Table . Relationship between antecedents, attributes, and consequences of large language models (LLMs) in nursing education.

Antecedents	Attributes	Consequences
• Technological infrastructure (eg, a device capable of running the LLM[a] and internet connection)	• Accessibility—easy to use across platforms; supports diverse users	• Enhanced cognitive skills and learning development (eg, improvements in critical thinking, clinical reasoning, decision-making, and learner confidence) • Linked to improved efficiency, creativity, self-efficacy, personal growth, communication, and problem-solving skills
• Technological advancements (eg, transformer architectures)	• Personalization—tailors content to user's learning needs, preferences, and goals	• Increased quality and accessibility of education: supporting educators in creating exam questions and simulation scenarios • Immediate access to information facilitates engagement, improving their learning experience • Supports global collaboration in nursing education
• Data availability: LLMs require and analyze extensive datasets	• Interactivity—real-time, dynamic responses; supports active learning and simulation integration	• Ethical and academic integrity concerns: raise questions around intellectual property and plagiarism
• Digital transformation in education	• Revolutionary nature—represents a paradigm shift in teaching; supports innovation in clinical and theoretical areas	• Practical limitations: may produce inaccurate information, weaken critical thinking and decision-making
• Shift toward competency-based, outcomes-focused education	—[b]	• Potential for bias and over-reliance: may perpetuate biases in nursing education
• Acceptance of AI[c] among students and faculty; social influence and motivation	—	—

[a]LLM: large language model.

[b]Not available.

[c]AI: artificial intelligence.

Attributes

Overview

When the attributes of a concept are unclear, practitioners may struggle to apply it effectively in essential tasks [23]. To assist with this, Rodgers' [23] fourth method of analysis includes the definition of attributes of interest. Through this process, recurring themes and key descriptors used to characterize LLMs in educational settings were identified, highlighting their impact and functionality. A total of 4 attributes were identified as the most consistently cited features, reflecting how LLMs adapt to individual needs, promote engagement, and transform nursing education. These identified attributes are (1) accessibility, (2) personalization, (3) interactivity, and (4) revolutionary nature.

Accessibility

A key defining attribute of LLMs in nursing education is their accessibility, a characteristic that has been highlighted across the literature as essential to their effectiveness in diverse educational settings, including undergraduate and graduate nursing programs [2,5,6,9,17,42,46]. The accessibility of LLMs enables students and educators to leverage LLMs without the barriers of cost or technical expertise [40]. LLMs are further distinguished by their accessibility on various devices, such as smartphones and laptops, allowing users to access their capabilities at any given moment, thus enhancing convenience and usability [43]. In addition, LLMs can significantly improve accessibility for non-English speakers and students with writing disabilities, as these individuals often face challenges with traditional methods of communication [42]. LLMs in nursing education offer new avenues for expressing ideas and demonstrating knowledge, breaking down language barriers [42]. Throughout the included literature, LLMs in nursing education were consistently highlighted for their accessibility, providing rapid and opportune access to vast amounts of information, allowing students and educators to efficiently retrieve and synthesize knowledge without the need to sift through extensive manuals or academic texts [16,18,45].

Personalization

Personalization was identified as a defining attribute of LLMs in nursing education, reflecting their innate ability to generate individualized learning experiences for users, adapting to one's unique needs, abilities, preferences, goals, and learning styles [18,26,36]. Numerous studies highlight LLMs' potential to improve nursing education via personalized interactions and responses when describing LLMs in nursing education [6,12,18,29,34,36]. ChatGPT in particular has been recognized for its ability to adapt to user preferences, enabling nursing students to customize its use in ways to achieve their individual

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learning goals [17]. The integration of LLMs offers a more personalized approach to nursing education, with students benefiting from individualized learning experiences [12]. Parker et al [29] emphasize ChatGPT's role as a "powerful self-learning" tool, highlighting its ability to engage with nursing students in personalized interactions. The personalization of LLMs extends to practical application in nursing education, as they can generate personalized study guides, act as an online tutor, and create tailored learning plans based on students' abilities to improve learning efficiency [18]. By individualizing learning opportunities, LLMs enhance learning efficiency, improve academic performance, and reinforce the value of personalization in nursing education [6,36].

Interactivity

Interactivity was identified as a defining attribute of LLMs in nursing education, particularly due to their ability to facilitate interactive learning and provide real-time feedback in response to user inputs [36]. LLM's ability to contextualize user queries promotes a bidirectional exchange, which is considered crucial in nursing education for reinforcing complex concepts [36]. Due to their interactivity, nursing educators are integrating LLMs into diverse settings, such as simulation-based education, to enhance the overall learning experience [46]. These simulations provide students with realistic patient interactions, helping them improve communication, history-taking, and clinical decision-making skills in a controlled environment [20,48]. Beyond simulations, LLMs are reshaping learning experiences by increasing student engagement and interaction [6,20]. This attribute distinguishes LLMs from other AI technologies, such as rule-based systems (eg, decision support systems), which lack the ability to adapt to user input in real time or facilitate an interactive educational experience [54]. LLMs' interactive capabilities set them apart from traditional chatbots by enabling more dynamic and meaningful conversations that encourage interactivity and adaptation in learning [6,9]. LLMs' advanced capabilities allow for deeper engagement through interactive learning experiences and LLM-generated study guides, which can assist students in developing critical thinking skills and gaining a more comprehensive understanding of course material [46].

Revolutionary Nature

The revolutionary nature of LLMs was identified as an attribute in nursing education due to their transformative impact across multiple dimensions of teaching, learning, and professional preparation [27,34,40,44,45]. LLMs in nursing education represent a paradigm shift, redefining traditional teaching methodologies by moving beyond passive didactic instruction toward dynamic, interactive, and technology-driven learning experiences [18,36]. Their revolutionary nature is reflected in their expansive potential to support skill development, clinical training, writing proficiency, research, and creativity, aligning with findings from non-nursing disciplines that position LLMs as a critical innovation in modern education [2,38]. Maykut et al [27] argue that the integration of LLMs into nursing education embodies the "fourth technological revolution," signifying a shift in how knowledge is digitalized, disseminated, and applied. ChatGPT stands out as a particularly influential LLM, offering unique opportunities to extend learning beyond the classroom by fostering knowledge acquisition, analysis, and application. Given its profound influence on student learning experiences, ChatGPT has emerged as a critical area of nursing research, necessitating ongoing evaluation of its effects on the learning process and overall academic performance [6]. As LLMs progress, their revolutionary nature will influence nursing education to evolve, bridging gaps in clinical preparedness, fostering digital literacy, and redefining the future of nursing education [27,45].

Antecedents

Antecedents are the events or phenomena that need to be present before LLM use in nursing education [23,24]. In this analysis, antecedents were identified as (1) technological infrastructure; (2) technological advancements; (3) data availability; (4) digital transformation in education; (5) the shift in nursing education toward competency-based, outcomes-focused learning; and (6) AI acceptance in nursing education. The primary antecedent of LLMs in nursing education is technological infrastructure, such as a device capable of running the LLM and an internet connection, ensuring accessibility for most educational settings [53]. Technological advancements, such as the development of transformer architectures (eg, GPT) are an antecedent as these developments allow LLMs to handle complex language tasks such as simulating clinical scenarios and providing instant feedback, making them valuable tools in nursing education [11,30,53].

Another antecedent is data availability; LLMs can assist students and educators by analyzing extensive datasets to generate personalized recommendations, customized learning experiences, immediate answers to clinical questions, and support clinical decision-making [55]. To enhance LLMs' effectiveness in diverse educational and practice settings, training LLMs with local datasets is essential [47]. This approach ensures response accuracy by aligning the model with the institution's specific practices while ensuring adherence to local policies and regulatory standards [47]. Concurrently, the "digital transformation of education," with the widespread adoption of learning management systems and internet-based platforms, acts as an antecedent to the integration of LLMs into nursing education [27,49].

The shift in nursing education toward competency-based, outcomes-focused learning acts as a key antecedent for LLMs in nursing education. This change is reflected prominently in guidelines such as the American Association of Colleges of Nursing recommended competencies [16,50] and the Canadian Association of Schools of Nursing National Nursing Education Framework [51]. However, it should be noted that this pedagogical emphasis on competency-based frameworks primarily represents a Western perspective. Not all literature reviewed explicitly addressed such an educational approach, and global variations in nursing curricula must be acknowledged. Despite these contextual differences, the increasing global focus on synthesizing skills and knowledge, alongside the integration of emerging technologies such as AI, aligns closely with the capabilities of LLMs to enhance competency development and

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clinical decision-making across diverse educational settings [16,50,51].

The growing acceptance of AI in nursing education serves as a crucial antecedent to the integration of LLMs, shaping both educators' and students' attitudes toward their adoption [52]. LLMs such as ChatGPT have generative and analytical capabilities that can reduce educators' workload [18]. From a student perspective, motivation to use LLMs is primarily driven by perceived value, including convenience, efficiency, and enhanced quality of their work [9]. Furthermore, subjective norms play a pivotal role in shaping students' decisions to adopt LLMs, as peer influence and social media exposure act as key determinants of new technology adoption [9]. The phenomenon of fear of missing out ("FOMO") further accelerates LLM use in nursing education as students may perceive themselves as missing out if they do not use AI tools that hold potential to improve their study performance [9]. In addition, the increasing integration of mobile phones, social media, and digital communication platforms is expected to drive the prevalence of LLM usage in nursing education [9]. LLMs' ability to enhance learning engagement and satisfaction further reinforces the growing shift toward AI acceptance in nursing education, emphasizing its role as a key antecedent in the adoption of LLMs [2]. However, organizational pressures, including restrictions from academic institutions, educators, and hospitals, may act as barriers to LLM adoption. Ma et al [9] found that some nursing students reported a diminished motivation to use LLMs due to prohibitions on use in specific contexts, whereas others experienced heightened curiosity due to the "forbidden fruit effect," where restrictions increased interest and engagement.

Consequences

Consequences are what occurs after or as a result of the concept being applied [56]. The included literature demonstrates several positive outcomes of LLMs in nursing education. The positive consequences have been grouped into two broad categories: (1) enhanced cognitive skills and learning development and (2) increased quality and accessibility of education. Alongside these consequences, some of the included literature raises concerns about possible negative consequences. While these concerns are emerging rather than empirically established, they warrant consideration as LLMs become more integrated into educational settings.

The integration of LLMs into nursing education has led to enhanced cognitive skills, including improvements in critical thinking, clinical reasoning, decision-making, and learner confidence [2,5,6,11,19,20,32,34,39,41,47,57]. Furthermore, the use of LLMs in nursing education has been linked to improved learning capabilities, efficiency, creativity, self-efficacy, personal growth, communication, and problem-solving skills [6,18,19,32,34,38,39,42]. Studies have found that LLMs provide personalized support, enabling students to grasp complex concepts more effectively and engage in self-directed learning and practice problem-solving in real time, maximizing their educational outcomes and professional skills [2,6,18-20,32,34,39,42]. While still emerging in practice, LLMs such as ChatGPT are increasingly used in nursing education, supporting educators in item generation and content preparation while expanding learning opportunities for students [7]. By assisting faculty members in generating simulation scenarios and exam questions, LLMs can reduce educators' workload, allowing them to focus on critical aspects of teaching, directly improving the quality of nursing education provided [5,7]. LLMs' ability to provide immediate access to information and instant feedback facilitates engagement, allowing learners to study efficiently based on their individual needs while improving their overall learning experience [17,19,41]. Furthermore, LLMs can enhance educational accessibility by supporting remote education for students in rural and underserved areas [5]. When integrated into nursing education, LLMs can facilitate global collaboration between nurse academics and students while blending traditional and digital learning approaches [5].

However, alongside these positive consequences, the literature also identifies several potential negative consequences associated with LLM use in nursing education. A frequently cited concern involves issues related to ethics and academic integrity. LLMs may generate content that lacks proper attribution, misrepresents sources, or closely resembles copyrighted materials, raising questions about plagiarism and intellectual property [9,18,19,29,30,34,39,42,47,57]. Another concern centers on the practical limitations of LLMs, particularly regarding the accuracy and currency of their output. Since LLMs depend on historical data and may not always reflect the latest clinical guidelines, they can inadvertently produce outdated or inaccurate information, which can pose a significant barrier to their safe application in practice-based education [5,13,18,34]. The potential for bias and over-reliance is also a critical area of concern. LLMs are trained on large datasets, often with limited transparency, which may embed or perpetuate existing biases in nursing education [18,19,30,33,57]. By providing immediate, automated responses, LLMs may weaken students' critical thinking, problem-solving skills, learner creativity, and ability to engage in independent analysis and decision-making [6,33]. Furthermore, the ease of access to LLMs could lead to automation bias, where students place undue trust in LLM-generated responses without critically evaluating their accuracy or applicability [18]. Assessing the true extent of these negative consequences is challenging, as students may underreport their dependence on LLMs, further complicating efforts to address this issue [9].

Empirical Referents

The sixth step of Rodgers' [23] evolutionary concept analysis requires the identification of concepts that are related to the concept of interest [23]. Instead, empirical referents or ways in which we see LLMs being used in nursing education will be discussed. This adaptation allows the concept analysis to provide more actionable insights in the field of nursing where practical application is critical [58]. This adjustment aligns with Rodgers' [23] framework as the method is inherently flexible and encourages adaptation to the concept's dynamic nature [23,59].

In nursing education, LLMs are used in three primary ways: (1) to support students in assignments and learning activities, (2) to assist faculty in developing and evaluating exam questions, and (3) to evaluate the performance of LLMs on nursing

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licensing exams. In undergraduate nursing education, LLMs are commonly used to enhance learning experiences by providing tutoring, generating explanations for complex nursing concepts, and assisting with academic writing [2]. For example, Tseng et al [38] found that nursing students frequently used ChatGPT for case report writing and academic support, although some struggled to connect nursing problems to individualized care plans due to overreliance on LLM-generated content. Similarly, Gonzalez-Garcia et al [6] observed that students using ChatGPT in coursework demonstrated improved academic performance, with women specifically reporting benefits in completing academic tasks. Some institutions have adopted structured LLM frameworks, such as OpenAI's CIDI (Context, Instructions, Details, Input) model, to facilitate decision-making through guided question strategies, differentiating it from more flexible systems like ChatGPT [32]. In addition, LLMs are being increasingly used to support simulation-based learning by generating clinical scenarios that help students refine critical thinking and problem-solving skills [5]. In graduate nursing education, LLMs are being used as research and programming support tools, such as assisting PhD students with data analysis [41] and guiding students on AI integration in coursework [16]. Furthermore, LLM-generated clinical data has been piloted in Doctor of Nursing Practice courses to develop competency and clinical judgment [30].

Faculty in nursing education have incorporated LLMs into the development and evaluation of exam questions to streamline item generation, assessment feedback, and case-based learning [7,29,33]. Cox et al [33] explored how ChatGPT can be used to generate National Council Licensure Examination for Registered Nurses (NCLEX-RN) examination questions, comparing LLM-generated items to those created by nursing educators. When in combination with human expertise, researchers found this LLM can assist faculty with item generation to help prepare nursing students for the NCLEX-RN examination [33]. Similarly, Parker et al [29] demonstrated the usability of LLMs in nursing education using ChatGPT as an automated writing evaluation (AWE) tool. Educators can enhance the feedback process without adding to their workload, while students can benefit from personalized feedback by integrating the AWE capabilities of this LLM into the writing process [29]. This integration allows for efficient, individualized support that accelerates learning and improves writing quality [29]. In addition, Higashitsuji et al [7] investigated the use of ChatGPT in case-based learning, where the faculty used the model to generate case scenarios significantly reducing the time required for case creation.

Researchers have assessed LLMs' ability to answer nursing licensure examination questions, evaluating their potential role in exam preparation and competency testing. Wu et al [39] analyzed the performance of LLMs on the National Nursing Licensure Examination (NNLE) in China and the NCLEX-RN in the United States and Canada. Through inputting exam questions to various LLMs, including OpenAI's GPT-4, GPT-3.5, and Google's PaLM, researchers compared their accuracy in responding to nursing-related content. This process allows educators and researchers to assess how well LLMs interpret and apply nursing knowledge under standardized testing conditions. The ways in which LLMs are being used in nursing education highlight their potential to serve as a valuable resource, aiding in the preparation for licensure exams and enhancing clinical decision-making skills [37,39].

Model Case

The model case, a significant component of Rodgers' [23] evolutionary concept analysis, is best identified through a real-world example rather than being constructed [23]. Including a model case that illustrates everyday instances of the relevant attributes helps clarify and strengthen the understanding of the concept [60]. The model case has been adapted from a real-world use case of ChatGPT described by Chang et al [32]; however, the specific identification of antecedents, attributes, and consequences has been applied based on the findings of this concept analysis.

In a third-year undergraduate nursing course focusing on health education design, students are tasked with creating a dietary education sheet tailored for pregnant women in their first trimester. This course is offered within a digitally progressive institution that has invested in advanced technological infrastructure and embraces AI integration as part of a broader educational transformation. Recent advancements in AI tools, the widespread availability of data, and the institutional shift toward competency-based, outcomes-focused learning have created an environment conducive to innovation. This setting reflects the growing acceptance of AI in nursing education and supporting the seamless adoption of LLMs to enhance teaching and learning practices. Recognizing the limitations of traditional teaching methods, the course integrates a revolutionary approach using an openly accessible LLM (ChatGPT). At the beginning of the course, students log into the LLM on their institution-provided laptops, which are part of a robust technological infrastructure supporting advanced learning tools. The LLM provides personalized guidance, addressing individual inquiries and offering tailored resources to meet each student's learning needs. The LLMs' adaptive responses clarify the student's doubts and introduce critical thinking prompts, challenging them to justify their choices based on the evidence. Throughout the course, the LLM facilitates ideation by allowing students to brainstorm solutions collaboratively. The interactive nature of the LLM transforms the learning experience into a dynamic, inquiry-based process. Students practice designing educational materials iteratively, receiving immediate feedback from the LLM, which they further refine in collaboration with their peers and instructors. This innovative, interactive framework fosters an environment where students can develop critical thinking skills and deepen their understanding of patient education. The students demonstrate enhanced cognitive abilities and learning development as evidenced by their ability to critically analyze complex health education scenarios and create effective solutions. Educators devote more time to mentoring and addressing individual learner needs using the LLM in this nursing course.

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Discussion

Principal Findings

Although the use of LLMs in nursing education is becoming increasingly prevalent, there has been significant oversight in clarifying their theoretical foundations and practical applications. Applying Rodgers' [23] method of concept analysis provides a deeper understanding of LLMs' unique qualities and applications within the context of nursing education. Based on the findings of this analysis, LLMs in nursing education can be defined as accessible, personalized, innovative, and interactive tools that create revolutionary learning experiences, often contributing to enhanced cognitive and skill development, as well as improvements in learning and teaching quality. Key characteristics frequently associated with LLMs in nursing education include accessibility, personalization, interactivity, and their revolutionary nature. One of the key findings of this concept analysis is the variation in terminology used to describe LLMs in nursing education. Various studies use different terms to define the use of LLMs in nursing educational contexts, making it challenging to form a unified understanding of the concept. Although more recent studies appear to be aligning around the term LLMs [5,8,9,31,35,38,61], there is still a lack of consistency in definitions. The term LLMs is continually evolving as the technology and its applications in nursing education develop [62]. It is important to establish a standardized terminology as these have been shown to have positive effects on clinical practice, enrich nurses' knowledge, and shift attitudes toward education and guidance [63]. Future research should prioritize refining and standardizing definitions to ensure clarity and facilitate more precise discourse in the field of nursing education.

As research on LLMs in nursing education continues to evolve, this analysis highlights an opportunity to explore their potential applications in nursing practice. The role of LLMs in clinical decision-making, patient care, and interprofessional collaboration remains underexplored, limiting our understanding of how LLMs may support or hinder nursing practice [9]. Similarly, Ma et al [9] suggest that nursing students, particularly those engaged in clinical practice, rely heavily on knowledge resources to ensure patient safety and quality care. This further emphasizes the need to examine how LLMs may influence these critical aspects of nursing practice. In addition, the outcomes of using LLMs in nursing education are not fully understood. While some studies report positive outcomes, such as enhanced student engagement, critical thinking, and problem-solving skills, others present a more balanced perspective, acknowledging both benefits and challenges, including ethical considerations, bias, and the risk of overreliance [2,5,6,9,11,18-20,32,34,35,38,39,41,42,47,57]. Given these are varied perspectives, further research can help build a clearer understanding of how LLMs influence nursing education and practice and whether their integration translates into meaningful improvements in nursing competency. One emerging ethical concern is the potential for gender bias in LLM outputs, which has been well-documented in recent research [64-66]. Gender bias can manifest in subtle ways, such as the reinforcement of stereotypically masculine traits in leadership examples or the undervaluing of female-associated attributes [64]. LLMs trained on gender-imbalanced datasets may unintentionally reproduce societal stereotypes, which could negatively affect how students perceive themselves and their professional roles [64].

As LLMs continue to be integrated into nursing education, efforts to establish structured guidelines on their implementation are still evolving. Some theoretical models have been proposed to help educators and students navigate the use of LLMs, yet their adoption varies across institutions. For instance, the IDEE framework created by Su and Yang [67], while not specific to nursing education, offers a structured approach for integrating AI into general education settings by identifying desired outcomes, determining appropriate levels of automation, ensuring ethical considerations, and evaluating effectiveness [17]. The IDEE framework offers a potential roadmap for educators looking to integrate LLMs and generative AI into their teaching practices. Similarly, Abujaber et al [43] applied a strengths, weaknesses, opportunities, and threats (SWOT) analysis to assess the integration of ChatGPT into nursing education, identifying both the advantages and challenges of its use. Abujaber and colleagues' [43] findings provide recommendations for educators, policymakers, and students to maximize benefits while mitigating risks. In addition, Blomquist et al [42] proposed a model that leverages existing decision-making and delegation frameworks to guide ethical LLM use in nursing practice. This approach suggests that nursing faculty and students could adopt structured decision-making principles to determine when and how LLMs should be applied. Furthermore, Goktas et al [68] developed specific guidelines for using OpenAI's GPT-4.0 in nursing education, using the prompt learning method to optimize student engagement and learning outcomes. Collectively, these frameworks highlight the diverse strategies being explored to ensure the effective and ethical integration of LLMs into nursing education, reinforcing the need for continued refinement and adaptation as these technologies evolve.

Limitations

Rodgers' [23] methodology of concept analysis, while effective in examining the attributes of a concept such as LLMs, has certain limitations when applied to contemporary technological phenomena in nursing education. First, the review was shaped largely by peer-reviewed studies from Western-based contexts, which may limit the transferability of findings to global or culturally diverse educational environments. This Western-centric lens risks overlooking region-specific challenges, values, or innovations in LLM use. In addition, the search strategy may have constrained the conceptual scope; the reliance on specific terms such as "LLMs" and "ChatGPT" likely excluded literature that described similar technologies using alternative terminology. As a result, relevant studies may have been unintentionally omitted. Although the thematic analysis in this analysis was informed by the principles of Elo and Kyngäs' [25] inductive content analysis, the absence of a formally structured analytic framework may limit the methodological rigor and replicability of category development and abstraction processes. Furthermore, while the negative consequences discussed are largely potential concerns rather than documented outcomes of LLM use in nursing education,

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they were included to reflect the emerging discourse and to encourage proactive consideration of possible risks as the technology continues to evolve. Finally, while the Rodgers [23] method emphasizes the evolutionary nature of concepts, it does not inherently accommodate the rapid pace and interdisciplinary complexity of technological innovation. As a result, a more inclusive, adaptive, and globally comprehensive approach may be necessary for future concept analyses involving emerging digital technologies in nursing education.

Conclusions

The concept of LLMs in nursing education represents a dynamic intersection of technology and pedagogy, marked by rapid evolution and untapped potential. This analysis reveals that while LLMs are reshaping learning through personalized, interactive, accessible, and revolutionary experiences, their meaning will continue to evolve alongside educational practices and technological advances. In addition, LLMs should be understood as adaptable tools whose value depends on thoughtful application and continuous evaluation. Moving forward, the nursing education community must foster a shared understanding of LLMs—one that balances innovation with caution, and usage with responsibility. As these technologies become increasingly embedded in educational and clinical contexts, future efforts should prioritize developing evidence-based guidelines, addressing conceptual ambiguities, and cultivating digital fluency among both learners and educators. Only then can LLMs be fully harnessed to enhance not just how nurses learn, but how they think, decide, and care.

Acknowledgments

JH gratefully acknowledges Smart'n, which provided a scholarship to support academic studies during the period in which this study was conducted.

Conflicts of Interest

JH is employed by a company that develops large language models. The company had no role in the design, analysis, or writing of this manuscript.

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Abbreviations:

AI: artificial intelligence
LLM: large language model
NCLEX-RN: National Council Licensure Examination for Registered Nurses

Edited by E Borycki; submitted 22.05.25; peer-reviewed by A Hartanto, R Kumar; revised version received 14.07.25; accepted 15.07.25; published 22.08.25.

Please cite as:
Harrington J, Booth RG, Jackson KT
Large Language Models in Nursing Education: Concept Analysis
JMIR Nursing 2025;8:e77948
URL: https://nursing.jmir.org/2025/1/e77948
doi:10.2196/77948

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Effect of an Extended Reality Simulation Intervention on Midwifery Students' Anxiety: Systematic Review

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Abstract

Background: Midwifery students often experience anxiety due to several factors, such as the clinical experiences faced. Simulation-based learning in nursing and midwifery studies using extended reality (XR) tools offers the opportunity to manage better educational processes while reducing this anxiety.

Objective: This study aims to evaluate the current knowledge and understanding of how the use of XR gesture-simulation-based tools allows a better understanding of the anxiety levels of midwives and nurses in educational settings.

Methods: We conducted a systematic review, a scientific literature search following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Using PubMed, IEEE, Scopus, and Web of Science, up to March 2024, 1005 articles were found to identify studies that reported the effectiveness of these technologies for gesture simulation in education and training on nursing and midwifery student anxiety. The inclusion-exclusion criteria were based on the PICO (population, intervention, control, and outcomes) framework. The population included nurses, midwives, and nursing and midwifery students of any kind using any virtual or augmented or mixed reality simulation training tool to perform a procedure aimed at reducing anxiety. In addition, the Cochrane risk of bias tool was used to evaluate the quality of the systematic review and the bias in the included studies. A narrative synthesis was conducted due to the heterogeneity of study designs and outcome measures. Key findings were summarized in a structured table and grouped according to the learning objective, simulating and performing procedures in an educational setting.

Results: Overall, 7 articles, involving a total of 428 participants, were included in this review. The findings indicate that XR can effectively reduce anxiety in midwifery and nursing education. However, the limited number of studies highlights a research gap in the field, particularly in the area of mixed reality, which warrants further exploration.

Conclusions: This systematic review highlights the potential of XR-based gesture-simulation tools in reducing anxiety among midwifery and nursing students. The included studies suggest that XR-enhanced training provides a more immersive and controlled learning environment, helping students manage stress and improve procedural confidence. However, the limited number of studies, methodological variations, and the underrepresentation of mixed reality applications indicate the need for further research. Future studies should focus on standardized anxiety measurement tools, larger sample sizes, and long-term impact assessments to strengthen the evidence base. Expanding research in this field could enhance the integration of XR technologies into midwifery and nursing education, ultimately improving both learning experiences and clinical preparedness.

(JMIR Nursing 2025;8:e68984) doi:10.2196/68984

KEYWORDS

anxiety; extended reality; gesture simulation; nursing education; midwifery education

Introduction

Anxiety is an emotion or state characterized by worry, tension, and physical manifestations such as increased blood pressure. Anxiety is often experienced in midwifery students due to heavy course load, high expectations, and the clinical experiences faced [1].

According to a mental health survey conducted by the National French Association of Midwifery Students (ANESF), with responses from 2000 students, 47% of the respondents showed a probable generalized anxiety disorder (as indicated by the

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GAD-7 test, General Anxiety Disorder-7, with a score of ≥10) [2,3].

Simulation-based learning is an important education modality because it allows students to learn from mistakes in a risk-free setting, acquire necessary competencies, practice decision-making, and significantly reduce potentially fatal medical errors [4]. More precisely, through gesture simulation, students can interact with virtual reality (VR) environments using hand movements and gestures, thereby reinforcing muscle memory and enhancing kinesthetic learning. This hands-on approach enables students to better grasp complex concepts, refine their motor skills, and simulate real-world scenarios with greater accuracy. In addition, gesture simulation fosters active engagement and participation, allowing students to feel more connected to the learning process and empowering them to take ownership of their education [5].

Extended Reality (XR) is a general term encompassing a range of immersive technologies, including Augmented Reality (AR), Virtual Reality (VR), Mixed Reality (MR):

1. AR overlays digital information, such as images, text, or 3D models onto the real-world environment viewed through a device's camera. The digital content is superimposed on the real world, enhancing the user's perception of reality [6].
2. VR completely immerses the user in a synthetic digital environment, replacing the real world with a simulated one. Users experience this artificial 3D environment through a headset that blocks out their physical surroundings [7].
3. MR seamlessly blends and anchors digital objects into the real world, allowing users to interact with physical and VR elements in real time. The VR objects in MR are integrated into and responsive to the real environment, creating a unified, interactive experience [8].

These tools blend physical and VR environments and over the last years, they have been in many fields, such as health care education or professional contexts, since they have the potential advantage of scalability, enhanced motivation, and cost savings [9].

By introducing XR simulation tools in midwifery education, the students can better understand complex concepts, practice skills in a safe environment, and build confidence in their abilities, reducing anxiety-inducing situations [10]. However, there is relatively limited research on the specific impact of these tools on factors such as confidence, anxiety, or decision-making capacities. Most studies focus primarily on performance outcomes or knowledge acquisition. Furthermore, while simulation in general has been extensively studied, research specifically addressing the use of XR tools in these contexts remains scarce [11]. This review aims to address these gaps by systematically analyzing the effectiveness of XR gesture-simulation tools in analyzing anxiety levels during educational training for midwives and nurses.

Methods

Research Question

The first step was the formulation of the research question, aiming to explore the impact of extended reality gesture-simulation-based tools on the anxiety levels of midwives and nurses involved in educational training. The research question "How much do we know about the effectiveness of extended reality gesture-simulation-based tools on the anxiety levels of midwives and nurses involved in educational training?" was formulated.

To answer the question, we performed the systematic review using the PICO (population, intervention, control, and outcomes) framework, which is an evidence-based practice to frame and answer a scientific endeavor [12]. The components of the framework applied in our study are as follows:

1. Population: Midwives and nurses of any type
2. Intervention: Extended reality gesture simulation-based training or simulation education intervention aimed at reducing anxiety
3. Comparison: Standard training methods or absence of specific anxiety-reduction interventions. Pre and postintervention anxiety levels
4. Outcome: Assessing anxiety levels or anxiety-related outcomes

The second category of keywords, related to the intervention, included: "extended reality" OR "XR" OR "augmented reality" OR "AR" OR "virtual reality" OR "VR" OR "mixed reality" OR "3D."The third and last category was related to the desired outcome, including: "anxiety" OR "anxious." The combination of all these keywords resulted in the final query:

> *("midwife" OR "obstetrics" OR "nurse" OR "nursing") AND ("mixed reality" OR "MR" OR "extended reality" OR "XR" OR "augmented reality" OR "AR" OR "virtual reality" OR "Simulation" OR "Simulated" OR "3D") AND ("anxiety" OR "anxious")*

Screening Criteria

Different search tools, including PubMed, IEEE, Scopus, and Web of Science, were used to perform the systematic research with the previously defined keywords. The database search and extraction were performed on March 25, 2024. Besides, the articles retrieved from another similar systematic review were analyzed to see whether they could be included [13].

In total, 1005 articles were found; the decision to include or exclude a study was based on the inclusion and exclusion criteria and quality assessment. A single author screened the articles, and the selection process and rationale were subsequently discussed with the other authors to finalize inclusion. Any disagreement between the reviewers regarding inclusion was resolved with discussion and a majority vote. After applying these criteria, 7 articles were selected for the review.

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Search Strategies

The search strategy focused on databases most relevant to health care and XR research, including PubMed, IEEE, Scopus, and Web of Science. These information sources were selected to ensure coverage of both medical and technological aspects of XR interventions in anxiety analysis during midwifery and nursing gesture simulation activities. Gray literature and conference proceedings were excluded due to resource constraints and difficulty in quality assessment. By not including gray literature and unpublished studies, there is a risk of publication bias, as studies with nonsignificant findings may be underrepresented.

A PubMed MeSH search was conducted to ensure the inclusion of relevant studies using the previously identified keywords to enhance the completeness of the findings. MeSH (Medical Subject Headings) is the National Library of Medicine's controlled vocabulary thesaurus, used for indexing articles for the MEDLINE/PubMED database [14]:

> *((“students, nursing”[MeSH Terms] OR “Obstetric Nursing”[MeSH Terms] OR “nursing students”[Title/Abstract] OR “midwifery”[MeSH Terms] OR “midwifery students”[Title/Abstract]) AND (“virtual reality”[MeSH Terms] OR “augmented reality”[Title/Abstract] OR “extended reality”[Title/Abstract]) AND (“anxiety”[MeSH Terms] OR “anxious”[Title/Abstract]))*

A total of 3 articles were found, the first one was focused on the discovery and visit to places, the second was a systematic review, and the third used VR to reduce anxiety by singing calming environments. Therefore, none of the articles were included in this systematic review.

Relevance and Topic Proximity: Inclusion and Exclusion Criteria

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology was used to search and screen articles [15]. In addition, the PRISMA checklist was completed to provide transparency and rigor in the systematic review process, in Checklist 1.

The initial choice was to narrow down the results by only selecting articles in English published in a peer-reviewed journal, randomized controlled trials (RCTs), nonrandomized, noncontrolled trials.

The second selection phase encompassed screening titles, keywords, and abstracts, followed by the removal of duplicate articles. Throughout the process, the inclusion and exclusion criteria explained in Table 1 were applied.

Table . Inclusion and exclusion criteria for article screening.

Element of the research question	Inclusion criteria	Exclusion criteria
Population	Nurses, midwives, and nursing and midwifery students of any kind	Any type of health care professional or other students, any other population such as patients
Intervention	Any virtual or augmented or mixed reality simulation training tool to perform a procedure (VR[a] glasses such as HoloLens, Oculus Rift, or any other type of device as the CAVE)[b] used to reduce *anxiety*	Any other tool or simulator not used in this setting
Comparator	XR[c] simulation vs other standard training methods, or pre and postintervention anxiety levels	N/A[d]
Outcome	Anxiety assessment	N/A
Study design, type of publication	Articles in English, French, and Spanish published in a peer-reviewed journal, randomized controlled trials (RCTs), non-randomized, non-controlled trials	Journal articles in other languages, conference papers, book chapters, reviews, meta-analysis pilot studies, proof of concept

[a]VR: virtual reality.

[b]CAVE: Cave Automatic Virtual Environment.

[c]XR: extended reality.

[d]N/A: Not available

Quality Assessment

The Cochrane Collaboration's Risk of Bias 2.0 tool [16,17] was used to evaluate the quality of the systematic review and assess the risk of bias in the included studies. The tool assesses five specific domains of bias: bias in the randomization process, bias in deviation from intended interventions, bias due to missing outcome data, bias in outcome measurement, and bias in the selection of the reported result.

Items were classified as “Low risk,” “High risk,” or “Some concerns.” The overall risk was “Low risk” if all five domains were rated as low risk, “High risk” if any domain was rated as high risk, and “Some concerns” for all other cases.

Result Analysis

To extract and analyze the resulting articles, data was extracted and collected systematically in a data collection form. A narrative synthesis was conducted due to the heterogeneity of study designs and outcome measures across included studies. Key findings were summarized in a structured table and grouped

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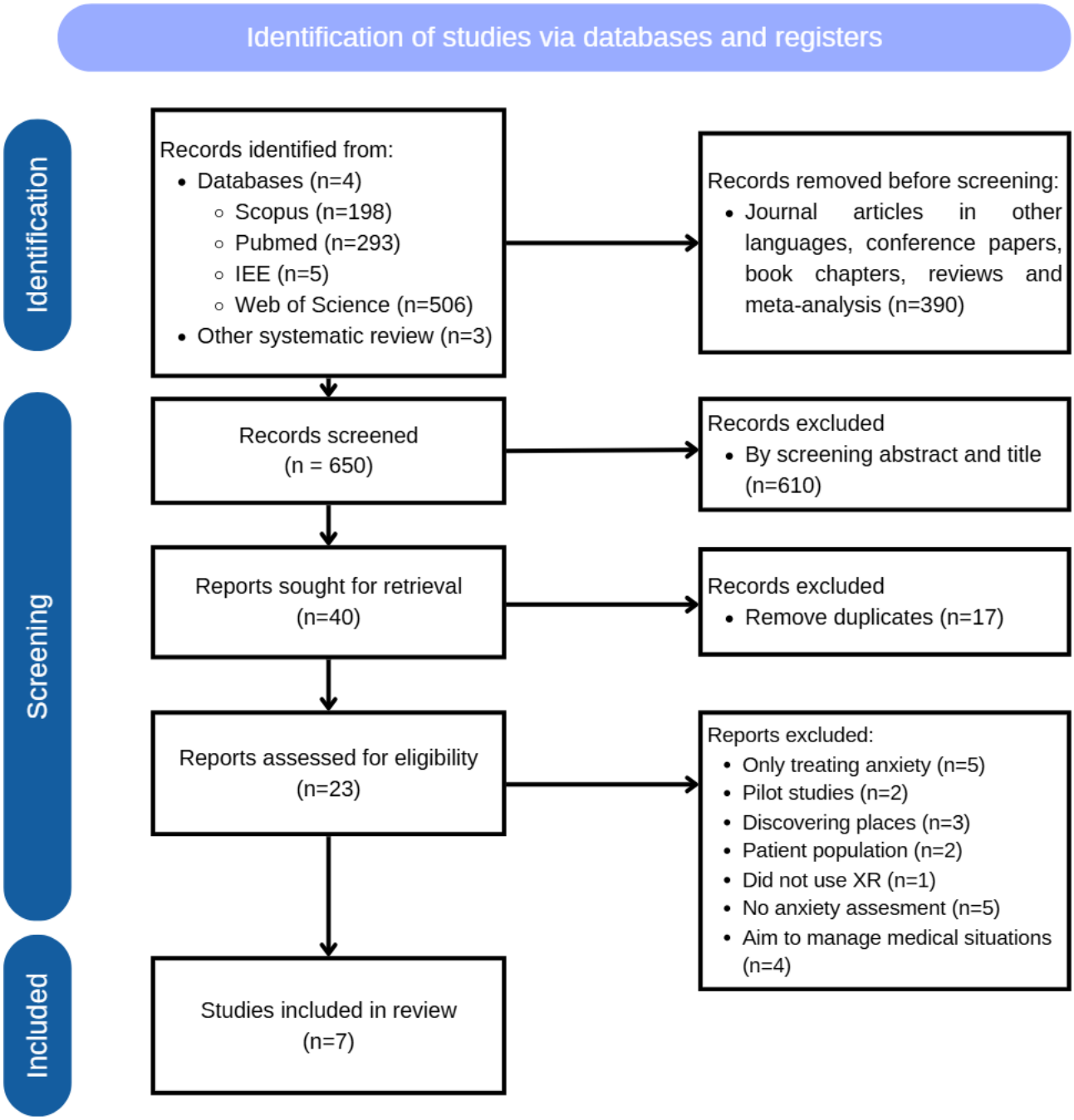
according to the learning objective (simulating and performing procedures using XR tools). A thematic analysis was used to identify common patterns in anxiety analysis across studies.

Results

Summary of the Chosen Articles

The systematic review of the literature is outlined in Figure 1. Table 2 and Table 3 summarize the results of the systematic review. Below is a brief summary of each of the articles included in the review.

Figure 1. PRISMA flow diagram. XR: extended reality.



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Table . Systematic review results.

Ttitle	Year	Author	Journal	Location	Risk of bias	Learning object	Study design / Intervention assignment	Population
The effects of neonatal resuscitation gamification program using immersive virtual reality: A quasi-experimental study	2022	Yang and Oh [18].	Nurse Education Today	Daejeon, South Korea	Some concern	Simulating and performing procedures	Pre and post-comparison, non randomized study	Nursing students (n=88)
Immersive virtual reality (VR) training increases the self-efficacy of in-hospital healthcare providers and patient families regarding tracheostomy-related knowledge and care skills A prospective pre-post study	2022	Chiang et al [19].	Medicine Open	Taipei, Taiwan	Some concern	Simulating and performing procedures	Prospective, randomized controlled, pre and postcomparison study	Health care providers (n=60)
Pediatric Chest Compression Improvement Via Augmented Reality Cardiopulmonary Resuscitation Feedback in Community General Emergency Departments: A Mixed-Methods Simulation-Based Pilot Study	2023	Kleinman et al [20].	The Journal of Emergency Medicine	Baltimore, United States	Some concern	Simulating and performing procedures	Unblinded, randomized, crossover simulation-based study	Nurses (n=36)
Effects of virtual reality training on decreasing the rates of needlestick or sharp injury in new-coming medical and nursing interns in Taiwan	2020	Wu et al [21].	Journal of Educational Evaluation for Health Professions	Taipei, Taiwan	Some concern	Simulating and performing procedures	Prospective cohort pre and postcomparison study	Medical and Nurses Interns (n=109)

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Ttitle	Year	Author	Journal	Location	Risk of bias	Learning object	Study design / Intervention assignment	Population
A mixed-methods feasibility study to assess the acceptability and applicability of immersive virtual reality sepsis game as an adjunct to nursing education	2021	Adhikari et al [22].	Nurse Education Today	Edinburgh, Scotland	Some concern	Simulating and performing procedures	Two-stage sequential mixed-methods feasibility study	Nursing students (n=19)
Virtual versus face-to-face clinical simulation in relation to student knowledge, anxiety, and self-confidence in maternal-newborn nursing: A randomized controlled trial	2016	Cobbett and Snelgrove-Clarke [23].	Nurse Education Today	Halifax, Canada	Some concern	Simulating and performing procedures	Controled, randomized pretest-posttest study	Nursing students (n=56)
Evaluation of practical exercises using an intravenous simulator incorporating virtual reality and haptics device technologies	2012	Jung et al [24].	Nurse Education Today	Seoul, Korea	Some concern	Simulating and performing procedures	Randomized control trial	First-year nursing students (n=60)

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Table . Study characteristics vs study intervention characteristics

Studies	Software and devices	Intervention activities/ duration	Variables	Intervention outcomes	Anxiety evaluation
Yang and Oh [18]	HMD:[a] Oculus Rift S (VR[b])	Neonatal resuscitation gamification-50 min	Knowledge, problem-solving, clinical reasoning ability, self-confidence, anxiety, and learning motivation	Anxiety decreased post intervention, no difference between groups	STAI[c]
Chiang et al [19]	HMD-VR Web-based VR Desktop Tablet Smartphone	Tracheostomy-related knowledge and care skills-2-h training; 15-min VR	Familiarity Confidence Anxiety Knowledge Skills	Improved comprehension and reduced anxiety at follow-up	Personalized Likert scale questionnaires
Kleinman et al [20]	HMD (AR[d])	Pediatric chest compressions-18 min course	Performance and anxiety (qualitative assessment)	Reduced anxiety	Qualitative invdividual interviews post intervention
Wu et al [21]	Game-based VR training	Training on needlestick or sharp injury time to finish the game	Performance and Anxiety (qualitative assesment)	Anxiety reduction, increase in confidence	Personalized Likert scale questionnaires
Adhikari et al [22]	3D computer-based simulation (VR)	Sepsis serious game - 20 - 30 min	Anxiety (NASC-CDM)[e], self-efficacy, acceptability, and applicability	Decreased anxiety	NASC-CDM before and after intervention
Cobbett and Snelgrove-Clarke [23]	F2F[f] high-fidelity manikin simulation. VCS[g] with a computer.	Newborn nursing - 2×45 min VR sessions	Simulation Completion Questionnaire, anxiety (NASC-CDM), knowledge	Higher anxiety for VR	NASC-CDM before and after intervention
Jung et al [24]	VR IV[h] training simulator using haptic skills.	Venipuncture training-10 min session	State trait anxiety, VAS[i], performance, and satisfaction	No difference between groups and anxiety decreased for all of them	Evaluated State-Trait Anxiety using a VAS before and after intervention

[a]HMD: head-mounted device

[b]VR: virtual reality

[c]STAI : State-Trait Anxiety Inventory

[d]AR: augmented reality

[e]NASC-CDM: Nursing Anxiety and Self-Confidence with Clinical Decision-Making Scale

[f]F2F: face-to-face

[g]VCS: Virtual Clinical Simulation

[h]IV: intravenous

[i] VAS: Visual Analogue Scale

Short Summary of Each Article

The Effects of Neonatal Resuscitation Gamification Program Using Immersive Virtual Reality: A Quasi-Experimental Study

This nonrandomized controlled simulation study with a pretest-posttest design evaluated a neonatal resuscitation gamification program using immersive VR [18]. Prelicensure nursing students were divided into intervention and control groups. The study assessed outcomes such as neonatal resuscitation nursing knowledge, problem-solving skills, clinical reasoning ability, self-confidence in practical performance, anxiety levels, and learning motivation. The simulation group presented lower anxiety levels, compared to the VR and control groups. Anxiety was measured with the STAI (State-Trait Anxiety Inventory), a commonly used questionnaire to assess an individual's tendency to suffer anxiety. Limitations include the inability to assess long-term effects through follow-up surveys and the lack of measurement for actual intervention competency reinforcement, relying solely on self-reported questionnaires.

Immersive VR Training Increases the Self-Efficacy of In-Hospital Health Care Providers and Patient Families Regarding Tracheostomy-Related Knowledge and Care Skills a Prospective Pre-Post Study

This prospective pre-post study compared health care providers' tracheostomy care training using immersive VR with head-mounted displays and web-based modules versus traditional text materials [19]. According to a personalized Likert-scale questionnaire, most providers in the VR group found that interactive visual demonstrations improved comprehension and reduced anxiety. Limitations included a small sample size, a short follow-up period, and reliance on self-reported feedback rather than quantitative measures of skill acquisition and patient outcomes. Larger, long-term studies

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with objective assessments are needed to evaluate the efficacy of VR training in improving tracheostomy care competency.

Pediatric Chest Compression Improvement Via Augmented Reality Cardiopulmonary Resuscitation Feedback in Community General Emergency Departments: A Mixed-Methods Simulation-Based Pilot Study

An unblinded, randomized, crossover simulation-based study evaluated whether augmented reality cardiopulmonary resuscitation (AR-CPR) improves chest compression performance in nonpediatric-specialized community emergency departments [20]. Participants performed chest compression with and without AR-CPR guidance in random order. Qualitative interviews suggested AR-CPR could be usable without device orientation, effective at cognitive offloading, and capable of reducing anxiety while boosting confidence. However, limitations included not excluding individuals with corrective eye lenses, which might affect the AR experience and the lack of feedback during non-AR-CPR cycles, unlike real-world scenarios where feedback devices are common.

Effects of Virtual Reality Training on Decreasing the Rates of Needlestick or Sharp Injury in New-Coming Medical and Nursing Interns in Taiwan

The prospective cohort pre and post study evaluated a new VR game, designed to teach safe and unsafe behaviors regarding universal precautions on needlestick and sharp injury prevention among incoming medical and nursing interns in Taiwan [21]. The game focused on making correct safety choices. Many participants reported reduced anxiety about preventing these injuries in the personalized Likert-scale questionnaires. However, the study's reliance on self-reported questionnaires could introduce reporting bias, and trainees might report behaviors aligning with their training, potentially skewing results.

A Mixed-Methods Feasibility Study to Assess the Acceptability and Applicability of Immersive Virtual Reality Sepsis Game as an Adjunct to Nursing Education

A 2-stage sequential mixed-methods feasibility study assessed the impact of an immersive VR sepsis game on preregistration nurses [22]. The study examined its effect on self-efficacy and perceptions of its acceptability and applicability in nursing simulation education. In the first stage, pre and postintervention self-efficacy scores were collected from 19 preregistration nurses using the Nursing Anxiety and Self-Confidence with Clinical Decision-Making Scale (NASC-CDM). The second stage used a descriptive qualitative approach to explore perceptions of the game. Results showed a significant 23.4% decrease in anxiety. Limitations included the small sample size, the novelty of the educational approach, and the measurement of self-efficacy at a single time point.

Virtual Versus Face-To-Face Clinical Simulation in Relation to Student Knowledge, Anxiety, and Self-Confidence in Maternal-Newborn Nursing: A Randomized Controlled Trial

This randomized pretest-posttest study compared the effectiveness of 2 maternal newborn clinical simulation scenarios: VR clinical simulation and face-to-face high-fidelity manikin simulation [23]. Although no statistically significant differences were found in student knowledge and self-confidence between the 2 modalities, anxiety scores, measured by the NASC-CDM, were higher for students in the VR simulation. Limitations included a small sample size, potential intervening variables, such as student motivation, interest, and technological competence, and a lack of orientation to the VR platform, which may have influenced their responses.

Evaluation of Practical Exercises Using an Intravenous Simulator Incorporating Virtual Reality and Haptics Device Technologies

This randomized control trial assessed the educational effectiveness of practical exercises using intravenous simulators with VR/haptics technologies [24]. First-year nursing students were assigned randomly to three groups: Group A (conventional intravenous arm), Group B (VR/haptics intravenous simulator), and Group C (both intravenous arm and simulator). Group C scored highest in venipuncture procedures, while Group B excelled in injections. Group C completed venipuncture faster than Group B and slightly quicker than Group A. State-trait anxiety was measured using a Visual Analogue Scale (VAS) before and after the intervention. All groups showed reduced anxiety postvenipuncture, with no significant differences. Limitations included insufficient practice time due to curriculum constraints and the study's single-school, single-country setting, which limits generalizability and cultural diversity.

Analysis of the Chosen Articles

Risk of Bias

After analyzing the risk of bias of the 7 articles included in the systematic review, summarized in Table 4, 1 [18] had a high risk in the randomization process because the participants were assigned systematically to the intervention and control groups. In total, 2 studies [21,22] lacked a control group and conducted pre and postintervention evaluations. The remaining 4 studies [19,20,23,24] demonstrated a low risk of bias.

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Table . Risk of bias of the included studies.

Author	Year	Randomization process	Deviations from intended interventions	Missing outcome data	Measurement of outcome data	Selection of the reported result	Overall bias
Yang et al [18].	2022	High risk	Low risk	Low risk	Some concern	Low risk	Some concern
Chiang et al [19].	2022	Low risk	Some concern	Low risk	Low risk	Low risk	Some concern
Kleinman et al [20].	2023	Low risk	Low risk	Low risk	Some concern	Low risk	Some concern
Wu et al [21].	2020	Not applicable	Low risk	Low risk	Some concern	Low risk	Some concern
Adhikari et al [22].	2021	Not applicable	Low risk	Low risk	Some concern	Low risk	Some concern
Cobbett and Snelgrove-Clarke [23].	2016	Low risk	Some concern	Low risk	Low risk	Low risk	Some concern
Jung et al [24].	2012	Low risk	Some concern	Low risk	Low risk	Low risk	Some concern

The risk of deviations from the intended intervention raised some concerns in 3 studies due to the motivation of the intervention group related to their interest in the technology [19,23,24]. No risk was detected due to missing outcome data. However, some concerns arose in studies [18,20,21], regarding outcome measurement, as only the intervention group was evaluated in certain aspects. Finally, no risk was identified in any of the studies concerning the selection of reported results. In conclusion, all studies presented some concerns, but none was deemed to have a high risk of bias overall.

Learning Object

All of the papers had a common general learning objective: simulating and performing procedures. However, the clinical foci covered in the selected papers differed.

Overall, 2 of the studies focused on reducing anxiety around newborn care. The first was with an immersive VR neonatal resuscitation gamification program, enabling hands-on experience in a VR environment [18]. The second, a simulation-based pilot study used AR to teach pediatric chest compression [20].

In total, 2 studies used serious games to teach and reduce anxiety in students. Occupational needle stick or sharp injury prevention was sought through a game of right and wrong choices for safe or unsafe universal precaution behaviors [21]. The other used a 3D, computer-based simulation sepsis game [22].

In 3 studies, they opted for a procedure-specific training, Cobbett and Snelgrove-Clarke [23], evaluated VR clinical simulation in preeclampsia and Group B *Streptococcus* scenarios. Another study divided the first-year nursing students into 3 groups, learning how to practice injections. A VR intravenous training simulator using haptic skills was evaluated, along with its effect on reducing students' anxiety toward this procedure [24]. Finally, in [19] used a combination of head-mounted display VR and smartphone application VR in an environment for tracheostomy-related materials. The VR teachings on how to dress the stoma or handle emergencies such as aspiration, aimed to reduce anxiety among health care providers.

Study Design

This analysis reveals significant methodological differences among the articles, particularly in their approaches to study design, including quasi-experimental, randomized controlled trials (RCTs), mixed methods, pre-post, and crossover designs.

RCTs ([20,23,24]) provide stronger evidence due to their randomization and ability to control the relationship between the XR interventions and outcomes. Quasi-experimental ([18]) and pre-post ([20,22,23]) designs are valuable for exploratory or feasibility research, but are less robust due to biases and limitations in establishing causality. Mixed-methods designs ([20,22]) add depth to the analysis by incorporating qualitative perspectives but lack the quantitative generalizability of RCTs. Finally, crossover designs ([20]) offer a unique advantage by enabling within-subject comparisons, which may result in more reliable conclusions about XR effectiveness.

The studies demonstrate that the choice of study design is dependent on the research goals, feasibility, and the need to balance internal validity, external validity, and depth of analysis. RCTs are the most robust and reliable for establishing causality, making them the gold standard for intervention studies. However, quasi-experimental designs and cohort studies provide practical alternatives for real-world contexts where randomization is not feasible. Meanwhile, mixed-methods designs offer depth and insights into user experiences, making them ideal for exploratory and feasibility studies, though their findings may be less generalizable. Finally, crossover designs effectively reduce variability and improve validity but require careful management to avoid carryover effects.

Participants

All the selected articles included nurses, midwives, or nursing and midwifery students of any kind. In total, 428 individuals participated in the studies, and 332 were nursing students, mixed with other medical students. Only 2 studies included 96 professional health care providers [19,20].

Exclusion criteria varied across the studies. In one case, they excluded those with previous clinical or VR experience,

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recruiting 88 prelicensure nursing students (VR group=31, simulation group=28, control group=29) [18]. The groups were homogeneous in sex, satisfaction with the nursing major, clinical practice training, and demand for XR education, but differed in anxiety levels.

Notably, 2 studies included third-year nursing students, with 56 and 19 participants, respectively [22,23]. The age ranges and gender proportions were similar: 20 - 44 years, mostly female (84%), with no previous degree (81%) in the former study, and 25 - 45 years, with 74% female in the latter. No statistical differences were found between the types of simulation groups.

One invited both 50 medical and 59 nursing interns [21]. Nursing interns were aged 17 - 22 years, and medical interns were 20 - 29 years. Female representation was 85% in nursing and 52% in medicine. The previous deep occupational experience was 34% in nursing and 61% in medicine.

In one study, 36 professional nurses (18 per group, AR and no AR) evenly distributed by age, sex, clinical role, and experience participated, with participants excluded based on their medical specialty [20]. Also involving 60 professional health care providers, including physicians, nurses, and respiratory therapists, in the study they randomly divided participants into regular and intervention groups, excluding those with incomplete training or questionnaires [19]. A similar exclusion criteria was applied to the same number of nursing students, ensuring homogeneity in age, gender, anxiety, and intravenous knowledge [24].

Devices Used to Create the Extended Reality Scenarios and Duration of the Intervention

In total, 6 articles used VR interventions, while one used AR [20]. Among included studies, 3 used a Head-Mounted device [18-20], 3 relied on computer-based simulations [22-24], and 1used a mobile device app.

The duration of the training sessions varied minimally across the studies, ranging from a 10-minute VR session [24], to a 50-minute gamification program [18]. Notably, only one conducted two sessions [23], while the others performed a single XR experiment.

Analysis and Anxiety Assessment Methods, Variables Evaluated

Throughout the studies, common elements were analyzed. The 7 articles evaluated anxiety using various methods, such as personalized Likert scale questionnaires [19,21]. Among them, 2 of the articles [22,23] useda specific tool to measure anxiety pretest and posttest, the NASC-CDM, which aims to provide insight into the emotional aspects of clinical decision-making, which can impact nursing performance and patient care outcomes [25].

A total of 2 studies assessed state-trait anxiety. One study distinguished between temporary anxiety influenced by environmental factors and the more stable, underlying trait anxiety [24]. Transient anxiety was measured using a Visual Analogue Scale, which consists of a 10-cm horizontal line with marked points corresponding to different levels of worry, such as “Not worried at all,” “Worried a little bit” and “Very worried,”. The chosen point on the VAS was converted to a numerical score for pre and posttest comparison. This analysis was performed and compared pre and post test. The other study [18] used the STAI, a 20-item questionnaire assessing state anxiety. Each item is rated on a 4-point Likert scale (1=not at all; 4=very much so), with a total score ranging from 20 to 80 (not 15 to 75 as stated in the original). Scores of 30 or lower indicate low or no anxiety, while scores of 31 or higher indicate high anxiety. The STAI’s Cronbach α was 0.93 at its development and 0.90 in this study.

Finally, in [20] they assessed anxiety by performing qualitative individual interviews while evaluating the rate and depth of chest compressions to provide AR feedback and therefore measure performance simultaneously.

Other aspects of the studies were evaluated, including knowledge pre and post test related to preeclampsia and group B strep, a Simulation Completion Questionnaire [23], knowledge related to neonatal resuscitation [18], or an multiple choice questionnaire on tracheostomy care and skills [19]. Another qualitative approach explores student nurses’ perceptions of the game [22], while others evaluated only the performance of the subjects, regardless of the knowledge acquisition [20,21].

Anxiety Outcomes After XR Intervention

After assessing and analyzing the results, most of the articles reported positive outcomes concerning anxiety reduction, as seen in the summary of anxiety outcomes in Table 5.

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Table . Anxiety outcomes in the included studies.

Author	Intervention	Assessment tool	Population	Outcome
Yang et al [18]	Intervention vs control; pre vs post test	STAI[a]	N=88; Intervention=31	Intervention: 59.14 (SD 9.62) to 56.72 (SD 7.50) Control: 59.50 (SD 8.35) to 57.65 (SD 6.86)
Chiang et al [19]	Intervention vs control; pre vs post test	Likert scale	N=60 ; Intervention=30	Intervention: reduced anxiety (mean 93%, SD 2%; *P*=.002 Control: reduced anxiety (mean 75% SD 6%; *P*=.002
Kleinman et al [20]	Interview postintervention	Qualitative interviews	N=36	Qualitative answers about decrease of anxiety
Wu et al [21]	Pre- post-intervention	Likert scale questionnaire	N=109	63.3% reported a decrease in anxiety
Adhikari et al [22]	Pre- post- intervention	NASC-CDM	N=19	23.4% decrease in anxiety 77.4 (SD 12.5 vs 59.3, SD 15.9; *P*<.001)
Cobbett et al [23]	Intervention vs control	NASC-CDM[b]	N=56 Intervention=27	Intervention: anxiety (mean 73.26, SD 19.95, SE mean 3.84) Control: anxiety (mean 57.75, SD 15.25, SE mean 2.88)
Jung et al [24]	Intervention versus control; Pre vs post test	STAI	n=60 Intervention =38	Intervention: pretest (mean 41.63, SD 9.30) and posttest (mean 39.52, SD 10.05) *P*=.29 Control: pretest (mean 46.97, SD 11.99) and posttest (mean 39.26, SD 10.90) *P*=.004

[a]STAI: State–Trait Anxiety Inventory

[b]NASC-CDM: Nursing Anxiety and Self-Confidence with Clinical Decision-Making Scale

In total, 4 studies reported decreased anxiety levels after the XR intervention. In [20], participant feedback supported that AR-CPR could be effective for cognitive offloading, reduction in performer anxiety, and increase in performer confidence in the care delivered. In the case of [21], 68% of nursing and 58% of medical interns reported that the extended reality intervention significantly decreased their anxiety about occupational needle injury prevention, and also in [22] the participants reported a 23.4% decrease in anxiety. In addition, in [19] at baseline, there were no significant differences between the intervention and regular groups. However, at follow-up, the intervention group showed significantly higher agreement with statements about increased familiarity (83% vs 76%, *P*=.04), enhanced confidence (92% vs 74%, *P*=.001), and reduced anxiety (93% vs 75%, *P*=.002). The VR intervention effectively improved familiarity, boosted confidence, and reduced anxiety in tracheostomy-related skills compared to the regular training.

One study [24] reported no statistical differences among the 3 groups. State anxiety and VAS for anxiety decreased in all groups after venipuncture.

A total of 2 studies reported higher anxiety in the intervention group. In [18] the anxiety score of the 3 groups decreased from pre-intervention to post-intervention (VR group: 59.14 (SD 9.62) to 56.72 (7.50); simulation group: 66.46 (8.60) to 57.65 (SD 10.35); and control group: 59.50 (8.35) to 57.65 (6.86). However, the VR group did not show significant improvement compared to the simulation and control groups, with the highest difference observed in the simulation one.

Also, anxiety scores were higher for students in the VR clinical simulation than for those in the face-to-face simulation [23]. However, the new technology rather than the VR simulation itself might have caused the increased anxiety. In addition, students were more comfortable with the mannequin, as they had previous exposure to this type of exercise.

Authors' Opinions and Main Limitations of the Studies

The authors consider that the studies provided improvement in knowledge [18], demonstrated feasibility [19], improved educational quality [20], presented a promising pedagogical approach [22], and were educationally and cost-effective, as they allowed for repeated simulations [23]. This characteristic among others, contributes to the reduction of anxiety [24].

Nevertheless, even if the results were positive, all the studies included in this review performed a small sample, single-school or medical center, single-country sessions, which is a significant

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limitation as it is not very representative. The authors suggest using larger sample sizes with random selection to increase generalizability and conducting multicenter studies.

Furthermore, in 3 studies, the evaluation method was qualitative and self-reported, which might also lead to report bias [19-21]. In addition, the long-term effect was not evaluated in any of the articles and often the evaluation was only made at one-time point [22].

Several limitations were related to the use of new technologies, in the study by [23], students preferred face-to-face simulations, citing the similarities to practicing in a "real" situation and the immediate debriefing. Students who did not like the VR clinical simulation often cited technological issues, such as "online program was slow", or "didn't know where to find things. Similarly, in [24] they noted that the results might have been affected by the students' IT expertise, while [18] pointed out that the unfamiliar VR environment could be a factor. In [22], they suggested that students more comfortable with technology might have been more willing to participate in the experiments.

An orientation activity built into the study design would be useful so that when the XR scenario is presented, students will not be focused on learning the software. Furthermore, the studies were often performed in a single session; multiple sessions would increase students' familiarity with the tools. On the other hand [18], suggests that it would be better to establish an MR environment, using hand tracking and physically practicing the skills, rather than using the HMD controllers. This approach would also reduce the learner's burden owing to unfamiliar environments, enabling experiences similar to reality.

Finally, none of the studies they engaged with the focus group (nurses and midwives) to identify and prioritize their real needs. A better approach would have been to perform a systematic conception method to translate their needs into tangible project objectives and features aligned with user expectations, rather than imposing the technological approach without working and thinking about the solution with them first.

Discussion

Limitations

The systematic review had several limitations. The research results could vary depending on the databases, languages, or types of articles included. Furthermore, the review focused on the use of extended reality for gesture simulation to reduce anxiety. Not many articles were found on this specific topic, highlighting a research gap. The results would differ if we included the use of these tools in other procedures, such as the management of medical situations or the treatment of anxiety with calming scenarios.

Future Research Directions

This systematic review was conducted in preparation for a follow-up study on XR gesture simulation educational training for midwifery students' anxiety management in the Midwifery Department at Grenoble Alpes University during the next academic year. The limited articles found in this review and their positive results highlight the research gap and underscore the importance of further exploring gesture simulation using XR tools to reduce student anxiety. Furthermore, the limitations found in the studies could be addressed by implementing a long-term follow-up with questionnaires, choosing a larger sample size, including diversity by testing in different centers, using MR, or engaging with the focus group.

The next intended study will focus on MR gesture simulation in an educational midwifery or nursing procedure. Collaboration with educators and users is essential to make an appropriate demonstrator, and the use a pre and post-test evaluation with diverse, evenly distributed participants from different centers and countries, to measure anxiety levels will be evaluated.

The first demonstrator prototype will be as follows:

1. Learning object: The learning object will be defined later on the development of the project, after discussing with the educators and students of the midwifery course.
2. Study design: RCT could be the primary methodology as it provides a more robust evidence by minimizing bias.
3. Participants: All of the 147 students at the Midwifery Department of the Grenoble Alpes University will be invited to participate in the study. The exclusion criteria will be incomplete training or questionnaires. Furthermore, depending on the learning object, only the promotion following the specific course will be included in the study, excluding the rest of the students. A posterior international demonstrator will be performed to validate the results obtained.
4. Device: To interact with the VR environment, Microsoft HoloLens 2 will be used, as the goal is to develop an MR tool. By seeing their hands, the students can physically practice the gestures to simulate and learn the procedure.
5. Anxiety Assessment Methods, Variables: Before and after the intervention, anxiety will be evaluated with the NASC-CDM [25,26], as it is specially designed for nursing students to measure stress and anxiety related to clinical procedures and academic responsibilities. n addition, slight modifications specific to our learning object will be added to the questionnaire.

Conclusions

The results of the systematic review encourage the development of an extended reality gesture or procedure simulation system to evaluate and manage anxiety for nurses and midwives. Positive outcomes have been achieved as an improved learning experience, educational effectiveness, feasibility examples, and anxiety reduction. However, the search revealed limited research addressing this issue globally and a potential gap in the MR field, since it has not been used in any of the studies, and could meet the requirements and needs of midwifery and nursing students.

Furthermore, there were some limitations to the systematic review, including variability in results due to database selection and a narrow focus on gesture simulation. Expanding the scope to include other uses of XR, such as in medical procedures or calming scenarios could provide broader insights.

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Acknowledgments

The authors would like to thank the Multidisciplinary Institute of Artificial Intelligence (MIAI) of Grenoble Alpes for the financial support of this research. This work was funded by the French National Research Agency (ANR) in the framework of the Investissements d'avenir program (ANR-10-AIRT-05) and the MIAI Cluster (ANR-23-IACL-0006).

Conflicts of Interest

None declared

Checklist 1
PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) Checklist
[PDF File, 61 KB - nursing_v8i1e68984_app1.pdf]

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Abbreviations

ANESF: National French Association of Midwifery Students
AR: augmented reality
AR-CPR: augmented reality cardiopulmonary resuscitation
GAD-7: General Anxiety Disorder-7
MeSH: Medical Subject Heading
MR: mixed reality
NASC-CDM: Nursing Anxiety and Self-Confidence with Clinical Decision-Making Scale
PICO: population, intervention, control, and outcomes
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RTCs: Randomized Controlled Trials
STAI: State-Trait Anxiety Inventory
VR: virtual reality
XR: extended reality

Edited by E Borycki; submitted 19.11.24; peer-reviewed by H El-Kechai, O Elijah; revised version received 07.02.25; accepted 16.03.25; published 18.06.25.

Please cite as:
Pérez de los Cobos Cintas C, Vuillerme N, Thomann G, Di Marco L
Effect of an Extended Reality Simulation Intervention on Midwifery Students' Anxiety: Systematic Review
JMIR Nursing 2025;8:e68984
URL: https://nursing.jmir.org/2025/1/e68984
doi:10.2196/68984

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Correction: Gamification as a Tool for Understanding Mental Disorders in Nursing Students: Qualitative Study

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Related Article:

Correction of: https://nursing.jmir.org/2025/1/e71921

(JMIR Nursing 2025;8:e83237) doi:10.2196/83237

In "Gamification as a Tool for Understanding Mental Disorders in Nursing Students: Qualitative Study" (JMIR Nurs 2025;8:e71921), the authors made two changes.

Under "Ethical Considerations," the first sentence has been changed from:

> *Ethical authorization to conduct the research was obtained from the Research Ethics Committee of the Instituto de Investigación Sanitaria Fundación Jiménez Díaz (CEI_PIC321-23_FJD).*

And now reads as follows:

> *The study was submitted to the Research Ethics Committee of the Instituto de Investigación Sanitaria Fundación Jiménez Díaz (CEIm-FJD) for review. Although the committee determined that the project fell outside its scope as it did not constitute biomedical research, it found no ethical objections to the documentation provided.*

Additionally, the following affiliation has been added for authors Pablo del Pozo-Herce, Alberto Tovar-Reinoso, and Ana Casaux Huertas (with all following affiliations renumbered accordingly):

> *Escuela de Enfermería Fundación Jiménez Díaz–Universidad Autónoma de Madrid (FJD-UAM), Campus de Villalba, Instituto de Investigación Sanitaria Fundación Jiménez Díaz (IIS-FJD, UAM), Madrid, Spain*

The corrections will appear in the online version of the paper on the JMIR Publications website, together with the publication of this correction notice. Because this was made after submission to PubMed, PubMed Central, and other full-text repositories, the corrected article has also been resubmitted to those repositories.

Submitted 04.09.25; this is a non–peer-reviewed article;accepted 10.09.25; published 22.09.25.

Please cite as:
Del Pozo-Herce P, Tovar-Reinoso A, García Carpintero-Blas E, Casaux Huertas A, Ruiz de Viñaspre-Hernández R, Martínez-Sabater A, Chover-Sierra E, Rodríguez-García M, Juarez-Vela R
Correction: Gamification as a Tool for Understanding Mental Disorders in Nursing Students: Qualitative Study
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URL: https://nursing.jmir.org/2025/1/e83237
doi:10.2196/83237

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Delivering an Electronic Health Record Based Educational Intervention Promoting Peri-Operative Non-Pharmacological Pain Care as Part of a Randomized Controlled Trial: Mixed Method Evaluation of Inpatient Nurses' Perspectives

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Abstract

Background: Best practice guidelines recommend educating surgical patients about non-pharmacological pain care (NPPC) techniques that can be used in addition to pain medication for perioperative pain management, given the risks for opioid misuse following surgery. As part of the parent non-pharmacologic options in postoperative hospital-based and rehabilitation pain management (NOHARM) clinical trial, we implemented the Healing After Surgery initiative, which leveraged the Epic electronic health record (EHR) to provide patients with education on NPPC techniques perioperatively. We disseminated educational materials directly to patients via the EHR patient portal and prompted patients to select the techniques they were most interested in using, which auto-populated the EHR so that their care team could view their preferences. We also built clinical decision support elements in the EHR to prompt and support inpatient nurses in providing patients with education and reinforcement for using their preferred NPPC techniques. Print materials, a website, a DVD, videos on hospital televisions, a toll-free number, and Zoom-based group calls provided additional education on NPPC techniques.

Objective: This study evaluated nurses' perceptions of barriers and facilitators to implementing the EHR-based Healing After Surgery initiative.

Methods: We invited inpatient nursing leaders and bedside nurses to participate in a semistructured interview. Inpatient nursing leaders were invited to complete a brief survey that asked them to rate their agreement with 7 items using a numeric rating scale (1=not at all, 10=a great deal).

Results: Interview findings from 29 nurses revealed: (1) nurses gravitated towards providing NPPC techniques they were familiar with, (2) the initiative was patient-centric with opportunities to better engage patients, and (3) nurses experienced challenges implementing and prioritizing the intervention in the inpatient setting due to competing demands in a pandemic and postpandemic environment. Interviews revealed mixed effectiveness of implementation strategies. We received survey responses from 47 nursing leaders who indicated that their staff knew about the Healing After Surgery initiative (mean=7.53, SD=1.77) and what they were expected to do (mean=7, SD=1.88). They thought the Healing After Surgery initiative supported patients' pain management needs (mean=6.76, SD=2.24), endorsed it as a priority (mean=7.02, SD=2.56), and encouraged staff to support it (mean=5.98, SD=2.78). They indicated staff experienced some burden supporting the initiative (mean=3.93, SD=2.47), but supported some variation of the initiative continuing once the parent trial ended (mean=7.72, SD=2.62).

Conclusions: Nurses understood the intervention's benefit but struggled to implement unfamiliar NPPC techniques and prioritize the initiative due to other clinical demands. Additional implementation strategies may be needed to better engage patients and facilitate intervention delivery.

Trial Registration: ClinicalTrials.gov NCT05166356; https://clinicaltrials.gov/study/NCT05166356

International Registered Report Identifier (IRRID): RR2-10.1007/s40122-022-00393-x

(JMIR Nursing 2025;8:e70332) doi:10.2196/70332

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KEYWORDS

non-pharmacological pain care; clinical decision support; electronic health record; nurse perspectives; pain management; patient education

Introduction

Patients undergoing a surgical procedure in the United States are often prescribed, and at times overprescribed, opioids for managing peri-operative pain [1,2]. Recent guidelines suggest a conservative approach to opioid prescribing and dosing [3] given the risk of improper opioid use post-operatively [4,5]. Other research suggests that limiting the duration of post-operative use may be more important than limiting dosage [6].

As the risks of addiction have become increasingly publicized, patients may be concerned about the risks associated with taking opioids [7]. A survey of patients who had undergone surgery found 30% endorsed concerns about developing an opioid addiction [8]. As a result, patients may desire information about appropriate medication use and how and when to discontinue use [9]. Preoperative education in this area has been found to be effective at reducing patients' opioid consumption [10-12].

When encouraging patients to limit opioid use, offering alternative strategies for managing postoperative pain becomes increasingly important [13]. In addition to nonopioid pain medications, nonpharmacologic pain management techniques may offer another means of pain management [14-17]. Patients may also benefit from having their care teams introduce nonpharmacological pain care (NPPC) during their postoperative recovery, as patients may be unlikely to incorporate these techniques on their own [18]. However, these techniques may not be routinely provided to patients [8,18].

Some nurses may not feel equipped to advise patients on the full spectrum of nonpharmacologic options [7]. Deficits in knowledge about and training in nonpharmacologic techniques and lack of time may prevent nurses from using them [19,20]. Oncology nurses, for example, were more likely to use nonpharmacologic techniques with patients if they thought those strategies were effective and they had institutional support (eg, time, equipment, knowledge, and peer, colleague, and administration support) for doing so [21]. Critical care nurses used techniques they possessed knowledge and training in, personally used, and perceived as legitimate and beneficial [19]. Importantly, nurses' beliefs of legitimacy and training may vary greatly for different non-pharmacological techniques [19]. Education on pain management in nursing school is sparse, and specifics of what to cover are determined by programs [22]. Nursing curricula may provide nurses with deficient knowledge of pain management, including NPPC [23], but providing specific training on NPPC can increase nurses' intentions to incorporate these techniques into their practice [24].

The Healing After Surgery initiative, evaluated in the nonpharmacologic options in postoperative hospital-based and rehabilitation pain management (NOHARM) clinically-embedded, pragmatic clinical trial [25], was designed to provide patients with education and support for incorporating NPPC techniques into their individualized perioperative pain management plans. Inpatient nurses played a large role in supporting the Healing After Surgery initiative by providing patients with educational resources on their preferred NPPC techniques (including directing them to interactive resources), delivering NPPC as feasible, and discussing NPPC as part of the discharge conversation. We received strong support and endorsement for nursing's involvement from enterprise nursing leadership. This mixed methods analysis explores inpatient nursing leaders' and bedside nurses' perceptions of barriers and facilitators to implementing the Healing After Surgery initiative. The goal was to understand aspects of the intervention and implementation strategies that promoted implementation and challenges nurses encountered with implementation to inform similar future efforts implementing large-scale EHR-based educational initiatives that rely heavily on nurses to support implementation. This manuscript was prepared in accordance with the consolidated criteria for reporting qualitative research (COREQ) guidelines [26].

Methods

Study Design

For this study, we conducted individual, semistructured interviews with nursing leaders and bedside nurses to obtain detailed feedback about facilitators and barriers to implementing the Healing After Surgery initiative in inpatient settings. We also conducted a brief, investigator-developed web-based survey, which was completed by inpatient nursing leaders to evaluate barriers and facilitators to the implementation of NPPC as part of the Healing After Surgery initiative.

The NOHARM Clinical Trial and Healing After Surgery Initiative

The NOHARM pragmatic clinical trial [25] used a stepped-wedge cohort cluster-randomized design. The trial was conducted in 31 surgical practices across six sites belonging to the Mayo Clinic Enterprise: Rochester, Minnesota; Phoenix, Arizona; Jacksonville, Florida; Mankato, Minnesota; Eau Claire, Wisconsin; and La Crosse, Wisconsin. Practices comprised the following surgical specialties: lung, cardiac, gynecology, obstetrics, transplant, colorectal, orthopedics. Practices were randomly assigned to clusters defined by site and surgical practice to initiate the Healing After Surgery initiative during one of five sequences (steps in the wedge) at seven-month intervals. The control comparator condition was usual care. At the start of the trial, all surgical practices underwent a seven-month control interval. The first group of surgical practices began delivering the intervention in March 2021, the second group began delivering the intervention in October 2021, the third group began delivering the intervention in May 2022, the fourth group began delivering the intervention in December 2022, and the fifth group began delivering the intervention in July 2023. Patient outcomes of the NOHARM trial comparing patients undergoing the intervention to those who received usual care and qualitative research on patients' perceptions of their

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experiences with the intervention will both be reported elsewhere. The present manuscript focuses on nurses' experiences delivering the Healing After Surgery initiative.

The Healing After Surgery initiative introduced surgical patients to 13 evidence-based NPPC techniques via a Healing After Surgery guide that was automatically sent to their EHR patient portals when they were identified as having a qualifying surgery within the next 30 days. The 13 NPPC techniques included movement techniques (walking, yoga, tai chi), physical techniques (transcutaneous electrical nerve stimulation (TENS), massage, acupressure, cold or heat), and relaxation techniques (meditation, guided imagery, aromatherapy, relaxing breathing, muscle relaxation, and music listening). Patients were encouraged to select up to three NPPC techniques of greatest appeal using the guide, which created discrete structured EHR data elements, which drove clinical decision support (CDS) including provider interfaces. Patients' NPPC choices were viewable in discipline-specific EHR workflow. These interfaces allowed inpatient care teams (eg, inpatient nurses, physical and occupational therapists) to view and support patients' preferences. If a patient had not indicated their NPPC preferences or their preferred techniques were not appropriate, inpatient nurses were instructed to share educational resources on the different NPPC techniques and encourage the patient to choose (other) NPPC techniques and enter the patient's preferences into the EHR. Inpatient nurses were encouraged to provide patients with educational materials on their preferred NPPC techniques and deliver NPPC for pain relief as feasible and compatible with existing nursing workflows. Healing After Surgery videos on hospital televisions, print materials stocked on inpatient floors, and information about NPPC techniques that auto-populated the patient's discharge summary supported inpatient nurses' educational efforts.

Epic CDS tools included best practice advisories for the provision of preferred NPPC for elevated pain, education points for preferred NPPC, a clickable Healing After Surgery banner at the top of the patient's chart to indicate Healing After Surgery initiative participation, and task reminders to educate the patient on NPPC [25] were built into the EHR to support inpatient nurses in delivering the initiative. There was also a designated pager nurses could call with questions. Nurses were encouraged to direct patients to interactive resources staffed by the research team (eg, Healing After Surgery patient toll-free number, Healing After Surgery Zoom-based group calls held three times a week) and a Healing After Surgery website, if they did not have the time or knowledge for more in-depth discussions of the patient's preferred NPPC techniques.

Inpatient nurses were onboarded to this program via an online educational module. The study's implementation team worked with nursing unit leaders to determine the best way to provide additional education and support to nurses. The implementation team was comprised of a diverse group of study team members including implementation researchers, physicians, nurses (eg, nurse scientist, clinical nurse specialist, and nurse manager), physical therapists, a physical therapy assistant, an occupational therapist, and study coordinators who cumulatively possessed implementation research and clinical expertise. Examples of additional education and support provided by the implementation team included presenting at staff meetings or professional development days or holding drop-in sessions with lunch or snacks for staff. We also offered in-person and online TENS training to teach nurses how to use the TENS machines we provided to their units. Nurses who started their job after this initial onboarding had access to the online educational module, but this was not required education for all new employees.

Upon implementation, members of the implementation team intermittently stopped by units to provide additional support. The implementation team also used secure messaging (available through the EHR) to offer nurses one-on-one support and to encourage them to ask questions. However, these supports were only available to day shift nurses. Our team also held wellness events for staff about midway through the trial, in which staff could stop by a room where members of our team offered some of the NPPC techniques.

Interview Design

Interviews were semistructured, using an interview guide developed by the study team, including those with clinical and research expertise. Interview questions were informed by the Consolidated Framework for Implementation Research (CFIR) 2.0 [27], which is a well-known implementation framework consisting of 5 domains (innovation, outer setting, inner setting, individuals, and implementation process) that contain related constructs. This framework can help elucidate what helped or hindered implementation. Interview questions were developed before, and independently of, survey development.

Survey Design

The brief survey, housed in the web-based platform, RedCap, had 2 questions that asked about participants' general characteristics (eg, work site and nursing role). In total, 7 additional items asked participants to indicate the extent to which staff knew about the initiative and what was expected of them to support the initiative; the extent to which the initiative helped support patients' pain management needs; how burdensome it was for staff to support the initiative; how big of a priority it was for their staff to support the initiative; how much they continued to encourage and remind staff to support the initiative; and to what extent they would support a variation of the initiative becoming part of standard care after the trial ended. These 7 questions were rated on a 10-point numeric rating scale, and participants were provided the anchors, 1=not at all, 10=a great deal. Participants could also select "unable to assess" as a response. Survey items were generated by members of the study team (including nursing professionals, a researcher, and physicians), whose experience helping implement the intervention informed key questions for nursing leadership to assess how implementation was going. The survey was reviewed by a member of the study team with expertise in survey research but was not pilot tested.

Sample

Nursing leaders (eg, supervisors, administrators, interim managers, clinical nurse specialists, and nursing education specialists) from inpatient floors that regularly cared for Healing After Surgery patients from each of the 31 surgical practices included in the NOHARM trial were invited to participate in a

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brief survey and interview. Inpatient nurses who regularly delivered bedside care to Healing After Surgery patients from the 31 surgical practices were also eligible to participate in interviews.

Recruitment

We had originally planned to invite nursing leaders to participate in an interview approximately one year after their unit had begun delivering the Healing After Surgery initiative to give their unit time to adopt the intervention. This meant nursing leaders would be recruited at different timepoints depending on which of the 5 timepoints their surgical practice had been randomized to begin delivering the intervention as part of the parent trial. Our goal was to recruit 2 - 3 key inpatient nursing stakeholders from all 31 surgical practices. (Sometimes inpatient units cared for patients from multiple surgical practices or patients from a single surgical practice were cared for across multiple surgical floors with different nursing leadership and staff).

We emailed inpatient nursing leaders from the first group of surgical practices to begin delivering the Healing After Surgery initiative approximately 15 months later and invited them to participate in a 30-minute interview. The email informed nursing leaders they could also identify a representative for their unit (eg, charge nurse) who may be interested in participating. We emailed nursing leaders from the second group of surgical practices to begin delivering the Healing After Surgery initiative approximately one year after their units had begun intervention delivery. We also included information about the opportunity for bedside nurses to participate in an interview in study newsletters sent to inpatient nursing leaders from the first 2 groups of practices to begin delivering the intervention. However, recruitment was challenging, likely due to the COVID-19 pandemic environment and high rates of nursing leadership and staff turnover. Thus, we modified our recruitment email to more clearly state we were seeking 1 nursing leader and 1 bedside nurse from each surgical practice to participate in an interview and recontacted nursing leaders from the first 2 practice groups. Bedsides nurses were instructed to contact the study team if interested in participating in a research interview. Including both a nursing leader and bedside nurse from each practice increased the likelihood of achieving broad representation from the 31 surgical practices. In addition, because bedside nurses were directly involved in delivering the Healing After Surgery initiative to patients, their perspectives on facilitators and barriers to implementation complement the perspectives of nursing leaders, who oversaw implementation of the Healing After Surgery initiative on their unit but were not directly involved in its delivery to patients.

The third group of practices to begin delivering the intervention received the updated recruitment email approximately 1 year after they began delivering the intervention. However, because of ongoing challenges with recruitment and high rates of leadership and staff turnover, we recruited nurses from the fourth group of practices approximately six months after they began delivering the initiative and recruited nurses from the fifth group of practices approximately three months after they began delivering the initiative. These shorter intervals between beginning delivery of the initiative and recruitment were intended to minimize the likelihood of turnover while providing enough time for practices to adopt the initiative. For surgical practices that experienced leadership turnover and for which we had not met our recruitment goal, we invited new leaders to participate in interviews.

Ultimately, we invited 113 nursing leaders and bedside nurses to participate in an interview. We contacted bedside nurses about participating in an interview after they emailed us to express interest. The total number of nurses eligible to participate in an interview therefore exceeded 113, but it was impossible to determine how many additional bedside nurses may have become aware of the opportunity to participate via newsletter or heard about it from their leadership but never contacted us. A maximum of three recruitment attempts were made.

To offer nursing leaders a less time-consuming way to provide their feedback on the initiative and allow us to evaluate facilitators and barriers to implementation, we invited 78 nursing supervisors, administrators, managers, nursing education specialists, and clinical nurse specialists that represented the 31 surgical practices to complete a brief survey between July and December 2023. Recruitment was conducted via in-person outreach, email, or telephone. Nursing leaders from the fifth group of practices to begin delivering the initiative were not recruited to complete the survey until at least approximately three months since they had begun delivering the intervention, to ensure adequate exposure to the initiative. A maximum of 3 recruitment attempts were made.

Procedure

Print surveys were delivered with pre-addressed envelopes. Surveys returned through the health care enterprise's internal mail system were entered into Qualtrics by the study coordinator. Those who preferred to complete the survey online were emailed a link to the Qualtrics survey. A study coordinator entered responses into Qualtrics for any participants who preferred to complete the survey via phone.

For the interviews, two female, PhD-level researchers (SAM and CT) conducted the interviews. SAM is a research associate, and CT is a nurse scientist. Both had extensive interview and qualitative research experience from other research projects. SAM has also attended a workshop on rapid qualitative analysis and a workshop on qualitative analysis in implementation science. SAM and CT helped implement the Healing After Surgery initiative, so some participants were familiar with them from study implementation activities. Participants were informed at the start of the interview that the interviews were being conducted for the purpose of understanding what went well and what did not in terms of implementation. Interviews were conducted via telephone or a web-based video platform, Zoom, and only attended by the interviewer and participant. All interviews were recorded, and the audio was transcribed verbatim.

Ethical Considerations

For the survey, completion of the survey was taken as assent to participate, and those who did not wish to participate could choose not to. Participants provided verbal consent for

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participating in an interview. Respondents received $35 remuneration for completing a survey and $50 remuneration for completing an interview. Survey data were reported in aggregate. Exemplary quotes were attributed to a participant ID number assigned by the study team to protect participants' identities. The Mayo Clinic Institutional Review Board approved all procedures, #21 - 007898.

Analytic Strategy

We calculated descriptive statistics for responses gathered from the leadership surveys. Numeric responses were averaged across survey respondents as a whole and by site.

For the nurse interviews, we used Rapid Analysis [28,29] to summarize interview transcripts. Rapid analysis is a technique that can be used when the results are needed to modify implementation strategies of evidence-based interventions [30]. Consistent with the rapid analytic approach which follows a deductive process, SM developed a Summary Template containing domain labels based on the interview guide questions to facilitate summarizing and organizing key information from interview transcripts. For the first three interviews, SAM, CT, and KS (a Senior Clinical Research Coordinator) independently completed summaries by summarizing information from the interview transcripts as bullet points under the appropriate domain. They met to discuss their summaries after each of these three interviews to establish consensus for completion. Remaining interview transcripts were summarized by either SAM, CT, or KS, independently. SAM reviewed all completed summaries, making minor edits, before uploading them into Nvivo software by Lumivero [31]. In Nvivo, the text for each summary was coded to the corresponding domain on the summary template, and the text for each domain was queried. SAM and CT created analytic memos for queried domains, identifying key themes and how they fit within CFIR 2.0. SAM and CT met to discuss key themes and their correspondence with CFIR 2.0 constructs and arrived at consensus via discussion. CT and SAM further consolidated key themes within CFIR 2.0 via independent preparation of memos and discussion.

Results

Qualitative Findings

We interviewed 29 of the 113 inpatient nurses (26% response rate) invited to participate between June 2022 and November 2023. Of those interviewed, 13 were in leadership roles and 16 were in clinical, direct patient care roles; 27 were female and 2 were male. Participants worked in Rochester, Minnesota (n=10); Phoenix, Arizona (n=7); Jacksonville, Florida (n=4); Eau Claire, Wisconsin (n=3); La Crosse, Wisconsin (n=2); and Mankato, Minnesota (n=3). They cared for the following types of surgical patients: colorectal (n=3), obstetrics (cesarean section; n=5), gynecological (n=3), cardiac ICU (n=3), pulmonary and thoracic (n=1), transplant (n=3), orthopedic (n=5), cardiac and lung (n=4), gynecological and orthopedic (n=1), and colorectal and gynecological (n=1). Interviews lasted 32 minutes on average (minimum=20 minutes, maximum=47 minutes).

Interviews revealed the following three themes related to barriers and facilitators to the implementation of the Healing After Surgery initiative: (1) nurses tended to gravitate towards NPPC techniques they were familiar with, (2) the initiative was patient-centric, but opportunities remained to better engage patients via increased care team communication, and (3) nurses experienced challenges implementing and prioritizing the intervention in the inpatient settings due to competing demands experienced in the pandemic and postpandemic environment. CFIR 2.0 constructs that correspond to each theme are shown in parentheses.

Nurses Tended to Gravitate Toward NPPC Techniques They Were Familiar With (Compatibility, Innovation Deliverers–Capability, and Available Resources–Materials & Equipment)

The initiative's focus on pain management incorporating non-pharmacologic techniques broadly aligned with the Health Care System's current approach to patient care. However, nurses varied in their receptiveness towards (eg, thoughts about appropriateness of inpatient use) and familiarity with different NPPC techniques and perceived the availability of resources to vary. More specifically, walking, application of ice, music, and relaxation techniques were available in current practice, while techniques such as yoga, tai chi, and acupressure were not. There were mixed impressions regarding the compatibility of TENS (transcutaneous electrical nerve stimulation), aromatherapy, and massage with nursing practice. Some nurses were concerned they may be asked to deliver techniques for which they felt they lacked the training or resources (eg, extra time or special equipment) to deliver. As one participant described it,

> *"it's just that it's time, massage is time, TENS unit is time…and unfortunately, I feel like that has been very short lately."* [(P18, lines 531 - 532).]

There was a tendency for nurses to discuss NPPC techniques with patients that they were personally familiar with and avoid discussing techniques they were less familiar with or lacked resources to provide. One nurse stated,

> *"I don't know the first thing about tai chi, or…how we would be able to implement that in the inpatient setting at least. Maybe once they go home, they could utilize that more."* [(P1, lines 38 - 40).]

However, some units were resourceful with figuring out how to get the supplies they needed, such as ordering essential oils to support aromatherapy.

Initiative Viewed as Patient-Centric, but Opportunities Remained to Better Engage Patients via Increased Care Team Communication (Recipient-Centeredness, Assessing Needs–Innovation Recipients, and Engaging Innovation Recipients)

Offering options for nonpharmacologic pain management empowered patients by offering pain management solutions that extend beyond the scope of medications, allowing patients to be active participants in their pain management plan. One nurse shared,

> *"I feel like this is just another part of nursing, and we should have, to be honest, probably been doing this all along... I think patients are very receptive to*

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it, very thankful for it, and I feel like it makes a significant difference when it's done". [(P13, lines 776 - 782).]

NPPC was viewed as particularly helpful for patients who were reticent to take opioids and for use in conjunction with medications for individuals experiencing severe pain. Patients tended to gravitate toward more familiar techniques such as walking, application of cold or heat, or relaxed breathing; however, there were medical situations and priorities that made engaging in NPPC impractical. For instance, persons with serious, acute needs, those who had emergency surgery, new mothers who had a cesarean section, and patients who were intubated were not good candidates for the intervention.

Nurses also identified missed opportunities to increase patient engagement and felt strongly that conversations about NPPC use should be initiated before surgery. They emphasized that patients would likely be more engaged if they had heard about the Healing After Surgery program from their providers in advance, as an example:

I don't know if this is something that they're currently doing, but I do think that having providers share the same message….really helps…and not just in those times where… nursing can't necessarily do it because of timing… but… have that as part of their normal kind of workflow or discussion points with patients. [(P21, lines 363 - 371).]

While it fell within the scope of nursing practice to support NPPC, there were suggestions to engage others in delivery, including physicians, virtual RNs, and nurse technicians. Nurse technicians are members of the health care team that function under the direct supervision of a registered nurse, performing basic patient care tasks such as vital signs and assistance with activities of daily living.

Challenges Implementing and Prioritizing the Intervention in the Inpatient Setting (Physical Infrastructure, Relative Priority, Critical Incidents, Work Infrastructure, Individuals–Mid-Level Leaders–Capability, Motivation, Deliverer-Centeredness, and Mission Alignment)

The intervention was introduced during the COVID-19 pandemic, and although the elective surgical patient population targeted by the intervention did not typically have a COVID-19 infection, the pandemic indirectly impacted the delivery of the intervention due to staff burnout and changes to work infrastructure. Nurses noted bed shortages, higher patient to staff ratios, and caring for higher acuity patients as barriers to delivering the intervention and NPPC. Patients also had shorter hospital stays than in years prior. One nurse shared:

just five years ago, a knee or a hip would be in the hospital for probably a minimum of three days. Now…we got about one and a half to two days maybe. And that's from the time they check in down at the desk.... So when I say that 1.5, we're really getting about 24 hours with the patient to do this education…that's probably our biggest challenge, but that's across the board... [(P7; 501 - 521).]

The COVID-19 pandemic also created an environment of increased staff and leadership turnover. New leaders were unfamiliar with what training on the intervention staff had received. With leadership turnover, the intervention got deprioritized, and many leaders did not do much to convey support for the initiative, particularly after the initial roll-out:

…we've…had a lot of leadership turnover in the last couple of years... and we're… in the limbo of interim managers and all of that right now. So it's… hard because I feel like we've missed a lot of that solidarity of the same person and that support just 'cause everyone's trying to pick up the pieces and just get us through until the next manager takes over… right when they rolled out, they were super supportive…since then, we've…been in this limbo [(P24; 385 - 400).]

Many saw this initiative as something extra and deprioritized it when faced with short staffing and other tasks. One nurse stated:

…the way that they staff us for… our floors …you don't have extra time to do…the education that you want to be able to do…these extra interventions that you wanna do. You have enough time to do …the bare minimum stuff…if it's a really good day, and everything is going perfectly, sometimes you get those extra moments [(P18; 175 - 180).]

For new nurses joining units, the priority was on developing their basic nursing skills. One nurse shared,

… when your staff… is stretched and they're new you have to go back to the basics to make sure that everyone has the basic skills…and NOHARMs is… very important, but it's not a basic skill. So it doesn't go to the top of my list [laughter].

(P5; 346 - 354).

In this context, some nurses tended to look towards medications first for faster results.

A few nurses thought that this initiative should be prioritized, and it was a reasonable ask. A few leaders also communicated the importance of the initiative or how it aligned with broader goals for patient care and opioid reduction. One nurse manager stated,

…we have to realize that we are… hurting people more than helping them with our heavy-handed narcotic passing. And so just knowing that importance and expressing that to the team, I felt like it is a high-priority item…you're always gonna be able to make an excuse about something being a low-priority problem, you know?...—as a nurse manager, it can be overwhelming to decide what you fit where, but it doesn't mean that you can't fit it. [(P2; lines 483 - 501).]

Leaders who conveyed support did so via existing communication channels (eg, email and huddle), and some went out of their way to make sure staff were informed (eg, posting fliers in the breakroom). Interviewees suggested getting support

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from additional councils and quality and practice committees might have enhanced support.

Mixed Effectiveness of Implementation Strategies (Design, Access to Knowledge & Information, Implementation Leads, Engaging Innovation Deliverers, and Tailoring Strategies)

Nurses reflected on several evidence-based implementation strategies used by the research team or units themselves to facilitate implementation of the intervention, which had varied success. Implementation strategies were part of the Expert Recommendations for Implementing Change (ERIC) list of strategies [32]. These are summarized in Table 1.

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Table . Nurses' reflections on different ERIC[a] implementation strategies used.

Description of implementation strategies	Exemplary quotes
ERIC implementation strategies: Develop educational materials, Distribute educational materials, Conduct educational meetings	
The study team developed a robust plan for educating nurses about the intervention and how to support its delivery, including assigning a MyLearning module via the institution's web-based educational platform for staff and offering to present at staff meetings or hold drop-in sessions. However, nurses thought that they had received a general overview on the intervention, but additional training and follow-up were needed. They shared that MyLearning modules are sometimes forgotten because of the amount of modules they are assigned to watch and that drop-in sessions and presentations at staff meetings likely do not capture all staff. Interviews also highlighted the lack of a systematic process for training new hires and nurses who "float" to different floors despite high rates of staff turnover and float nursing coverage on floors.	"…I have done so many MyLearning on it. [Laughter] don't remember if I—was there one? I don't even know..." P8; lines 227 - 230 "Because of the turnover on the floor that the initial education was just before we got there, a lot of us. I think that might be a… barrier." P17; 113 - 119
ERIC implementation strategy: Identify and prepare champions	
The study team did not explicitly ask units to identify champions or super-users, and interviews revealed this rarely occurred organically. Nurses discussed the high rate of staff turnover and the number of new staff as interfering with recruiting champions for initiatives in general. However, some nurses identified those in leadership roles on their unit as super users (eg, clinical nurse specialist, nursing educational specialist, team leads, charge nurse). A couple also shared that their unit had a champion at one point, who then left.	"I think everyone's pretty good at like trying to bounce ideas off each other and things like that. And I think everyone's pretty open to… trying alternatives… but …I'm not aware of somebody… it's kind of hard right now with the staff turnover. We have so many young staff members. So, we're having a hard time … filling positions on unit council, and filling positions on… all the different things like that. But we do have… a falls champion, and a pressure ulcer champion… we have two wellness champions. But it's not always super easy to get those positions filled." *P18; 566 - 586* "…we…chose to make our team lead groups, so we've got 12 team leads, 6 that're core, that's their primary job, and 6 that're relief, which means they fill in as needed our super-user group, just because there's always one of them on either day shift or night shift. And they can be that…go-to person if somebody has questions." *P15; 423 - 428*
ERIC implementation strategy: Remind clinicians	
Nurses generally viewed the clinical decision support (CDS) elements in the electronic health record (EHR) as helpful and compatible with nursing workflow. Some nurses were not aware of some of the CDS, which suggests they were not overly intrusive.	"seemed very straightforward and similar to what we… had previously done with other educational elements." P3; 386 - 390
Many respondents reported that they or their leaders shared information in meetings or huddles, checked in with staff during rounding, and put information about the intervention in emails/newsletters.	"reminders… emails, huddles…the little… daily interactions to say…. 'Hey, have you guys been doing this?' Or, 'What's been working? What's not?' ….I think they're pretty good about… reminding us… that we're still a part of that and… our goal is to.. do this… it's become a part of my practice that, even if I have a patient that's not a NOHARM patient, I'm still… talking about those same points with them." P19; 315 - 323
ERIC implementation strategy: Provide local technical assistance	
The study team used the EHR-based messaging system, secure chat, to offer to answer nurses' questions about intervention delivery and Epic EHR documentation. Some nurses thought this was helpful and unintrusive. However, others thought messages sent by the study team got lost with other messages they received, were of lower priority, and may have been confusing to float nurses, who did not regularly work on that inpatient floor and may have been unfamiliar with the initiative.	"…through secure chat… is very beneficial 'cause… I do know that there have been times where you guys have noticed that maybe we weren't following through with the plan the way we should, and there's that, 'Hey, please remember this patient wants to do X, Y, and Z.'… it's a gentle way of letting us know that, "Hey, there's this other thing out there," without being…. waiting by the door, waiting for that nurse to come out and then… accosting them in the hallway, so to speak." P7; 460 - 473
ERIC implementation strategy: Conduct educational outreach visits	
Members of the implementation team stopped by inpatient floors to support staff, which was perceived to be helpful. However, night shift nurses were not well engaged.	"I think definitely having someone on the unit to be there to… answer questions, to actually physically show you the chart is definitely more helpful than a MyLearning. [Laughter] I think that you just hafta click through 'cause it's another required education." P12; 266 - 270 "…I personally work a lot of night shifts… so I haven't seen anybody from No Harm come around besides the one-day shift when they rolled this out and gave us information…" P24; 568 - 576
ERIC implementation strategy: Audit and feedback	

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Description of implementation strategies	Exemplary quotes
Some nursing leaders shared report data provided by the research team on how their unit was doing with intervention delivery in emails/newsletters.	"… when you give us updates of where we're at as far as meeting the percentages of… patients that have done their selection…I'm trying to remember if it also talks about the discharge teaching…we share those results in our newsletters. We do a weekly newsletter, so when… you guys send us that, then we… share that in our newsletter that we send out to the staff." P5; 390 - 405
ERIC implementation strategy: Change physical structure and equipment	
Few nurses reported tailoring implementation of the intervention but modifications that were reported were mostly related to changing the location of Healing After Surgery-related resources to make them more accessible.	"…we started putting on each individual pod—so it's more accessible—... aromatherapy kits. Where it was in one central location behind the team lead's, it is now available to every pod in our med room... As well as printouts right there of the list, so it's easily accessible rather than trying to dig through a drawer or look it up on the intranet to try to print something out. It's just right there and available..." P19; 523 - 532

[a]ERIC: Expert Recommendations for Implementing Change [32].

Survey Findings

We received survey responses from 47 of the 78 (60% response rate) nursing leaders invited. See Table 2 for respondents' work site and professional role. Overall, leaders thought their staff knew what the Healing After Surgery initiative was (mean=7.53, SD=1.77), and that their staff knew what they were expected to do to support the initiative (mean=7, SD=1.88). The initiative was perceived to support patients' pain management needs (mean=6.76, SD=2.24), but added some burden to staff (mean=3.93, SD=2.47). Leaders endorsed the Healing After Surgery initiative as a priority (mean=7.02, SD=2.56) and rated their ongoing encouragement of staff to support the initiative slightly lower (mean=5.98, SD=2.78). Generally, nursing leaders supported the Healing After Surgery program becoming part of standard care once the clinical trial ended (mean=7.72, SD=2.62).

Respondents from the hospital located in Rochester, Minnesota, rated burden from this initiative the highest (mean=5, SD=2.68), and their ongoing encouragement for staff to support this initiative (mean=4.73, SD=2.24) and support for this initiative to continue (mean=6.09, SD=2.63) the lowest of all sites. Respondents from the hospital in Phoenix, Arizona, rated the ability of the initiative to help them better meet patients' pain management needs (mean=8.25, SD=1.60) and their interest in having the initiative continue in some form (mean=8.75, SD=1.76) the highest of all sites. Respondents from the hospital in La Crosse, Wisconsin, rated staff's knowledge of what the initiative was (mean=9.33, SD=1.15) and staff's knowledge of what was personally expected (mean=8.6, SD=2.31) of them highest of all sites. See Table 3 for nursing leaders' responses by site (and to view the survey questions).

Table . Survey participants by role and site.

Site	Nurse administrator	Nurse manager	Interim nurse manager	Clinical nurse specialist	Nursing education specialist	Other	Total
Rochester, Minnesota	1	7	—[a]	2	1	—	11
Phoenix, Arizona	—	4	1	1	3	3	12
Jacksonville, Florida	—	7	—	1	1	—	9
Eau Claire, Wisconsin	—	4	—	1	2	—	7
La Crosse, Wisconsin	—	2	—	—	1	—	3
Mankato, Minnesota	—	2	—	2	1	—	5

[a]Not applicable.

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Table . Mean (SD) responses to individual survey items by site.

Question	Rochester, MN	Phoenix, AZ	Jacksonville, FL	Eau Claire, WI	La Crosse, WI	Mankato, MN
To the best of your knowledge, to what extent do your staff know what the Healing After Surgery initiative is?	6.55 (1.51)	8.5 (1.51)	7.22 (2.17)	7.43 (1.51)	9.33 (1.15)	7 (1.41)
To the best of your knowledge, to what extent do your staff know what they are personally expected to do to support the Healing After Surgery initiative?	6.36 (1.50)	8.17 (1.80)	5.89 (1.90)	7.29 (1.38)	8.67 (2.31)	6.2 (1.48)
To what extent has the Healing After Surgery initiative helped you and your staff better support patients' pain management needs?	6.36 (2.62)	8.25 (1.60)	6.44 (2.13)	5.71 (1.89)	5 (2.83)[a]	6.75 (2.22)[a]
How burdensome has it been for your staff to support the Healing After Surgery initiative?	5 (2.68)	3.18 (2.44)[a]	3.89 (2.85)	3.14 (1.46)	4 (3.61)	4.4 (1.95)
How big of a priority is it to you that your staff support the Healing After Surgery initiative?	5.91 (2.34)	7.75 (2.09)	8.56 (1.67)	5.57 (3.60)	7 (2.65)	7 (2.71)[a]
Outside of early implementation efforts, how much have you continued to encourage and remind staff to support the Healing After Surgery initiative? (eg, email reminders, discussions, etc.)	4.73 (2.24)	5.33 (3.26)	6.78 (2.82)	7.43 (2.51)	7.33 (2.52)	6 (2.55)
To what extent would you support a variation of the Healing After Surgery Program becoming part of standard care once the trial ends?	6.09 (2.63)	8.75 (1.76)	8.44 (2.01)	7.43 (2.51)	7.67 (2.52)	8 (0.71)

[a]One participant from the site selected "unable to assess" so their response is not included in the mean.

Discussion

Principal Findings

This study describes nurses' perceptions of NPPC and implementation of the Healing After Surgery initiative across diverse surgical practices within a single healthcare system spanning multiple geographic locations. The Healing After Surgery initiative was developed as a low-touch intervention designed to provide patients with peri-operative education and support for using NPPC for perioperative pain management. This educational initiative was intended to cover the perioperative period and include all members of the surgical care team, addressing inadequacies in education on pain

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management and opioid safety and setting of pain expectations previously reported [33]. During the pre-operative period, patients were assigned an educational Healing After Surgery guide upon surgical scheduling. Ambulatory nurses and preoperative evaluation clinic staff encouraged patients to complete the guide and offered additional educational materials during preoperative visits. Surgeons were also encouraged to voice their support of the initiative to patients. Inpatient nurses were designated as having a key role in intervention delivery by providing patients with education on their preferred NPPC techniques and delivering them as feasible during the postoperative inpatient stay.

To minimize the burden of intervention delivery on inpatient nurses, we developed multimodal educational resources (eg, print resources, website, DVD, and videos available on hospital televisions) designed to support patients in self-administration of NPPC. For example, print materials and a brief video guided patients through finding pressure points and applying pressure to facilitate patients' use of acupressure. Videos on the website guided patients through tai chi and gentle yoga movements geared towards a surgical patient population. Moreover, training provided to nurses instructed them to provide patients with these resources (eg, give patients print materials stocked on their floor, navigate to the NPPC educational videos on the hospital television). Nurses were also told that they did not need to be experts in the NPPC techniques. Nurses could discuss NPPC techniques as their knowledge and time allowed and refer patients needing more support to the Zoom-based group calls and toll-free number.

Interview and survey responses revealed that the initiative was thought to be patient-centric and help meet patients' pain management needs. Nursing leaders were supportive of NPPC practice integration and its continuation notwithstanding some burdens in supporting the program. However, challenges to implementing the Healing After Surgery initiative identified via the interviews included nurses' lack of familiarity with some of the NPPC modalities and lack of time to educate patients on NPPC due to other aspects of patient care that took priority. Further, some of the implementation strategies employed could be modified to better support implementation.

Four of the ERIC implementation strategies utilized to support nursing implementation of the Healing After Surgery initiative included developing educational materials, distributing educational materials, conducting educational meetings, and conducting outreach visits [32] with the goal of training nurses how to deliver the intervention. However, these strategies (eg, an assigned web-based educational module, presentations at staff meetings, "drop-in sessions," and at-the-elbow support) may have failed to adequately reach all nurses due to high rates of staff turnover, nursing float coverage (eg, nurses taking shifts on a unit that was not their usual unit), or nurses not being scheduled to work during these supports. Moreover, these efforts made nurses aware of available patient educational resources and CDS developed as a reminder of what to do and to facilitate documentation. Education on the NPPC techniques was a lesser focus. We thought nurses would be familiar with many of the techniques because pain management, including self-management strategies, is an essential competency for nurses [34-36]. We also thought nurses would be comfortable directing patients to educational materials or the toll-free number and Zoom-based group calls for NPPC techniques while realizing they may have lacked the time or knowledge to educate patients on the techniques. However, most nurses gravitated to those NPPC modalities already integrated into their practice (eg, walking, application of ice) and avoided discussing techniques they were not sure how to use (eg, tai chi and acupressure). Although nurses are likely introduced to NPPC during their training and include basic techniques such as application of cold or heat and walking into their practice, they may benefit from additional training in the use of techniques that they are less familiar with and not comfortable discussing with patients. Similarly, a survey of critical care nurses found that roughly 80% and 59% reported no training or knowledge in tai chi and acupressure, respectively [19]. Furthermore, only roughly 1% of those who reported no training or knowledge in these techniques utilized them as part of their practice [19]. Anecdotal conversation during the implementation of the Healing After Surgery initiative suggested that giving patients materials without being able to discuss them may run counter to nursing practice. This might explain why some nurses avoided mentioning NPPC techniques they were not comfortable with altogether.

To normalize NPPC use in hospitals, it may be important to bolster nurse knowledge and familiarity with relevant, evidence-based pain modalities via additional training [19,37-41], and nursing curriculums should consider integrating more information about NPPC [37,42]. Education could take the form of brief in-services [37], patient stories, hands-on learning, e-learning, lunch-and-learns, education days, and speaking with colleagues [7]. However, it is important to ensure that night shift nurses have the same access to these opportunities as day shift nurses. We only provided implementation support (eg, presentations at huddles and staff meetings, pager support, at-the-elbow support on inpatient floors) during daytime hours. Some practices may have overcome this by having charge nurses or team leads be super users (eg, clinical champions), but this was driven by units themselves and not routinely adopted.

Additional education on NPPC may also help address concerns about the appropriateness and feasibility of some of these techniques that persisted despite emphasizing in the nursing training that our educational materials were created for a surgical patient population. Delivering techniques such as yoga or tai chi to patients in the hospital was perceived to be impractical. Further, although we had not initially planned on educating critical care nurses on how to support the Healing After Surgery initiative, some of the included surgical practices routinely admitted patients to the intensive care unit (ICU) following their procedure, and in cases of high hospital census, patients could spend more time there. Thus, in partnership with ICU nursing leadership, we determined that critical care nurses may be able to introduce NPPC to patients depending on the patient's stage of recovery. However, past studies have described patient-related barriers to pain management in intensive care units [43], and whether the Healing After Surgery initiative was appropriate

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for patients on critical care units varied depending on their status.

Some of the interviewees also described competing patient care priorities and suggested that inpatient units are not ideal for teaching NPPC to patients. For instance, some nurses perceived NPPC as an "extra" and relied on pharmacological pain management as a fast and effective method of alleviating pain. Our findings suggest that current inpatient systems and processes within our hospital enterprise may not allow enough time for nurses to readily deliver NPPC for pain management despite strong endorsement from the enterprise and participating surgical departments for implementing the HAS initiative. Literature has noted that nurse staffing ratios may impede pain management [38,44,45] and NPPC use [40,42], and competing demands on nurses' time may also impede NPPC use [39,41,42,44,45]. The implementation strategies we utilized to prompt, support, and motivate nurses to provide patients with NPPC education (eg, CDS clinician reminders, local technical assistance via EHR-based messaging, and audit and feedback data on completion of NPPC selections and NPPC education) may have limited effectiveness if time and competing priorities remain important barriers. One helpful implementation strategy used by some units was changing the physical location of some Healing After Surgery-related resources to make them more accessible to staff (eg, less time and effort to retrieve materials). However, small modifications like this may be insufficient to overcome time constraints imposed by higher patient to staff ratios and higher acuity patients, exacerbated by the pandemic. The healthcare enterprise in which this initiative was delivered may consider more explicitly voicing prioritization of NPPC provision (and how this should be prioritized compared to other nursing responsibilities) and ensure nurses are given the necessary time [39], if the goal is for this to become a routine part of peri-operative pain management.

Interviews also suggested that patients could benefit from the patient's surgeon also discussing NPPC with patients. We did encourage surgeons to voice their support of the HAS initiative to patients, but it is unclear to what extent this occurred. Moreover, there may be an opportunity for advanced practice providers (APPs) to voice their support of NPPC as well, although we minimally engaged them as part of the initiative. A prior survey of APPs conducted at one of the hospitals in which the present study took place found that APPs held positive beliefs about NPPC, but discussion about the benefits and risks of NPPC occurred inconsistently [46]. However, if surgeons and APPs consistently voice support for NPPC, this may help create an organizational culture in which discussion about NPPC as part of peri-operative pain management is normalized and expected.

Strengths and Limitations

This study gathered interview data from inpatient nursing leaders and bedside nurses and survey data from inpatient nursing leaders on the barriers and facilitators to implementing a program designed to provide patient education and support for use of NPPC for peri-operative pain management. CFIR 2.0 guided the qualitative data collection and interpretation, adding to its theoretical rigor. Furthermore, our findings add to the literature by including inpatient nurses from diverse surgical practices and sites that varied in academic status, rurality, and size. Some site differences did emerge, perhaps due to competing priorities, adequacy of staffing, nursing leaders' own biases, patient volumes, and hospital culture. The variation in the support at different locations may also reflect the overall complexity with size of each facility, surgical volumes, culture, resources, and complexity of care during the time the study was conducted during the COVID-19 pandemic. However, only nurse leaders were offered participation in the survey, and the number of respondents from each site varied, so it is unclear to what extent survey findings reflected the opinions of each site. It is also possible that the opinions and perspectives of the nursing leaders may or may not adequately reflect the opinions and perspectives of all involved bedside nurses. Further, although our response rate was 60% for the survey and 26% for the interviews, we make no definitive claim of representativeness because all hospital sites belong to the same health care enterprise, instead focusing on the range of issues identified in this context. Nonetheless, our findings, particularly from the interviews, were fairly balanced in terms of identifying facilitators and barriers to implementation, suggesting our results were not skewed in one direction.

The study began during the COVID-19 pandemic, which provided a unique implementation context that might have influenced our findings. However, our interviews suggested that the elective surgical nature of this patient population did not seriously impact their experience. Instead, COVID-19 more indirectly impacted inpatient surgical units in terms of staffing and higher rates of staff turnover. It may also be difficult to compare findings from our research to that of other studies that have used validated implementation measures because survey items were generated by the members of the research team and not taken from a validated scale. Nonetheless, the items have face validity and achieved our objective of understanding nursing leaders' perceptions of facilitators and barriers to the implementation of the Healing After Surgery initiative.

Conclusions and Future Directions

Our findings highlight important lessons learned during the implementation of a novel EHR-facilitated initiative into inpatient nursing practices that incorporate additional education and provision of non-pharmacologic options for managing pain. This trial provides feedback on the use of technology to align care to meet guidelines for comprehensive pain management initiated prior to surgery and during recovery at home. Our findings highlight a need for earlier education and increased availability of resources to support the use of NPPC. Moreover, our findings suggest challenges and opportunities for better engagement of inpatient nurses for any practice change at the inpatient nurse level, given the anticipated persistence of similar complexity of care and short lengths of stay. Our findings also highlight a challenge inherent to large-scale pragmatic trials that require engaging and training a large number of intervention providers to deliver an intervention with fidelity. Future efforts may explore other ways of strategically augmenting implementation resources to effectively engage care teams. There are opportunities to enhance nurses' role in pain management with educational support for NPPC in academic

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programs, through orientation support, virtual nursing roles, and ongoing professional development support.

Acknowledgments

We thank Madison Runyan for her effort recruiting participants and scheduling interviews. We would also like to thank Jewel Podratz, Amanda Courtright-Lim, and Amanda Nelson for their administrative support for the study.

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This work was funded by the NIH through the HEAL Initiative, award number UH3 AG67593-04, and by the NIA and the National Institute of Neurological Disorders and Stroke (NINDS). The PRISM Resource Coordinating Center, award number U24AT010961, and the NIH, through the HEAL Initiative, provided logistical and technical support. The authors take sole responsibility for the content, which does not necessarily represent the views of the NIH or HEAL Initiative.

Data Availability

The interview transcript data for this paper will not be made available to protect the privacy of interview participants. De-identified, aggregate level data collected from the web-based survey is available upon reasonable request to the corresponding author.

Authors' Contributions

SAM, CT, KS, SC, SL, JH, MM, JT, and AC contributed to conceptualization of the study. KS, SC, JH, SL, and MM assisted with study recruitment. SAM, CT, and KS contributed to the analytic methods. SAM and CT prepared the first draft of the paper. All authors reviewed drafts, provided edits, and approved of this final version.

Conflicts of Interest

None declared.

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Abbreviations

CDS: clinical decision support
CFIR: Consolidated Framework for Implementation Research
EHR: electronic health record
ERIC: Expert Recommendations for Implementing Change
NOHARM: Nonpharmacologic Options in postoperative Hospital-based and Rehabilitation pain Management
NPPC: nonpharmacological pain care
TENS: transcutaneous electrical nerve stimulation

Edited by E Borycki; submitted 19.12.24; peer-reviewed by M Gates, S Tucker; revised version received 21.04.25; accepted 07.05.25; published 17.07.25.

Please cite as:
Minteer SA, Tofthagen C, Sheffield K, Cutshall S, Launder S, Hein J, McGough M, Audeh CM, Tilburt JC, Cheville AL
Delivering an Electronic Health Record Based Educational Intervention Promoting Peri-Operative Non-Pharmacological Pain Care as Part of a Randomized Controlled Trial: Mixed Method Evaluation of Inpatient Nurses' Perspectives
JMIR Nursing 2025;8:e70332
URL: https://nursing.jmir.org/2025/1/e70332
doi:10.2196/70332

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Shift-to-Shift Information Transfer: Phenomenological Study of Nurses' Experiences

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Abstract

Background: Handovers represent a critical moment for patient safety, where the effective transfer of information between nurses is essential. In this context, digital documentation systems such as identification, diagnosis, evolution, activities, support (IDEAS) have been implemented to standardize and enhance the quality of clinical handovers.

Objective: This study aims to explore nurses' perceptions in the hospital setting regarding information transfer during shift changes. Specific objectives included identifying the perceived strengths and weaknesses of the handover process, as well as the difficulties and improvement proposals reported by nurses.

Methods: A qualitative study with a phenomenological approach was conducted. Semistructured interviews were carried out with nurses from the Hospital Universitario Insular de Gran Canaria who had experience using the IDEAS system, between June 2023 and September 2024, until data saturation was reached. After transcribing the interviews, an inductive thematic analysis was performed to identify emerging themes using both descriptive and interpretative approaches. Axial coding through co-occurrence analysis, analytical triangulation, and reflexivity strategies was incorporated to strengthen the credibility and consistency of the findings. Atlas.ti software (version 25.0.1; Scientific Software Development GmbH) was used for the analysis. The study was approved by the local ethics committee (code: 2023-244-1).

Results: From the interviews (n=15), 6 subthemes were identified and grouped into three main themes: (1) nurses (difficulties and improvement proposals in information transfer, strengths and weaknesses in the handover process), (2) patients (electronic health records: Benefit for patients, transfer of patient information), and (3) records (Comments on the form, information management). Participants valued the structured access to clinical information provided by the IDEAS system. However, they reported limitations such as poor data prioritization, editing difficulties, outdated information, and a lack of integration between nursing and medical records. In addition, training deficiencies and variability in system use, particularly among less experienced professionals, were noted. Suggestions for improvement included redesigning the handover form, automating updates, incorporating brief clinical summaries, and providing ongoing training.

Conclusions: While the IDEAS system represents an improvement over previous handover methods, its effectiveness remains constrained by technical, organizational, and cultural barriers. Optimizing the system requires clinically oriented redesigns, alongside training strategies and an institutional culture that promotes shared responsibility for documentation quality. These elements are essential for establishing a safer, more standardized, and patient-centered clinical handover model.

(JMIR Nursing 2025;8:e81703) doi:10.2196/81703

KEYWORDS

communication; nursing; patient handoff; electronic health records; continuity of patient care; patient safety; qualitative research

Introduction

The proper handover of patient care, or the transfer of information regarding a patient's treatment, is essential to ensure patient safety, reduce unnecessary risks associated with health care delivery [1,2], and maintain continuity of care [3]. The Agency for Healthcare Research and Quality defines this process as a standardized method for transferring information, along with authority and responsibility, during transitions in patient care [1].

In this context, poor communication has been identified as one of the main contributing factors to hospital-related errors. According to Ong and Coiera [4], such errors can occur both during shift changes and intrahospital transfers between different

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departments. Recommended strategies to improve communication include: formalizing the coordination process prior to transfer without interruptions, planning for discharge in advance, involving the multidisciplinary team actively in the handover, introducing the role of the liaison nurse, increasing available staffing, and implementing a centralized repository to facilitate access to patient information [4].

The standardization of the content and structure of handovers has also been proposed as an effective measure to reduce sentinel events resulting from inaccurate or ineffective communication. These tools involve structured handover models that incorporate checklists to ensure the consistent transmission of essential information, thereby preventing the omission of critical data and contributing to improved clinical safety and patient satisfaction [3]. The scientific literature reports a growing number of such standardized methods [5].

One of the most widely used tools internationally for nurse-to-nurse handovers is the Situation, Background, Assessment, Recommendation (SBAR) protocol, which has been recommended by the Joint Commission International since 2007. However, this model may present limitations in managing patients with complex chronic conditions [5]. Variants of the SBAR protocol have been developed to include additional clinically relevant information. Among them is the Introduction, Situation, Background, Assessment, Recommendation (ISBAR) model [6], which is recommended by the World Health Organization due to its brevity, conciseness, and predictable structure [7,8]. Other variants include the Identify, Situation, Observation, Background, Agreed plan, Read back (iSoBAR) model, developed in Australia, and the Illness severity, Patient summary, Action list, Situation awareness and contingency planning, Synthesis by receiver (I-PASS) model, created in the United States for pediatric settings [5].

The implementation of the ISBAR protocol and its variants has been shown to significantly improve the quality of clinical information transfer, strengthen interprofessional communication, and increase trust among health care professionals. Nurses who use ISBAR report being able to convey patient information in a structured, fast, and efficient manner. Moreover, when professionals have greater access to patient data, they tend to ask more questions and gain a better understanding of the care plan during handover. Thus, the use of this protocol contributes to the development of more effective communication skills in clinical settings [9].

The Identification, Diagnosis, Evolution, Activities, Support (IDEAS) model, in turn, is particularly recommended for information transfer between different health care services or units. This model defines a minimum data set through 5 key components [5].

The use of these structured frameworks for clinical handover has led to improvements in the quality and comprehensiveness of information transfer, in interprofessional collaboration, and in perceived outcomes related to patient safety, quality of care, and health outcomes [10]. However, incomplete handovers and deficiencies in information exchange between health care professionals still persist, which may lead to adverse events for patients [6].

Thus, a properly conducted clinical handover should reduce failures in continuity of care, errors, and patient harm in both hospital and community settings. Nevertheless, in practice, this information transfer is often performed inadequately, omitting critical details and including irrelevant data [8]. Factors such as constant activity, tasks requiring continuity, workload pressure, phone calls, other types of interruptions, and delays in the start of shifts can negatively interfere with the handover process.

Aware of this situation, the Hospital Universitario Insular de Gran Canaria (HUIGC) has adopted the IDEAS model for information transfer during nursing shift changes, based on nurses' documentation within the electronic health record (EHR). In light of this, the general objective of this study was to explore the perceptions of nurses working in inpatient units at HUIGC regarding the transfer of information during handovers. The specific objectives included identifying the perceived strengths and weaknesses of the handover process, as well as exploring the difficulties encountered and potential areas for improvement as perceived by the nursing staff.

Methods

Study Design

A qualitative study was conducted based on the phenomenological paradigm, combining Husserl descriptive perspective [11] with Heidegger interpretive hermeneutics [12].

Experience or Role of Researchers

The research team was composed of 5 professionals (2 women and 3 men), 3 of whom (MJM-G, NM-L, and YTS-D) were nurses working at HUIGC, with clinical and management experience. The other 2 researchers held PhDs in Nursing and Health Sciences. One of them (CAR-S) worked in the hospital's research support unit and served as a faculty member at the University of Las Palmas de Gran Canaria (ULPGC), while the second (HGdlT) was also a full professor at ULPGC. Both had previous experience in applying qualitative methodologies. The remaining authors had no prior contact with any of the participating nurses.

Participants and Sampling

The HUIGC is a tertiary-level university hospital that is part of the Complejo Hospitalario Universitario Insular Materno Infantil, located in the Canary Islands, Spain.

The target population consisted of nurses from various inpatient units who used the IDEAS information transfer model as the method for nursing handover, implemented through the EHR.

Initial participant recruitment was conducted using convenience sampling. Subsequently, to enrich and diversify the range of perspectives, theoretical sampling was used to include new informants who could provide relevant insights into specific aspects of the phenomenon under study [13]. Following the theoretical recommendations of Hennink et al [14], code saturation can typically be reached with 9 participants; however, between 16 and 24 interviews are needed to achieve meaning saturation. Therefore, a minimum sample size of 16 participants was estimated for the study.

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Included in the study were nurses working in the inpatient units of HUIGC during the study period, with at least 1 year of clinical experience in that setting. Nurses not directly involved in patient care in inpatient units, such as unit supervisors, area supervisors, or general supervisors, were excluded.

Data Collection

The interviews were conducted by 2 of the researchers (NM-L and YTS-D) between June 2023 and September 2024. Prior communication was established with participants in order to schedule interviews at times that would not interfere with clinical duties. The interviews were held in quiet, interruption-free spaces within the hospital setting, using offices either within or near the units to avoid unnecessary travel during the participants' workday.

Relevant sociodemographic variables were collected from key informants, including age, sex, years of professional experience, time spent working in inpatient care, academic qualifications, and typical work shift, in order to contextualize the narratives obtained. In addition, the researchers recorded notes in a field journal. Each interview lasted approximately 30 minutes and was guided by a semi-structured interview script, which is presented in Textbox 1.

Textbox 1. Semistructured interview guide.

1. What is your opinion about the current handover model?
2. What advantages would you describe in using the new model compared to the previous way of working?
3. What disadvantages or difficulties have you identified in this new handover model?
4. In your opinion, how would you improve this working model?
5. Have you noticed any lack or absence of information between the EHR data and the new model?
6. Are you familiar with any information transfer models implemented during shift changes at other hospitals where you have worked?
7. Could you describe any errors that have affected patient safety related to the transfer of information, both before and after the implementation of the new model?

Data Analysis

The interviews were audio-recorded using a mobile phone and subsequently transcribed verbatim after each session. This process was carried out continuously, allowing for a progressive analysis of the data and the identification of relevant excerpts, thus facilitating initial coding and the emergence of analytical categories through an open coding procedure [15].

The analysis followed the classical methodological approach proposed by Glaser and Strauss [16], which involves categorizing information based on the identification of descriptive codes or meaning units (MUs) grouped into emerging analytical categories (subthemes), until theoretical saturation is achieved. Subsequently, a selective coding phase was conducted, in which similar analytical categories were refined and integrated, selecting those most substantiated to identify the core theoretical categories explaining the phenomenon under study. Finally, axial coding was performed through the analysis of category co-occurrences. The analysis of co-occurrences involves identifying and examining the relationships between categories that frequently appear together within the data. This method enables a deeper exploration of how concepts are interconnected in participants' narratives, uncovering patterns, associations, and emerging themes. By highlighting these interrelations, co-occurrence analysis provides valuable insights into the structure and meaning of the phenomena, enhancing the overall rigor and depth of qualitative analysis [17].

The analysis was conducted using Atlas.ti software (version 25.0.1; Scientific Software Development GmbH). The results were presented through verbatim excerpts and co-occurrence tables, allowing for both descriptive analysis and a deeper interpretation of the data.

Rigor and Trustworthiness

Once the interviews were transcribed, participants were asked to review and validate the content of the conversations to ensure the accuracy and fidelity of the narratives collected. In addition, data triangulation was applied by comparing the transcriptions with the notes recorded by the researchers in the field journal.

To ensure methodological rigor, the criteria proposed by Lincoln and Guba [18,19] were followed. Credibility was achieved through detailed data collection, which was verified by the informants. Transferability was supported by a thorough description of the setting, participants, context, and methods. Dependability was assessed through external review by an expert (HGdlT) who was not involved in data collection or analysis. Confirmability was established through triangulation between the transcribed data and the researchers' field notes, as well as through reflexivity regarding the researchers' own potential biases.

Furthermore, the study adhered to the guidelines of the Consolidated Criteria for Reporting Qualitative Research (COREQ) [20], which establish standards for quality and transparency in qualitative studies.

Ethical Considerations

All ethical principles concerning confidentiality, anonymity, and the exclusive use of data for research purposes were strictly upheld throughout the study. The collection, processing, and storage of personal data complied with current legislation. Moreover, the fundamental ethical principles outlined in the Nuremberg Code, the Declaration of Helsinki, and the Belmont Report were observed, ensuring informed consent, the right to autonomous decision-making, and the protection of participants at all times. The study was approved by the Research Ethics

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Committee of the Hospital Universitario Doctor Negrín de Gran Canaria, Las Palmas (code 2023-244-1).

Results

Participant Characteristics

Of the 16 informants, 1 withdrew their participation after the interview was conducted; therefore, only 15 participants were included in the analysis. Their sociodemographic characteristics are presented in Table 1.

Table . Sociodemographic characteristics of participants.

Participants (P)	Sex	Age (years)	Years of experience	Years in unit	Academic degree	Employment type	Work shift
P1	Female	43	20	15	Master's	Permanent	Day shift (8 h)
P2	Male	35	9	3	Grade	Interim	Day shift (8 h)
P3	Female	35	14	4	Grade	Interim	Rotating shift (12 h)
P4	Male	39	11	11	Grade	Interim	Rotating shift (12 h)
P5	Female	25	3	3	Grade	Temporary	Rotating shift (12 h)
P6	Female	33	12	6	Grade	Interim	Rotating shift (12 h)
P7	Female	41	20	20	Master's	Interim	Rotating shift (12 h)
P8	Female	42	21	10	Master's	Permanent	Rotating shift (12 h)
P9	Female	42	21	20	Diploma	Permanent	Morning shift (8 h)
P10	Female	37	9	9	Grade	Interim	Rotating shift (12 h)
P11	Female	46	25	23	Diploma	Permanent	Rotating shift (12 h)
P12	Female	26	4	2	Grade	Temporary	Rotating shift (12 h)
P13	Female	35	5	3	Master's	Temporary	Rotating shift (12 h)
P14	Female	43	10	8	Master's	Interim	Rotating shift (12 h)
P15	Female	33	11	10	Grade	Interim	Rotating shift (12 h)

Themes

The content analysis included a total of 173 MUs, distributed across 6 subthemes, which were grouped into three overarching themes: (1) nurses (difficulties and improvement proposals in information transfer, n=27 MUs; strengths and weaknesses in the handover process, n=19 MUs); (2) patients (EHR: benefit for patients, n=22 MUs; transfer of patient information, n=21 MUs); and (3) records (comments on the form, n=30 MUs; information management, n=54 MUs). The main themes and subthemes are presented in Table 2, and the full coding tree is available in Multimedia Appendix 1.

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Table . Themes and subthemes.

Themes	Subthemes
Nurses	• Difficulties and improvement proposals in information transfer • Strengths and weaknesses in the handover process
Patients	• Electronic health records: benefit for patients • Transfer of patient information
Records	• Comments on the form • Information management

Theme 1: Nurses

Difficulties and Improvement Proposals in Information Transfer

Nurses' perceptions revealed a mismatch between the design of the handover form and the actual needs of those using it daily.

Although the system provided a structured framework, many professionals perceived it as impractical and overloaded with data of limited immediate value, which made interpretation difficult, especially in high workload contexts.

Among the main issues identified were the presence of excessive or irrelevant information and unclear visual organization, both of which hindered a fast and effective handover:

> *I want it to be as simple as possible and something visual, quick… I want to know the patient's diagnosis, how their day has gone, the most important things.* [P7]

> *I'm not interested in you telling me there's a blood test and that there's a red tube, green tube…* [P7]

A recurring complaint was the persistence of outdated clinical records, such as removed catheters or drains, which continued to appear in the form. This lack of updating generated confusion and increased the risk of clinical errors:

> *You remove the drain… but that handover information never gets deleted…* [P7]

In addition, the care search system was described as inefficient and unintuitive, making it difficult to locate or update care entries. The inclusion of irrelevant elements for certain units was also criticized, as it cluttered the system without adding value:

> *The search tool is super crappy… you end up typing it yourself, otherwise it takes forever…* [P7]

> *I get newborn care options… I work with adults, I don't need to bathe a newborn.* [P7]

Another significant limitation identified was the lack of proper nursing assessments, which compromised the quality of the handover and highlighted the need for greater professional involvement in recordkeeping:

> *Nurses don't do the assessment properly… they don't update the care plans…* [P4]

Improvement proposals were organized around three main areas: reviewing content, automating the updating of care records, and reorganizing the system's visual and functional layout. Regarding the first area, participants offered several suggestions to optimize the usefulness and relevance of the recorded content:

> *It should be divided into sections, and the information we need should be highlighted: vital signs, oxygen, care, diagnosis… background in a summarized way.* [P7]

> *For me, it should be more concise, I'm a very structured and simple person…* [P4]

Participants also suggested highlighting priority care and presenting information in a more structured and concise format to allow for quicker reading and better decision-making during handovers:

> *Maybe they could prioritize the important background items, because the truth is, they often include a whole lot of history… hypertensive, diabetic, and I don't know, a prior stroke or something more relevant.* [P2]

> *I would highlight the care section… it would help me, especially if I'm new to that place.* [P10]

Redundant or irrelevant information was also targeted for removal, with an emphasis on prioritizing the most critical elements for immediate care:

> *First things first: vital signs, care, patient diagnosis, summarized background…* [P7]

Another key issue was the need for the system to automatically remove suspended interventions or care entries from the record, to prevent confusion caused by outdated information:

> *When you remove the IV line, it shouldn't still appear… same with the urinary catheter…* [P7]

> *They shouldn't appear anymore once you've discontinued them on the form…* [P9]

Despite the identified shortcomings, several participants acknowledged that the current system represented progress compared to traditional paper-based handovers, as it centralized information and allowed for updated summaries. Among the specific suggestions, participants recommended making certain key data more visible for daily management, such as the patient's medical record number or contact phone:

> *It wouldn't hurt to have the patient's phone number appear… the medical record number in a larger font…* [P8]

Finally, participants proposed redesigning the medical orders section to limit its content to active instructions, removing

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obsolete or duplicate entries, thereby facilitating a quicker and more accurate interpretation of the patient's clinical status:

> *The medical orders section is useless… you don't see the referrals or the canceled blood tests…* [P7]

Strengths and Weaknesses in the Handover Process

The implementation of the digital system for handover represented progress in terms of speed, standardization, and access to clinical information, helping to prevent duplicated tasks and improve continuity of care. However, digitalization alone did not guarantee a safe and efficient handover if human and organizational factors were not considered. Its effectiveness depended on the staff's commitment to keeping the information updated and aligned with the patient's actual condition, particularly in settings with high turnover or the onboarding of new professionals. To fully capitalize on the benefits of technology, it was necessary to redesign the system's format, enhance its interoperability with other clinical tools, and promote a shared culture of responsibility regarding the quality of information.

Although nurses appreciated having a structured document to guide the transmission of information, they warned that overreliance on written support could reduce the rigor of verbal communication:

> *…overall, the information is pretty good because it serves as a guide.* [P10]

> *Not so much the model itself, but… at the nursing level, I think people get too comfortable sometimes, knowing that everything's written down…* [P10]

In terms of strengths, one of the most valued improvements was the automation of data entry, which reduced the time required to prepare the handover report:

> *It saves a lot of time… before you had to keep changing, modifying, and it was extra work…* [P8]

Unified access to information allowed for the generation of a centralized document with updated clinical data, facilitating review and printing at the beginning of the shift. This prevented duplicate entries and enabled quicker reading:

> *With this handover, you already have everything uploaded… you update the care plans and print it directly…* [(P7]

Content standardization also contributed to greater uniformity in format, reducing the risk of omissions or errors due to subjective interpretations:

> *It has made things easier… everything is uploaded automatically now…* [P8]

Among the main weaknesses, participants pointed out the persistence of outdated information, such as devices or treatments that had already been discontinued, which led to confusion and potential clinical errors:

> *We remove a basic catheter and it still shows up… old information.* [P9]

> *In the handover it still shows that they have an IV line from July 2nd…* [P7]

Another issue was the overload of poorly prioritized content, making it difficult to quickly identify what was essential for immediate care:

> *I just want to know the patient's name, diagnosis, and what I need to do for them…* [P7]

> *Honestly, personal history… more concise, more visual.* [P4]

The system also offered little flexibility to edit records, which forced nurses to delete and re-enter information:

> *You should be able to edit the care entries… instead of deleting the whole thing.* [P7]

Another relevant aspect was the reliance on individual professional judgment to keep records up to date, which created variability in the quality of handovers:

> *You're not going to write that the patient needs their nails cut… if they're being discharged tomorrow.* [P7]

> *People get too comfortable… since it's already written, they think it'll be read and don't put as much effort into explaining the shift.* [P10]

Finally, participants identified shortcomings in the visibility of critical information, such as prescribed medications or active medical orders, which complicated decision-making during handovers:

> *The medication doesn't appear… even insulin prescriptions, you have to go looking for them.* [P10]

Theme 2: Patients

EHRs: Benefit for Patients

Overall perceptions of the IDEAS system were predominantly positive regarding its contributions to patient care. Nurses appreciated the quick and centralized access to key clinical data, which facilitated decision-making and contributed to more agile and safer care. The ability to consult patient history, treatments, and vascular access instantly was highlighted as a significant advantage:

> *…you have the vascular access there and all the basic and necessary information you need to talk about the patient.* [P4]

The system was also perceived as an improvement over previous models, both in terms of time-saving and the organization of the handover:

> *…you don't have to keep duplicating information or re-entering everything again…* [P7]

The existence of a common and structured support system helped ensure continuity of care and minimized the risk of information loss between shifts:

> *…you see the diagnoses more concisely, the care measures more highlighted, so you kind of know how to guide yourself with the patient.* [P2]

In addition, IDEAS allowed for a quick understanding of a patient's clinical status, even when the nurse had not previously cared for them:

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> *…a mini patient progress summary would really help when you don't know the patient.* [P8]

Having essential information such as allergies, critical history, or active care plans readily available provided a sense of security, especially in situations that required quick decision-making:

> *…you have that handover in front of you with your care plans, allergies… in the end, that's something important you need to have there…* [P10]

Among the main limitations, participants identified information overload and dispersion, particularly in the patient history and care sections, where excessive or irrelevant data were often included:

> *…you might get half a page of history… when the basics would just be hypertension, diabetes…* [P4]

They also questioned the frequent use of "copy and paste" without individualized assessment:

> *…all the care entries are just dumped in without evaluating the patient… you have to delete what isn't useful.* [P7]

Despite these shortcomings, the system was acknowledged as an improvement in terms of efficiency, organization, and reliability:

> *…I've rated it so positively… because it's organized and makes it easier to give the handover.* [P10]

Nevertheless, participants stressed the need to simplify the format, make it more visual, and better adapt it to the characteristics of the patient and the workflow of each unit:

> *…so many words all over the place that you wonder: what am I actually supposed to focus on?* [P7]

Transfer of Patient Information

The transfer of patient information was perceived as a key aspect of care quality, and the IDEAS system introduced notable improvements compared to previous models. One of the most valued features was the ability to quickly identify priority care tasks according to the patient's clinical condition:

> *Care priorities, I mean, the first thing they tell you during the handover, how the patient is doing overall, the care areas where you have to focus more…* [P2]

Participants highlighted the need for a more visual, hierarchical, and concise format that would allow quick access to essential information without having to read long texts:

> *…so that the handover makes the information easier to access.* [P2]

The integration of the system with the EHR was also appreciated, as it ensured traceability, legal consistency, and data reliability:

> *This model comes directly from the Drago program, which is supposed to be legal, and when you enter all the correct information, everything that's reflected in the patient record shows up in the handover.* [P4]

This structure also helped reduce errors associated with overreliance on verbal communication:

> *Sometimes the information wasn't accurate… and what my colleague told me often had nothing to do with reality, important data were omitted.* [P5]

Nevertheless, several limitations were noted, such as the difficulty of retrieving relevant information when managing multiple patients, particularly when data were poorly organized:

> *It's not functional at all, not practical… you waste a lot of time searching, because of course… you've got 14 patients…* [P7]

Another weakness was the lack of integration between different professionals, especially between doctors and nurses, which led to gaps in information essential for care planning:

> *Sometimes the information doesn't come through completely… and I would highlight the nurse's shift note, the latest blood pressure readings, the glucose levels…* [P10]

In addition, there were cases where information failed to appear in the handover report due to incomplete documentation in the relevant forms:

> *If it's not filled out in the forms, then it won't show up in the printed handover.* [P2]

Some nurses expressed a preference for more functional formats that allowed them to focus on the most essential aspects of the patient:

> *When I take over the shift, I write down on a sheet what really matters to me about the patient (diagnosis, care).* [P4]

Others noted that when the system was used properly, it reduced the time spent drafting the handover report and allowed more focus on direct patient care:

> *They don't put as much effort into explaining the handover… since everything is written down, it's like: there it is, you'll read it.* [P10]

Overall, the system was positively evaluated. Improvements were acknowledged in workflow organization, information accessibility, and the quality of the handover. However, participants emphasized the need for enhancements in data visualization, content simplification, and adaptation to the specific needs of nursing care and interdisciplinary collaboration:

> *…I would highlight a few more things related to nursing… I think it would be helpful and would make our work easier, especially when starting the daily care routine.* [P10]
>
> *I like the model we're using, I see it as an advantage.* [P10]

Theme 3: Records

Comments on the Form

The IDEAS form was valued for its ability to integrate a large amount of clinical information, offering a comprehensive and

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detailed view of the patient's condition. However, this wealth of data did not always prove functional in daily practice due to the lack of content prioritization and a poorly structured visual layout, which hindered the quick identification of key elements for immediate care. Technical limitations were noted, including difficulties in editing errors, the rigidity of the form's design, and limited usability, all of which discouraged efficient use:

> *If I make a mistake in one word, I have to delete the whole thing to… do it again, and the forms look terrible…* [P7]
>
> *If we all updated everything, the shift report itself would be much more complete and efficient.* [P7]

Despite these difficulties, the system was perceived as an improvement over verbal handovers or handwritten formats. Its structure and level of detail helped reduce errors due to omission and improved continuity of care:

> *The information is quite good because it serves as a guide for us.* [P10]

To enhance the tool, participants agreed on the need for a more agile model, with better content prioritization, increased interoperability among professionals, and less unnecessary informational load. Suggested improvements included enabling editing without having to delete the entire record, summarizing nonpriority information, and synchronizing forms across clinical roles:

> *I should be able to summarize it and keep it that way, not depend solely on what the doctor has written…* [P7]
>
> *If you fill out the forms properly with the drains, the IV lines… all you need to write is how the patient is doing.* [P7]

Information Management

One of the most frequently reported weaknesses was the lack of record updating. In many cases, discontinued interventions or care measures remained visible in the system, leading to confusion and increasing the risk of clinical errors:

> *We remove a drain and it still shows up…* [P9]
>
> *Not everyone reviews them… not everyone updates them…* [P8]

Limited interoperability between different areas of the system and among professional roles was also noted. The lack of connection between what physicians recorded and what was accessible to nurses or nursing assistants created fragmentation:

> *It would be better if the care plans created by physicians were transferred directly to the assistants' section.* [P10]

The excess of redundant information, without a clear prioritization structure, complicated access to relevant data and increased the cognitive load on staff:

> *In the same box, it shows the IV line, the catheter, then the diet—everything is a bit mixed up…* [P7]
>
> *I would structure it so that the most necessary information stands out: vital signs… care, diagnosis…* [P7]

Technical difficulties were also cited regarding the modification of care plans, which required deleting the entire entry instead of editing, hindering the correction of errors:

> *Every time there's an admission, you have to enter all the information… you have to close Word and can't type…* [P7]

Another reported limitation was the lack of synchronization between medical diagnoses and nursing functional patterns, affecting the consistency of the clinical record:

> *The medical diagnosis changes… and the nursing one hasn't been updated…* [P8]

Despite these issues, professionals positively valued the IDEAS system as an improvement over previous handover models, emphasizing its contribution to preventing information loss and facilitating continuity of care:

> *The current format for handover is useful, since it summarizes many aspects of the patient.* [P4]

Co-Occurrences

The co-occurrence analysis revealed the highest number of relationships between the subthemes information management and comments on the form (n=84), followed by information management and strengths and weaknesses in the handover process (n=82). The remaining co-occurrences are presented in Table 3.

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Table . Co-occurrence analysis between subthemes.

Subthemes	Comments on the form (n)	Difficulties and improvement proposals in information transfer (n)	Strengths and weaknesses in the handover process (n)	Information management (n)	Electronic health record: Benefit for patients (n)	Transfer of patient information (n)
Comments on the form	0	57	71	84	64	59
Difficulties and improvement proposals in information transfer	57	0	66	67	46	39
Strengths and weaknesses in the handover process	71	66	0	82	56	52
Information management	84	67	82	0	58	58
Electronic health record: Benefit for patients	64	46	56	58	0	56
Transfer of patient information	59	39	52	58	56	0

Discussion

Principal Findings

The transfer of clinical information between nursing professionals during shift changes remains a critical process to ensure patient safety and continuity of care [5]. In this study, tensions were identified between the perceived benefits of the IDEAS system and its functional and organizational limitations. While this digital tool is recognized for centralizing access to key information, participants noted that structural and functional barriers persist, hindering clear, accurate, and useful communication. These findings align with previous studies that have highlighted how fragmented records, lack of standardization, excessive irrelevant or outdated information, and system rigidity compromise the quality of handovers and increase the risk of clinical errors [4,21,22].

From an organizational perspective, structured communication models such as SBAR, ISBAR, or IDEAS have proven effective by providing hierarchical and concise frameworks for transmitting essential data [9,23]. In the present study, nurses acknowledged that IDEAS has facilitated the automation of documentation and the centralization of information, thereby improving the efficiency of the process [10]. Unlike SBAR, ISBAR, or I-PASS, which primarily focus on verbal handovers, IDEAS emphasizes integration with the EHR, introducing unique challenges related to information accuracy, workflow adaptation, and usability. This distinction helps contextualize the specific benefits and limitations identified in this study, including the persistence of outdated data, difficulties in editing information, and a lack of flexibility—factors consistent with barriers previously reported in the literature, such as limited interoperability between records and the influence of organizational culture on effective system use [3,22].

Regarding the content of handovers, participants emphasized that IDEAS has improved accessibility to essential clinical data, such as diagnoses, vital signs, active care plans, and medication. However, difficulties were noted related to the overload of irrelevant or outdated information, which compromises the clarity of the clinical message and hinders decision-making. Nurses expressed the need for a simpler, visually clear, and sectioned format, focused on priority aspects such as diagnosis, vital signs, and active care. This need aligns with previous research showing that content simplification supports faster and safer decision-making [8,21], particularly through the use of standardized summaries that prioritize critical information [24,25].

Particularly, the usefulness of information emerged as a crosscutting MU that contributed relevant nuances to all identified subthemes and themes. In this regard, nurses appreciated having access to data on patients' medical history, vascular access, and recent clinical evolution, as these elements help build a comprehensive understanding of the patient's condition and facilitate care planning. This perception aligns with other studies emphasizing how concise and relevant information enhances clinical efficiency [24,26]. However, participants proposed incorporating brief clinical summaries to synthesize the patient's evolution, especially valuable when caring for unfamiliar patients, an idea that has also been validated in models such as I-PASS and iSoBAR [7,27].

A transversal criticism of the handover content concerned the inability to prioritize or rank clinical problems within the IDEAS system. Participants emphasized the need for a structured, visual, and concise model that would facilitate the rapid identification of the most relevant clinical data, tailored to the specific characteristics of each unit and the level of care burden. This proposal aligns with the demonstrated effectiveness of frameworks such as SBAR and ISBAR, which allow for the hierarchical organization of information centered on the patient's clinical status [9,23]. In addition, nurses highlighted the need to incorporate a more holistic view of care, including emotional

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and social dimensions of the patient—an aspect still insufficiently reflected in digital records, yet considered essential for comprehensive care [3,27].

Practical and Research Implications

Regarding the training received, a common concern that emerged was the absence of formal instruction on how to conduct clinical handovers. This gap results in considerable variability in clinical practice and is recognized as a risk factor for patient safety, particularly among professionals with less clinical experience [28,29]. Participants highlighted the value of being accompanied by a supervising professional during their early clinical experiences, underscoring the importance of guided mentorship in the development of both communicative and clinical skills, as previously emphasized by Martínez-Fernández et al [30] and Tacchini-Jacquier et al [31].

Complementarily, the incorporation of innovative educational strategies, such as virtual reality and role-playing, has been proposed for teaching structured models like ISBAR. Recent literature supports this approach, showing that such methodologies can enhance perceived competence, knowledge retention, and the confidence of novice professionals [29,32]. Moreover, these tools may help reduce variability in the execution of clinical handovers, even in settings where digital systems have already been implemented.

From the patient's perspective, the quality of clinical handover directly impacts their care experience. Nurses expressed appreciation for the ability to quickly access key information, such as medical history, current care plans, or vascular access, in line with studies that associate the use of structured systems with increased perceptions of safety and quality of care [6,26]. However, the lack of integration between medical and nursing records, particularly regarding nonpharmacological care, remains a critical limitation. This disconnect hinders a holistic understanding of the patient and compromises continuity of care [3,4].

From a health care management perspective, the implementation of tools such as SBAR has not only contributed to the reduction of incidents related to communication failures but also improved perceptions of safety and interprofessional collaboration [27,30]. However, for their implementation to be effective, these tools must be supported by complementary strategies, including ongoing training, regular audits, feedback mechanisms, and an institutional culture that recognizes clinical handover as a core component of patient safety [31,32].

Overall, although the IDEAS system represents a significant improvement over previous paper-based methods, structural, content-related, and organizational barriers persist that limit its potential impact. Participants proposed several practical improvements to enhance the system, which can be grouped into three categories:

1. Technical interventions, including automated updates to ensure information accuracy and reduce errors.
2. Organizational interventions, such as standardizing workflows and integrating information across different units, to improve usability and continuity of care.
3. Training interventions, encompassing structured guidance during early clinical experiences, mentorship, and the incorporation of innovative educational strategies like virtual reality and role-playing to strengthen competence and confidence in clinical handovers.

These interventions, together with an organizational culture focused on patient safety, emerge as key elements to achieve an effective, safe, and care-centered handover process.

Strengths and Limitations

One of the main strengths of this study lies in its phenomenological approach, which enabled an in-depth exploration of nurses' subjective experiences, revealing complex and contextual meanings that often remain hidden in quantitative research. In our analysis, Husserl descriptive phenomenology guided the initial coding of nurses' lived experiences, while Heidegger hermeneutics informed the interpretative stage, enabling us to situate these experiences within broader contextual and existential dimensions of nursing practice. The use of semistructured interviews facilitated openness and reflection among participants, enriching the quality of the data collected. Furthermore, the inclusion of diverse professional profiles (in terms of experience, seniority, and clinical units) provided a broader and more nuanced perspective on the phenomenon under study. The application of analytical triangulation strategies, along with peer review and critical reflection by the research team, contributed to enhancing the credibility and interpretative coherence of the analysis.

However, this study presents some limitations inherent to its phenomenological design. By focusing on the subjective experiences of a small group of nurses within a specific clinical context, the findings are not generalizable to other units, institutions, or organizational settings. Participants were drawn from different general hospitalization units where the IDEAS system was implemented; however, no staff from specialized units (eg, intensive care unit) were included, and specific unit information was omitted to maintain participant anonymity. Therefore, future research should include specialized units and other institutions to enhance the transferability of these findings. The purposive sampling strategy allowed for a rich and diverse description of the phenomenon, but it also entails a potential selection bias, as those who agreed to participate may have had a particular interest in or perspective on clinical handover.

Similarly, the interpretation of the data was influenced by the interaction between the researchers and the participants. While this is inherent to the phenomenological approach, it must be acknowledged as part of the research team's reflexive positioning. Although methodological strategies aimed at enhancing credibility and triangulation of the analysis were applied, the inherent subjectivity of the qualitative approach may influence the construction of categories and the interpretation of meanings. These limitations should be considered when assessing the scope, transferability, and applicability of the findings.

Conclusions

The IDEAS system has represented a significant step forward in structuring clinical handovers, improving access to and

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organization of information during shift changes. However, technical and organizational limitations remain that hinder its effectiveness, such as the lack of data prioritization, the presence of outdated information, and limited integration between medical and nursing records.

The experiences collected highlight a gap between the current design of the system and the real needs of nurses. To optimize its usefulness, the form must be redesigned toward a more visual, editable format focused on clinically relevant content. Proposed improvements include the automatic update of inactive care plans, the incorporation of brief clinical summaries, and increased visibility of key data.

Moreover, the system's effectiveness depends not only on technical enhancements but also on institutional commitment to training, a culture of safety, and shared responsibility in the use of clinical records. Integrating these elements will foster a safer, more efficient, and patient-centered handover process.

Acknowledgments

The authors would like to express their gratitude to all the nurses who participated in the study.

Funding

This study was funded by the Fundación Canaria Instituto de Investigación Sanitaria de Canarias (grant code ENF23/13).

Data Availability

The datasets generated or analyzed during this study are available from the corresponding author on reasonable request.

Authors' Contributions

Conceptualization: MJM-G (lead), CAR-S (equal).
Data curation: MJM-G, NM-L, YTS-D, CAR-S, HGdlT.
Formal analysis: CAR-S (lead), HGdlT (supporting).
Funding acquisition: MJM-G.
Investigation: MJM-G, NM-L, YTS-D, CAR-S, HGdlT.
Methodology: MJM-G, CAR-S, HGdlT.
Project administration: MJM-G (lead), CAR-S (equal), HGdlT (supporting).
Resources: MJM-G, CAR-S.
Supervision: CAR-S.
Validation: HGdlT. Visualization: CARS (lead), MJMG (supporting).
Writing – original draft: CARS (lead), HGdlT (supporting).
Writing – review and editing: CARS (lead), MJMG (supporting), NML (supporting), YTSD (supporting), HGdlT (supporting).

Conflicts of Interest

None declared.

Multimedia Appendix 1
Coding tree.
[DOCX File, 19 KB - nursing_v8i1e81703_app1.docx]

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Abbreviations

COREQ: Consolidated Criteria for Reporting Qualitative Research
EHR: electronic health record
HUIGC: Hospital Universitario Insular de Gran Canaria
I-PASS: Illness severity, Patient summary, Action list, Situation awareness and contingency planning, Synthesis by receiver
IDEAS: Identification, Diagnosis, Evolution, Activities, Support
ISBAR: Introduction, Situation, Background, Assessment, Recommendation
iSoBAR: Identify, Situation, Observation, Background, Agreed plan, Read back
MU: meaning unit
SBAR: Situation, Background, Assessment, Recommendation

Edited by E Borycki; submitted 01.08.25; peer-reviewed by H Wan, L Sousa; revised version received 22.09.25; accepted 26.09.25; published 28.11.25.

Please cite as:
Montoya-Garrido MJ, Rodríguez-Suárez CA, Mateos-López N, Santiago-Díaz YT, González-de la Torre H
Shift-to-Shift Information Transfer: Phenomenological Study of Nurses' Experiences
JMIR Nursing 2025;8:e81703
URL: https://nursing.jmir.org/2025/1/e81703
doi:10.2196/81703

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Exploring Health Professionals' Knowledge and Perceptions of Telehealth Implementation in Multisite Public Hospitals of East Wollega Zone, Oromia, West Ethiopia: Cross-Sectional Study

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Abstract

Background: A significant gap exists among health professionals regarding telehealth due to limited knowledge and varying perceptions. This disparity is particularly pronounced in low-income regions, where numerous barriers hinder its implementation.

Objective: This study aimed to assess the knowledge and perception of telehealth among health professionals in public hospitals in East Wollega, Oromia Region, Ethiopia.

Methods: A study was conducted with 397 health professionals in public health facilities in East Wollega Zone, selected through systematic random sampling. Data were collected via self-administered questionnaires from March 2024 to June 2024 and entered into EpiData (version 3.1; EpiData Association) and analyzed using SPSS (version 24; IBM Corp). Descriptive statistics, including percentages and frequency distributions, were used. The Hosmer and Lemeshow test assessed variable homogeneity. Significant variables *(P*<.05) in bivariable logistic regression analysis were included in multivariable logistic analysis and reported as adjusted odds ratios (AOR) with 95% CI.

Results: Findings indicated high levels of knowledge and perception among participants. Factors significantly associated with knowledge included educational status (AOR 4.22, 95% CI 3.45-13.12; *P*=.001), income between Ethiopian Birr 7001 - 9000 (a currency exchange rate of Ethiopian Birr 52=US $1 during the study period; AOR 3.255, 95% CI 1.790-8.878; *P*=.001), access to computers (AOR 2.414, 95% CI 1.046-14.764; *P*=.001), consultation sessions (AOR 2.389, 95% CI 1.961-10.158; *P*=.001), and smartphone use (AOR 3.027, 95% CI 2.797-14.729; *P*=.001). For perception, significant associations included income over 9000 Birr (AOR 2.675, 95% CI 2.271-19.277; *P*=.001), improving quality of life (AOR 1.786, 95% CI 1.575-22.587; *P*=.009), increased accessibility (AOR 1.244, 95% CI 1.061-11.333; *P*=.04), consultation sessions (AOR 4.777, 95% CI 2.318-15.062; *P*=.001), and smartphone use (AOR 3.836, 95% CI 2.900-13.573; *P*=.001).

Conclusions: Approximately two-thirds of participants demonstrated good knowledge and perception of telehealth. It is highly recommended to create awareness through educational programs for individuals with lower educational backgrounds and to improve access to technological devices.

(JMIR Nursing 2025;8:e71870) doi:10.2196/71870

KEYWORDS

East Wollega Zone; health professionals; knowledge; perception; telehealth

Introduction

In recent years, there has been significant interest in integrating telehealth into health care systems in both high- and low-income countries. Telehealth refers to the practice of providing medical care at a distance, using information and communication technologies to exchange valid information for diagnosis, treatment, disease prevention, research, and ongoing education of health care providers [1].

Telehealth strives to meet the needs of today's health care consumers and transform health care delivery. It enhances the quality of care by improving accessibility and efficiency, reducing the need for travel, providing clinical support, and overcoming geographic barriers, ultimately leading to improved patient outcomes [2]. In high-income countries, telehealth can significantly benefit the health care sector through three main approaches: (1) real-time communication, which connects patients with health care providers via video conferencing, home health monitoring devices, and phone consultations; (2) store-and-forward, which allows for sharing images, data, voice,

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or video with physicians for long-distance diagnosis; and (3) remote patient monitoring, which involves tracking patients' health parameters from home for ongoing evaluation and response [3].

Improving access to health services is crucial for achieving sustained improvements in health status. However, access to health care varies significantly between countries, particularly in low- and middle-income countries, which have less access to health services. Despite accounting for 90% of the world's diseases, low- and middle-income countries receive only 12% of global health expenditures due to challenges associated with access, equity, quality, and cost-effectiveness [4]. Modern information and communication technologies are transforming how individuals communicate and seek information, addressing contemporary global health issues [5]. For instance, research in India found that a lack of understanding, skills, and appropriate working conditions hindered the implementation of electronic health systems, with about 12% of health professionals showing low awareness of telehealth [6]. Conversely, a study in Saudi Arabia indicated that 88.5% of health care professionals were interested in telemedicine technologies [5].

In Nigeria, approximately 60.9% of health professionals were familiar with telehealth, and 78.1% expressed a willingness to adopt it in health care delivery. Despite some external challenges, such as institutional organization and clinical practice guidelines, there is considerable acceptance of telehealth among health care professionals [7]. In the United States, a rising willingness to use telemedicine was noted, increasing from 57% in 2015 to 69% in 2019, particularly among younger physicians [8]. Telehealth effectively addresses geographic barriers, connecting patients with specialized providers more efficiently [8-10].

Health care management and telehealth services lie at the intersection of information technology, health care, and information science, aiming to address personnel shortages and enhance medical services through the use of information in biomedicine [11,12]. However, the Pan American Health Organization identified several barriers to telehealth implementation, including inadequate technological infrastructure, organizational challenges, and a lack of economic resources and scientific evidence regarding its benefits [13]. In Iraq, factors influencing telehealth adoption include privacy concerns, cultural attitudes, and the availability of technical support, with regulatory issues, lack of organizational support, and insufficient knowledge being major barriers [14,15].

In Ethiopia, the government has initiated a national e-health strategy to streamline various electronic health initiatives despite the challenges that remain, particularly in rural areas, due to population growth, economic constraints, and a shortage of medical specialists [16]. Even though a framework for adopting telehealth was initiated, the knowledge and perceptions of health care providers were not explored particularly in the study area. Therefore, this study aimed to identify knowledge gaps and perceptions toward telehealth among health care providers and their associated factors as well as to inform strategies for effective implementation, ensuring that the health care services are accessible and of high quality.

Methods

Study Design

An institutional-based cross-sectional study design was used.

Study Setting and Population

The study was conducted in all 5 public hospitals in the East Wollega Zone of western Ethiopia, specifically 2 referral hospitals and 3 primary hospitals, from March 2024 to June 2024. The selected hospitals were Wollega Comprehensive Specialized Hospital, Nekemte Specialized Hospital, Gida Hospital, Arjo Hospital, and Sire Hospital. These public health facilities provide preventive, primary, general, referral, and specialized services, staffed by a total of 2917 health care providers. They serve a population of 1,500,999, comprising 726,741 females and 774,258 males, in both urban and rural areas of East Wollega Zone.

Study Population and Samples

The study included all 5 public hospitals in East Wollega Zone. The sampling frame consisted of a list of health care professionals working in these hospitals. Based on the nature of service delivery, health care professionals included were physicians, medical laboratory technologists, anesthetists and anesthesiologists, pharmacists, nurses, and midwives. Informed consent was obtained from all selected participants.

Eligibility Criteria

Inclusion Criteria

All health care professionals presented during the study period were included.

Exclusion Criteria

Health care professionals who were not willing to participate and not present during the study period were excluded.

Sample Size Determination

The sample size for the study was calculated using the formula for estimating a single population proportion, assuming a 95% CL and a marginal error (d) of 0.05. Since no previous studies in Ethiopia have addressed the variables proposed for this study, a population proportion of 50% will be considered.

Thus, the sample size will be

$$N=(z1-\alpha/2)2\times p(1-p)d2$$

$$ni=(1.96)2*0.5(1-0.50)(0.05)2=384$$

By using a 10% nonresponse rate, the final sample size was 422.

Sampling Procedures

For sampling and sample size calculation, the sampling frame was obtained from the respective human resources administrative offices, which provided the total number of health care providers working in the selected public hospitals of the East Wollega Zone; this was calculated to be 916. The total

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sample was calculated using proportional allocation and systematic random sampling techniques across all 5 hospitals.

To achieve proportional allocation, the constant K value was calculated, resulting in a value of 2. An initial number was randomly selected from 1 to 2, and a study participant was chosen at every second interval from all selected public health facilities in the East Wollega Zone. A total sample size of 422 was calculated from each hospital: Nekemte Specialized Hospital (n=159, 37.7%), Wollega University Comprehensive Specialized Hospital (n=122, 28.9 %), Sire Hospital (n=41, 10%), Arjo Hospital (n=47, 11%), and Gida Hospital (n=53, 13%)

Data Collection Tools and Procedures

In this study, the data collection used a comprehensive 3-part questionnaire designed to gather relevant information from participants. The first part of the questionnaire focused on demographic information, where participants provided details about their personal and professional backgrounds. This section included questions regarding their names, ages, sex, designations, computer knowledge, and professions, allowing for a thorough understanding of the respondents.

The second part aimed to assess the knowledge level of the participants regarding telehealth, validated and adapted from a previous study [17]. It comprised 11 statements, each requiring a "1=Yes" or "0=No" response. This scoring system enabled participants to achieve a minimum score of 0 and a maximum score of 11, reflecting their knowledge about telehealth. Although we used surveys with identical items from those published in the literature, formal psychometric validation of this measure was not conducted. Therefore, observed differences should be interpreted as descriptive rather than indicative of true differences in the underlying of this construct.

The third part evaluated the respondents' perceptions of telemedicine through 11 statements, adopted from previously validated tools [18]. Participants responded using a 5-point Likert scale, ranging from 0 (strongly disagree) to 4 (strongly agree). This section allowed for a cumulative score between 0 and 44, providing insights into how health care professionals perceived telehealth. Although we used surveys with identical items from those published in the literature, formal psychometric validation of this measure was not conducted. Therefore, observed differences should be interpreted as descriptive rather than indicative of true differences in the underlying of this construct.

To facilitate the data collection process, trained data collectors distributed the structured questionnaires to participants. A team of 4 data collectors and 2 supervisors was recruited to carry out this task over a period of 2 consecutive months.

Study Variables

Dependent Variable

The dependent variables were knowledge and perception of telehealth.

Independent Variables

The independent variables include sociodemographic factors such as age, sex, education level, experience, and income. In addition, the study examined exposure to information communication technology, as well as the clinical applications and benefits of telehealth. This comprehensive approach allowed for a thorough analysis of the factors influencing knowledge and perception regarding telehealth.

Operational Definition

Telehealth

Telehealth refers to the use of technology-driven virtual platforms to provide a range of health services, including information dissemination, disease prevention, monitoring, and medical treatment [19].

Knowledge

Knowledge refers to an individual's understanding and awareness of the concepts, practices, technologies, and applications associated with telemedicine. It is measured using 11 questions, with responses coded as 1="Yes" or 0="No." The minimum possible score is 0 and the maximum score is 11 [17]. Knowledge is divided into two types as follows: good knowledge where individuals score above the average mean on all knowledge-measuring questions, and poor knowledge where individuals score below the average mean on all knowledge-measuring questions.

Perceptions

The process of recognizing and interpreting telemedicine, measured on a 5-point Likert scale ranging from 0 (strongly disagree) to 4 (strongly agree), with a minimum score of 0 and a maximum score of 44 [18]. Perception is divided into two types as follows: good perception where respondents score above the average mean (>22) on all perception-measuring questions, and poor perception where respondents score below the average mean on all perception-measuring questions.

Ethical Considerations

Official approval to conduct this study was obtained from the Office of Research and Technology Transfer Vice President at Wollega University. A letter of permission was then distributed to the respective hospitals, ensuring that all necessary approvals were in place to proceed with the study. Informed consent was obtained from all study participants, making it clear that their participation was voluntary and that they could withdraw at any time. The privacy of the study participants was ensured by removing personal identities, and their data were not disclosed to other parties. Moreover, participants' confidentiality was upheld by protecting their data, which was only shared for the purpose of the study based on the consent obtained.

Data Quality Control

To ensure the quality of the data collected, all questionnaires were developed in English and subsequently translated into Afan Oromo, the local language. This translation was then retranslated back into English by experts to verify accuracy. A pretest was conducted with 5% of the sample size at Ghimbi General Hospital prior to the main data collection. Data

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collectors and supervisors received 1 day of training to prepare them for their roles. During the data collection phase, the data were cleaned, coded, and checked for consistency and completeness. A double-entry method was used to enhance data quality, allowing for cross-checking of any inconsistent entries and responses.

Data Processing and Analysis

After data collection, the information was cleaned, edited, coded, and entered into EpiData (version 3.1; EpiData Association). It was then exported to SPSS Windows version 24 (IBM Corp) for analysis. Descriptive statistics, including percentages, ratios, frequency distributions, and pie charts, were used to summarize the data. The Hosmer and Lemeshow test will be used to evaluate the homogeneity of the variables. All variables that are significant at a $P<.05$ in the bivariable analysis were included in the multivariate logistic regression analysis. To ascertain the most suitable variables for the multivariate logistic regression, a backward stepwise goodness-of-fit approach was used. Finally, multivariate logistic regression analysis was conducted, reporting adjusted odds ratios (AORs) at 95% CIs, with a significance level set at $P<.05$.

Dissemination of Results

The final report of the study was submitted in both soft and hard copies to the Wollega University Institute of Health Sciences Research Affairs Directorate, School of Nursing and Midwifery, Department of Nursing. The document was also distributed to each hospital participating in the study. In addition, the findings were presented in national and international workshops and conferences.

Results

Distribution of Sociodemographic Characteristics of the Participants

A total of 397 participants were enrolled in the study, resulting in a response rate of 94.1%. Among the respondents, the majority were male participants (n=238, 59.9%). Approximately half of the participants, 199 out of 397 (50.1%), were aged between 30 and 39 years. In terms of ethnic background, 382 out of 397 (96%) participants identified as Oromo, and Afan Oromo was the predominant language spoken by 383 out of 397 (96.5%) participants.

Regarding professional affiliation, most participants were nurses, comprising 221 out of 397 (55.7%), followed by physicians, who accounted for 60 out of 397 (15.1%). In addition, over half of the respondents, 227 out of 397 (57.2%), identified as Protestant. In relation to work experience, nearly half, 197 out of 397 (49.6%), reported serving for a duration of 6 to 10 years, with the majority earning a monthly wage between Ethiopian Birr 7001 and 9000 (a currency exchange rate of Ethiopian Birr 52=US $1 during the study period; Table 1).

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Table . Distribution of sociodemographic characteristics of health professionals working in public hospitals of western Ethiopia, 2021 (N=397).

Variable	Value, n (%)
Sex	
Male	238 (59.9)
Female	159 (40.1)
Age (y)	
20 - 29	143 (36.0)
30 - 39	199 (50.1)
>40	55 (13.9)
Ethnicity	
Amhara	11 (2.8)
Oromo	382 (96.2)
Others[a]	4(1.0)
Religion	
Protestant	227 (57.2)
Orthodox	111 (28.0)
Muslim	52 (13.1)
Others	7 (1.8)
Marital status	
Single	161 (40.6)
Married	236 (59.4)
Language	
Afan Oromo	383 (96.5)
Amharic	9 (2.3)
Others[b]	5 (1.3)
Profession	
Nurse	221 (55.7)
Midwifery	53 (13.4)
Pharmacist	35 (8.8)
Medical laboratory technician	23 (5.8)
Medical doctor	60 (15.1)
Anesthetist and anesthesiologists	5 (1.3)
Experience (y)	
1 - 5	77 (19.4)
6 - 10	197 (49.6)
11 - 15	85 (21.4)
>16	38 (9.6)
Income (Birr)[c]	
3000 - 5000	30 (7.6)
5001 - 7000	121 (30.5)
7001 - 9000	183 (46.1)
>9000	63 (15.9)

[a]Others: Tigre and Guraghe.

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[b]Others: Tigrigna and Guraghign.

[c]A currency exchange rate of Ethiopian Birr 52=US $1 during the study period.

Health Professionals' Exposure to Information and Communication Technology (ICT)

Participants' familiarity with various types of information technology services is essential for the effective implementation of telehealth among health professionals. Regarding smartphone use, the majority, 246 out of 397 (62%), reported owning a smartphone. However, more than half, 220 out of 397 (55.2%), had never participated in training on computer systems and ICT, while over a third, 150 out of 397 (37.8%), had received introductory-level training. In addition, a significant portion, 305 out of 397 (76.8%), did not use computers regularly. Among those who did, 137 out of 397 (34.5%) primarily used computers for word processing and database management, while 113 out of 397 (28.5%) used them for entertainment purposes.

In terms of internet use, 167 out of 397 (42.1%) accessed the internet daily, followed by 72 out of 397 (18.1%) who reported weekly use. When examining the types of internet applications, more than half, 212 out of 397 (53.4%), indicated they used social media, followed by email and messaging services, which were used by 79 out of 397 (19.9%). Furthermore, regarding the use of medical-related websites, nearly two-thirds, 260 out of 397 (65.5%), reported that they had not visited such sites (Table 2).

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Table . Exposure to information communication technology among health professionals working in public hospitals in East Wollega, western Ethiopia, 2021 (N=397).

Variables	Value, n (%)
Smartphone use	
Yes	246 (62)
No	151 (38)
Computer and ICT[a] training	
Never attended	220 (55.4)
Introductory level	150 (37.8)
Certificate and above	27 (6.8)
Computer use	
Yes	92 (23.2)
No	305 (76.8)
Benefits of computer use	
Word processing and database management	137 (34.5)
Internet access	110 (27.7)
Entertainment	113 (28.5)
For more than 1 service	37 (9.3)
Frequency of internet use	
Every day	167 (42.1)
Twice a week	65 (16.4)
Every week	72 (18.1)
Every month	51 (12.8)
Less once a month	42 (10.6)
Types of internet application use	
Email services	79 (19.9)
Social media	212 (53.4)
Messaging applications	79 (19.9)
Cloud storage services	27 (6.8)
Medical-related website visits	
Yes	137 (34.5)
No	260 (65.5)

[a]ICT: information and communication technology.

Clinical Applications and Benefits of Telehealth

In the context of increasing digitalization and technological advancements in health care, telehealth presents a range of clinical applications. This study revealed that the majority of telehealth applications—160 out of 397 (40.3%) participants—are focused on chronic conditions, followed by gynecological diseases, which accounted for 93 out of 397 (23.4%) participants. When considering the specific purposes of telehealth, nearly two-thirds, or 119 out of 397 (30%) participants, viewed it as a means to enhance accessibility and convenience, while one-fourth, 100 out of 397 (25.2%), believed it improves patients' quality of life.

Regarding sources of information about telehealth, nearly two-thirds of participants reported that they learned about it from the internet (141 out of 397, 35.5%) and from colleagues (134 out of 397, 33.8%). Furthermore, more than two-thirds of the study participants, totaling 267 out of 397 (67.3%), had not attended telemedicine consultation sessions (Table 3).

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Table . Clinical applications and benefits of telehealth among health professionals working in public hospitals in East Wollega, western Ethiopia, 2021 (N=397).

Variables	Value, n (%)
Clinical application of telehealth	
Gynecological disorder	93 (23.4)
Chronic diseases	160 (40.3)
Infectious diseases	38 (9.6)
Pediatrics disorders	25 (6.3)
Mental illness	46 (11.6)
For all	24 (6.0)
Do not know	11 (2.8)
Benefit of telehealth	
Improve quality of life	100 (25.2)
Improve access and convenience	119 (30)
Reduce cost	48 (12.1)
Reduce isolation	88 (22.2)
Ensure data safety and security	42 (10.6)
Telehealth information source	
Colleague	134 (33.8)
Internet	141 (35.5)
Workshop or training session	87 (21.9)
News and radio	17 (4.3)
Others[a]	18 (4.5)
Alternative tasks for difficult cases	
Refer to another hospital	265 (66.8)
Schedule an appointment	69 (17.4)
Review previous cases and literature	63 (15.9)
History of attendance in telehealth consultation sessions	
Yes	130 (32.7)
No	267 (67.3)

[a]Others: webinars, books, journals, and peer networking.

Level of Knowledge and Perceptions of Implementing Telemedicine Among Health Professionals

The findings of this study revealed that 270 (68.01%) health professionals had a good level of knowledge about telemedicine, while 127 (32%) were poorly knowledgeable. Regarding perceptions of telehealth medicine implementation, 247 (62%) professionals expressed a positive perception, whereas 150 (38%) had a negative view.

Bivariable Logistic Regression Analysis of Factors Associated With Knowledge of Telehealth Implementation

In the bivariable logistic regression analysis, several variables were found to be significantly associated with knowledge of implementing telehealth. Specifically, the factors identified include sex, educational level, work experience, computer and ICT training, level of income, computer use, previous attendance at telemedicine consultations, and smartphone use; all with a significance level of $P<.05$ (Table 4). These findings suggest that demographic and training-related factors may play a crucial role in enhancing health care professionals' understanding and implementation of telehealth practices.

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Table . Bivariable logistic regression analysis of factors associated with good knowledge of implementing telehealth among health professionals working in public hospitals of western Ethiopia, western Ethiopia, 2021 (N=397).

Variables	Knowledge[b], n (%)		COR[a] (95% CI)	*P* value
	Good	Poor		
Sex				
Male	141 (59.2)	97 (40.8)	2.958 (1.841-4.752)	.001[c]
Female	129 (81.1)	30 (19.9)	1	
Education				
Diploma	11 (40.7)	16 (59.3)	1	
Bachelor's degree	177(66)	91 (34)	1.040 (1.261-6.348)	.012[c]
Master's degree	32 (76.2)	10 (23.8)	1.538 (1.636-13.244)	.004[c]
Medical doctor	50 (83.3)	10 (16.7)	1.984 (2.610-12.266)	.001[c]
Experience (y)				
1 - 5	34 (44.2)	43 (55.8)	1	
6 - 10	136 (69)	61 (31)	0.322 (0.140-0.741)	.008[c]
11 - 15	73 (85.9)	12 (14.1)	0.928 (0.423-1.949)	.805
>16	27 (71.1)	11 (28.9)	2.478 (0.978-6.279)	.056
Computer and ICT[d] training				
Never attended	142 (64.5)	78 (35.5)	1	
Introductory level	104 (69.3)	46 (30.7)	0.106 (0.081- 0.986)	.047[c]
Certificate and above	24 (88.9)	3 (11.1)	0.096 (0.066-0.780)	.018[c]
Income (Birr)[e]				
3000 - 5000	11 (36.7)	19 (63.3)	1	
5001 - 7000	71 (58.7)	50 (41.3)	0.387 (0.278-1.667)	.395
7001 - 9000	159 (86.9)	24 (13.1)	4.11 (1.23-9.12)	.001[c]
>9000	29 (46)	34 (54)	1.510 (0.910-3.075)	.103
Computer use				
Yes	157 (89.2)	19 (10.8)	2.067 (1.583-7.610)	.001[c]
No	113 (51.1)	108 (48.9)	1	
Attendance of telehealth consultation				
Yes	120 (92.3)	10 (7.7)	4.236 (2.700-18.641)	.001[c]
No	150 (56.2)	117 (43.8)	1	
Smartphone use				
Yes	136 (55.3)	110 (44.7)	4.852 (3.628-11.203)	.001[c]
No	134 (88.7)	17 (11.3)	1	

[a]COR: crude odds ratio.

[b]Dependent variable: knowledge.

[c]Significance at $P<.05$.

[d]ICT: information and communication technology.

[e]A currency exchange rate of Ethiopian Birr 52=US $1 during the study period.

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Multivariable Logistic Regression Analysis of Factors Associated With Knowledge of Implementing Telehealth

All variables significant at a $P<.05$ in the bivariable logistic regression were included in the multivariable logistic regression analysis. The following factors were found to be significantly associated with knowledge of implementing telehealth: higher educational level (Master's degree and above), higher income level, access to computer usage, attendance at telehealth consultation sessions, and access to smartphone use.

Individuals with a higher educational status, such as MD and above, were nearly 3 times more likely to have knowledge of implementing telehealth compared to those with only a diploma (AOR 2.797, 95% CI 2.019-26.872). Those holding an MD and above were about as likely to be knowledgeable about implementing telehealth compared to diploma holders (AOR 4.22, 95% CI 3.45-13.12). Regarding income level, individuals earning between 7000 and 9000 birr monthly were more than 4 times more likely to be knowledgeable about implementing telehealth compared to those earning between 3000 and 5000 birr (AOR 4.11, 95% CI 1.23-9.12).

In terms of computer use, individuals with experience using computers were over twice as likely to be knowledgeable about implementing telehealth compared to those without such experience (AOR 2.414, 95% CI 1.046-14.764). Moreover, those who had attended telehealth consultation sessions were more than twice as likely to possess knowledge about implementing telemedicine compared to those who had not attended such sessions (AOR 2.389, 95% CI 1.961-10.158). Finally, smartphone users were nearly 3 times more likely to be knowledgeable about implementing telehealth compared to nonusers (AOR 3.027, 95% CI 2.797-14.729; Table 5).

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Table . Multivariable logistic regression analysis of factors associated with knowledge of implementing telehealth among study participants, western Ethiopia (2021; N=397).

Variables	Knowledge[c], n (%)		COR[a] (95% CI)	*P* value	AOR[b] (95% CI)	*P* value
	Good	Poor				
Education						
Diploma	11 (40.7)	16 (59.3)	1		1	
Bachelor's degree	177 (66)	91 (34)	1.040 (1.261-6.348)	.012	1.539 (0.587-5.008)	.324
Master's degree	32 (76.2)	10 (23.8)	1.538 (1.636-13.244)	.004	1.852 (1.689-14.044)	.006
MD and above	50 (83.3)	10 (16.7)	1.984 (2.610-12.266)	.001	4.22 (3.45-13.12)	.001[d]
Income (Birr)						
3000 - 5000	11 (36.7)	19 (63.3)	1		1	
5001 - 7000	71 (58.7)	50 (41.3)	0.387 (0.278-1.667)	.395	1.558 (0.696-32.410)	.112
7001 - 9000	159 (86.9)	24 (13.1)	2.050 (4.033-14.960)	.001	3.255 (1.790-8.878)	.001[d]
>9000	29 (46)	34 (54)	0.510 (0.910-3.075)	.103	1.291 (0.949-13.940)	.060
Computer use						
Yes	157 (89.2)	19 (10.8)	2.067 (4.583-13.610)	.001	2.414 (1.046-14.764)	.001[d]
No	113 (51.1)	108 (48.9)	1		1	
Attendance of telehealth consultation						
Yes	120 92.3)	10 (7.7)	2.236 (4.700-18.641)	.001	2.389 (1.961-10.158)	.001[d]
No	150 (56.2)	117 (43.8)	1		1	
Smartphone use						
Yes	136 (55.3)	110 (44.7)	1.852 (3.628-11.203)	.001	3.027 (2.797-14.729)	.001[d]
No	134 (88.7)	17 (11.3)	1		1	

[a]COR: crude odds ratio.

[b]AOR: adjusted odds ratio.

[c]Dependent variable: knowledge of implementing telehealth.

[d]Significance at *P* value ≤.05.

In the bivariable logistic regression analysis, several variables were found to be significantly associated with the perception of implementing telehealth. Specifically, the factors identified include sex, work experience, computer and ICT training, level of income, computer usage, previous attendance at telehealth consultations, daily internet use, perceived benefits of telemedicine for improving quality of life, accessibility of services, convenience, and smartphone use at a significance level of *P*<.05 (Table 6).

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Table . Bivariable logistic regression analysis of factors associated with perceptions of implementing telehealth among health professionals working in public hospitals of western Ethiopia (N=397).

Variables	Perception[a], n (%)		COR[b] (95% CI)	*P* value[c]
	Good	Poor		
Sex				
Male	106 (45.5)	132 (55.5)	0. 476 (10.310-0.733)	.001
Female	44 (27.7)	115 (72.3)	1	
Experience (y)				
1 - 5	12 (15.6)	65 (84.4)	0.185 (0.076-0.447)	.001
6 - 10	79 (40.1)	118 (59.9)	0.669 (0.334-1.344)	.259
11 - 15	19 (50)	19 (50)	0.889 (0.413-1.911)	.763
>16			1	
Computer and ICT[d] training				
Never attended	121 (55)	99 (45)	0.549 (0.071-0.635)	.006
Introductory level	103 (68.7)	47 (31.3)	0.965 (0.125-1.164)	.090
Certificate and above	23 (85.2)	4 (14.8)	1	
Income (Birr)[e]				
3000 - 5000	7 (23.3)	23 (76.7)	1	
5001 - 7000	33 (27.3)	88 (72.7)	1.157 (0.412-3.322)	3.32
7001 - 9000	97 (53)	86 (47)	0.866 (0.695-2.992)	.325
>9000	13 (20.6)	50 (79.4)	3.467 (2.207-8.526)	.001
Computer use				
Yes	91 (51.7)	85 (48.3)	1.807 (1.482-3.390)	.001
No	156 (70.6)	65 (29.4)	1	
Attendance of telehealth consultation				
Yes	82 (63.1)	48 (36.9)	3.609 (3.187-7.842)	.001
No	68 (25.5)	199 (74.5)	1	
Smartphone use				
Yes	186 (75.6)	60 (24.4)	3.520 (2.957-7.075)	.001
No	61 (40.1)	90 (59.6)	1	
Frequency of internet use				
Every day	114 (87.7)	16 (12.3)	4.781 (1.623-21.722)	.007
Twice a week	34 (47.2)	38 (52.8)	1.294 (0.209-2.665)	.652
Every week	18 (35.3)	33 (64.7)	0.788 (0.122-1.699)	.241
Every month	37 (39.8)	56 (60.2)	0.376 (0.196-2.408)	.557
Less once a month	33 (82.5)	7 (17.5)	1	
Not at all	9 (81.8%)	2 (18.2%)	1.368 (0.931, 16.582)	.063
Benefit of telehealth				
Improve quality of life	15 (15)	85 (85)	4.159 (3.811-19.709)	.001
Improve access and convenience	35 (29.7)	83 (70.3)	2.288 (1.752-7.510)	.001
Reduce cost	34 (70.8)	14 (29.2)	0.462 (0.263-1.507)	.299
Reduce isolation	40 (45.5)	48 (54.5)	1.607 (0.874-3.852)	.108
Ensure data safety and security	26 (60.5)	17 (39.5)	1	

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[a]Dependent variable: perceptions of implementing telehealth.

[b]COR: crude odds ratio.

[c]Significance at $P \leq .05$.

[d]ICT: information communication technology.

[e]A currency exchange rate of Ethiopian Birr 52=US $1 during the study period.

Multivariable Logistic Regression Analysis of Factors Associated With Perceptions of Implementing Telehealth

All variables that were significant at a *P* value of <.05 in the bivariable logistic regression were included in the multivariable logistic regression analysis. The following factors were found to be significantly associated with perceptions of implementing telehealth: higher income level, work experience, attendance at telehealth consultation sessions, perceived benefits of telehealth, and access to smartphone use.

Individuals with 1 to 5 years of experience were less likely to have a positive perception of implementing telehealth compared to those with more than 16 years of experience (AOR 0.0562, 95% CI 0.020-0.233). Regarding income level, individuals earning more than 9000 birr monthly were nearly 3 times more likely to have a positive perception of implementing telehealth compared to those earning between 3000 and 5000 birr (AOR 2.675, 95% CI 2.271-19.277).

In terms of the perceived benefits of telemedicine, individuals who experienced its use for improving quality of life were nearly twice as likely to have a positive perception of implementing telehealth compared to those who perceived it primarily for ensuring data safety and security (AOR 1.786, 95% CI 1.575-22.587). In addition, individuals who perceived telehealth as a means of improving accessibility and convenience were 1.244 times more likely to have a positive perception compared to those focused on data safety and security (AOR 1.244, 95% CI 1.061-11.333).

Moreover, those who had attended telehealth consultation sessions were nearly twice as likely to possess a positive perception of implementing telehealth compared to those who had not attended such sessions (AOR 4.777, 95% CI 2.318-15.062). Finally, smartphone users were nearly 2 times more likely to have a positive perception of implementing telehealth compared to nonusers (AOR 3.836, 95% CI 2.900-13.573)(Table 7).

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Table . Multivariable logistic regression analysis of factors associated with perceptions of implementing telehealth among health professionals working in public hospitals of western Ethiopia (2021; N=397).

Variables	Perception[c], n (%)		COR[a] (95%)	*P* value	AOR[b]	*P* value
	Good	Poor				
Experience (y)						
1 - 5	12 (15.6)	65 (84.4)	0.289 (0.076-0.447)	.001	0.056 (0.020-0.233)	.001[d]
6 - 10	79 (40.1)	118 (59.9)	0.401 (0.334-1.344)	.259	0.139 (0.024-1.263)	.051
11 - 15	19 (50)	19 (50)	0.918 (0.413-1.911)	.763	1.095 (0.027-2.556)	.066
>16			1		1	
Income (Birr)						
3000 - 5000	7 (23.3)	23 (76.7)	1		1	
5001 - 7000	33 (27.3)	88 (72.7)	1.157 (0.412-3.322)	3.322	0.512(0.205-13.547)	.632
7001 - 9000	97 (53)	86 (47)	1.366 (0.695-2.992)	.325	1.277(0.813-15.820)	.092
>9000	13 (20.6)	50 (79.4)	2.467 (2.207-8.526)	.001	2.675(2.271-19.277)	.001[d]
Attendance of telemedicine consultation						
Yes	82 (63.1)	48 (36.9)	4.609 (3.187-7.842)	.001	4.777(2.318-15.062)	.001[d]
No	68 (25.5)	199 (74.5)	1		1	
Smartphone use						
Yes	186 (75.6)	60 (24.4)	3.520 (2.957-7.075)	.001	3.836 (2.900-13.573)	.001[d]
No	61 (40.1)	90 (59.6)	1		1	
Benefit of telehealth						
Improve quality of life	15 (15)	85 (85)	4.159 (3.811-19.709)	.001	1.786 (1.575-22.587)	.009[d]
Improve access and convenience	35 (29.7)	83 (70.3)	2.288 (1.752-7.510)	.001	1.244 (1.061-11.333)	.040[d]
Reduce cost	34 (70.8)	14 (29.2)	0.462 (0.263-1.507)	.299	1.222 (0.163-3.942)	.801
Reduce isolation	40 (45.5)	48(54.5)	1.607(0.874, 3.852)	.108	2.817 (0.604-8.478)	.225
Ensure data safety and security	26 (60.5)	17(39.5)	1		1	

[a]COR: crude odds ratio

[b]AOR: adjusted odds ratio.

[c]Dependent variable = perceptions of implementing telehealth.

[d]Significance at $P \leq .05$.

Discussion

Main Findings

The limited implementation of telehealth in Ethiopia, with less than 10% adoption, can be attributed to several factors hindering its advancement [20,21]. In this cross-sectional study, we aimed to assess the level of knowledge and perception of health professionals regarding telemedicine implementation in the East Wollega Zone of the Oromia region, western Ethiopia. We identified significant factors associated with the knowledge and perception of telehealth implementation among targeted individuals, which contribute to the digitalization of global health care systems for better access to health care services.

Comparison With Prior Work

The results indicated that approximately 68.01% (270/397) of participants possessed a good level of knowledge, which exceeds

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that reported in previous research conducted in referral hospitals in northwest Ethiopia (56.4%, 37.6%, 65.8%, and 40.7%), and Saudi Arabia (46.1%) [18,22-25]. Conversely, the knowledge level in our study was higher than findings from Nigeria and Iran (34.5% and 3.9%, respectively) [26,27] . This disparity may be linked to lower accessibility to information and training regarding telehealth at the national level, geographical impact to access relevant resources, and impact of the COVID-19 pandemic, as studies conducted during the outbreak.

Furthermore, our findings revealed that 62% (247/397) of health professionals held a positive perception of implementing telehealth, surpassing the results of a study conducted in Addis Ababa, Ethiopia, where approximately 60.9% of professionals expressed a positive perception toward telehealth [28,29]. In contrast, it was lower compared to the studies reported in India, where 73.14% of participants had a positive perception, and in Saudi Arabia, where the figure was 90%; another study reported 65.2% positive perception of implementing telemedicine in India [18,29,30]. These differences may reflect variations in technological advancement, accessibility, and economic conditions across the regions studied.

In this study, higher educational status was identified as an independent factor associated with knowledge of telehealth, considering the joint effects of other variables. Professionals with a higher level of education were 3 times more likely to possess good knowledge of implementing telemedicine compared to those with a lower educational level, such as a diploma. This finding aligns with a study conducted in northern Ethiopia, which revealed that individuals with a degree or higher had significantly increased knowledge scores related to telehealth [31]. These similarities suggest that a higher educational level contributes to greater exposure to various sources of information about telehealth, thereby enhancing understanding.

Moreover, the findings of this study indicated that health professionals with access to smartphones were nearly twice as likely to have a positive perception of implementing telehealth compared to non-users. This is consistent with a study conducted in central Ethiopia, which found that participants with sufficient access to computers or smartphones were more likely to have a favorable perception of using telehealth than those lacking adequate devices (32). This similar finding underscores the importance of accessibility to technological resources for exchanging information and disseminating knowledge about the purpose of telehealth, thereby enhancing positive beliefs toward its implementation [28].

Study Limitations

This study has several limitations as follows:

1. Self-reported data: the study relies on self-reported measures of knowledge and perceptions, which may introduce bias. Respondents might overestimate their knowledge or provide socially desirable answers.
2. Design approach: as a cross-sectional study, it captures data at a single point in time, which may not reflect changes in knowledge or perceptions over time or lacks causal-effect relationship.
3. Potential response bias: participants may have differing levels of familiarity with telehealth, leading to variations in responses that could affect the study's outcome.
4. Limitation of psychometrics properties testing: although we used surveys with identical items from those published in the literature, formal psychometric validation of this measure was not conducted in this study.

Conclusions

In conclusion, the findings of the study revealed a relatively higher level of knowledge and perception in implementing telehealth. Educational status, income, computer and smartphone use, and exposure to telehealth training were factors associated with the knowledge of implementing telehealth, whereas income level, work experience, exposure to telehealth training sessions, perceived benefits of telehealth, and access to smartphone use were factors associated with the perception of telemedicine.

Based on the study's findings, it is recommended to enhance educational programs for health professionals to improve their knowledge of telehealth, particularly targeting those with lower educational backgrounds. Increasing access to smartphones and computers, along with providing regular training sessions and awareness campaigns about the benefits of telehealth, will further bolster positive perceptions. In addition, addressing income disparities and fostering collaborative learning environments can significantly contribute to a more favorable attitude toward telehealth implementation.

Acknowledgments

First, the authors would like to acknowledge Almighty God for granting them a healthy life to conduct this study. Next, the authors extend their appreciation to Wollega University for their approval and financial support, which made this research possible. Furthermore, the authors are grateful to all members of their research group for their collaborative and interactive participation throughout the study process, contributing significantly to its success. Finally, the authors would like to thank the respective hospitals and participants for their willingness and active participation, as well as for sacrificing their time for this study.

Data Availability

All relevant data are included within the manuscript and the supplementary materials, which can be accessed from the authors upon reasonable request.

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Authors' Contributions

AOA conceptualized the ideas and oversaw the entire manuscript process, while all other authors contributed to designing the study and drafting the manuscript. They have all approved the final version and agreed to take responsibility for all aspects of the work.

Conflicts of Interest

None declared.

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Abbreviations

AOR: adjusted odds ratio
ICT: information and communication technology

Edited by E Borycki; submitted 29.01.25; peer-reviewed by C Gibson-Gill, O Nguyen; revised version received 08.11.25; accepted 09.11.25; published 04.12.25.

Please cite as:
Oluma A, Gudeta TA, Olana MD, Daba AB, Dinagde DG, Yadesa AT, Atomsa L, Tesema TM
Exploring Health Professionals' Knowledge and Perceptions of Telehealth Implementation in Multisite Public Hospitals of East Wollega Zone, Oromia, West Ethiopia: Cross-Sectional Study
JMIR Nursing 2025;8:e71870
URL: https://nursing.jmir.org/2025/1/e71870
doi:10.2196/71870

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Impact of COVID-19 Pandemic–Induced Changes in Clinical Practicums on the Mental Health of Newly Graduated Nurses: Longitudinal Study

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Abstract

Background: The COVID-19 pandemic disrupted nursing education worldwide, particularly clinical practicums, reducing opportunities for hands-on learning. Newly graduated nurses have reported increased stress, reduced confidence, and a higher risk of burnout. However, few studies have examined the long-term mental health effects of these disruptions.

Objective: This study aimed to longitudinally examine how changes in clinical practicums during the COVID-19 pandemic affected the mental health of nurses who graduated in the academic year 2021-2022.

Methods: A quantitative longitudinal study was conducted at 3 time points: June 2022, September 2022, and December 2022. This study assessed the nurses' demographic data and the perceived impact on the students of disruptions in domain-specific and integration practicums, practicum formats, and clinical difficulty. Instruments used included the Nursing Job Stressor Scale, the Maslach Burnout Inventory, and adapted items for measuring intention to leave the profession. Participants were categorized into high- and low-impact groups. A 2-way ANOVA was used to examine mental health indicators over time.

Results: Participants who perceived a greater impact of practicum disruptions reported substantially higher levels of clinical difficulty and stressors. In the September 2022 survey, those perceiving less impact from the integration practicum reported a stronger intention to continue nursing. In the December 2022 survey, emotional exhaustion, a core component of burnout, was significantly higher in the high-impact group.

Conclusions: The perceived quality and extent of clinical practicum experiences significantly influenced the psychological burden and career intentions of newly graduated nurses. Disruptions caused by the COVID-19 pandemic may have lasting effects on nurses' mental health. These findings underscore the need for continuous workplace support and targeted mental health interventions for early-career nurses to ensure safe and sustainable nursing practice.

(JMIR Nursing 2025;8:e79556) doi:10.2196/79556

KEYWORDS

nurses; COVID-19; stress; burnout; intention to leave; longitudinal study

Introduction

Background

In December 2019, the first case of COVID-19 was reported in Wuhan, China. The World Health Organization subsequently declared the outbreak a public health emergency of international concern [1]. The global spread of COVID-19 had a profound impact on society as a whole. In particular, the health care sector worldwide experienced significant changes, such as the restructuring of care systems, strengthening of infection control, and resource shortages. Nursing education, which accords immense importance to experiential learning, was also significantly affected. In many countries and regions, hospitals suspended or restricted clinical practicums for nursing students, pivoting toward online training [2,3]. Nursing students indicated that the COVID-19 pandemic significantly increased their stress levels, exacerbating their psychological burden [4].

In Japan, many hospitals ceased accepting students to avoid the spread of infection, resulting in a substantial reduction in traditional clinical practicums at nursing universities. Instead, they introduced on-campus simulations and exercises [5,6]. While these changes were necessary for public health reasons, they raised several challenges from the perspective of fostering practical nursing competencies.

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The psychosocial aspects of the COVID-19 pandemic, such as restrictions on practicum opportunities, are also believed to have adversely affected nursing students' mental health [7]. Clinical practicums aim to integrate and enhance nursing knowledge, skills, and attitudes, cultivating the ability to provide appropriate care based on accurate situational judgment [8]. Therefore, limitations on such experiences may severely hinder the development of these competencies.

Indeed, comparative research on students whose practicum formats were altered because of the COVID-19 pandemic indicates that those who had even 1 week of on-site practicum acquired greater practical learning in response to nursing problems than those who underwent only on-campus training [9]. Furthermore, surveys targeting newly graduated nurses have revealed that the quantity and quality of clinical practicums during school significantly influence postgraduate practical abilities [10].

A lack of practical competence is not only an educational issue but also a mental health concern. Among different occupational categories in health care, novice nurses report the highest stress levels, with "anxiety over one's own nursing competence" cited as a major contributing factor [11]. This suggests that the limitations on clinical practicums induced by the COVID-19 pandemic may have a direct impact on the concerned individuals' mental health.

Of particular concern is burnout, which consists of 3 dimensions: emotional exhaustion, depersonalization, and reduced personal accomplishment [12]. Nurses are regularly exposed to multiple stressors, such as excessive workload, interpersonal conflicts, and shift work, which can easily induce burnout. If left unaddressed, burnout can progress to serious outcomes such as depressive symptoms and increased turnover intentions [13].

Among younger nurses, difficulties adapting to clinical settings and low self-efficacy are known to exacerbate burnout [14]. Newly graduated nurses experience a period of intense emotional, physical, and intellectual stress as they transition from the role of student to that of a professional nurse [15]. This phase is characterized by uncertainty, role confusion, and loss of confidence, all of which can heighten vulnerability to burnout. From a broader perspective, work adaptation theories such as the theory of work adjustment by Dawis and Lofquist [16] emphasize the importance of achieving a balance between individual needs and environmental demands. Insufficient adaptation during this early stage can lead to dissatisfaction, stress, and eventual turnover. Therefore, for nurses whose practicums were affected by the COVID-19 pandemic, mental health support systems in the workplace, as well as educational interventions aimed at improving interpersonal and stress-coping skills, are essential.

Moreover, social support from supervisors and colleagues, the maintenance of work-life balance, and cultivation of psychologically safe work environments are all critical for preventing burnout and maintaining mental health. Nevertheless, research on the impact of changes in clinical practicums during the COVID-19 pandemic on the mental health of newly graduated nurses remains limited. As nurse mental health is closely linked to turnover and the quality of care, more research should focus on the quality of educational experiences during training to inform effective support strategies.

Purpose of This Study

This study aimed to longitudinally examine how changes in clinical practicums owing to the COVID-19 pandemic affected the mental health of nurses who graduated in the academic year 2021 - 2022. We adopted the following terminology related to clinical practicums [17]:

- *Clinical practicum* refers to educational experiences designed to cultivate the ability to apply knowledge and skills in practical nursing settings by integrating and understanding nursing theory and practice. It includes learning one's role as a member of a health care team and developing the ability to provide nursing care through collaboration and cooperation with professionals in the health, medical, and welfare fields. The practicum encompasses content in adult (chronic and acute care), gerontological, psychiatric, maternal, and pediatric nursing.
- *Integration and practice of nursing* refers to educational experiences aimed at understanding both membership and leadership roles as a nurse in team-based, interprofessional medical care settings. Additionally, it includes developing fundamental abilities for nursing management.

Methods

Participants

This study targeted 225 nurses who had completed basic nursing education and were employed for the first time within 1 year after graduation in the academic year 2021-2022 at 39 hospitals (out of the total of 336 hospitals) in Hyogo Prefecture, Japan, who consented to participate.

Research Design and Survey Periods

We conducted a quantitative longitudinal study over 3 time points: June 2022, September 2022, and December 2022. The first, second, and third surveys were conducted from June 1 to 30, 2022; September 1 to 30, 2022; and December 1 to 31, 2022, respectively.

Survey Content

Basic demographic attributes assessed included sex, age, years of experience, and department. Regarding the impact of clinical practicums on students, participants subjectively rated their perceived impact of clinical practicums (in adult, gerontological, psychiatric, pediatric, and maternal nursing) and the integration and practice of nursing practicum on a 5-point Likert scale ranging from "very much affected" (5 points) to "not affected at all" (1 point).

The participants were also asked to indicate the actual form of clinical practicum implementation from the following 5 options: "all practicums conducted in clinical settings," "partially substituted with on-campus training," "partially substituted with online training," "all substituted with on-campus training," and "all substituted with online training." Subsequently, they rated the degree of difficulty experienced in clinical practice owing

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to the changes in clinical practicums on a 5-point Likert scale from “very much felt” (5 points) to “not felt at all” (1 point).

Measurement Tools

Stressors

We used the Nursing Job Stressor Scale developed by Higashiguchi et al [18]. This instrument contains 33 items describing potentially stressful situations in nursing and includes the following 7 subscales: “conflict with other nursing staff,” “nursing role conflict,” “conflict with physicians/autonomy,” “dealing with death and dying,” “qualitative workload,” “quantitative workload,” and “conflict with patients.” Higher scores indicate greater perceived stress.

Burnout

We measured burnout using the Maslach Burnout Inventory [12] originally developed by Maslach et al [19] and later adapted by Tao and Kubo [20]. The instrument consists of 17 items across 3 dimensions: “emotional exhaustion,” “depersonalization,” and “personal accomplishment.” The reliability and validity of the scale have been confirmed. Responses are provided on a 5-point scale from “always present” to “absent.” Higher scores in “emotional exhaustion” and “depersonalization” and lower scores in “personal accomplishment” indicate a higher likelihood of burnout.

Intention to Leave the Job

We assessed participants’ intention to leave using items developed by Ohue et al [13], which were based on the categories defined by Tsuchie and Nakamura [21]. The items used were “wants to quit working as a nurse,” “wants to switch hospitals or departments,” and “wants to continue working as a nurse.” Responses were provided on a 5-point Likert scale ranging from “always present” to “absent,” with higher scores indicating a stronger intention to leave.

Data Collection Procedure

We used the paid version of Google Forms to create both the survey and a corresponding QR code. After obtaining approval from the ethics review board, we explained, both in writing and verbally, the purpose and content of the study to the directors of nursing at participating hospitals to obtain their consent. Upon approval, we sent the research materials, including a printed explanation of the study and a survey form with a QR code, to the nursing departments of each hospital. Ward nurse managers were then responsible for explaining the study to eligible nurses and distributing the survey invitation and questionnaire.

Nurses who agreed to participate in the study accessed the survey via the QR code provided on the printed form. Responses to all instruments were collected at the 3 aforementioned time points using the same survey content. The survey was anonymous. The participants completed the first survey via the QR code on the printed form. The second and third surveys were distributed via email to the addresses provided by the participants. We conducted longitudinal data linkage using voluntarily registered email addresses, which were deleted upon completion of the study.

Data Analysis

We calculated descriptive statistics (frequencies and percentages) for the participants’ demographic characteristics and the mean and SD for their ages. We categorized the participants into 2 groups for each practicum domain: a low-impact group (responses of “not affected at all,” “not very affected,” or “neutral”) and a high-impact group (responses of “somewhat affected” or “strongly affected”) regarding the perceived impact of the clinical practicums and the integration and practice of nursing practicum.

After confirming normality, we conducted an ANOVA to examine differences in mental health variables by survey time (June 2022, September 2022, and December 2022) and practicum impact group (high vs low). We adopted a significance level of $P<.05$ for all analyses. All statistical analyses were performed using SPSS Statistics for Windows (version 26; IBM Corp).

Ethical Considerations

This study was conducted with the approval of the Ethics Committee of the University of Hyogo. We submitted written requests for participation to the administrators of participating facilities. Only those facilities that agreed were included in the study. We provided a written explanation of the study to all potential participants. Only those who gave informed consent were included. The written explanation clarified that participation or withdrawal from the study was entirely voluntary and would not result in any disadvantage. It also clarified that the data would be used exclusively for this study. All collected data were statistically processed using code numbers, ensuring privacy and confidentiality, and no personally identifiable information was disclosed. Participants were compensated for their time and contribution to this research. Compensation included a gift card valued at JP ¥500 (US $3.19). Compensation was determined to be appropriate, noncoercive, and commensurate with the expected time and effort required for participation. Information about compensation was clearly stated in the consent form and communicated to participants before enrollment.

Results

Participant Demographics

Table 1 shows the number of participants and their demographic data. In the first survey, conducted in June 2022, a total of 225 newly graduated nurses responded (n=18, 8% men and n=207, 92% women). The second survey, conducted in September 2022, yielded 140 responses (n=10, 7.1% men and n=130, 92.9% women), and the third survey in December 2022 had 85 respondents (n=5, 5.9% men and n=80, 94.1% women). Of these, 73 nurses (n=2, 2.7% men and n=71, 97.3% women) completed all 3 surveys without missing data and, thus, were included in the final analysis. This represented a response rate of 32.4% (73/225). The average age of the participants was 23.23 (SD 3.68) years. The main reasons for dropping out of the study included changing jobs, changes in work arrangements, and refusal to answer the survey questions. We conducted 2-tailed independent *t* tests to compare completers and

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noncompleters at baseline for stressors, burnout, and turnover intention scores, finding no significant differences. As such, attrition did not result in substantial systematic bias.

Table . Basic attributes of the participants (N=73).

Attributes	Participants, n (%)
Sex	
Male	2 (2.7)
Female	71 (97.3)
Education	
Vocational school	19 (26.0)
Junior college	1 (1.4)
University	47 (64.4)
Postgraduate school	6 (8.2)
Qualification	
Nurse	71 (97.3)
Midwife	2 (2.7)
Work shift	
Day shift only	13 (17.8)
3-shift rotation	15 (20.5)
2-shift rotation	45 (61.6)
Department	
General ward	49 (67.1)
Obstetrics and gynecology ward	1 (1.4)
Pediatric ward	5 (6.8)
Intensive care unit	11 (15.1)
Operating room	6 (8.2)
Psychiatric ward	1 (1.4)
Acceptance of patients with COVID-19 at their hospital	
Accepting patients with severe disease	13 (17.8)
Accepting patients with moderate disease	5 (6.8)
Accepting patients with mild disease	27 (37)
Not accepting patients	28 (38.4)

Perceived Impact of Each Clinical Practicum

Table 2 presents the results on the perceived impact of the integration and practice of nursing practicum. A total of 11% (8/73) of the respondents reported being “not affected at all,” 21.9% (16/73) reported being “not very affected,” 5.5% (4/73) reported being “neutral,” 34.2% (25/73) reported being “somewhat affected,” and 27.4% (20/73) reported being “strongly affected.” Regarding the actual implementation method of this practicum, 30.1% (22/73) of the participants experienced it entirely in clinical settings, 46.6% (34/73) experienced a partial substitution with on-campus training, 5.5% (4/73) experienced a partial substitution with online training, 12.3% (9/73) had full substitution with on-campus training, and 5.5% (4/73) experienced full substitution with online training. Regarding domain-specific clinical practicums (adult, geriatric, psychiatric, pediatric, and maternal nursing), most participants reported being “somewhat affected” (38/73, 52.1%) followed by “strongly affected” (19/73, 26%). Regarding the implementation of domain-specific clinical practicums, most participants (55/73, 75.3%) experienced partial on-campus substitution.

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Table . Degree of impact of each clinical practicum on students (N=73).

	Participants, n (%)
Integrated nursing practicum	
Not affected at all	8 (11)
Not very affected	16 (21.9)
Neutral	4 (5.5)
Somewhat affected	25 (34.2)
Strongly affected	20 (27.4)
Specific impact on the integrated nursing practicum	
Entirely clinical practicum	22 (30.1)
Partial use of on-campus training for clinical practicum	34 (46.6)
Partial use of online training for clinical practicum	4 (5.5)
Entirely on-campus practicum	9 (12.3)
Entirely online practicum	4 (5.5)
Each clinical practicum (adult, maternity, pediatric, geriatric, and psychiatric nursing)	
Not affected at all	2 (2.7)
Not very affected	14 (19.2)
Neutral	0 (0)
Somewhat affected	38 (52.1)
Strongly affected	19 (26)
Specific impact on the domain-specific practicum	
Entirely clinical practicum	4 (5.5)
Partial use of on-campus training for clinical practicum	55 (75.3)
Partial use of online training for clinical practicum	9 (12.3)
Entirely on-campus practicum	4 (5.5)
Entirely online practicum	1 (1.4)

Perceived Practicum Impact and Difficulty in Clinical Practice by Period

To examine the relationship between practicum experience and perceived difficulty in clinical practice, we divided participants into high- and low-impact groups based on their responses. Those who answered with “somewhat affected” or “strongly affected” were categorized into the high-impact group, whereas those who responded with “not affected at all,” “not very affected,” or “neutral” were categorized into the low-impact group. We conducted an ANOVA with time (June 2022, September 2022, and December 2022) and practicum impact level as factors. The analysis revealed significant interaction effects across the 3 time points (Table 3). Further analysis of simple main effects showed that, at all survey time points, the high-impact group for both the integration and domain-specific practicums reported significantly greater difficulty in clinical practice.

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Table . Perceived practicum impact and difficulty in clinical practice by period (time 1: June 2022; time 2: September 2022; time 3: December 2022). Scores represent responses on a 5-point Likert scale.

Time	Low impact for specific clinical practicums on students (score), mean (SD)		High impact for specific clinical practicums on students (score), mean (SD)		Main effect—specific clinical practicums			Main effect—integrated clinical practicum			Interaction		
	Low impact for integrated clinical practicum on students	High impact for integrated clinical practicum on students	Low impact for integrated clinical practicum on students	High impact for integrated clinical practicum	*F* test (*df*)	*P* value	η^2	*F* test (*df*)	*P* value	η^2	*F* test (*df*)	*P* value	η^2
1	2.18 (0.98)	3.50 (0.58)	3.36 (1.15)	3.23 (0.86)	2.00 (1, 59)	.16	0.04	3.46 (1, 59)	.07	0.06	5.08 (1, 59)	.03	0.09
2	3.27 (1.01)	4.00 (0.82)	3.86 (1.23)	2.58 (1.10)	1.28 (1, 59)	.26	0.02	0.56 (1, 59)	.46	0.01	7.33 (1, 59)	.01	0.13
3	3.00 (1.10)	4.00 (0.82)	3.64 (1.22)	2.62 (1.20)	0.90 (1, 59)	.35	0.02	0.00 (1, 59)	.97	0.00	6.70 (1, 59)	.01	0.12

Perceived Practicum Impact and Stressors by Period

As shown in Table 4, the results of a 2-way ANOVA revealed a significant interaction for “interpersonal stressors in the workplace” in the second survey (September 2022) and “interpersonal stressors with patients” in the third survey (December 2022). In both cases, the high-impact group for the integration practicum reported significantly higher stress levels than the low-impact group for the domain-specific practicums. Although we found no interaction for “stress related to physicians,” we observed significant main effects for both practicum types.

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Table . Perceived practicum impact and stressors by period (time 1: June 2022; time 2: September 2022; time 3: December 2022). Scores represent responses on a 5-point Likert scale.

Time	Low impact for specific clinical practicums on students (score), mean (SD)		High impact for specific clinical practicums on students (score), mean (SD)		Main effect—specific clinical practicums			Main effect—integrated clinical practicum			Interaction		
	Low impact for integrated clinical practicum on students	High impact for integrated clinical practicum on students	Low impact for integrated clinical practicum on students	High impact for integrated clinical practicum on students	*F* test (*df*)	*P* value	η^2	*F* test (*df*)	*P* value	η^2	*F* test (*df*)	*P* value	η^2
The total strain													
1	2.46 (0.25)	2.25 (0.7)	2.48 (0.64)	2.44 (0.71)	0.25 (1, 59)	.62	0	0.37 (1, 59)	.54	0.01	0.17 (1, 59)	.68	0
2	2.45 (0.68)	2.95 (0.37)	2.51 (0.38)	2.55 (0.56)	0.89 (1, 59)	.35	0.02	2.33 (1, 59)	.13	0.04	1.63 (1, 59)	.21	0.03
3	2.64 (0.62)	2.6 (0.69)	2.7 (0.61)	2.74 (0.66)	0.22 (1, 59)	.64	0	0 (1, 59)	>.99	0	0.04 (1, 59)	.85	0
Nursing role conflict													
1	2.65 (0.75)	3 (1.07)	2.54 (0.66)	2.77 (0.64)	0.53 (1, 59)	.47	0.01	1.47 (1, 59)	.23	0.03	0.06 (1, 59)	.80	0
2	2.69 (0.93)	3.1 (0.68)	2.29 (0.88)	2.67 (0.63)	2.62 (1, 59)	.11	0.05	2.35 (1, 59)	.13	0.04	0 (1, 59)	.96	0
3	2.69 (0.81)	2.85 (1.01)	2.29 (1.13)	2.69 (0.78)	0.87 (1, 59)	.35	0.02	0.88	.35	0.02	0.17 (1, 59)	.68	0
Conflict with physicians													
1	2.19 (0.69)	2.14 (1.44)	2.4 (0.98)	2.27 (1.09)	0.23 (1, 59)	.63	0	0.07	.79	0	0.01 (1, 59)	.91	0
2	2.22 (0.89)	2.82 (0.65)	2.76 (0.75)	2.43 (0.72)	0.08 (1, 59)	.78	0	0.29	.59	0.01	3.29 (1, 59)	.08	0.06
3	2.31 (1.05)	2.43 (0.58)	1.98 (1.31)	2.53 (0.84)	0.11 (1, 59)	.74	0	0.98	.33	0.02	0.41 (1, 59)	.52	0.01
Death and dying													
1	1.55 (0.7)	1.3 (0.89)	1.67 (1.36)	1.62 (1.09)	0.37 (1, 59)	.54	0.01	0.16	.69	0	0.07 (1, 59)	.79	0
2	1.95 (1.06)	2.9 (0.42)	1.7 (1.06)	2.01 (1)	2.85 (1, 59)	.10	0.05	3.51	.07	0.06	0.92 (1, 59)	.34	0.02
3	1.82 (1.29)	2.4 (0.63)	1.66 (1.39)	2.06 (1.17)	0.37 (1, 59)	.55	0.01	1.43	.24	0.03	0.05 (1, 59)	.83	0
Qualitative workload													
1	1.73 (1.35)	1.75 (1.37)	1.64 (1.25)	1.55 (1.38)	0.1 (1, 59)	.75	0	0.01	.94	0	0.02 (1, 59)	.90	0
2	1.77 (1.36)	2.56 (0.88)	1.54 (1.16)	1.88 (1.09)	1.39 (1, 59)	.24	0.03	2.15	.15	0.04	0.32 (1, 59)	.57	0.01
3	1.91 (1.31)	1.88 (0.85)	1.43 (1.22)	1.88 (1.15)	0.36 (1, 59)	.55	0.01	0.27	.61	0.01	0.36 (1, 59)	.55	0.01
Quantitative workload													
1	3.25 (0.68)	2.5 (0.26)	3.3 (0.73)	3.07 (0.71)	1.76 (1, 59)	.19	0.03	4.53	.04	0.08	1.28 (1, 59)	.26	0.02

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Time	Low impact for specific clinical practicums on students (score), mean (SD)		High impact for specific clinical practicums on students (score), mean (SD)		Main effect—specific clinical practicums			Main effect—integrated clinical practicum			Interaction		
	Low impact for integrated clinical practicum on students	High impact for integrated clinical practicum on students	Low impact for integrated clinical practicum on students	High impact for integrated clinical practicum on students	*F* test (*df*)	*P* value	η^2	*F* test (*df*)	*P* value	η^2	*F* test (*df*)	*P* value	η^2
2	3.04 (0.86)	3.1 (0.74)	3.2 (0.68)	2.99 (0.85)	0.01	.92	0	0.07	.79	0	0.25 (1, 59)	.62	0
3	3.35 (0.74)	2.95 (1.1)	2.94 (1.25)	3.07 (0.88)	0.19	.67	0	0.17	.68	0	0.63 (1, 59)	.43	0.01
Conflict with patients													
1	3.25 (0.7)	2.9 (0.2)	3.27 (0.66)	3.19 (0.75)	0.44	.51	0.01	0.86	.36	0.02	0.35 (1, 59)	.56	0.01
2	3.2 (0.93)	3.15 (0.72)	3.31 (0.7)	3.15 (0.9)	0.04	.84	0	0.14	.71	0	0.04 (1, 59)	.85	0
3	3.47 (0.69)	3.15 (1.01)	3.31 (1.09)	3.18 (0.8)	0.05	.82	0	0.61	.44	0.01	0.1 (1, 59)	.75	0
Conflict with other nursing staff													
1	2.73 (1.01)	1.88 (0.85)	2.32 (1.07)	2.52 (0.98)	0.13	.73	0	0.94	.34	0.02	2.43 (1, 59)	.13	0.05
2	2.68 (0.92)	3.13 (0.85)	2.39 (1.24)	2.75 (1.11)	0.81	.37	0.02	1.18	.28	0.02	0.01 (1, 59)	.91	0
3	3.32 (0.56)	2.25 (0.87)	3.36 (0.63)	3.21 (0.9)	3.69	.06	0.07	5.43	.02	0.1	3.14 (1, 59)	.08	0.06

Perceived Practicum Impact and Burnout by Period

We also examined burnout using a 2-way ANOVA (Table 5). We did not find statistically significant interaction effects but identified significant main effects. In the third survey (December 2022), scores for “emotional exhaustion” were significantly higher in the high-impact groups for both the integration and domain-specific practicum types compared with the corresponding low-impact groups.

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Table . Perceived practicum impact and burnout by period (time 1: June 2022; time 2: September 2022; time 3: December 2022). Scores represent responses on a 5-point Likert scale.

Time	Low impact for specific clinical practicums on students (score), mean (SD)		High impact for specific clinical practicums on students (score), mean (SD)		Main effect—specific clinical practicums			Main effect—integrated clinical practicum			Interaction		
	Low impact for integrated clinical practicum on students	High impact for integrated clinical practicum on students	Low impact for integrated clinical practicum on students	High impact for integrated clinical practicum on students	*F* test (*df*)	*P* value	η^2	*F* test (*df*)	*P* value	η^2	*F* test (*df*)	*P* value	η^2
Emotional exhaustion													
1	3.71 (0.85)	3.8 (0.71)	3.67 (1.06)	3.51 (0.9)	0.28	.60	0.01	0.01	.91	0	0.17	.68	0
2	3.67 (0.76)	3.55 (0.87)	3.93 (0.99)	3.85 (0.91)	0.83	.37	0.02	0.11	.74	0	0	.95	0
3	3.6 (0.69)	3.05 (1.11)	4.13 (0.63)	3.52 (0.97)	3	.09	0.06	4.11	.05	0.07	0.01	.91	0
Depersonalization													
1	2.02 (0.72)	2.08 (0.8)	2.12 (1.29)	1.97 (0.97)	0	.99	0	0.01	.91	0	0.1	.76	0
2	2.36 (0.98)	2.08 (0.7)	2.73 (1.22)	2.45 (0.94)	1.14	.29	0.02	0.67	.42	0.01	0	>.99	0
3	2.32 (0.66)	2.08 (0.65)	2.43 (1.03)	2.35 (0.95)	0.37	.54	0.01	0.27	.61	0.01	0.06	.80	0
Personal accomplishment													
1	7.55 (3.72)	10.5 (4.73)	5.79 (4.08)	7.38 (4.79)	2.7	.11	0.05	2.35	.13	0.04	0.21	.65	0
2	7.09 (3.86)	11.75 (4.65)	6.64 (4.68)	7.15 (5.21)	2.44	.12	0.05	2.57	.12	0.05	1.65	.20	0.03
3	5.73 (3.85)	8.25 (3.3)	8.71 (6.51)	6.42 (3.9)	0.14	.71	0	0.01	.94	0	2.36	.13	0.04

Perceived Practicum Impact and Intention to Leave by Period

Finally, regarding intention to leave the job, we observed a significant interaction effect in the second survey (September 2022) for the item "want to continue working as a nurse" (Table 6). Simple main effect analysis indicated that, in the low-impact group for the integration practicum, those in the low-impact group for the domain-specific practicums showed a significantly stronger intention to remain in the profession than those in the high-impact group. We found no interaction effect for the item "want to quit being a nurse" but noted a significant main effect in the third survey (December 2022), with the high-impact group for the domain-specific practicums showing a significantly greater intention to leave the nursing profession compared with the low-impact group.

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Table . Perceived practicum impact and intention to leave by period (time 1: June 2022; time 2: September 2022; time 3: December 2022). Scores represent responses on a 5-point Likert scale.

Time	Low impact for specific clinical practicums on students (score), mean (SD)		High impact for specific clinical practicums on students (score), mean (SD)		Main effect—specific clinical practicums			Main effect—integrated clinical practicum			Interaction		
	Low impact for integrated clinical practicum on students	High impact for integrated clinical practicum on students	Low impact for integrated clinical practicum on students	High impact for integrated clinical practicum on students	*F* test (*df*)	*P* value	η^2	*F* test (*df*)	*P* value	η^2	*F* test (*df*)	*P* value	η^2
Wants to quit working as a nurse													
1	2.64 (1.43)	2.75 (0.96)	2.86 (1.41)	2.5 (1.21)	0	.97	0	0.08	.78	0	0.29	.59	0.01
2	2.27 (1.19)	2.75 (1.71)	2.36 (1.39)	1.92 (1.29)	0.69	.41	0.01	0	.96	0	1.04	.31	0.02
3	3.55 (1.21)	2.5 (1)	3.71 (1.14)	3.62 (1.02)	3.07	.09	0.06	2.44	.12	0.05	1.67	.20	0.03
Wants to switch hospitals													
1	3.09 (1.58)	2.75 (0.5)	3.5 (1.09)	3.08 (1.32)	0.72	.40	0.01	0.78	.38	0.02	0.01	.92	0
2	3 (1.41)	2.25 (1.89)	2.64 (1.6)	2.54 (1.3)	0.01	.94	0	0.78	.38	0.01	0.44	.51	0.01
3	3.55 (1.21)	3.5 (1.73)	2.71 (1.2)	3.31 (1.32)	1.38	.25	0.03	0.39	.53	0.01	0.54	.47	0.01
Wants to continue working as a nurse													
1	2.82 (1.17)	2.5 (1.29)	3.14 (1.29)	3.12 (1.37)	1.15	.29	0.02	0.16	.70	0	0.11	.74	0
2	2.27 (1.01)	3.25 (1.26)	3 (1.57)	2.31 (1.44)	0.05	.82	0	0.09	.76	0	3.2	.08	0.06
3	2.91 (1.22)	3.5 (0.58)	3.43 (1.45)	3.27 (1.43)	0.1	.75	0	0.22	.64	0	0.67	.42	0.01

Discussion

Principal Findings

This longitudinal study examined the impact of COVID-19 pandemic–induced changes in clinical practicums on newly graduated nurses' perceived difficulty in clinical practice, stressors, burnout, and intention to leave the profession using a 2-way ANOVA by response periods. We analyzed the extent of the perceived impact of clinical practicums. Nearly 62% of the participants (45/73) reported effects on the integration and practice of nursing practicum, whereas 78% (57/73) reported effects on domain-specific practicums. The most common form of alteration was partial substitution with on-campus training. These results are consistent with those reported by Sugawara et al [5] that most newly graduated nurses in this cohort experienced changes in their practicums owing to the COVID-19 pandemic. In our study, participants who experienced full clinical training demonstrated higher practical problem-solving ability than those whose training was replaced with other formats. Given that the 2022 cohort experienced shortened practicums or substitutions with online or on-campus alternatives, these modifications may have influenced their clinical readiness and problem-solving behaviors.

Regarding perceived difficulty in clinical practice, we found significant interaction effects at the 3 time points (June 2022, September 2022, and December 2022) between the perceived impact of domain-specific and integration practicums. Our analysis of simple main effects revealed that participants who experienced greater impacts from both practicum types reported significantly higher difficulty in clinical practice. Taguchi et al [22] previously reported that newly graduated nurses during the COVID-19 pandemic experienced challenges in comprehensively assessing patients' needs across physical, psychological, and social domains, suggesting that reduced practicum time may have hindered the acquisition of these skills. Taken together, these findings indicate that the restriction on clinical learning opportunities during the COVID-19 pandemic

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substantially impeded the development of practical skills, manifesting as increased perceived difficulty in clinical settings.

In terms of stressors, we identified significant interactions for "interpersonal strain within the workplace" in September 2022 and "interpersonal strain with patients" in December 2022. In both cases, those who experienced higher impacts from the integration practicum reported significantly higher levels of strain than those in the low-impact group for the domain-specific practicums. This suggests that reduced practicum opportunities may have compromised the development of interpersonal skills and the ability to adapt to workplace environments.

Although the interaction was not significant for "strain in relationships with physicians," both practicum types showed significant main effects, indicating their independent contributions to increased stress. In response to the pandemic, institutions revised educational programs to include alternative learning methods, such as observing senior nurses and providing mental health support [23]. However, the lack of direct exposure to interprofessional interactions during practicums may have limited participants' understanding of nurse-physician relationships, contributing to stress. Alternatively, as Ohue et al [10] suggested, decreased clinical experience may lower self-confidence in nursing practice, which in turn may increase stress related to relationships with physicians. These findings suggest that limitations in practicum opportunities owing to the COVID-19 pandemic may have hindered the acquisition of interpersonal and interprofessional collaboration skills, leading to increased strain in relationships within the workplace and with patients and physicians. Such stressors may ultimately increase the risk of job turnover, highlighting the urgent need for comprehensive support systems in both educational and clinical settings.

Regarding burnout, main effects were evident for "emotional exhaustion" in the December 2022 survey, with higher scores observed in the high-impact groups for both the domain-specific and integration practicum types. This suggests that restrictions in clinical practicum environments contribute to psychological burden, particularly emotional fatigue, after entering clinical practice. Emotional exhaustion is defined as a state of feeling emotionally overextended and depleted by one's work [24]. During the COVID-19 pandemic, the lack of opportunities to develop interpersonal skills through hands-on training likely rendered newly graduated nurses more vulnerable to early stress and burnout. Manabe et al [23] identified that first-year nurses who recognized stressors related to "lack of nursing competence" also reported lower personal accomplishment, emphasizing the need for support tailored to changes in stress and coping patterns during the first year, as well as the need to enhance nursing competence.

These results can also be interpreted through theoretical frameworks of role transition and work adjustment. Duchscher [15] described the "transition shock" experienced by newly graduated nurses in the acute stage of adaptation, characterized by emotional disorientation, self-doubt, and stress as they transition from student to professional roles. Our findings—higher difficulty in clinical practice, interpersonal strain, and emotional exhaustion among those with reduced practicum experience—are consistent with this concept, suggesting that insufficient practical exposure intensified transition shock during the early employment period. Furthermore, from the perspective of work adaptation theory [16], inadequate preparation during the educational stage may have disrupted the balance between individual abilities and workplace demands, thereby hindering successful adjustment to the professional environment. This mismatch likely contributed to the sustained stress and burnout and increased turnover intention observed in the high-impact groups. Integrating these theoretical perspectives helps explain how educational disruptions translate into psychological maladaptation and occupational instability among new nurses.

Regarding intention to leave, we identified a significant interaction for the item "want to continue working as a nurse" in the September 2022 survey. Simple main effects indicated that, among those in the low-impact group for the integration practicum, those in the low-impact group for domain-specific practicums were significantly more likely to intend to continue in the profession. This suggests that limitations in both practicum types adversely influence the intention to continue in the nursing profession. Meanwhile, we found no interaction for the item "want to quit nursing" but noted a significant main effect in the December 2022 survey, with higher scores among participants who had experienced greater impacts in domain-specific practicums. Ohue et al [13] also reported associations among stressors, burnout, and intention to leave among nurses. In other words, COVID-19 pandemic–related limitations in clinical practicums may contribute to elevated stress and burnout, which then increase turnover intention.

In summary, our study revealed that changes in domain-specific and integration practicums owing to the COVID-19 pandemic significantly impacted not only the practical competencies of newly graduated nurses but also their mental health and career continuity. The participants in the high-impact groups showed elevated difficulty in clinical practice, greater stress, higher emotional exhaustion, and a stronger intention to leave, all of which are potential risk factors for early attrition. Considering the theoretical frameworks of transition shock and work adaptation, these findings highlight the importance of structured transition programs, mentorship, and organizational support to mitigate new nurses' initial adjustment difficulties and facilitate smoother professional adaptation.

One limitation of our study pertains to the retention rate across the 3 survey time points. Although we confirmed that attrition did not introduce substantial systematic bias, we cannot rule out the possibility that the participants who remained in the study differed in unmeasured ways from those who dropped out. As such, the findings may primarily reflect the experiences of nurses who were able to continue in the profession during the first year. Generalizations to all newly graduated nurses should be made with caution.

Moving forward, follow-up systems, mental health support, and continuing education to strengthen clinical skills are essential for graduates whose training was adversely impacted because of the pandemic. Future pandemics or emerging infectious diseases may again prevent clinical training in actual health care

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settings. Therefore, strategies for ensuring meaningful clinical practicums even under restrictive conditions must be explored. Future practicum models should be strengthened and specified to better prepare nursing students for clinical realities. For example, hybrid models combining on-campus simulation with limited in-person clinical exposure could allow students to practice technical and interpersonal skills safely. Structured mentorship programs, where experienced nurses guide students through critical learning points even under restricted conditions, may enhance practical competence and confidence. Additionally, short-term, intensive "juvenile monetary practicums" or condensed clinical rotations focused on high-priority skills could be integrated to ensure essential hands-on experience without compromising safety. Implementing these concrete strategies may mitigate the negative impact of restricted clinical access and support new nurses' smoother transitions into professional practice.

Conclusions

This study examined the impact of COVID-19–related changes in clinical training on newly graduated nurses' perceived difficulty in clinical practice, stressors, burnout, and intention to leave across 3 survey time points. The findings revealed that newly graduated nurses who subjectively perceived a greater impact from both domain-specific and integration practicum types reported higher levels of difficulty in clinical practice and stressors, with the influence of the integration practicum being particularly pronounced. In the second survey (September 2022), the intention to continue working as a nurse was significantly higher among those who perceived less impact from the integration practicum, indicating that practicum experiences may impact career commitment. In the third survey (December 2022), emotional exhaustion was significantly higher in the high-impact group, suggesting a relationship with burnout.

Our results suggest that the quality and extent of clinical practicum experiences significantly influence the psychological burden and occupational retention intentions of newly graduated nurses. For those whose training was adversely impacted because of the COVID-19 pandemic, continuous support systems and enhanced mental health care in clinical settings are essential.

Acknowledgments

The authors would like to thank all individuals and institutions that contributed to this study. They also appreciate the valuable feedback from reviewers that helped improve this manuscript.

Funding

This research was funded by a Japan Society for the Promotion of Science Grant-in-Aid for Scientific Research (KAKENHI; 24K13590).

Data Availability

The datasets generated or analyzed during this study are available from the corresponding author upon reasonable request.

Authors' Contributions

TO was involved in all aspects of the study, including conception, design, data collection, analysis, and manuscript preparation. YO contributed to data collection. Both authors reviewed and approved the final version of the manuscript.

Conflicts of Interest

None declared.

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Edited by E Borycki; submitted 24.06.25; peer-reviewed by MA Zoubi; revised version received 03.11.25; accepted 09.11.25; published 23.12.25.

Please cite as:
Ohue T, Ohue Y
Impact of COVID-19 Pandemic–Induced Changes in Clinical Practicums on the Mental Health of Newly Graduated Nurses: Longitudinal Study
JMIR Nursing 2025;8:e79556
URL: https://nursing.jmir.org/2025/1/e79556
doi:10.2196/79556

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Sociotechnical Needs of Registered Nurses in the Heart Failure Hospitalizations of African American Patients: Cross-Sectional Study

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Abstract

Background: The African American population is disproportionately impacted by congestive heart failure (CHF). The impact includes a hospitalization rate that is 2.5 times higher and a hospital stay that is, on average, a quarter of a day longer compared with Caucasians. Notably, nursing care has been associated with nearly a 30% decrease in hospitalizations and readmissions. Previous studies have demonstrated that registered nurses (RNs), working in conjunction with electronic health record systems to conduct care tasks, may optimize length of stay in African Americans with CHF.

Objective: This study aimed to identify the needs of RNs who performed sociotechnical tasks, the perceived importance of these sociotechnical tasks, and the perceived performance of these tasks by RNs, in relation to the length of stay of their African American patients with CHF.

Methods: The study used an observational, cross-sectional survey design in RNs who were randomly selected from a total population of 3498 RNs who provided care to 22,703 African American patients with CHF within 113,543 heart failure hospitalizations between January 1, 2015, and January 1, 2024. The RNs were retrospectively stratified into 2 groups based on EHR data: those whose African American patients had a mean length of stay of 10 days or less (Group A) and those whose mean length of stay was greater than 10 days (Group B). Descriptive statistics, Cohen *d*, and a 2-sided unpaired *t* test were used to analyze the data.

Results: The total sample of 200 RNs responded to the survey (100% survey completion rate). Group A (100 RNs) reported the least important task as drawing conclusions about how to use the EHR to care for African American patients (mean 4.66, SD 1.82). The least important task in Group B (100 RNs) was reading published research on African American patients (mean 4.88, SD 1.70). Group A reported performing best in caring for African American patients (mean 5.61, SD 1.44). Group B reported performing best at caring for all patients (mean 5.86, SD 1.04). A total of 17 significant sociotechnical needs were identified among groups. In total, 2 sociotechnical needs were unique to group B: caring for patients (ie, the full scope of social and technological processes in nursing care; Cohen *d*=0.32, 95% CI 0.04-0.59; *P*=.04) and working with information related to a patient's CHF in the EHR (eg, laboratory results, discharge summaries, or radiographic images) to care for the patient (Cohen *d*=0.33, 95% CI 0.05-0.61; *P*=.03).

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Conclusions: Lengths of patient stay may be reduced by identifying and addressing sociotechnical needs through targeted training, nursing care interventions, and RN-led risk stratification guidelines for working with EHRs to reduce lengths of stay in those who are disproportionately impacted by CHF.

(JMIR Nursing 2025;8:e75080) doi:10.2196/75080

KEYWORDS

socio-technical; human factors; EHR; registered nurses; health disparities; heart failure; electronic health record

Introduction

According to the American Heart Association's (AHA) 2024 heart disease and stroke update, nearly 6.7 million adults in the United States have congestive heart failure (CHF), a 12% increase since 2018 [1]. The prevalence of CHF is on track to reach the projected 46% increase from 2012 to 2030, affecting more than 8 million Americans [1]. African American men and women have the highest CHF-related, age-adjusted death rate, compared to other races [2,3] African American patients have an increased CHF hospitalization rate of nearly 2.5 times greater than Caucasians and a quarter of a day longer length of hospital stay, which are directly impacted by a substantial number of patient, provider, and social determinants of health factors that constrain guideline-directed medical therapy [1,3-5]. These longer lengths of stay increase the likelihood that African American patients experience iatrogenic complications that worsen their state of health [6,7]. Therefore, clinicians seek to optimize lengths of stay.

Tailored clinical care through guideline-directed medical therapy and specialized workflows for procedural treatments are innovative approaches to addressing hospitalization rates [8-11]. The AHA, American College of Cardiology, and the Heart Failure Society of America issued the 2022 joint AHA, American College of Cardiology, and Heart Failure Society of America guideline for the management of heart failure [9]. The guideline is the most recent directive for the design of future research on the effectiveness of nonclinical strategies directly related to hospitalization outcomes, such as assessing the efficacy and safety of including hydralazine isosorbide in the guideline-directed medical therapy of African American patients [9]. The guideline also included nonclinical strategies such as "addressing evidence gaps in women, racial, and ethnic populations" and "identifying the characteristics of systems of care (eg, disciplines and staffing, electronic health records (EHR), and models of care) that optimize guideline-directed medical therapy" [9].

Within systems of care, the use of multidisciplinary care teams that include cardiologists, advanced nurse practitioners, registered nurses (RNs), social workers, and dietitians has been shown to optimize guideline-directed medical therapy [9]. Multidisciplinary care teams with high levels of engagement from RNs have demonstrated the strongest associations with improved outcomes in African American patients with CHF [12,13]. The care provided by RNs within these teams has been associated with a 30% decrease in hospitalizations and a 31% decrease in readmissions over a 7-year period [12,13]. However, evidence of their effect on African American patients with CHF has been limited to simply assessing how the presence or absence of RNs on care teams is associated with hospitalizations and length of stay [12-14]. The care tasks performed by RNs in CHF management and care coordination are expansive, ranging from escalating and de-escalating care during hospitalization to discharge planning and care transitions. These tasks also include the use of invasive monitoring tools such as pulmonary artery catheters to educate patients on CHF in areas such as managing sodium intake, monitoring weight, and recognizing early signs and symptoms of decompensation [15,16].

Previous studies have identified EHRs as conduits of high-quality care delivery [12-14,17]. Evidence suggests that RNs, working in conjunction with EHRs to conduct these care tasks, affect care and outcomes [18-21]. As a result, this care management increases adherence to guideline-directed medical therapy and care plans. However, variation in how RNs perform these care tasks may indirectly contribute to differences in lengths of stay, which has been more directly driven by heart failure severity and social determinants of health [8-14,22-24]. These care tasks are defined as sociotechnical tasks, which are composed of any combination of the social (eg, interactions between RNs and patients) and technical (eg, EHRs, patient data, information, and tools) components of nursing care [25,26]. Additional examples of sociotechnical tasks are provided by the most widely recognized conceptual framework in the domain, sociotechnical framework for health information technology by Meeks et al [25] and Sittig and Singh [26] (Table 1). The 8 dimensions within the framework are empirically supported and serve as a foundation for examining sociotechnical tasks in nursing care [26]. For example, the first dimension of the framework is hardware and software computing infrastructure, which focuses on how RNs interact with, use the EHR, and its risk-specific indices [26]. When these tasks are important in care, but are performed poorly, a sociotechnical need exists [27].

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Table . In total, 8 dimensions of Sittig and Singh's sociotechnical framework for health information technology [26].

Dimension	Dimension focus	Dimension components
Hardware and software computing infrastructure	Focuses on how RNs[a] interact with and overall use of the EHR[b] and risk-specific indices	Computers, monitors, printers, and devices used to access the EHR
Clinical content	Focuses on how RNs work with CHF[c]-related textual, numeric, and imaging data within the EHR	Structured and unstructured data, information, and knowledge stored in the EHR
Human-computer interface	Focuses on the accessibility aspects of the EHR and risk-specific tools within the EHR that RNs see, touch, or hear as they assess patient risk	EHR design, functionality, feature availability, and ergonomic alignment of the EHR interface
People	Focuses on the humans associated with all aspects of the design, development, implementation, and RNs' use of the EHR	Software developers, IT teams, system configuration, EHR training personnel, other clinicians, and patients
Workflow and communication	Focuses on how an RN works within clinical processes to ensure a patient with CHF receives the care they need when they need it	Engagement, collaboration, and cohesion between individuals and teams, EHR communication and messaging tools, and the alignment of EHR features with processes in care delivery
Internal organizational features	Focuses on how an RN works with policies, procedures, and the organizational culture of stratifying risk with the EHR	Organizational structures, leadership, and resources; IT policies and procedures
External rules and regulations	Focuses on how an RN works with external laws and requirements that facilitate or constrain the design, development, implementation, use, and evaluation of the EHR	Federal, state, and local laws that regulate the use of the EHR
Measurement and monitoring	Focuses on how an RN evaluates the consequences of EHR use in stratifying risks	Continuous evaluation of EHR features and functions, the development of methods and metrics

[a]RN: registered nurse.

[b]EHR: electronic health record.

[c]CHF: congestive heart failure.

Sociotechnical needs represent specific opportunities for additional training, care delivery improvements, and other interventions related to patients, providers, or social determinants of health [25,26]. If needs are addressed, the quality of care may improve, and the lengths of stay of patients may be optimized. These sociotechnical needs, the importance of the tasks, and their performance in relation to length of stay have not been examined. Yet, 96% of nonfederal acute care hospitals in the United States have adopted a certified EHR [28]. RNs may be most effective in working with the EHR and the information contained within it to perform real-time, in-hospital assessments to reduce poor outcomes and prevent mortality and longer lengths of stay [12]. Therefore, the aim of this study was to identify the needs of RNs who performed sociotechnical tasks, the perceived importance of these sociotechnical tasks, and the perceived performance of these tasks by RNs, in relation to the length of stay of their African American patients with CHF.

Methods

This study was designed and reported in accordance with the guidelines of the Checklist for Reporting Results of Internet E-Surveys (CHERRIES) checklist [29].

Study Design

This was a single-site study that used an observational, cross-sectional survey design. The observational nature of the study used EHR data from the Arkansas Clinical Data Repository to retrospectively track a target population of 3498 RNs who provided care to 22,703 patients with CHF within 113,543 heart failure hospitalizations between January 1, 2015, and January 1, 2024. The repository houses data extracted from the EPIC EHR and legacy systems and has been a secure source of data for other clinical and translational studies of the population [30]. A total of 200 RNs were randomly selected using stratified random sampling based on the mean length of stay of their African American patients. An adapted version of the Hennesey-Hicks Needs Analysis survey was administered to all RNs in the sample. Descriptive statistics, difference score, Cohen *d* coefficient, and a 2-sided unpaired *t* test were used to identify the perceived importance of these sociotechnical tasks, the perceived performance of these tasks by RNs, and their sociotechnical needs in relation to the length of stay of their African American patients with CHF.

Ethical Considerations

The study procedures (protocol approval number #276211) were reviewed and approved by the University of Arkansas for Medical Sciences institutional review board. A dataset was provided to the study team by the repository that contained a

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deidentified list of patients and RNs, an edge list containing pseudonyms that linked patients with each RN who provided care during their hospitalization, health severity variables, and the length of stay of each African American patient's hospitalization. A subsequent data request identified the names and email addresses of the 200 RNs who were surveyed. The RNs were provided with informed consent through email. The informed consent document embedded within the email included a basic description of the purpose of the study, the anticipated length of time survey completion, details on how data would be stored and accessed (where and how long), and contact information for the principal investigator. Data protection processes included not sharing individual responses outside of the study team, aggregating responses, segmenting access to identifying data and responses within the study team, storing data on only 1 university-encrypted laptop with multiple firewalls, and deleting identifying information after the study closed on June 30, 2025. After reviewing and agreeing to the informed consent presented through email, RNs were routed to the survey. A waiver of documentation of the informed consent process was granted by the institutional review board because the study presented only minimal risk for loss of confidentiality. The consent document is provided in Multimedia Appendix 1.

Development and Pretesting

The survey, endorsed by the World Health Organization, is globally used within health care to assess task importance, performance, and needs of RNs and other clinicians [27]. In total, 33 previous studies of clinical practice have demonstrated the survey's translation, cultural adaptation, and psychometric reliability in revealing the needs of RNs and other clinicians [27]. The standard survey contained 30 items consisting of basic care tasks [30]. After adaptation, a total of 22 items were in the final survey and represented the sociotechnical tasks performed by RNs during the provision of care. The survey instrument is provided in Multimedia Appendix 2.

Of the 22 final items, items 1 - 14 were adapted from the basic items on the standard survey. The items were modified in alignment with the psychometric requirements of the survey manual [27]. For example, item number 1 of the standard survey required RNs to rate the following statement: "Establishing a relationship with patients." The item was adapted for this study to state, "Using the EHR to establish a relationship with African American patients who have CHF." The survey allowed for the removal and substitution of 8 of the standard items without compromising the psychometric properties (ie, reliability and validity) of the instrument. In total, 8 of the standard survey items were removed because they did not align with the objective of the study.

The remaining items, items 15 - 22, were directly adapted from all 8 dimensions of the study's conceptual framework, which is Sittig and Singh's sociotechnical framework for health IT [26] (Table 1). The framework was chosen because it is the most comprehensive framework for understanding how RNs work with EHRs to improve patient outcomes.

The survey was pilot-tested for usability and technical functionality among an independent group of 5 RNs who reflected the sampling frame of the target population. The changes included increasing reminder intervals from monthly to biweekly, condensing introductory text for questions, and removing duplicate demographics data collection.

Recruitment and Selection of RNs

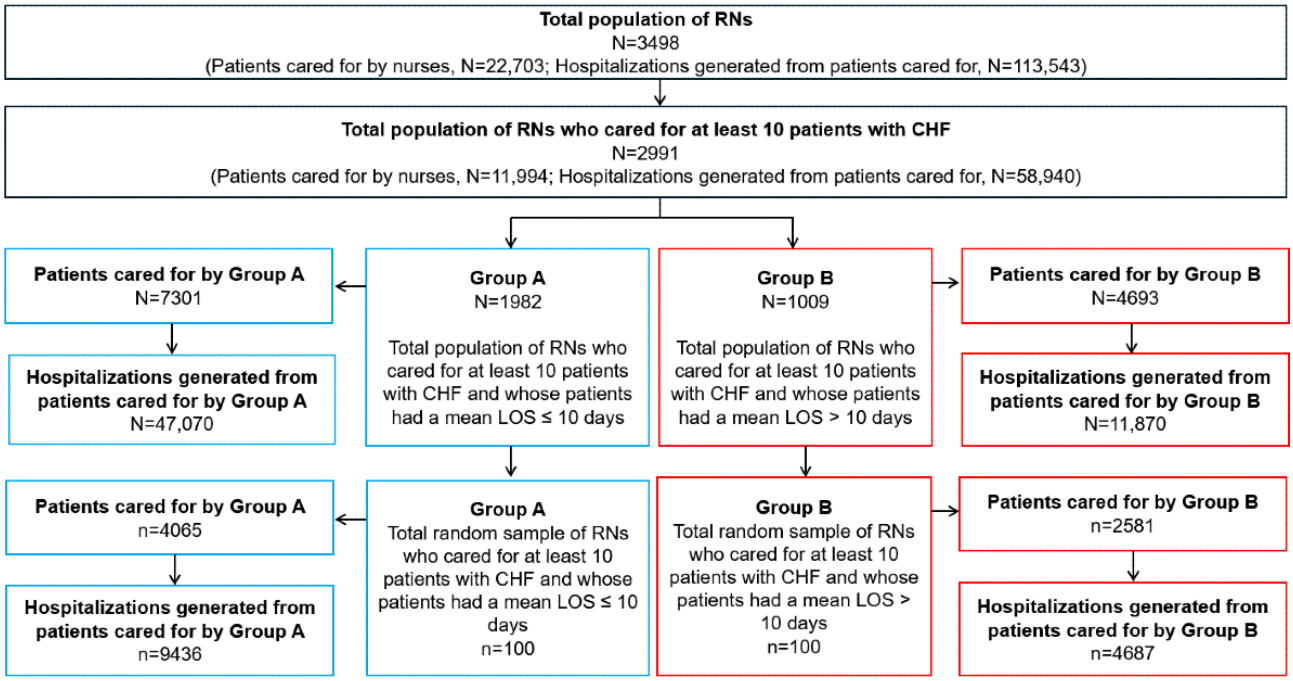
The study was conducted on the main campus of an academic health center in a primarily rural state. The hospital has 535 beds, which generated the study data. Patients from all 75 counties of the state were cared for by RNs at the hospital. This included patients from counties with heart failure–related death rates that are twice the national average, of which more than 35% of residents lived in poverty [31-33].

A total of 3498 RNs were ranked numerically based on the mean length of stay of their patients with CHF. A sample of 200 RNs (100 per group; Group A and Group B) was randomly selected based on the mean length of stay of their patients with CHF being either above or below the mean of the total population of RNs (ie, 10 days). The RNs were not prospectively assigned to groups before they provided care to patients within the hospitalizations that generated lengths of stay. The RNs were retrospectively assigned to groups using a 10-day threshold based on whether their patients with CHF had short or long lengths of stay. Short and long lengths of stay did not distinguish between patients who received and did not receive optimal care. Optimal care was defined as the hospital's provision of guideline-directed medical therapy [9] The 10-day threshold was selected because it represented the mean length of stay of patients with CHF in the total population of 3498 RNs. Additionally, patients with a length of stay of more than 10 days have a 52% higher risk of 30-day readmission and a 71% higher risk of mortality during 30 days of discharge, which could have confounded the length-of-stay outcomes [34]. Assuming a 2-sided type I error rate of 5%, with a sample size of 100 per group, the study was powered at 80% to detect an effect size of 0.29 or larger under the null hypothesis of zero effect size. The sample size estimates were obtained for effect size corresponding to sociotechnical needs using a one-sample *t* test and calculated using the proprietary PASS software [35].

From the total population, a sample of 200 RNs was recruited and divided into 2 groups (Figure 1): Group A consisted of 100 RNs whose patients had a mean length of stay of 10 days or less (ie, patients with shorter lengths of stay), and Group B consisted of 100 RNs whose patients had a mean length of stay of more than 10 days (ie, patients with longer lengths of stay). RNs who cared for fewer than 10 patients with CHF were excluded from the selection to minimize the potential of selecting RNs who lacked sufficient experience in CHF care.

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Figure 1. Flow diagram of registered nurse selection. CHF: congestive heart failure; LOS: length of stay; RN: registered nurse.



Survey Administration

The survey was administered between November 15, 2024, and January 31, 2025. During the administration of the survey, RNs were instructed to reflect on their entire career of experiences working with EHRs to care for patients with CHF, not at any specific points in time. RNs were also instructed to reflect on their experiences working with all EHRs and not to focus on any specific EHR product or company.

Using a closed survey approach, all 200 RNs completed an electronic version of the same survey through the university-based, REDCap (Research Electronic Data Capture system; Vanderbilt University) [36,37]. Email addresses were loaded into the system and managed by one member of the study team for automated biweekly survey reminders and to prevent multiple entries from the same individual. Each RN received a custom survey link, which allowed the study team to determine completion.

The following demographic variables for the study were collected via the survey: sex, race, ethnicity, the number of years working as an RN, and the number of years working with patients who had chronic illnesses. None of the survey questions were mandatory, and the RNs could have ended the survey at any time.

The RNs manually rated all 22 survey items (sociotechnical tasks) on a 7-point Likert scale in 4 categories (Rating A-D). The RNs rated approximately 5 survey items on each of the 6 pages of the web-based survey in REDCap. The RNs were able to modify their ratings by toggling back and forth through the survey items before submission. Their ratings reflected how important the sociotechnical task was to their job (Rating A) and how well they were currently performing the sociotechnical task (Rating B). Higher ratings indicated greater perceived importance and perceived performance [27]. A sociotechnical need was defined as the difference between the performance and the importance of a task [27]. The sociotechnical need was the primary endpoint of the study. Similarly, the survey also assessed each group's preferred approach to addressing any sociotechnical need through either care delivery intervention not related to training (Rating C) or through additional training alone (Rating D).

After completing the survey, RNs received a US $25 gift card for their participation. The offering of the gift card was disclosed to the RNs during the informed consent process.

Other Variables

In total, 2 additional variables were provided within the data request to understand health severity in the patients cared for by both groups of RNs. The Van Walraven Elixhauser Comorbidity Score is a comorbidity-based measure of each patient's overall health severity and is a valid and reliable predictor of in-hospital mortality [9,12,13]. Left ventricular ejection fraction, the percentage of blood pumped through the left ventricle of the heart, was captured via transthoracic echocardiogram during hospitalization and was used as a specific measure of heart function [9,12,13]. These variables have been established as measures of severity in African American patients with heart failure in the 2022 AHA, American College of Cardiology, or Heart Failure Society of America guideline for the management of heart failure and in previous studies [9,12,13].

Bias

The selection of the survey tool as the study instrument minimized the potential for self-response bias because it has been psychometrically validated as providing valid and reliable information about task importance, performance, and needs. Stratified random sampling was applied to select the RNs from within each group. This improved the representation of the population in the sample, external validity, and the ability of the findings to be generalized to other states with similar

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characteristics (ie, rural, only one academic health center). Blinding was applied to reduce the potential influence of subjectivity in assessment and social desirability bias. The survey respondents and the study team members who administered the survey were blinded to group membership.

Demographic Analysis

Descriptive statistics were presented using the mean and SD for continuous variables and frequencies and percentages for categorical variables. Descriptive statistics for demographic variables were presented for the overall sample and by study group.

Analysis of Sociotechnical Task Importance, Performance, and Sociotechnical Need by Group

The sociotechnical need was calculated for each of the 22 sociotechnical items on the survey as the difference between overall mean responses to perceived importance (rating A) and perceived self-performance (rating B) [27]. A positive value indicated a need for a specific sociotechnical task (ie, high importance with low performance; the task was being performed at a level below its importance) [27]. A value of 0 indicated no need for a specific sociotechnical task (ie, the task was being performed at the same level of its importance) [27]. A negative value indicated no need for a specific sociotechnical task (ie, the task was being performed at a level above its importance) [27].

The difference score was tested for statistical significance using a 2-sided unpaired *t* test for each of the 22 survey items in each of the 2 study groups. To account for the multiplicity problem, we further obtained the false discovery rate–adjusted *P* values using Benjamini-Hochberg's approach [38]. Statistical significance was determined using a false discovery rate–adjusted 2-sided *P* value threshold of .05, and uncertainty in parameter estimates was reported using a 2-sided 95% CI.

Similarities and Differences in the Size of Sociotechnical Needs

The effect size of the difference score was estimated for each of the 22 tasks using the Cohen *d* coefficient [39]. The magnitude of effect size was determined using the following cutoffs that are (1) 0.20 for a small effect size, (2) 0.50 for a moderate effect size, (3) 0.08 for a large effect size, and (4) 1.30 for a very large effect size [39]. A forest plot was used to visualize the size of differences in sociotechnical needs by group.

Similarities and Differences in the Rank of Priority of Significant Sociotechnical Needs

Cohen *d* values were ranked numerically within each group. A bump chart illustrated how each socio-technical need differed in priority, by group.

Preferred Approach to Addressing Sociotechnical Needs by Group

The mean values of Rating C (addressing sociotechnical needs by addressing care delivery barriers that were not related to training) and Rating D (addressing sociotechnical needs through additional training, alone) were ranked numerically within each group for each of the 22 survey items. A higher mean in either rating indicated the preferred approach to addressing the sociotechnical need. A clustered bar chart was used to visualize the mean of each group's preferred approach to any identified sociotechnical need.

Results

Overview

All 200 RNs completed the survey (100% survey completion rate), and there was no attrition. The 200 RNs provided care to 6646 African American patients with CHF within 14,123 heart failure hospitalizations between January 1, 2015, and January 1, 2024. All 200 RNs responded to all survey questions, and there were no missing data.

Demographic Analysis Results

Based on survey data from the RNs, females were the largest sex, accounting for 82% (163/200, 82%) RNs in the overall sample (Table 2). Females were also the largest in each group, including 86% (86/100) from Group A and 77 (77/100) from Group B. Caucasian American patients were the largest racial group, accounting for 72% (144/200) of RNs in the overall sample, in Group A 72% (72/100), and in Group B 72% (72/100). Non-Hispanic and non-Latino RNs were the largest ethnic group, accounting for 92% (184/200) in the overall sample, 91% (91/100) in Group A, and 93% (93/100) in Group B.

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Table . Survey demographic characteristics of registered nurses by group.

Characteristics	Overall	Group A	Group B
Sex, n (%)			
Female	163 (82)	86 (86)	77 (77)
Male	34 (17)	12 (12)	22 (22)
Unknown	3 (1.5)	2 (2)	1 (1)
Race, n (%)			
Caucasian American	144 (72)	72 (72)	72 (72)
African American	30 (15)	13 (13)	17 (17)
Asian American	11 (6)	6 (6)	5 (5)
American Indian or Alaskan Native	2 (1)	1 (1)	1 (1)
Native Hawaiian or Other Pacific Islander	1 (0.5)	0 (0)	1 (1)
Other race	12 (6)	8 (8)	4 (4.0)
Ethnicity, n (%)			
Non-Hispanic or Latino	184 (92)	91 (91)	93 (93)
Hispanic or Latino	9 (4.5)	5 (5)	4 (4)
Unknown	7 (3.5)	4 (4)	3 (3)

Based on EHR data on the RNs, Group A provided care for more patients with CHF than Group B, as evidenced by their larger mean number of patients with CHF cared for, with 414 (SD 415) versus 223 (SD 165) patients, respectively (Table 3). Group A also had a larger number of years of experience working as an RN than RNs who had patients with a mean length of stay of more than 10 days (Group B), with means of 11.97 (SD 7.97) versus 9.40 (SD 7.39), respectively. Group A had a larger number of years of experience working with patients who had chronic illnesses than group B, with means of 11.29 (SD 7.92) versus 8.97 (SD 6.83), respectively. The mean Van Walraven Elixhauser Comorbidity Score of patients (overall health severity) was approximately the same in patients cared for by RNs in Group A and Group B, 18.37 (SD 12.39) and 18.76 (SD 12.36), respectively. The mean left ventricular ejection fraction of patients (heart failure severity) was also approximately the same in patients cared for by RNs in Group A and Group B, 50.13 (SD 14.78) and 50.09 (SD 14.54), respectively.

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Table . Electronic health record characteristics of the registered nurses and their patients by group.

Characteristics	Mean (SD)	Median (IQR)	Range
Number of patients with CHF[a] cared for as an RN[b]			
Overall	319 (329)	218 (327)	10-1995
Group A	414 (415)	284 (381)	10-1995
Group B	223 (165)	164 (233)	10-840
Number of years working as an RN			
Overall	10.68 (7.78)	8 (9)	1.50-38
Group A	11.97 (7.97)	10 (10.25)	1.50-38
Group B	9.40 (7.39)	7 (7.50)	1.50-35
Number of years working with patients who had chronic illnesses as a registered nurse			
Overall	10.13 (7.46)	8 (8.25)	0-38
Group A	11.29 (7.92)	8.50 (9)	0-38
Group B	8.97 (6.83)	7 (7.50)	1.50-35
Patient length of stay (days)			
Overall	9.77 (3.19)	9.99 (4.13)	1.68-18.24
Group A	7.28 (2.37)	8.21 (2.74)	1.68-9.97
Group B	12.27 (1.50)	12.32 (1.73)	10.01-18.24
Patient Van Walraven Elixhauser Comorbidity Score (health severity)			
Overall	18.50 (12.37)	17 (17)	–14 to 66
Group A	18.37 (12.39)	17 (17)	–14 to 66
Group B	18.76 (12.36)	18 (16)	–11 to 66
Left ventricular ejection fraction (heart failure severity)			
Overall	50.12 (14.70)	55 (20)	5-80
Group A	50.13 (14.78)	55 (20)	5-80
Group B	50.09 (14.54)	55 (20)	10-75

[a]CHF: congestive heart failure.

[b]RN: registered nurse.

Sociotechnical Task Importance Results

As shown in Table S1 in Multimedia Appendix 3, RNs in both groups rated all 22 tasks as having a high level of importance (>4) in improving the outcomes of African American patients with CHF. In both groups, the most important task was managing the overall workload of patients with the EHR (item 14; Group A: mean 6.36, SD 1.17; Group B: mean 6.63, SD 0.71). In RNs who had patients with a mean length of stay of 10 days or less, the least important task was drawing conclusions about how to use the EHR to care for African American patients (item 6; 4.66, SD 1.82). In RNs who had patients with a mean length of stay of more than 10 days, the least important task was reading published research on African American patients with CHF (mean 4.88, SD 1.70).

Sociotechnical Task Performance Results

Table S1 in Multimedia Appendix 3 also presents results on task performance. In RNs who had patients with a mean length of stay of 10 days or less, the task that was performed the best was caring for African American patients with CHF (item 4; mean 5.61, SD 1.44). In RNs who had patients with a mean length of stay of greater than 10 days, the task that was performed the best was caring for all patients with CHF (item 3; mean 5.86, SD 1.04). In both groups, the task that was performed the poorest was reading published research on African American patients with CHF (item 2; Group A: mean 3.90, SD 1.96; Group B: mean 3.83, SD 1.78).

Significant Sociotechnical Need Results

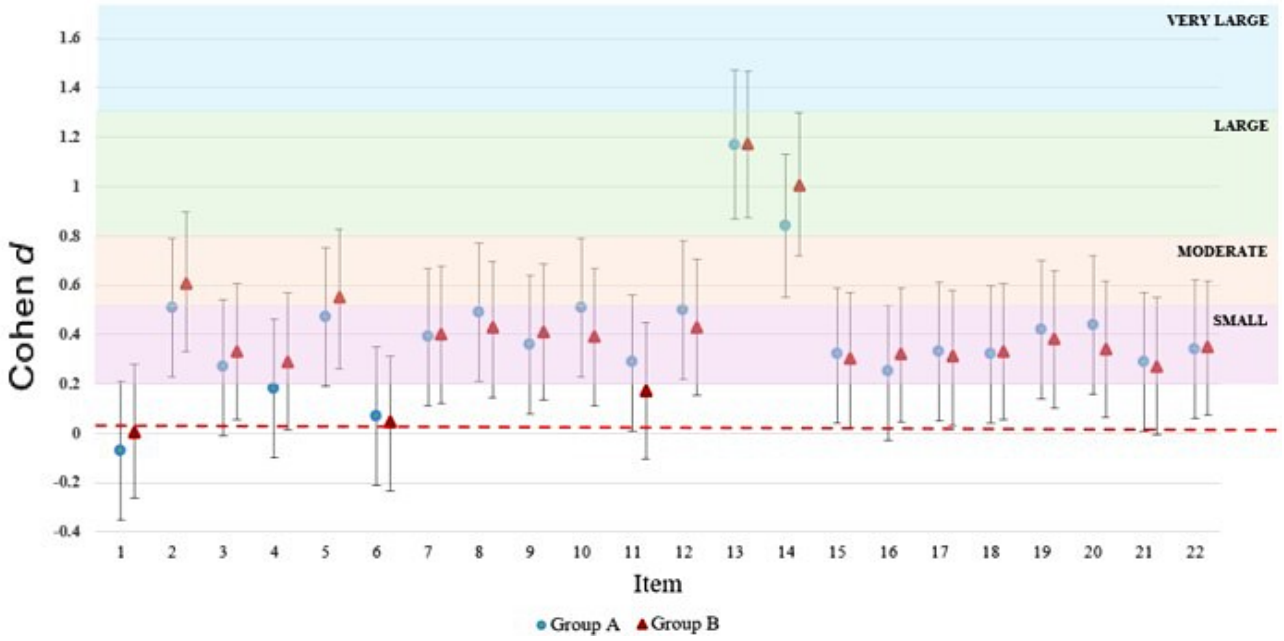
Sociotechnical needs were identified in 17 of the 22 survey items as evidenced by a statistically significant difference (false discovery rate–adjusted P values <.05) between RN ratings of importance and performance (Table S2 in Multimedia Appendix 3). In both groups, there were no sociotechnical needs identified in 5 of the 22 tasks (items 1, 4, 6, 11, and 21: P>.05). In total, 13 of the 17 sociotechnical needs (items 2, 5, 7 - 10, 12 - 14, 18 - 20, and 22) were the same in both groups.

There were 2 additional sociotechnical needs unique to RNs who had patients with a mean length of stay of 10 days or less (items 15 and 17), as shown in Table S2 in Multimedia

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Appendix 3 and Figure 2. These needs were working with hardware and software related to the EHR to care for a patient with CHF (Cohen *d*=0.32, 95% CI 0.04-0.59; *P*=.04) and working with the design of the EHR (eg, parts of the EHR's screens that you can see, touch, or hear) as they retrieved information to provide care to patients with CHF (Cohen *d*=0.33, 95% CI 0.05-0.61; *P*=.03).

Figure 2. Forest plot of the size of significant sociotechnical need by group.



There were also 2 additional sociotechnical needs unique to RNs who had patients with a mean length of stay of more than 10 days (items 3 and 16). These needs were caring for patients with CHF (Cohen *d*=0.32, 95% CI 0.04-0.60; *P*=.04) and working with information related to a patient's CHF in the EHR (eg, laboratory results, discharge summaries, or radiographic images) to care for the patient (Cohen *d*=0.31, 95% CI 0.03-0.58; *P*=.047).

Similarities in the Size of Significant Sociotechnical Needs Among Groups

Of the 13 sociotechnical needs that were common among both groups, 10 were similar in size. The 2 largest sociotechnical needs (item 13 and 14) were the same in both groups, as defined by a Cohen *d* of greater than or equal to 0.80 in both groups: personally coping with burnout in their clinical environment (Group A: Cohen *d*=1.17, 95% CI 0.87-1.47; *P*<.001 and Group B: Cohen *d*=1.17, 95% CI 0.87-1.47; *P*<.001) and managing their overall workload of patients with the EHR (Group A: Cohen *d*=0.84, 95% CI 0.55-1.13; *P*<.001 and Group B, Cohen *d*=1, 95% CI 0.71-1.30; *P*<.001). The only moderate-sized sociotechnical need that was the same in both groups was reading published research on African American patients with CHF (item 2: Group A Cohen *d*=0.51, 95% CI 0.23-0.79; *P*<.001 and Group B Cohen *d*=0.60, 95% CI 0.32-0.89; *P*<.001). Figure 2 presents 7 additional small training needs that were similar in size among groups (items 7 - 9, 18 - 20, and 22).

Differences in the Size of Significant Sociotechnical Needs Between Each Group

Of the 13 sociotechnical needs that were common among groups, 3 sociotechnical needs differed in size between groups. Giving patient education information to African American patients or their caregivers (item 5) was a small need in RNs who had patients with a mean length of stay of 10 days or less, (Group A: Cohen *d*=0.47, 95% CI 0.19-0.75; *P*=.003), but a moderate need in RNs who had patients with a mean length of stay of more than 10 days (Group B, Cohen *d*=0.54, 95% CI 0.25-0.82; *P*<.001). Collecting relevant information on the social determinants of health (eg, education, health literacy, safe housing, and access to nutritious food) from the EHR (item 10) was a moderate need in RNs who had patients with a mean length of stay of 10 days or less (Group A: Cohen *d*=0.51, 95% CI 0.23-0.79; *P*<.001), but a small need in RNs who had patients with a mean length of stay of more than 10 days (Group B: Cohen *d*=0.38, 95% CI 0.1-0.66; *P*=.02). Accessing clinical resources to care for their patients with CHF (item 12) was a moderate sociotechnical need in RNs who had patients with a mean length of stay of 10 days or less (Group A, Cohen *d*=0.50, 95% CI 0.22-0.78; *P*=.003), but a small need in RNs who had patients with a mean length of stay of more than 10 days (Group B: Cohen *d*=0.42, 95% CI 0.14-0.70; *P*=.01).

Similarities in the Rank of Priority of Significant Sociotechnical Needs in Each Group

The top 3 sociotechnical needs in both groups were the same (Figure 2): personally coping with burnout in their clinical environment (item number 13), managing their overall workload of patients with the EHR (item number 14), and reading published research on African American patients with CHF (item number 2), respectively. Accessing clinical resources to care for their patients with CHF (item number 12) was ranked fifth in both groups. Undertaking health promotion and prevention tasks to care for African American patients with CHF (item number 8) was ranked sixth in both groups. Within

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Figure 2, items with statistically significant sociotechnical needs (P<.05) are denoted by an asterisk.

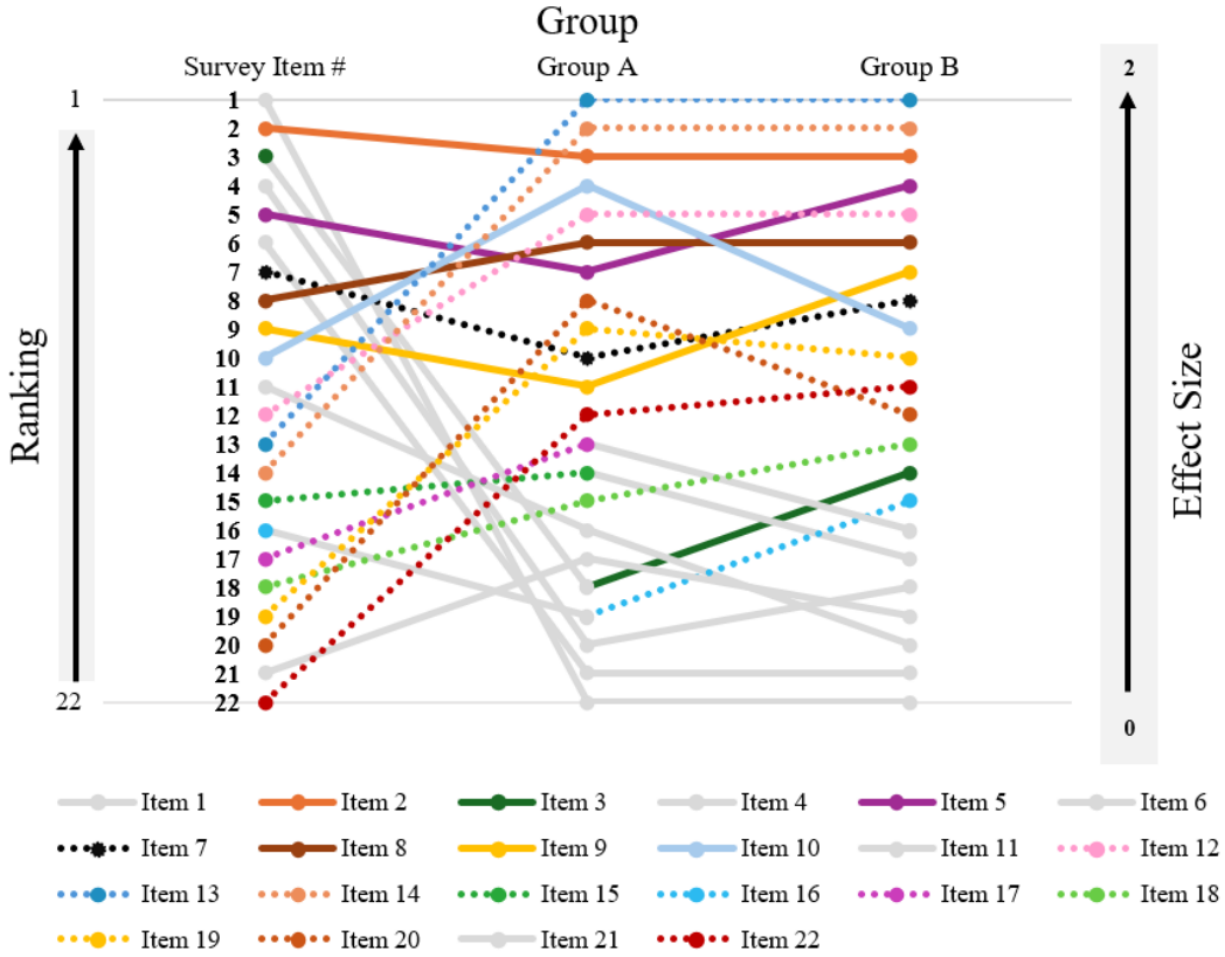
Differences in the Rank of Priority of Significant Sociotechnical Needs in Each Group

Figure 3 ranked all 22 sociotechnical tasks in each group from greatest need (ie, 1) to the least (ie, 22) by Cohen *d*. Within Figure 3, items with no sociotechnical needs (P≥.05) were represented by solid gray lines and circles. The figure demonstrates how each of the significant sociotechnical needs changed in perceived priority in RNs who had patients with a mean length of stay of 10 days or less compared to those who had patients with a mean length of stay of more than 10 days.

Three items were ranked higher in RNs who had patients with a mean length of stay of 10 days and less than RNs who had patients with a mean length of stay of more than 10 days, including: collecting relevant information on the social determinants of health from the EHR (item 10; group A: 4th and group B: 9th), working within internal organizational policies, procedures, and culture related to the EHR to care for patients with CHF (item 20; Group A: 8th, and Group B: 12th), and using current processes to share information that provides each patient with CHF with the care they need at the time they need it (item 19; Group A: 9th and Group B: 10th).

In total, 5 items were ranked higher in RNs who had patients with a mean length of stay of more than 10 days than in RNs who had patients with a mean length of stay of 10 days and less, including (1) giving patient education information to African American patients or their caregivers (item 5; group A: 7th and group B: 4th), (2) using risk scores or other information from the EHR to improve a patient's health (item 7; group A: 10th and group B: 8th), (3) assessing African American patients' clinical needs using the EHR (item 9; group A: 11th and group B: 7th), (4) continuously evaluating the quality of care that results from their use of the EHR to provide care for patients with CHF (item 22; group A: 12th and group B: 11th), and (5) the training or performance of other people in their environment who use the EHR (item 18; group A: 15th and group B: 13th).

Figure 3. Cohen *d* ranking of significant sociotechnical needs by group.



In total, 4 additional sociotechnical needs only ranked in one of the groups due to a lack of significance in the other group. Working with hardware and software related to the EHR to care for a patient with CHF (item number 15) ranked 14th among RNs who had patients with a mean length of stay of 10 days or less (Group A), but was not significant in RNs who had patients with a mean length of stay of more than 10 days (Group B). Working with information related to a patient's CHF in the EHR to care for the patient (item 16) ranked 15th in RNs who had patients with a mean length of stay of more than 10 days (Group

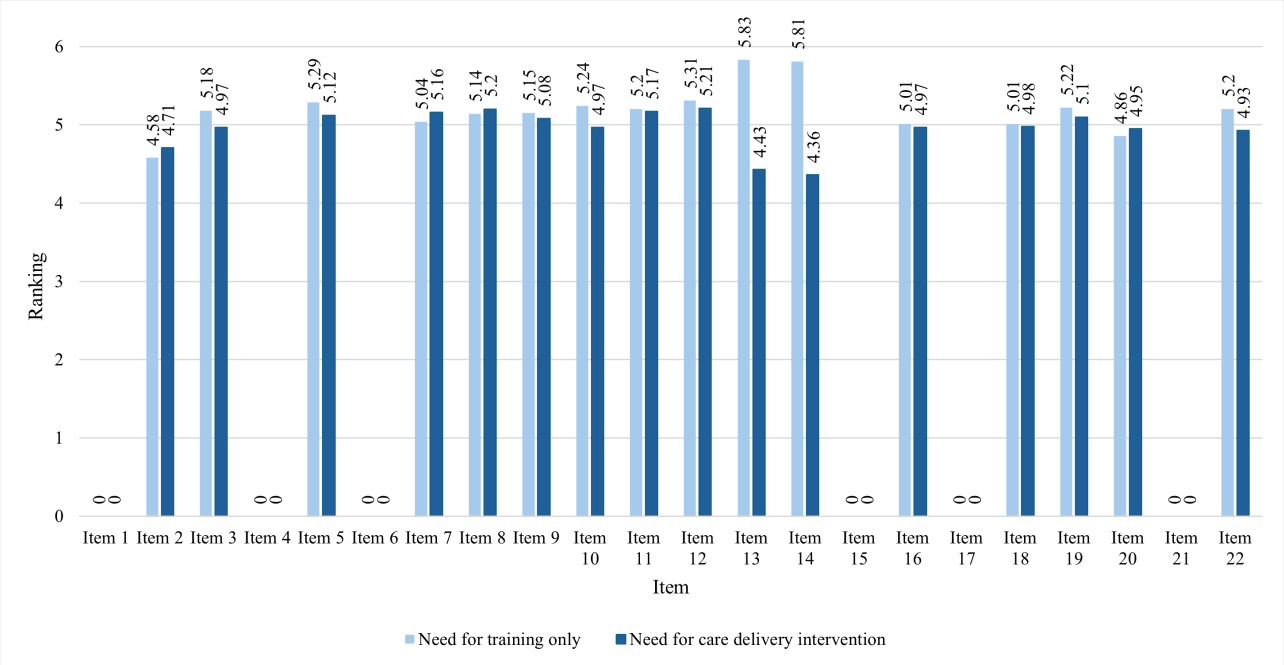
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B), but was not significant in RNs who had patients with a mean length of stay of 10 days or less (Group A). Working with the design of the EHR to retrieve information to provide care to patients with CHF (item number 17) ranked 13th among RNs who had patients with a mean length of stay of 10 days or less (Group A), but was not significant in RNs who had patients with a mean length of stay of more than 10 days (Group B). Caring for patients with CHF (item 3) was ranked 14th in RNs who had patients with a mean length of stay of more than 10 days (Group B) but was not significant in RNs who had patients with a mean length of stay of 10 days or less (Group A).

Preferred Training and Care Delivery Barriers by Group

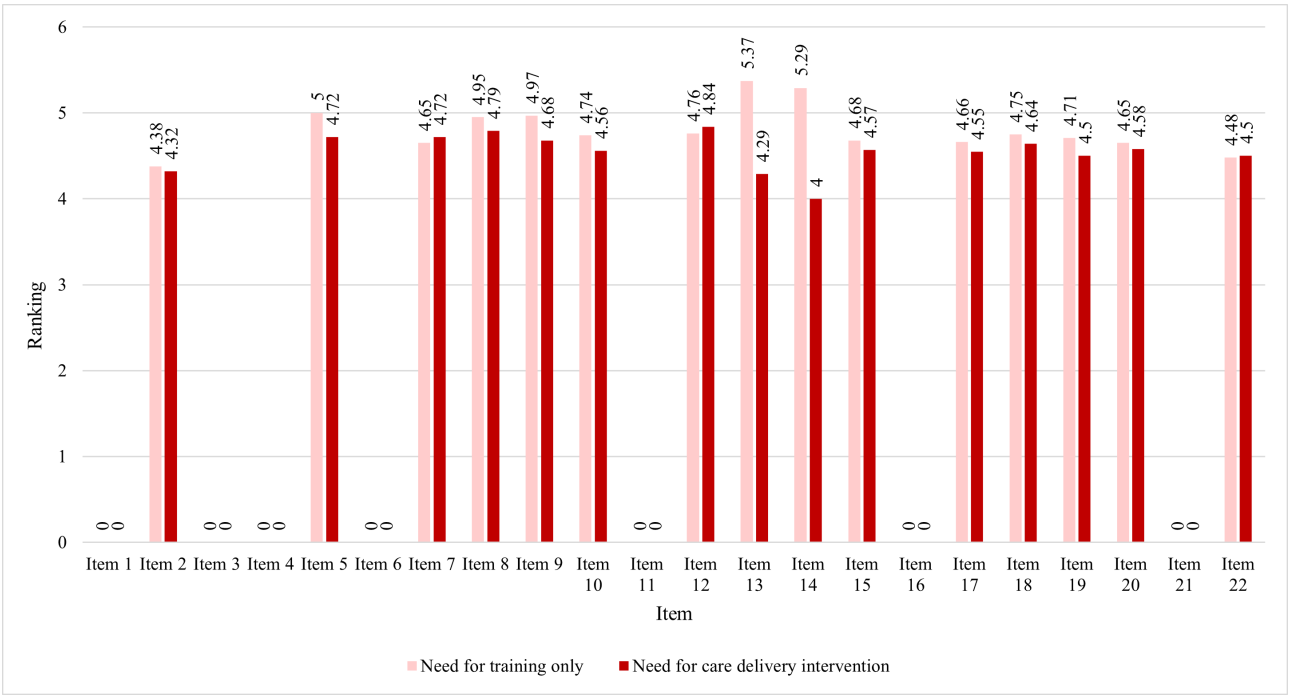
Figures 4 and 5 present the mean ratings of the RNs' preferred approaches to addressing the significant sociotechnical needs by addressing care delivery barriers that were not related to training (Rating C) or through additional training alone (Rating D). Higher ratings represent a preferred approach. For example, in using risk scores or other information from the EHR to improve a patient's health (item 7), RNs who had patients with a mean length of stay of 10 days or less (Figure 4) and RNs who had patients with a mean length of stay of more than 10 days (Figure 5) preferred to have the sociotechnical need met by addressing care delivery barriers that were not related to training. RNs who had patients with a mean length of stay of 10 days or less (Group A) preferred training alone in 12 of the needs (items 2, 5, 8, 9, 10, 13, 14, 15, 17, 18, 19, and 20), while they preferred to have care delivery barriers addressed in 3 sociotechnical tasks (items 7, 12, and 22). RNs who had patients with a mean length of stay of more than 10 days (Group B) preferred training alone in 10 of the needs (items 3, 5, 9, 10, 12, 13, 14, 16, 19, and 22), while they preferred to have care delivery barriers addressed in 3 sociotechnical tasks (items 2, 7, 8, and 20).

Figure 4. Preferred approaches for significant sociotechnical needs in Group A.



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Figure 5. Preferred approaches for significant sociotechnical needs in Group B.



Discussion

Overview

The study identified 17 sociotechnical needs of RNs that indicate specific opportunities for additional training, care delivery, EHR improvements, and other interventions related to patients, providers, and social determinants of health.

Summary of Key Findings

In total, 2 sociotechnical needs were unique to RNs who had patients with long lengths of stay: working with information related to a patient's CHF in the EHR and caring for patients with CHF. Giving patient education information to African American patients or their caregivers was an additional need that ranked as a higher priority in RNs who had patients with long lengths of stay, when compared to those who had patients with short lengths of stay. The 2 largest sociotechnical needs were the same in both groups and were related to RNs' perceptions of their workload: managing their overall workload of patients with the EHR and personally coping with burnout in their clinical environment. Patients cared for by both groups of RNs had approximately the same levels of overall health severity and heart failure severity, indicating that differences in lengths of stay may not be solely influenced by these factors of a patient's health severity. The finding also indicates that there may be other patient, provider, and structural factors, such as the high burden of social determinants of health on African Americans, that may be attributed to length of stay. Addressing these factors in addition to the sociotechnical needs of RNs could provide a more comprehensive and effective approach to reducing lengths of stay and mortality.

The Potential for Reducing Long Lengths of Stay

One of the largest sociotechnical needs that was unique to RNs who had patients with long lengths of stay reflected the full scope of social and technological processes performed by RNs during care delivery, caring for patients with CHF. A similar sociotechnical need was ranked as a higher priority in RNs with long lengths of stay: assessing African American patients' clinical needs using the EHR. These tasks are based on crucial assessments that include the active monitoring of symptoms, vital signs, fluid intake and output, and daily weight measurement [15]. The extent to which these assessments are performed is critical to the effective provision of care by other care team members [12,15]. These findings showed that the unaddressed sociotechnical needs of RNs may be associated with longer lengths of stay. RNs who had patients with long lengths of stay preferred to have these needs addressed by additional training, suggesting that care delivery barriers had a lesser influence on their performance or needs. Additional evidence-based training could be provided through the American Association of Heart Failure RNs' Heart Failure Certification, which has standardized the specialized CHF knowledge base of RNs and regulates the clinical experiences of RNs in heart failure care [15].

Another sociotechnical need that was unique to RNs who had patients with long lengths of stay was working with information related to a patient's CHF in the EHR to care for the patient. The EHR contains data from an array of laboratory tests (eg, troponin, basic metabolic panel, magnesium, hemoglobin A_{1c}, urinalysis, lipid profile, liver function tests, and a complete blood count) [15]. These tests are used to distinguish between worsening CHF and symptoms such as shortness of breath that mimic other illnesses [15]. For example, laboratory tests containing information on B-type natriuretic peptide levels and pulmonary artery pressure are used as biological markers for monitoring heart function [15]. RNs review, use, and monitor these data to escalate and de-escalate care provided by other members of the care team [15,16]. Our findings suggest that long lengths of stay may be reduced through additional training

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in retrieving, using, and monitoring these data because these data and information are nationally recognized indicators of hospitalizations and widely used in remote monitoring [15,40,41].

Giving patient education information to African American patients or their caregivers was ranked as a higher priority by RNs who had patients with longer lengths of stay when compared to those with shorter lengths of stay. The size of the need was small in RNs with shorter lengths of stay, but a moderate-sized need in RNs with longer lengths of stay. These differences in the rank and size of the need could be related to the longer lengths of stay. For hospitalized African American patients with CHF, education information provided by the RN is the sole opportunity to review and discuss signs, symptoms, laboratory results, medications, dietary restrictions, fluid management, and follow-up care [15]. RNs educate patients in a manner that is more understandable than other care team members who may use more lengthy and complex medical jargon [15]. An RN's ability to translate complex medical terminology is limited by the patient's education and understanding of care components, such as the patient's regimen, purpose, and dosing of heart failure medications [24]. The preferred approach to addressing this need was training. For example, this could include additional training on the RN's retrieval of a medication synopsis from an optimized medication administration record. Training related to using this synopsis could be provided. This process may provide additional opportunities to expand the capacity of EHRs to support RNs who may use sources external to EHRs for tasks such as searching for medications on a one-by-one basis for patient education.

An RN's ability to use this information to educate patients is also critical to patient self-management of their CHF, as the complex nature of CHF care requires multiple transitions between providers and frequent transitions between health care systems [16]. This initial education (and ongoing education) is critical to a patient's ability to establish a baseline understanding of their CHF case and conduct any self-assessment of any deviations or worsening symptoms [16]. This education provides patients with the ability to more effectively communicate changes in their symptoms with various members of their multidisciplinary and specialty care teams. Patient education may be optimized in RNs who use evidence-based methods such as teach-back techniques, message repetition, role-playing, and clinic aids such as brochures and videos [16]. These techniques verify patient understanding, which could be highly effective in African Americans who are burdened by health literacy [3,16].

Potential Contributions of the EHR and Its Data

EHR use is frequently not optimized in heart failure management [22]. Previous research on care transitions has shown that seamless postdischarge support from family, caregivers, and primary care providers optimizes outcomes and adherence to the plan of care [9,15,22,23]. The EHR can support care transition by addressing social determinants, such as clinician biases and resistance to evaluating African American patients for advanced heart failure therapies [9,15,16,23]. EHRs can also be optimized to identify daily discharges to support referrals for patients to cardiologists, as African American patients are also less likely to receive care from a cardiologist during a heart failure hospitalization [9]. Strategies such as automated reminders using push notifications in patient portals and among scheduling departments may optimize care transition. EHRs can also be optimized to provide referrals to home care agencies, palliative care, and longer-term services by facilitating high-quality, structured communication focused on shared decision-making [9,15,16]. The EHR could automate referrals when patients meet criteria or have a provider in the loop, alerting the system to let the primary team know that the patient meets criteria and force an active decision to refer or not refer to palliative care [15]. For longer-term care services, the EHR can facilitate notifications via case managers that assist with postacute discharge arrangements [15].

EHRs facilitate the storage and retrieval of standardized education materials, generally developed by reputable sources such as the AHA and professional associations [24]. Traditional approaches to CHF management have previously limited patient education to information based on the management of symptoms, weight, and vital signs, which require less education when compared to the more complex biomarkers produced by remote monitoring tools [15,40,41]. Contemporary approaches, such as the use of remote monitoring tools, facilitate real-time adjustments of care plans based on data collected through tools such as the CardioMEMS system [41]. The CardioMEMS system, for example, provides RNs with early notification of fluid build-up. The system identifies pressure and fluid build-up weeks before a potential hospitalization, compared to traditional approaches that rely on symptoms to develop [15]. Traditional approaches rely on the patient to be in the same physical location as the RN (ie, a hospitalization or clinic visit) or for the patients to capture their weight and vital signs, remotely, at regular intervals, and communicate changes in, for example, weight, to the RN [15,40,41]. This process requires physical tools and technologies such as scales, blood pressure cuffs, and pulse oximeters. It is not likely that the high rates of poverty in the African American communities that were cared for by the RNs allow patients to absorb the costs of these tools [31-33]. The use of these tools in both traditional and advanced CHF management approaches may optimize education toolkits to support the RNs in intervening by contacting the patient to identify and address the cause of the pressure and fluid build-up [40-42]. These data and information could be fed into the EHR manually or automatically through remote monitoring tools. This data could fuel EHR alerts to RNs and patients regarding significant changes and deviations from established thresholds for weight, heart rate, and blood pressure, which are early signs of fluid build-up and worsening heart function [40-42]. For patients, notifications from patient portals that acknowledge worsening heart function may encourage patients to seek out additional care instead of patients waiting for any number of care team members to reach out to them, which could increase the patient's likelihood of more severe symptoms and readmission. These processes rely on the patient's understanding of their CHF and their ability to communicate relevant information to the RN for effective triage. The significant reliance on people to understand, assess, and communicate

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information within this process is an opportunity for artificial intelligence algorithms to supplement this process. These algorithms could support the timely detection and communication of invisibles that are not recognized by patients and relieve some of the cognitive burden of complex sociotechnical tasks performed by RNs.

Limitations

The study used an observational, cross-sectional study design, which could not infer that nursing care caused lengths of stay or that the EHR had a significant effect on length of stay. The study design found statistically significant and meaningful sociotechnical needs of RNs who had patients with lengths of stay of 10 days or less, and in RNs who had patients with lengths of stay of more than 10 days. Empirical evidence suggests that lengths of stay may be more directly associated with or caused by variables such as CHF severity, patient adherence to evidence-based therapies, self-management behaviors, and social determinants of health [9,12,13].

Identifying patterns in nursing care by retrospectively stratifying RNs into groups based on the mean length of stay of their patients was a broad approach to assessing nursing expertise, care priorities, and length of stay. Although patients cared for by both groups of RNs had relatively the same left ventricular ejection fraction and Van Walraven Elixhauser Comorbidity Score, it is possible that patients with a longer length of stay were sicker, as defined by other hemodynamic values. It may also be possible for patients with longer lengths of stay to have received inadequate medical care before admission, were less compliant to the prescribed plan of care, had significant social, psychological, or resource barriers (eg, health literacy, cognitive impairment, lack of caregiver support), or were more likely to be approaching end of life where even optimal care would have been futile. Controlling for these and other variables of severity in additional studies that use experimental designs will be most impactful in evaluating and inferring causation between the socio-technical tasks and patients' length of stay.

Future studies should use specific evidence-based heart failure therapy guidelines to define optimal care, such as assessing the sociotechnical tasks in relation to groups whose African American patients were prescribed a combination of hydralazine and isosorbide dinitrate at discharge, compared to patients who were not. Defining optimal care based on heart failure guidelines that assess and address social determinants of health (eg, scheduling and coordinating transportation to follow-up visits within 7 days of discharge) may be most impactful.

The timing of the survey administration may not have accurately captured every sociotechnical need during each hospitalization of each patient because the sociotechnical needs of RNs may vary over time. It was not possible to administer the survey to every RN during each hospitalization without disrupting patient care and increasing the potential for acquiescence bias. To minimize the potential impact of this limitation, RNs were instructed to reflect on their entire career of experiences working with EHRs to care for patients with CHF, not at any specific point in time. To avoid bias toward or against any EHR, RNs were instructed to reflect on their entire career of experiences working with all EHRs and not to focus on a specific EHR or company.

Conclusions

RNs who had African American patients with long lengths of stay had unique sociotechnical needs. Lengths of patient stay may be reduced by addressing these needs through training, nursing care, RN-centered EHR interventions, and RN-led risk stratification guidelines for working with EHRs to optimize lengths of stay in African American patients who are disproportionately impacted by CHF.

Acknowledgments

The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Funding

Research reported in this publication was supported by the National Institute of Nursing Research of the National Institutes of Health (award R21NR021063). The data request to the repository was facilitated by the University of Arkansas for Medical Sciences' Translational Research Institute, which is funded by the National Center for Advancing Translational Sciences of the National Institutes of Health (award UL1 TR003017; principal investigator: James). The funders did not play any role in the study design, data collection, analysis, decision to publish, or preparation of the manuscript.

Data Availability

All data reported in the manuscript are freely available in the Open Inter-university Consortium for Political and Social Research (openICPSR) repositories and can be accessed from [43].

Authors' Contributions

TBW conceptualized and operationalized the study, including designing the survey, data collection processes, data visualizations, and interpretation, registered nurse recruitment, manuscript writing, and securing funding for the study. MB conceptualized the study, led data analysis and interpretation, and contributed to manuscript writing. MYG, PP, and TM-S contributed to survey design, data interpretation, and manuscript writing. CP-V contributed to data interpretation and manuscript writing. ES led the

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administration of the survey and contributed to manuscript writing. AC administered survey incentives and contributed to data interpretation and manuscript writing. RR, LP, and KWS contributed to manuscript writing.

Conflicts of Interest

KWS has equity in HoopCare, Inc, hDrop Technologies, Inc, Decisio Healthcare, Inc, and Datafy, LLC. KWS also has licensed intellectual property owned by Vanderbilt University and the University of Arkansas for Medical Sciences. No funding was provided by commercial interests.

Multimedia Appendix 1
Informed consent email.
[PDF File, 119 KB - nursing_v8i1e75080_app1.pdf]

Multimedia Appendix 2
Survey instrument.
[PDF File, 103 KB - nursing_v8i1e75080_app2.pdf]

Multimedia Appendix 3
Tables for sociotechnical task importance, performance, and needs.
[PDF File, 179 KB - nursing_v8i1e75080_app3.pdf]

Checklist 1
CHERRIES Checklist.
[PDF File, 150 KB - nursing_v8i1e75080_app4.pdf]

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Abbreviations

AHA: American Heart Association
CHERRIES: Checklist for Reporting Results of Internet E-Surveys
CHF: congestive heart failure
EHR: electronic health record
REDCap: Research Electronic Data Capture
RN: registered nurse

Edited by E Borycki, K Cato; submitted 27.03.25; peer-reviewed by J Thrift, K McCauley, UM Kinnunen; revised version received 28.07.25; accepted 06.10.25; published 12.12.25.

Please cite as:
Williams TB, Bimali M, Garza MY, Parker P, Paladino-Vaden C, Seker E, Crump A, Rice R, Prince L, Massey-Swindle T, Sexton KW Sociotechnical Needs of Registered Nurses in the Heart Failure Hospitalizations of African American Patients: Cross-Sectional Study JMIR Nursing 2025;8:e75080
URL: https://nursing.jmir.org/2025/1/e75080
doi:10.2196/75080

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Original Paper

Limited Moderating Effect of Podcast Listening on Work Stress and Emotional Exhaustion Among Nurses During the COVID-19 Pandemic: Cross-Sectional Study

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Abstract

Background: The COVID-19 pandemic placed unprecedented pressure on health care systems worldwide, significantly impacting frontline health care workers, especially nurses. These professionals faced considerable psychological stress from caring for patients with COVID-19 and the fear of spreading the virus to their families. Studies report that more than 60% (132/220) of nurses experience anxiety, depression, and emotional exhaustion, which adversely affect their mental health and the quality of care they provide.

Objective: This study aimed to investigate the relationship between work-related stress and emotional exhaustion among nurses and to assess whether listening to podcasts moderates this association.

Methods: A cross-sectional online survey was conducted between March 1, 2023, and March 31, 2023. A total of 271 clinical nurses, aged 20 years to 65 years, were recruited for the study. Participants were divided into 2 groups: experimental group consisting of regular podcast listeners (n=173) and control group comprising nonlisteners (n=98). Ethical approval for this study was obtained from the local ethics committee (IRB number YGHIRB20230421B). Validated scales were used to measure work stress, emotional dissonance, and emotional exhaustion. Data analysis included descriptive statistics, independent *t* tests, and structural equation modeling to examine the relationships between variables.

Results: No statistically significant differences were found between the experimental and control groups in terms of overall work stress (mean difference=–0.09, 95% CI –0.31 to 0.13; *P*=.42) or emotional exhaustion (mean difference=0.07, 95% CI –0.15 to 0.29; *P*=.53). Emotional dissonance emerged as a significant predictor of emotional exhaustion in both the experimental (β=0.476, *P*<.001) and control (β=0.321, *P*=.01) groups. Nurses reporting higher workloads had significantly higher emotional exhaustion levels (experimental group: β=0.302, *P*<.001; control group: β=0.327, *P*=.002). Podcast listening demonstrated only a slight, nonsignificant moderating effect.

Conclusions: Although podcasts alone may not significantly reduce work stress or emotional exhaustion among nurses, there was a potential, albeit limited, moderating effect of podcasts on emotional well-being. They could serve as a supplementary tool for emotional support. However, broader and more comprehensive interventions are required to address the underlying causes of stress and emotional exhaustion in this population. More in-depth exploration and recommendations are possible by analyzing the content and patterns of listening. Further research is needed to examine the long-term benefits of integrating podcasts with other digital tools for holistic stress management in health care settings.

(JMIR Nursing 2025;8:e70640) doi:10.2196/70640

KEYWORDS

work stress; emotional exhaustion; podcasts; nurses; COVID-19; mental health

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Introduction

Background and Significance

Following the initial outbreak in December 2019, the COVID-19 pandemic rapidly spread across the globe, resulting in a severe public health crisis. The pandemic imposed immense pressure on health care systems worldwide, particularly affecting frontline health care workers who bear significant responsibilities and endure substantial psychological stress. These health care workers made great sacrifices and contributions to combat the pandemic, yet they faced challenges such as nursing staff shortages, which had a profound impact on the global health care sector. Nurses were not only tasked with caring for patients with COVID-19 but also worried about transmitting the virus to their families, further exacerbating their psychological stress and adversely affecting their mental health [1].

Work Stress and Emotional Exhaustion Among Nurses

Studies indicate that more than 60% (132/220) of nurses experience anxiety, depression, and emotional exhaustion due to prolonged patient care, impacting both their physical and mental well-being, as well as the quality of patient care they provide [2]. For instance, research by Lai et al [3] revealed that 126 of 250 nurses (50.4%) exhibit symptoms of depression, 112 of 251 nurses (44.6%) experience anxiety, 85 of 250 nurses (34%) experience insomnia, and as many as 179 of 250 nurses (71.5%) report distress. These data highlight the issue of emotional exhaustion among nurses in high-pressure environments.

The Potential Role of Digital Interventions in Stress Management

The mental health challenges faced by nurses have drawn attention to the need for strategies to improve their psychological well-being. Previous research has predominantly focused on improving work environments and workplace ethics, while few explored the efficacy of digital media interventions for managing stress within health care settings. These interventions range from mobile apps to web-based programs targeting diverse populations including adolescents, health care workers, and patients with cancer [4-7]. With the advancement of information and network technologies, new media tools such as podcasts have gained attention. Podcasts, as an unofficial platform that crosses institutional and organizational boundaries, offer anonymity and flexibility, making them a potential resource for helping nurses manage stress and emotions.

The Rise of Podcasts and Their Use in Health Care

With the progression of information and network technologies, podcasts have emerged as a popular form of media in Taiwan. In our survey, 201 of 250 participants (80.3%) reported using the internet to access online news or lifestyle information. Podcasts, although introduced in the early 2000s, gained substantial popularity during the COVID-19 pandemic and became part of the stay-at-home economy [8]. Due to a feeling of companionship and flexibility, podcasts have become a popular companion media format. A report by Commonwealth Magazine [9] indicated that most podcast listeners use podcasts for relaxation and entertainment, while programs like “Med persona” cater to the personal needs of health care professionals and inspire their professional development.

Research Gap and Study Rationale

Podcasts are becoming increasingly important for supporting the emotional health and resilience of nurses, especially in the face of the challenges posed by the COVID-19 pandemic. These podcast programs provide essential resources for health care professionals, offering guidance and shared experiences to help nurses cope with the emotional labor and psychological stress often encountered in their work. However, despite their growing popularity, there is limited empirical research investigating the actual effectiveness of podcasts in reducing work-related stress and emotional exhaustion among nurses. This study aimed to fill this research gap by systematically examining whether podcast listening can serve as a useful tool for emotional support and stress relief in nursing practice.

Objectives and Research Questions

The primary objective of this study was to investigate the impact of work-related stress on emotional exhaustion among nurses and to determine whether listening to podcasts can mitigate this effect. The study aimed to provide empirical evidence regarding the effectiveness of podcasts as a tool for emotional management and stress relief among nursing staff.

To achieve this objective, we focused on 2 main research questions: (1) Can listening to podcasts help nurses manage their emotions and alleviate work -related stress? and (2) Can podcasts modulate the level of emotional exhaustion among nurses?

By addressing these questions, the study aimed to gain a deeper understanding of the potential benefits of incorporating podcasts into stress management and emotional support programs for nurses, ultimately enhancing their overall well-being and job performance.

Methods

Study Design and Participants

The study used convenience sampling to ensure the accuracy and reliability of the study results. The participants were clinical care providers aged between 20 years and 65 years. The participants were divided into 2 groups: experimental group consisting of nurses who regularly listened to podcasts and control group comprising nurses who did not listen to podcasts. This grouping facilitated a comparative analysis of the potential impact of podcast listening on alleviating work-related stress and emotional exhaustion among nurses.

Exclusion criteria included any hearing impairments, ensuring that the selected sample accurately met the study’s requirements.

Data Collection Procedures

During the recruitment process, participants in the experimental group were introduced to the study via a recorded message played by podcast hosts. This message explained the study's purpose, objectives, and instructions for completing the questionnaire. Participants in the control group received the

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same information in written form on the introduction page of the online survey platform. Participants were assured that their data would be used solely for research purposes, their privacy would be protected, and their participation was voluntary. They were informed their rights would not be affected if they chose not to participate. Those who agreed to participate were asked to sign a consent form and were then provided with a link to the online survey.

Data collection was conducted through a noninvasive online questionnaire. Participants were informed that they could withdraw from the study at any time if they felt uncomfortable. The questionnaire was administered by experienced researchers, and all responses were securely stored in a cloud database. Participants' identities were anonymized using research codes to protect their privacy, in compliance with personal data protection laws and relevant regulations.

If participants felt any discomfort while completing the questionnaire, they were allowed to terminate their participation at any time.

Statistical Analysis

During the study period, from March 1, 2023, to March 31, 2023, a total of 271 valid questionnaires were collected. The experimental group consisted of 173 nurses who regularly listened to podcasts, and the control group consisted of 98 nurses who did not listen to podcasts. The analysis focused on demographic attributes such as age, marital status, number of children, educational background, nursing experience, department, position, level of advancement, emotional disposition, and podcast listening habits.

This descriptive analysis provides a comprehensive overview of the demographic and occupational characteristics of the study participants, laying the foundation for further analysis of the relationships between these variables and the outcomes of interest.

Ethical Considerations

All procedures of this study adhered to ethical guidelines. Contact information for the primary researcher and detailed instructions for submitting responses were provided. Informed consent was obtained from all participants, and all data were anonymized. No incentives nor rewards were offered. Ethical approval for this study was granted by the Yuan's General Hospital Ethics Committee (Institutional Review Board approval number: YGHIRB20230421B).

Results

Participant Characteristics

A total of 271 nurses participated in the study. Most participants were aged between 21 years and 39 years (187/271, 69%) and held a university-level education (221/271, 81.5%). The majority were unmarried (144/271, 53.1%), had no children (159/271, 58.7%), and had between 2 years and 20 years of nursing experience (205/271, 75.7%). Most held clinical nursing positions (229/271, 85.4%) and were distributed across various hospital departments, including the emergency department (22/271, 8.1%) and internal medicine (31/271, 11.4%) and surgical (54/271, 19.9%) wards. In terms of emotional disposition, most participants reported having a positive outlook (212/271, 78.2%). Among podcast listeners, the majority had been listening for less than 3 months (80/173, 46.1%). Detailed demographic information is presented in Table 1.

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Table 1. Demographic data of the study participants (n=271).

Variable	Results, n (%)
Age (years)	
21-29	90 (33.2)
30-39	97 (35.8)
40-49	65 (24)
50-59	18 (6.6)
60-69	1 (0.4)
Marital status	
Unmarried	144 (53.1)
Married	121 (44.6)
Divorce	6 (2.2)
Widowed	0 (0)
Separated	0 (0)
Education	
Specialist	20 (7.4)
2-year junior college program	16 (5.9)
University	221 (81.5)
Master	13 (4.8)
PhD	1 (0.4)
Nursing experience (years)	
0-1	22 (8.1)
2-10	123 (45.4)
11-20	82 (30.3)
21-30	34 (12.5)
31-40	9 (3.3)
41-50	1 (0.4)
Number of children	
0	159 (58.7)
1	41 (15.1)
2	62 (22.9)
3	9 (3.3)
>4	0 (0)
Service department	
Outpatient department	47 (17.3)
Emergency Department	22 (8.1)
Operating room	19 (7)
Intensive Care Unit	39 (14.4)
Medical Ward	31 (11.4)
Surgical Ward	54 (19.9)
Obstetrics and gynecology	18 (6.6)
Pediatrics	1 (0.4)
Other single	40 (14.8)
Emotional personality	

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Variable	Results, n (%)
Positive emotions	212 (78.2)
Negative emotions	59 (21.8)
Nursing duties	
Nurse	229 (84.5)
Nursing team leader	18 (6.6)
Deputy director of nursing	6 (2.2)
Head nurse	17 (6.3)
Nursing supervision	1 (0.4)
Nursing director	0 (0)
Advanced level	
New staff	2 (0.7)
<1 year of clinical work experience	25 (9.2)
>1 year of clinical work experience, completed the first-year clinical competency training for nursing staff, and passed the review successfully	41 (15.1)
>2 years of clinical work experience, completed the second-year clinical competency training for nursing staff, and passed the review successfully	142 (52.4)
>3 years of clinical work experience, completed the third-year clinical competency training for nursing staff, and passed the nursing association's case report review successfully	38 (14)
>4 years of clinical work experience, completed the fourth-year clinical competency training for nursing staff, and passed the nursing association's administrative project review successfully	23 (8.5)
Podcast listening habits (n= 173)	
1 month	46 (26.6)
3 months	34 (19.5)
6 months	18 (10.4)
1 year	24 (13.9)
1-3 years	32 (18.5)
3-5 years	13 (7.5)
5-10 years	5 (2.8)
>10 years	1 (0.6)

Age (χ^2_4=49.158, *P*=.09; Table 2) and marital status (χ^2_2=2.223, *P*=.33) were not significantly different between the experimental and control groups. The number of children was significantly different between the 2 groups (χ^2_2=12.215, *P*=.007). In the experimental group (ie, nurses who regularly listen to podcasts), a higher proportion of participants were childless (61/98, 62%), whereas in the control group, a greater number of nurses had children (75/173, 43.4%). This difference may impact how nurses cope with work stress and experience emotional exhaustion, as studies have shown that nurses with children face additional family caregiving responsibilities, which may exacerbate their psychological stress. Additionally, since the number of children was a significant factor, it should be considered in the interpretation of the results to avoid potential confounding effects. There were no significant differences between the groups in educational level (χ^2_3=5.742, *P*=.22), nursing experience (χ^2_4=36.885, *P*=.38), department (χ^2_5=14.571, *P*=.07), position (χ^2_2=1.911, *P*=.75), advancement level (χ^2_2=2.058, *P*=.84), and emotional disposition (χ^2_1=0.512, *P*=.47). Independent *t* tests revealed no significant differences between the experimental and control groups regarding workload (t_{269}=–.879, *P*=.51) and emotional exhaustion (t_{269}=0.295, *P*=.30). These findings suggest that podcast listening did not significantly affect the levels of work stress or emotional exhaustion among the nurses in this study (Tables 2 and 3).

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Table 2. Comparison of the distribution of individual variables between the 2 groups.

Variables	Experimental group (n=98), n (%)	Control group (n=173), n (%)	χ^2 (*df*)	*P* value
Age (years)			49.158 (4)	.09
21-29	41 (41.9)	49 (28.3)		
30-39	36 (36.7)	61 (35.3)		
40-49	16 (16.3)	49 (28.3)		
50-59	5 (5.1)	13 (7.5)		
60-69	0 (0)	1 (0.6)		
Marital status			2.223 (2)	.33
Unmarried	57 (58.2)	87 (50.3)		
Married	40 (40.8)	81 (46.8)		
Divorced	1 (1)	5 (2.9)		
Widowed	0 (0)	0 (0)		
Separated	0 (0)	0 (0)		
Number of children			12.215 (3)	.007
0	61 (62.2)	98 (56.6)		
1	21 (21.4)	20 (11.6)		
2	12 (12.2)	50 (28.9)		
3	4 (4.1)	5 (2.9)		
>4	0 (0)	0 (0)		
Education			5.742 (4)	.22
specialist	8 (8.2)	12 (6.9)		
2-year junior college program	7 (7.1)	9 (5.2)		
University	82 (83.7)	139 (80.3)		
Master	1 (1)	12 (6.9)		
PhD	0 (0)	1 (0.6)		
Nursing experience (years)			36.885 (5)	.38
0-1	12 (12.2)	10 (5.8)		
2-10	45 (46)	78 (45.1)		
11-20	32 (32.7)	50 (29)		
21-30	7 (7.1)	27 (15.6)		
31-40	2 (2)	7 (4)		
41-50	0 (0)	1 (0.5)		
Service department			14.571 (7)	.07
Emergency department	18 (18.4)	29 (16.8)		
Operating room	2 (2)	20 (11.6)		
Intensive care unit	8 (8.2)	11 (6.4)		
Medical ward	13 (13.3)	26 (15)		
Surgical ward	13 (13.3)	18 (10.4)		
Obstetrics and gynecology	25 (25.5)	29 (16.8)		
Pediatrics	9 (9.2)	9 (5.2)		
Other single	0 (0)	1 (0.6)		
Nursing duties			1.911 (3)	.75

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Variables	Experimental group (n=98), n (%)	Control group (n=173), n (%)	χ^2 (*df*)	*P* value
Nurse	85 (86.7)	144 (83.2)		
Nursing team leader	7 (7.1)	11 (6.4)		
Deputy director of nursing	2 (2)	4 (2.3)		
Head nurse	4 (4.1)	13 (7.5)		
Nursing supervision	0 (0)	1 (0.6)		
Nursing director	0 (0)	0 (0)		
Advanced level			2.058 (5)	.84
New staff	1 (1)	1 (1)		
<1 year of clinical work experience	11 (11.2)	14 (8.1)		
>1 year of clinical work experience, completed the first-year clinical competency training for nursing staff, and passed the review successfully	17 (17.3)	24 (13.9)		
>2 years of clinical work experience, completed the second-year clinical competency training for nursing staff, and passed the review successfully	50 (51)	92 (53.2)		
>3 years of clinical work experience, completed the third-year clinical competency training for nursing staff, and passed the nursing association's case report review successfully	12 (12.2)	26 (15)		
>4 years of clinical work experience, completed the fourth-year clinical competency training for nursing staff, and passed the nursing association's administrative project review successfully	7 (7.1)	16 (9.2)		
Emotional personality			0.512 (1)	.47
Positive emotions (optimistic character)	79 (80.6)	133 (76.9)		
Negative emotions (pessimistic character)	19 (19.4)	40 (23.1)		

Table 3. Comparison of emotional exhaustion between the experimental group and control group.

Tests	Experimental group(n=98), mean (SD)	Control group(n=173), mean (SD)	*P* value
Workload	5.21 (1.11)	5.09 (1.13)	.51
Patients' or relatives' requirements	4.96 (1.19)	4.47 (1.30)	.39
Patient suffering	4.98 (1.11)	4.95 (1.25)	.24
Team collaboration problems	4.31 (1.09)	4.30 (1.12)	.80
Emotional dissonance	4.65 (1.38)	4.61 (1.30)	.77
Emotional exhaustion	4.80 (1.16)	4.78 (1.07)	.30

Descriptive Statistics of Key Variables

In this study, the primary contributors to emotional exhaustion among nursing staff included heavy workloads, difficult patient interactions, and the distress of witnessing patient suffering. Specifically, "too many patients to care for" was scored the highest, at a mean of 5.41, in the workload category, indicating that the large number of patients significantly increased work stress, leading to emotional dissonance and eventual exhaustion. In the category of patient and family demands, "communicating with difficult or demanding patients" received a mean score of 5.13, highlighting the challenges nurses faced with handling difficult communication, which further exacerbates emotional exhaustion. Additionally, "witnessing patient pain and suffering" received a mean score of 5.30, reflecting the emotional toll on nurses who felt powerless to alleviate patient suffering, resulting in emotional buildup and exhaustion.

Regarding team cooperation, "lack of recognition for career development" received a mean score of 4.58, suggesting that the lack of acknowledgment for professional growth contributes to burnout and diminished enthusiasm for advancing in the nursing profession. In terms of emotional dissonance, "my emotions displayed for professional reasons are not consistent with my true feelings" received a mean score of 4.69, showing how the need to suppress personal emotions to meet professional standards leads to negative emotional buildup and exhaustion. Finally, "I feel exhausted at the end of the workday" received the highest mean score, at 5.30, in the emotional exhaustion category, underscoring the intense pressure and stress nurses experienced daily, leading to significant emotional exhaustion (Table 4).

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Table 4. Questionnaire content related to each variable.

Variables	Questionnaire content	Results, mean (SD)[a]	Dimension score, mean[b]
Workload			5.02
w1	Insufficient time to accomplish tasks	4.59 (1.33)	
w2	Too many patients	5.41 (1.27)	
w3	Being assigned too many different tasks	5.25 (1.19)	
w4	Lack of vacation time	4.87 (1.33)	
w5	Having so much work that everything cannot be done well	4.98 (1.27)	
Patients' and relatives' requirements			4.81
pr1	Dealing with difficult/demanding patients	5.13 (1.29)	
pr2	Dealing with difficult/demanding relatives	5.05 (1.39)	
pr3	Patients and/or family hostility or violence	4.59 (1.41)	
pr4	Lack of cooperation with the patient	4.74 (1.37)	
pr5	Conflict between the patient and their family	4.56 (1.40)	
Patient suffering			5.02
ps1	Seeing the physical pain and suffering in patients	5.30 (1.24)	
ps2	Physical deterioration in patients	5.22 (1.31)	
ps3	No therapeutic hope	4.79 (1.33)	
ps4	Worrying about patients' loneliness	4.92 (1.24)	
ps5	Being confronted with denial of the disease	4.89 (1.33)	
Team collaboration problems			4.35
tcp1	Lack of recognition for work well done	4.53 (1.27)	
tcp2	Experiencing conflicts with co-workers	4.14 (1.38)	
tcp3	Unpleasant colleagues	4.18 (1.257)	
tcp4	Disagreeing with physicians' practices	4.44 (1.26)	
tcp5	Poor communication between coworker	4.21 (1.283)	
tcp6	No reward for career development andadvancement	4.58 (1.384)	
Emotional dissonance			4.61
ed1	The emotions that I feel in my job do not correspond to those Iwould like to feel.	4.57 (1.358)	
ed2	My work situation brings me to experience emotions different than those I would like to feel.	4.61 (1.374)	
ed3	I experience a discrepancy between the emotions I consider to beprofessional and what I feel.	4.57 (1.35)	
ed4	The emotions I show in order to be professional are not consistent with my inner feelings.	4.69 (1.413)	
Emotional exhaustion			4.75
ee1	I feel used up at the end of the workday.	5.3 (1.18)	
ee2	I feel fatigued when I get up in the morning and have to face another day on the job.	5.28 (1.201)	
ee3	I've become more callous toward people since I took this job.	4.63 (1.345)	
ee4	Working with people directly puts too much stress on me.	4.53 (1.31)	
ee5	I feel recipients blame me for some of their problems.	4.59 (1.332)	
ee6	I feel frustrated by my job.	4.35 (1.267)	
ee7	Working with people all day is really a strain for me.	4.59 (1.337)	

[a]Based on the Lister 7-point method (possible score ranging from 1 to 7).

[b]Mean of all item scores within a specific dimension (eg, stress, satisfaction, emotional state).

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Structural Equation Modeling and Partial Least Squares Results

This study used partial least squares to assess the reliability and validity of the collected questionnaire data. The analysis focused on internal consistency, convergent validity, and discriminant validity to ensure the accuracy of the data. Reliability was evaluated using Cronbach α and composite reliability. Both indicators demonstrated high reliability for all constructs, with Cronbach α values exceeding 0.86 and composite reliability values greater than 0.89, indicating strong internal consistency. Convergent validity was assessed using factor loadings and average variance extracted (AVE). Factor loadings primarily aim to explore whether the predefined factor model aligns with the collected observational data. This process examines whether the number of factors and the factor loadings of the observed variables meet expectations, thus validating the model's consistency with the empirical data. All item factor loadings were greater than 0.7, showing a strong relationship between items and their respective constructs. The AVE values were greater than 0.5, confirming that the constructs captured sufficient variance from their items. Discriminant validity was evaluated by comparing the square root of the AVE values with the correlations between constructs. All constructs exhibited good discriminant validity, with the square root of AVE exceeding the correlations between constructs, indicating that these constructs are distinct from one another (Tables 5-7).

To enhance the statistical interpretability of the correlations between constructs, we calculated the *P* values for the correlation coefficients presented in Table 7 using Pearson correlation analysis. As shown in Table 7, given the sample size of 271, all interconstruct correlations reached statistical significance ($P<.001$).

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Table 5. Questionnaire aspects for factor loading.

Questionnaire aspects (analysis code)	Factor loading
Workload	
w1	0.860
w2	0.896
w3	0.874
w4	0.925
Patients' and relatives' requirements	
pr1	0.915
pr2	0.913
pr3	0.938
pr4	0.924
pr5	0.925
Patient suffering	
ps1	0.904
ps2	0.930
ps3	0.901
ps4	0.915
ps5	0.909
Team collaboration problems	
tcp1	0.917
tcp2	0.906
tcp3	0.759
tcp4	0.931
tcp5	0.836
tcp6	0.882
Emotional dissonance	
ed1	0.964
ed2	0.969
ed3	0.973
ed4	0.937
Emotional exhaustion	
ee1	0.785
ee2	0.802
ee3	0.891
ee4	0.879
ee5	0.884
ee6	0.899
ee7	0.880

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Table 6. Reliability and validity of the questionnaire.

Questionnaire constructs	Cronbach α	CR[a]	AVE[b]
ed[c]	0.972	0.973	0.923
ee[d]	0.947	0.948	0.741
pr[e]	0.959	0.961	0.852
ps[f]	0.950	0.951	0.832
tcp[g]	0.934	0.936	0.761
w[h]	0.920	0.932	0.791

[a]CR: composite reliability.
[b]AVE: average variance extracted.
[c]ed: emotional dissonance.
[d]ee: emotional exhaustion.
[e]tcp: team collaboration problems.
[f]ps: patient suffering.
[g]pr: patients' and relatives' requirements.
[h]w: workload.

Table 7. Discriminant validity of the questionnaire, based on Pearson r correlation values (n=271).

Questionnaire constructs	ed[a]	ee[b]	pr[c]	ps[d]	tcp[e]	w[f]
ed						
r	0.961	0.797	0.648	0.615	0.738	0.664
P value	__g	<.001	<.001	<.001	<.001	<.001
ee						
r	0.797	0.861	0.628	0.561	0.760	0.745
P value	<.001	—	<.001	<.001	<.001	<.001
pr						
r	0.648	0.628	0.923	0.604	0.670	0.686
P value	<.001	<.001	—	<.001	<.001	<.001
ps						
r	0.615	0.561	0.604	0.912	0.536	0.503
P value	<.001	<.001	<.001	—	<.001	<.001
Tcp						
r	0.738	0.760	0.670	0.536	0.872	0.617
P value	<.001	<.001	<.001	<.001	—	<.001
w						
r	0.664	0.745	0.686	0.503	0.617	0.889
P value	<.001	<.001	<.001	<.001	<.001	—

[a]ed: emotional dissonance.
[b]ee: emotional exhaustion.
[c]tcp: team collaboration problems.
[d]ps: patient suffering.
[e]pr: patients' and relatives' requirements.
[f]w: workload.
[g]Not applicable.

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Discussion

The Impact of Emotional Dissonance on Emotional Exhaustion

The findings support the hypothesis that emotional dissonance leads to emotional exhaustion among nursing staff, which is consistent with previous research showing that emotional dissonance depletes emotional resources and contributes to burnout.

The Impact of Work-Related Factors on Emotional Dissonance

Workload had a significant positive effect on emotional dissonance in the control group (t_{269}=2.257, P=.02) but not in the experimental group (t_{269}=1.467, P=.14). Patient and family demands did not significantly affect emotional dissonance in either group. Caring for patients who were suffering showed a marginal effect in the experimental group (t_{269}=1.948, P=.051) but was not significant in the control group. Teamwork issues significantly influenced emotional dissonance in both groups (t_{269}=5.925, P≤.001)

The Impact of Work-Related Factors on Emotional Exhaustion

Workload significantly impacted emotional exhaustion in both groups (experimental group: t_{269}=4.283, P<.001; control group: t_{269}=3.082, P=.002). The effects of patient and family demands and caring for suffering patients were not significant. Teamwork issues were significantly associated with emotional exhaustion in both groups (experimental: t_{269}=2.239, P=.03; control: t_{269}=2.522, P=.01).

Moderating Effects of Listening to Podcasts on Work-Related Factors

None of the hypothesized moderating effects of podcast listening were statistically significant. The effects of workload, patient and family demands, caring for patients who are suffering, teamwork issues, and emotional dissonance on emotional exhaustion were not significantly moderated by podcast use (all P values >.05).

The model explained a substantial portion of the variance in emotional dissonance (experimental: R^2=0.618; control: R^2=0.629) and emotional exhaustion (experimental: R^2=0.731; control: R^2=0.711), but podcast listening did not significantly moderate the relationships among the studied variables (Table 8).

Table 8. Path coefficients.

Hypotheses	Experimental group			Hypothesis supported?	Control group			Hypothesis supported?
	Path coefficient	*t* (*df*)	*P* value		Path coefficient	*t* (*df*)	*P* value	
Emotional dissonance and emotional exhaustion	0.476	6.427 (269)	<.001	Yes	0.321	2.583 (269)	.01	Yes
Patients' and relatives' requirement and emotional dissonance	0.123	1.135 (269)	.26	No	0.113	0.660 (269)	.51	No
Patient suffering and emotional dissonance	0.173	1.948 (269)	.051	Yes	0.179	1.403 (269)	.16	No
Team collaboration problems and emotional dissonance	0.507	5.925 (269)	<.001	Yes	0.348	2.961 (269)	.003	Yes
Workload and emotional dissonance	0.125	1.467 (269)	.14	No	0.299	2.257 (269)	.02	Yes
Patients' and relatives/ requirements and emotional exhaustion	–0.004	0.044 (269)	.97	No	–0.021	0.167 (269)	.87	No
Patient suffering and emotional exhaustion	0.045	0.853 (269)	.39	No	0.047	0.490 (269)	.32	No
Team collaboration problems and emotional exhaustion	0.168	2.239 (269)	.03	Yes	0.293	2.522 (269)	.01	Yes
Workload and emotional exhaustion	0.302	4.283 (269)	<.001	Yes	0.327	3.082 (269)	.002	Yes

Emotional Dissonance and Emotional Exhaustion

This study found a significant positive correlation between emotional dissonance and emotional exhaustion among nursing staff. Specifically, as emotional dissonance increases, so does the risk of emotional exhaustion. This pattern was observed in both the experimental group (nurses who regularly listened to podcasts) and control group (nurses who did not listen to podcasts). However, the emotional dissonance levels were slightly lower in the experimental group, suggesting that listening to podcasts may have a mild mitigating effect. The data showed that emotional dissonance is a significant predictor of emotional exhaustion. These findings are consistent with previous research, confirming that emotional dissonance depletes emotional resources, ultimately leading to emotional exhaustion among nursing staff.

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Workload, Emotional Dissonance, and Emotional Exhaustion

The results indicated significant positive correlations between workload and both emotional dissonance and emotional exhaustion. High workloads increased the risk of these outcomes, especially for nurses who did not listen to podcasts. In the experimental group, the path coefficient for the impact of workload on emotional dissonance was 0.125 (t_{269}=1.467, P=.14), which was not significant, while in the control group, it was 0.299 (t_{269}=2.257, P=.02), indicating a significant effect. Similarly, the path coefficients for the impact of workload on emotional exhaustion were 0.302 (t_{269}=4.283, P<.001) in the experimental group and 0.327 (t_{269}=3.082, P=.002) in the control group. These findings suggest that, although podcasts may help alleviate some stress, they are not sufficient to prevent emotional exhaustion under high workload conditions.

Patient and Family Demands

The impact of patient and family demands on emotional dissonance and emotional exhaustion was minimal. Neither the experimental nor control group exhibited significant effects from these demands. For emotional dissonance, the path coefficient was 0.123 (t_{269}=1.135, P=.26) in the experimental group and 0.113 (t_{269}=0.660, P=.51) in the control group. For emotional exhaustion, the coefficients were –0.004 (t_{269}=0.044, P=.97) in the experimental group and –0.021 (t_{269}=0.167, P=.87) in the control group. This suggests that the professional skills and emotional management strategies of nursing staff effectively mitigate the impact of patient and family demands.

Caring for Patients Who Are Suffering

In the experimental group, caring for patients who are suffering had an almost significant impact on emotional dissonance (path coefficient 0.173; t_{269}=1.948, P=.051), but it was not significant in the control group (path coefficient 0.179; t_{269}=1.403, P=.16). However, its impact on emotional exhaustion was not significant in either group. This suggests that, although caring for patients who are suffering may lead to emotional dissonance, it does not necessarily result in emotional exhaustion, possibly due to effective emotional management and professional support systems.

Teamwork Issues

Teamwork issues showed a significant positive correlation with both emotional dissonance and emotional exhaustion. In the experimental group, the path coefficient for emotional dissonance was 0.507 (t_{269}=5.925, P<.001), and for emotional exhaustion, it was 0.168 (t_{269}=2.239, P=.03). In the control group, the coefficients were 0.348 (t_{269}=2.961, P=.003) and 0.293 (t_{269}=2.522, P=.01), respectively. These results indicate that issues such as poor communication and conflict within teams significantly increase stress, leading to emotional dissonance and exhaustion.

Podcasts as a Moderating Factor

The study explored whether listening to podcasts could mitigate the effects of workload, patient demands, caring for patients who are suffering, and teamwork issues on emotional dissonance and exhaustion. However, the moderating effects of podcasts were generally not significant. For example, in the experimental group, the moderation of the impact of workload on emotional dissonance (P=.14) was not significant. Similarly, podcasts did not significantly reduce the impact of patient demands or teamwork issues on emotional exhaustion.

Comparison With Previous Work

This study builds on existing research that has explored the relationship between emotional dissonance, workload, and emotional exhaustion among health care professionals. Previous studies, such as those by Bakker and Heuven [10] and Diestel and Schmidt [11], established a significant link between emotional dissonance and emotional exhaustion, highlighting the harmful effects of emotional labor on health care workers. Our findings confirm these studies, showing that emotional dissonance is a key predictor of emotional exhaustion in nursing staff. However, our research adds a new dimension by examining the potential moderating role of podcast listening in this relationship. Although the impact of emotional dissonance on exhaustion remains substantial regardless of podcast use, the slight alleviation observed in the experimental group suggests that podcasts may offer some emotional relief, an aspect not explored in earlier studies.

In terms of workload, our findings align with the existing literature, emphasizing the stress induced by high workloads in health care professionals. Studies by Glasberg et al [12] and Garrosa et al [13] highlighted that heavy workloads bring immense stress, leading to emotional exhaustion. Our study confirms these findings but also introduces the novel consideration of podcasts as a potential buffer. However, the effects of podcasts were insufficient and did not counteract the overwhelming impact of high workloads, suggesting the need for more comprehensive interventions.

Furthermore, unlike previous studies that mainly focused on the direct effects of patient demands and teamwork issues on emotional health, our study investigated these factors in the context of podcast use. Although the impact of patient demands on emotional dissonance and exhaustion was minimal, teamwork issues were found to have a significant impact, consistent with prior research. However, the moderating role of podcasts in mitigating these effects was limited, offering a nuanced understanding of the boundaries of digital media interventions in high-stress work environments.

Factors Influencing the Study Results

The findings of this study indicate that the number of children the nurses had significantly differed between the 2 groups (P=.007), which may influence the interpretation of work stress and emotional exhaustion outcomes. Previous research has suggested that nurses with children may have heavier family responsibilities, leading to differences in their stress adaptation and emotional regulation compared with those without children. Particularly during the COVID-19 pandemic, nurses not only faced clinical stress but also the combined burden of childcare, household responsibilities, and health care duties, which could further contribute to increased emotional exhaustion.

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However, we did not conduct a subgroup analysis to explore the impact of the number of children on the moderating effect of podcast listening. Therefore, future research should consider incorporating this variable into the model and using multivariate regression analysis or moderation effect analysis to control for potential confounding factors, ensuring the accuracy of study results.

Strengths and Limitations

Strengths

This study has several strengths, including innovative use of podcasts, comprehensive analyses, and the ability to apply the findings in a practical setting.

This study is among the first to explore the use of podcasts as a tool for emotional support and stress management among nursing staff. By incorporating emerging digital media tools, the research offers new insights into how health care professionals can leverage technology to improve their emotional well-being. Regarding the analysis, the study thoroughly examines multiple sources of stress, including emotional dissonance, workload, patient demands, and teamwork issues, providing a holistic view of the factors leading to emotional exhaustion in nursing. The findings also have direct implications for health care institutions and policymakers, suggesting practical measures such as integrating podcast programs into emotional support strategies for nursing staff. Nevertheless, the generalizability of these findings to a broader nursing population should be interpreted with caution and warrants further validation in diverse clinical settings.

Limitations

At the same time, the study had some limitations, including sample representativeness, its cross-sectional design, the use of self-reported data, variations in podcast content and listening patterns by the participants, a potential lack of generalizability due to the cultural and linguistic context, and differences in the number of children the nurses had between the groups.

The study's sample was limited to specific regions and health care institutions, which may affect the sample representativeness and restrict the generalizability of the findings. Different regions or types of health care institutions may have varying stressors and coping mechanisms. Additionally, the accessibility and adoption of digital interventions such as podcasts may differ across health care settings, further impacting the applicability of the results.

This cross-sectional study was conducted at a single point in time, making it challenging to capture the dynamic nature of stress and emotional exhaustion over time. Therefore, the long-term impact of podcast use on emotional well-being could not be assessed. Future longitudinal studies are needed to examine whether continued engagement with podcasts can lead to sustained emotional support and stress reduction among health care professionals.

The reliance on self-reported data introduces the possibility of subjective biases, such as social desirability or recall bias, which may affect the accuracy of the results. Participants may have provided responses based on perceived expectations rather than their actual experiences. Additionally, objective measures, such as physiological indicators of stress (eg, cortisol levels, heart rate variability), were not included, limiting the study's ability to validate findings through biometric data.

The study did not account for the variation in podcast content, format, duration, and listening frequency, all of which could influence the results. Different types of podcasts may have varying effects on emotional support and stress reduction. For instance, content focused on relaxation techniques or peer support may provide stronger psychological benefits than general entertainment podcasts. Furthermore, the study did not assess individual differences in podcast engagement, such as the extent to which participants actively absorbed content versus using it as background noise. Future research should consider categorizing podcast types and evaluating their differential effects on emotional well-being.

The study was conducted in Taiwan, and cultural factors may influence how caregivers perceive stress and use podcasts. In collectivist cultures like Taiwan, social and familial expectations may shape nurses' stress coping strategies differently than in individualistic cultures. Additionally, the availability of health-related podcasts in the local language may affect accessibility and engagement. The effectiveness of podcasts as an emotional support tool may vary depending on cultural attitudes toward digital health interventions and professional well-being. As a result, the findings may not be directly applicable to different cultural settings, and cross-cultural comparisons would be beneficial in future studies.

One of the limitations of this study was the significant difference in the number of children that nurses had between the groups, which may affect the internal validity of the research findings. Since nurses with children may experience higher levels of stress and emotional exhaustion, this factor should be considered when interpreting the results to account for its potential impact on the study findings. Future research may consider conducting subgroup analyses to explore the effects of varying family responsibilities on the moderating effect of podcast listening.

Additionally, the cross-sectional design limits the ability to infer causality. Future studies are recommended to adopt a longitudinal approach to further examine the long-term impact of podcast listening on emotional exhaustion.

Future Research Directions

Therefore, future research should consider longitudinal study designs, expanding the sample diversity, analyzing podcast content, conducting comparative studies across health care professions, integrating podcasts with other digital tools, and conducting cross-cultural comparisons.

Longitudinal designs with sufficient time duration could track the impact of podcast use on emotional well-being over time. Furthermore, future longitudinal studies could help better understand the long-term impact of the variables examined in our research. This approach would help determine the long-term benefits or drawbacks of integrating podcasts into emotional support programs for health care professionals.

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To enhance the generalizability of the findings, future studies should include more diverse samples, covering different regions, health care environments, and cultural contexts. This would provide a broader understanding of how podcasts can be utilized across various settings.

Future research should also analyze the specific content and quality of the podcasts used by health care professionals. Understanding which types of content are most effective in reducing stress and emotional exhaustion could lead to more targeted and effective podcast programs.

Exploring the use of podcasts across different health care professionals (eg, doctors, pharmacists, physical therapists) could reveal how podcast interventions can be customized to address the unique stressors faced by each group.

Combining podcasts with other digital tools (eg, mobile health apps or online counseling platforms) could create a more comprehensive emotional support system for health care workers. Future research should explore the synergies of using multiple digital resources for stress management.

Comparative studies between different countries and cultures would help determine how cultural factors influence the acceptance and effectiveness of podcasts as a stress management tool. This could lead to more culturally sensitive interventions in global health care settings.

Conclusion

This study highlights the significant impact of work-related stress on emotional exhaustion among nursing staff and explores the potential of podcasts as a digital intervention to mitigate these effects. The findings indicate a strong association between higher work stress and increased emotional exhaustion, which poses critical challenges for both the well-being of nursing professionals and the quality of patient care. However, the findings of this study also suggests that regular engagement with podcasts, particularly those focused on emotional management and stress relief, may provide a beneficial coping mechanism, contributing to reduced emotional exhaustion among nurses.

The results provide evidence supporting the integration of podcasts as a supplementary psychological support tool within health care institutions. By incorporating digital mental health interventions such as podcasts, institutions can offer accessible and flexible psychological support, ultimately improving job satisfaction, emotional resilience, and overall well-being among nursing staff. Additionally, the study underscores the need for policy initiatives to actively promote and support digital interventions aimed at improving the mental health and professional development of health care workers.

Despite these insights, certain limitations must be acknowledged. The study identified a significant difference in the number of children between groups, which may influence stress coping mechanisms and the moderating effect of podcast listening. Future research should control for this variable to ensure an accurate evaluation of podcast interventions. Moreover, although podcasts may serve as a viable supplementary intervention, their moderating effect remains limited, indicating the need for further exploration into comprehensive psychological support strategies.

Future studies should investigate the long-term effects of podcast engagement, assess its efficacy across diverse health care settings and cultural contexts, and explore potential synergies with other digital or traditional psychological support programs. The integration of podcasts and similar digital tools represents a promising avenue for enhancing the psychological support systems available to nursing professionals, potentially improving health care outcomes and bolstering the resilience of the health care workforce.

Conflicts of Interest

None declared.

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Abbreviations

AVE: average variance extracted

Edited by E Borycki; submitted 28.12.24; peer-reviewed by DH Shih, HM Hsu; comments to author 14.03.25; revised version received 29.03.25; accepted 30.03.25; published 16.04.25.

Please cite as:
Li Jung L, Chou PC, Wu YH
Limited Moderating Effect of Podcast Listening on Work Stress and Emotional Exhaustion Among Nurses During the COVID-19 Pandemic: Cross-Sectional Study
JMIR Nursing 2025;8:e70640
URL: https://nursing.jmir.org/2025/1/e70640
doi:10.2196/70640
PMID:40159623

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An Expert Knowledge Algorithm and Model Predicting Wound Healing Trends for a Decision Support System for Pressure Injury Management in Home Care Nursing: Development and Validation Study

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Abstract

Background: Home-visiting nurses have difficulty selecting appropriate pressure injury (PI) management despite using clinical practice guidelines in various home-visiting settings. Clinical decision support systems can help home-visiting nurses' decision-making.

Objective: This study aimed to develop a care algorithm reflecting the expertise of a wound expert nurse and a predictive model for the change of PI severity to inform home-visiting nurses to receive actual consultation.

Methods: First, an existing algorithm was modified by semistructured interviews with a certified wound expert nurse. Case information was input into both base and high-expertise algorithms, which provided care recommendations across 9 fields: (1) pressure relief; (2) nutritional management; (3) shear relief; (4) moisture management; (5) wound dressing use; (6) care for physical factors including bone prominence, obesity, joint contractures, and periwound edema; (7) care for systemic disorder; (8) selection of wound dressings, ointments, and negative pressure wound therapy; and (9) wound cleansing. An expert interviewee assessed the high-expertise algorithm's recommendations on a 5-point scale, comparing them to the base algorithm and their own clinical judgment. To measure the algorithm's applicability, agreement proportions were calculated as the number of vignettes where the care recommendation was considered appropriate or total number of vignettes. To measure the algorithm's alignment, improvement proportions were calculated as the number of vignettes where the care recommendation improved or total number of vignettes excluding vignettes when the existing and high-expertise algorithm both showed an appropriate recommendation. Expected healing levels were evaluated by a 4-point scale where 4 indicates the high-expertise algorithm can "much improve" the case. Second, predictive distributions of changes in DESIGN-R 2020 score, PI severity score, were estimated with a hierarchical Bayesian model. The best model determined using training data (n=42) calculated coverage probabilities of 90% prediction interval in test data (n=34). The coverage probability of a 90% prediction interval was defined as follows: the number of times when actual scores were within the 90% prediction interval or the number of assessments when the prediction was conducted.

Results: The agreement proportions were 0.92 (33/36), 0.75 (27/36), and 0.89 (32/36) for each round. The improvement proportions were 0.73 (8/11), 0.25 (3/12), and 0.76 (13/17), respectively. The expected healing level was 2.67, 3.00, and 3.25, respectively. Coverage probabilities of 90% prediction interval in the test data were 0.67 (4/6), 0.83 (5/6), 0.86 (6/7), and 0.80 (8/10), respectively.

Conclusions: This study developed an algorithm reflecting the expertise and a model to estimate predictive distributions of changes of DESIGN-R 2020 score for developing clinically applicable clinical decision support systems for home-visiting nurses providing appropriate PI management.

(JMIR Nursing 2025;8:e65716) doi:10.2196/65716

KEYWORDS

algorithm; care recommendation; clinical decision support system; home care; pressure injury

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Introduction

Pressure injury (PI) is a localized damage to either the skin or the underlying tissue, or to both, caused by pressure and shear [1] and has various negative impacts on patients and the health care economy [2,3]. Although prevention is the most important for PIs, nurses must select the most appropriate management for early healing when a PI occurs. As home health care has become highly developed, home-visiting nurses are increasingly faced with managing more severe PIs. In hospitals, PIs are managed without worsening because of the standardized care environment, the presence of wound specialists, and the appropriate application of clinical practice guidelines. On the other hand, in home care settings, the care environment is diverse, and accessibility to specialists is limited, making it difficult to implement the standardized care recommended by the guidelines. There, it is difficult to heal severe PIs at home. In fact, the proportion of severe PIs extending beyond the dermis was 38.8% in home-visiting settings compared with 20.1% in university hospitals in Japan [4]. As a result, home-visiting nurses who are not specialized in PI management have difficulty determining appropriate care because clinical guidelines of PI management do not provide a specific recommendation to each case [1,5]. In this situation, there is a high need for consultation with specialists. Sood et al reported that preexisting wound treatment was altered in 64% of cases when home-visiting nurses consulted wound experts [6]. However, the number of experts who can provide knowledge is not always sufficient in some countries and regions. While there are more than 2500 certified wound, ostomy, and continence (WOC) nurses in Japan, approximately 90% belong to hospitals, especially those with many beds [7]. The fact that the utilization proportion of the public payment system, in which a WOC nurse visits a PI patient's home together with a home-visiting nurse, is <5% indicates the difficulty of home-visiting nurses to undergo consultation from a WOC nurse [8]. Although telemedicine or telenursing can improve accessibility for expertise [9] and patient outcomes [6,10], the high prevalence of PIs in home care settings, ranging from 3.3% to 11.1% [11], makes it difficult to provide consultation for all cases requiring specialized management.

This study focused on a clinical decision support system (CDSS) to address this challenge. A CDSS provides assessment and care recommendations based on individual patient characteristics to support decision-making [12]. Although few studies have reported the effect of the CDSS on PI management [13,14], it could help determine care strategies, especially for less experienced nurses [14].

Knowledge-based CDSSs are designed based on clinical practice guidelines and consolidated expert opinions. Evidence is essential, but its coverage is narrow. Expert opinions also lose flexibility in the consensus method. Therefore, existing CDSS recommendations are often immature and unacceptable to nurses, especially in diverse home-visiting settings [15]. In contrast, expertise covers not only knowledge from previous studies but also considerations for clinical situations and patient preferences [16]. It indicates that reflecting an expert nurse's expertise to an existing care algorithm may make the CDSS mature and clinically applicable. However, such a CDSS has not been developed.

Additionally, a CDSS needs to inform home-visiting nurses that consultation from an expert nurse is needed when the CDSS algorithm cannot address the patient's management appropriately as a fail-safe mechanism. The appropriateness of the CDSS for the patient is indicated by comparing the actual healing progress of the wound with the expected healing progress under expert consultations. While many previous studies have predicted the healing trajectory of PIs by point estimation [17-20], distributional estimation is more informative in determining how much worse the wound is than predicted. Xu et al [21] modeled the healing trajectory using a generalized linear mixed model but did not use information that experts generally consider, such as wound location, status, or the patient's general condition. A review of previous studies found no studies that used PI location or patient characteristics to estimate the predictive distribution of PI healing.

The goal is to develop a CDSS with 2 features: (1) a care selection algorithm that reflects the expertise of PI experts and (2) a fail-safe system that informs nurses whether they should receive an actual consultation. As the first step, we have conducted 2 studies: the development of a care algorithm that reflects the expertise of a wound expert nurse (Study I) and a predictive model that estimates the predictive distribution of the changes in PI severity score (DESIGN-R 2020) [22,23] with patients' information (Study II).

Methods

Study I

Outline

First, a base care algorithm and an optimal expert were selected to develop an algorithm reflecting PI management expertise. Next, semistructured interviews were conducted with the expert nurse about the algorithm's content. During the interviews, the interviewee was asked to review the base algorithm. The researcher (AA) modified it to make a high-expertise algorithm based on the interviewee's comments. Finally, the researcher (AA) verified that the high-expertise algorithm reflected the expertise of the interviewees better than the base algorithm. This process was conducted in 3 rounds using PI clinical vignettes. The algorithm was modified based on the interviewee's feedback at the end of each round.

This algorithm was developed for PI care of nonterminally ill older patients at home to promote wound healing. Since the pathophysiology of PIs in the lower extremities is more complicated than that in other parts of the body, PIs in the lower extremities were excluded from this study.

The base and high-expertise algorithms were implemented as a system that automatically outputs care recommendations in response to the input information with Python 3.9.7 (Python Software Foundation, USA).

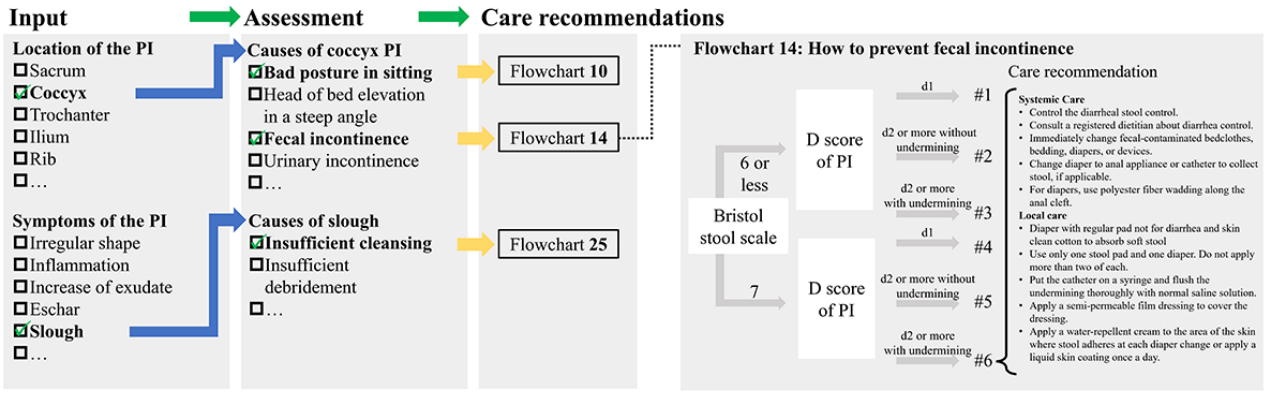
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A Base Algorithm

As if-then rules and flowcharts are easy for health care professionals to understand and reflect expertise intuitively, we adopted an algorithm composed of these as the base algorithm. Among several care algorithms for PI management using flowcharts [24-26], this study selected the algorithm developed by Sanada [24] as a base algorithm. We selected this algorithm because it extensively describes nursing skills to be performed based on the causes of PI development and delayed wound healing.

The base algorithm was developed with the evidence and multiple expert opinions obtained by a consensus method in 2003 [27]. The algorithm improved PI healing compared to the control group in a hospital in an observational study, and after that, it was modified by applying to actual cases [27]. As shown in Figure 1, the algorithm consists of lists of PI locations and symptoms, sublists of causes of PI occurrence or delayed healing, and care flowcharts corresponding to the items in the sublists. When a nurse inputs information about the location and symptoms of the patient's PI into the algorithm, a corresponding sublist of causes of PI occurrence or delayed healing and flowcharts to select appropriate care are proposed to the user.

Figure 1. Care algorithm for pressure injury. PI: pressure injury.



Interviewee and Interviewer

The base algorithm was updated and modified to fit the situation of the current PI management in home care settings by interviews with a WOC nurse. A WOC nurse with a high level of expertise in PI management was recruited as an interviewee. The interviewee had >30 years of clinical experience and was capable of providing consultation on hard-to-heal PI management at home care settings in a previous study [9]. The interviewer attended approximately 10 PI consultations with the interviewee and appropriately interpreted the interviewee's consultations. Furthermore, the interviewer had received training in interviewing from a qualitative research expert beforehand. Both the interviewee (HS) and the interviewer (AA) were members of the authors.

Development and Verification of a Care Algorithm

Development of a Care Selection Algorithm Based on a Review of the Base Algorithm

Semistructured interviews were conducted with the interviewee. The interviewee reviewed the lists, sublists, and flowcharts of the base algorithm and reported any points she considered inappropriate for PI management in older patients at home. The interviewer modified the base algorithm according to the interviewee's remarks. The interviewer continued the interview until there were no unclear points in the interviewee's comments.

Test and Modification of the Care Algorithm Using Clinical Vignettes

The purpose of this process was to test how well the high-expertise algorithm developed in the previous process reflected the expertise of the interviewee, using PI clinical vignettes including PI photographs. First, the information of the case of PIs was input into the base and high-expertise algorithms. Both algorithms output care recommendations in 9 fields: (1) pressure relief; (2) nutritional management; (3) shear relief; (4) moisture management; (5) wound dressing use; (6) care for physical factors including bone prominence, obesity, joint contractures, and periwound edema; (7) care for systemic disorder; (8) selection of wound dressings, ointments, and negative pressure wound therapy; and (9) wound cleansing. These 9 fields were selected based on expert opinion. For instance, "Pressure relief" was included because PIs arise from sustained pressure, making this the most critical aspect of PI management. Likewise, "Moisture management" was incorporated because the skin becomes fragile under conditions such as incontinence, leading to maceration, which can significantly affect PI healing. The interviewee compared both outputs and evaluated the recommendations by the high-expertise algorithm on a 5-point scale: (0) both base and high-expertise algorithms perfectly agree with one's thoughts, (1) worse than the base algorithm, (2) as bad as the base algorithm, (3) better than the base algorithm, and (4) better than the base algorithm and perfectly agrees with one's thought. This procedure was performed in multiple vignettes, and the researcher (AA) calculated the agreement and improvement proportions. We treated that high similarity between the

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algorithms and the expert's thoughts indicated the good performance of the algorithm because this study aimed to develop a care algorithm reflecting the expert thoughts.

The agreement proportion was defined as (the number of vignettes where score=0, 3, 4 or the total number of vignettes), and a higher number indicates better clinical applicability of the high-expertise algorithm. The improvement proportion was defined as (number of vignettes where score=3, 4 or number of vignettes where score=1, 2, 3, 4) and indicated the closeness of the high-expertise algorithm to the interviewee's thoughts. If the score was 0 for all vignettes in 1 field, the improvement proportion of the field was defined as "NULL." The evaluations were conducted in 3 rounds. After rounds 1 and 2, the interviewer asked about the disagreement between the high-expertise algorithm and the interviewee's thoughts. The high-expertise algorithm was modified again based on her comments.

Finally, the interviewee rated the level of expected healing when all recommendations from the high-expertise algorithm were applied to the PI on a 4-point scale: (1) worsens, (2) stagnates, (3) improves, and (4) much improves. The score was rated once per vignette.

Details of Clinical Vignettes

The clinical vignettes for the test were devised by researchers based on records of the first assessment in which the interviewee provided consultations with nurses for PI management. In these records, patients were in home care or immediately after hospitalization, and their detailed records were available. If there were multiple PIs in 1 patient, the wound with the highest severity was used for the clinical vignettes. These records were collected when home-visiting nurses consulted the WOC nurse for PIs that did not show healing progress despite >2 weeks of management by home-visiting nurses. Cases in which a patient or their family expressed withdrawal of consent, PI was at the lower extremity, or there was no record to determine information were excluded. The vignettes were randomly assigned so that each round had the same number of cases.

Study II

Outline

The authors determined predictors that are effective in estimating a predictive distribution of changes in the DESIGN-R 2020 score between assessments when an expert provides consultations [22,23]. Additionally, we developed a predictive model based on the selected predictors. DESIGN-R 2020 is a tool for evaluating PIs based on 7 parameters: depth, exudate, size, inflammation or infection, granulation tissue, necrotic tissue, and pocket size. The DESIGN-R 2020 score shows the sum of the 6 items, excluding depth. A higher score indicated a more severe PI with a longer healing time.

Data Source

Among records of the assessments in which the interviewee provided consultations with home-visiting nurses for PI management in a previous study [10], information on patients with d2 or deeper PIs was used in Study II. Multiple PIs in 1 patient were included as different PIs. Cases in which a patient or their family expressed withdrawal of consent, PI was in the lower extremity, consultations were conducted only once, and there was no record to judge predictors were excluded. The data were split into training and test data at a ratio of 80:20. To demonstrate the time robustness of the prediction model, 20% of the cases with longer follow-up periods were selected as test data.

Determining Predictors in Hierarchical Bayesian Model

Method Choice

Considering that the object is distribution estimation and the effect of predictors can vary for each individual, a hierarchical Bayesian regression model (HBR) was selected. The HBR is a method used to explain the distribution of a target variable assuming that the effect of predictors follows different distributions for each individual. Unlike generalized linear mixed models, HBR can estimate a posterior predictive distribution of target variables for which normality cannot be assumed, such as changes in DESIGN-R 2020 score. We used the HBR because it accounts for variability at both the patient and lesion levels and allows incorporation of prior knowledge, providing robust estimation even with limited data. By explicitly modeling uncertainty and hierarchical structure, the approach enables patient-specific predictions and can be updated as new data become available. The Markov chain Monte Carlo (MCMC) with the No U-Turn Sampler [28] was used to estimate the parameters. MCMC sampling was performed using the C++ compiler in Stan [29] and R [30]. The number of chains was set to 3, and 40,000 sampling iterations were performed after 10,000 warmups from the marginal posterior distribution per chain. Convergence of the MCMC samples to a stationary distribution was determined by the Gelman-Rubin R-hat statistic [31] and visually checking the trace plots.

Predictors

The predictors were as follows: the number of days from the latest assessment to the next assessment (DurationForNext) and its squared value, the number of days from the first assessment to the latest assessment (DurationFromDay0) and its squared value, DESIGN-R 2020 score at the first assessment and latest assessment, DESIGN-R 2020 subscale at the latest assessment, PI risk assessment factor items [32] (ability to change posture on bed, ability to maintain posture in chair, abnormal bony prominence, joint contracture, malnutrition, skin wetness, skin fragility [edema or skin tear]), and comorbidities (dementia, diabetes, liver disease, cardiovascular disease, cerebrovascular disease, respiratory disease, and cancer). Details of care were not used because there were no records to precisely determine them. Since the DESIGN-R 2020 subscales are classified as "Large" (severe) and "Small" (mild) based on their scores [22,23], the predictors were binarized as dummy variables according to the classification. For example, if the E score was 6, it was converted to "large" E, and if the E score was 1 or 3, it was converted to "small" e. When the E score was 0, both dummy variables were treated as 0.

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Model Design

Let DESIGN-R 2020 score for a PI i at day t be yit, and the changes in the DESIGN-R 2020 score after s days from day t bedi(t,s). Then, we designed the HBR as follows:

di(t,s)=yit+s-yit=fXit,s

fXit,s=Xi(t,s)βi+ i(t,s)

i(t,s)~Normal(0,σ2)

1ss2x1(t) xk(t)

βi~MultiNormal(μβ→,ΣChol)

μβ→=μintercept,μβs,μβx1,, μβxk,Tor

μintercept,μβs,μβs2μβx1,, μβxk,T

where

Xit,s is a vector of predictors at day t.

βi is a parameter vector depending on PI i.

i(t,s)is an error term following a normal distribution with mean 0 and variance σ2.

μβ→ is a hierarchical mean parameter vector of a multivariate normal distribution βi follows. μβ→ expresses the fixed effects of predictors.

ΣChol is a Cholesky factor of the variance-covariance matrix of a multivariate normal distribution βi follows.

Since di(t,s) was often negative, logarithmic transformation for di(t,s) was not conducted. The prior distributions of the parameters were set as follows:

σ~Normal+(0,100)

μβs,μβs2μβx1,, μβxk,~Normal(0,1)

μintercept~Normal(0,10)

Σchol=diagζβ→·ΩChol

ζβ→= ζIntercept, ζβs,ζβs2,ζβ1, ζβk~Student_t+(4, 0, 1)

ΩChol~LkjCorr(4)

where

ζβ→ is a hierarchical variance parameter vector of βi. ζβ→ expresses the random effects of predictors.

Ωchol is a Cholesky factor of the correlation matrix that follows the Lewandowski-Kurowicka-Joe distribution [33] with a shape parameter of 4.

Predictor Selection

Predictors that improve the fitness of the data when added to the base model were determined in the training data. The base model was set as a model that predicts di(t,s)with only s, that is, DurationForNext. Then, the base model was set to M0, and the model with s and another predictor p was set to Mp. Subsequently, the posterior probabilities [34] of Mp for M0 were calculated for all p under the assumption that the prior probabilities of Mp and M0 are equal. Posterior probability represents the probability that Mp is closer to the true model compared to M0. We selected all predictors whose posterior probability was >0.95 and developed a predictive model with all combinations of the selected predictors. The combination with the highest log marginal likelihood was regarded as the candidate for the best model. After 5 repetitions of determining a candidate of the best model in 80% of the randomly separated training data, log marginal likelihoods were calculated for the candidates in all training data. The model with the highest log marginal likelihood in the 5 candidates was determined to be the best model. The log marginal likelihoods were the mean value of 5 approximations computed by bridge sampling using the Warp-III method [35] with R package “bridgesampling” [36].

Validation of the Best Model Using Test Data

The changes in the total DESIGN-R 2020 score from each assessment to the next assessment were predicted using the test data with the best model. ζβ→ at the first prediction was set to 0. We calculated a coverage probability of 90% prediction interval to verify the performance of the predictive model. The coverage probability of a 90% prediction interval was defined as follows: the number of times when actual scores were within the 90% prediction interval or the number of assessments when the prediction was conducted. If this value is close to 0.9, it supports the possibility that the best model can estimate the changes in DESIGN-R 2020 score.

Ethical Considerations

This study was approved by the Ethics Committee of the Graduate School of Medicine, the University of Tokyo (No. 2021277NI). All patients were provided with the opportunity to opt out of the study. All data were handled in a manner that ensured participants could not be individually identified. No honoraria or other forms of compensation were provided for participation in this study.

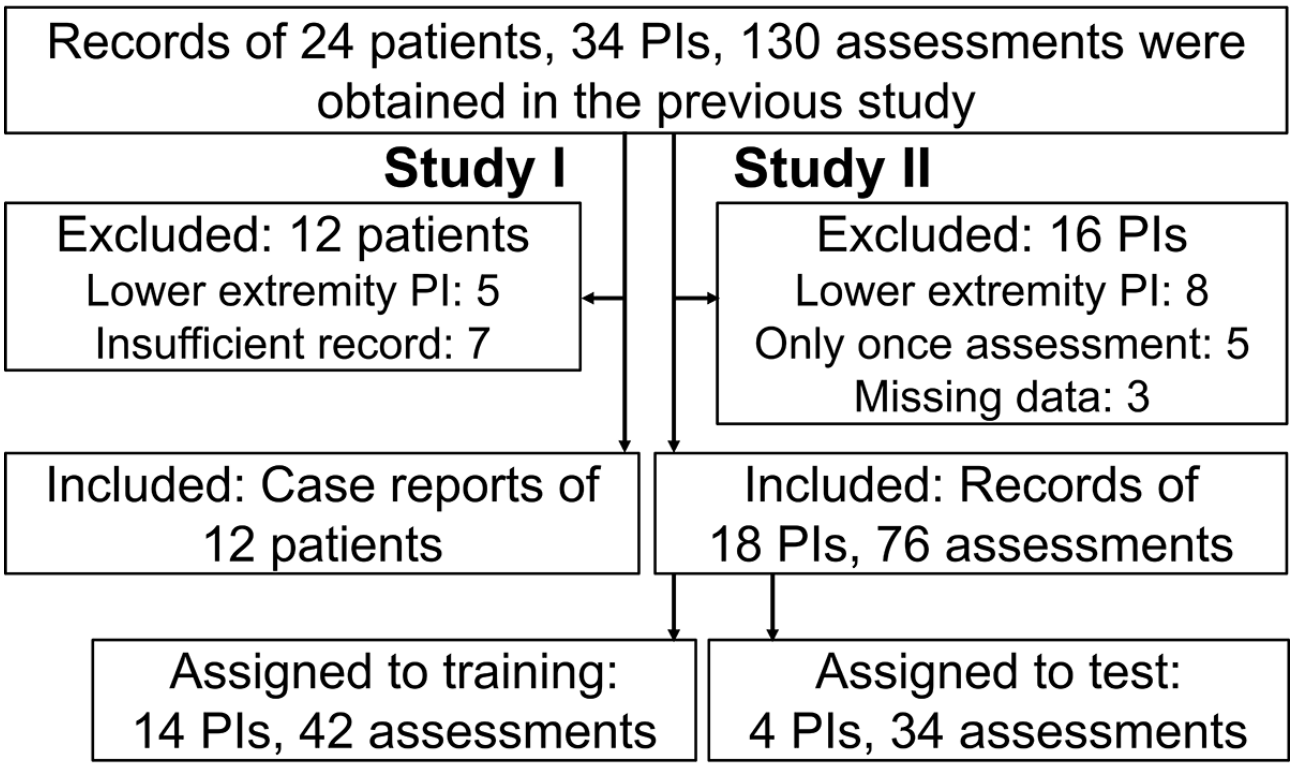
Results

Study I

A total of 12 clinical vignettes were used in this study (Figure 2). Figure 3 represents a detailed example of care recommendations based on the high-expertise algorithm. The sample size was 4 in all rounds. The results of the high-expertise algorithm test are listed in (Tables 1and 2).

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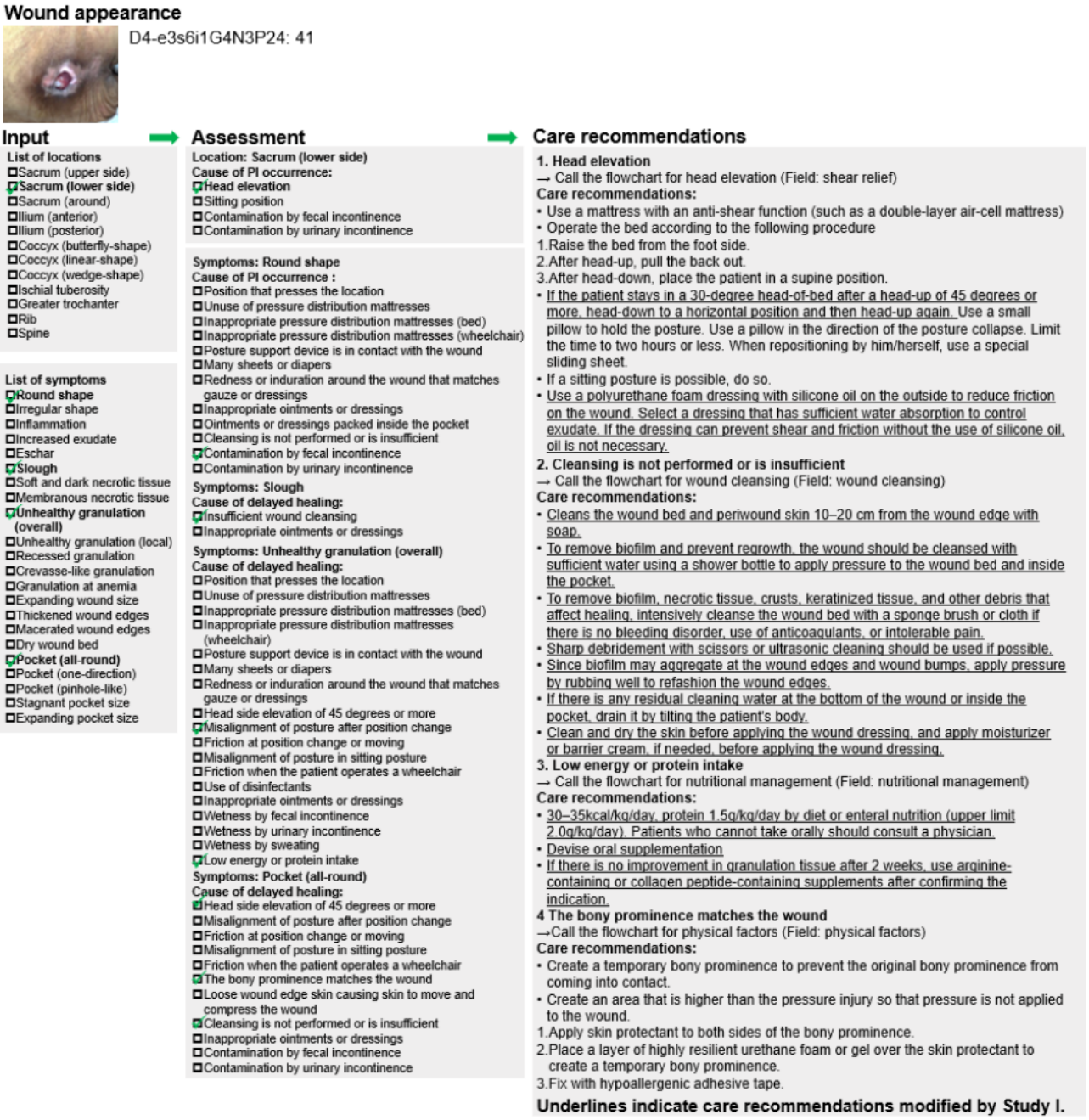
Figure 2. Flowchart showing process of inclusion. PI: pressure injury.



The means of agreement proportion were 0.92 (33/36), 0.75 (27/36), and 0.89 (32/36) for each round, and the means of improvement proportion were 0.73 (8/11), 0.25 (3/12), and 0.76 (13/17), respectively. The mean expected healing scores were 2.67, 3.00, and 3.25, respectively.

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Figure 3. Examples of care recommendation outputs.



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Table . Result of the test of the modified algorithm with clinical vignettes: the agreement proportions.

Fields	Round 1 (n=4)	Round 2 (n=4)	Round 3 (n=4)
Pressure relief	0.75 (3/4)	1.00 (4/4)	1.00 (4/4)
Nutritional management	1.00 (4/4)	1.00 (4/4)	0.75 (3/4)
Shear relief	1.00 (4/4)	0.75 (3/4)	1.00 (4/4)
Moisture management	0.75 (3/4)	1.00 (4/4)	0.75 (3/4)
Wound dressing use	1.00 (4/4)	1.00 (4/4)	1.00 (4/4)
Care for physical factor	1.00 (4/4)	1.00 (4/4)	1.00 (4/4)
Care for systemic disorder	0.75 (3/4)	0.75 (3/4)	0.75 (3/4)
Selection of wound dressings, ointments, and negative pressure wound therapy	1.00 (4/4)	0.25 (1/4)	0.75 (3/4)
Wound cleansing	1.00 (4/4)	0.00 (0/4)	1.00 (4/4)
Total	0.92 (33/36)	0.75 (27/36)	0.89 (32/36)

Table . Result of the test of the modified algorithm with clinical vignettes: the improvement proportions.

Fields	Round 1 (n=4)	Round 2 (n=4)	Round 3 (n=4)
Pressure relief	0.50 (1/2)	NULL	NULL
Nutritional management	1.00 (1/1)	1.00 (1/1)	0.67 (2/3)
Shear relief	NULL	0.50 (1/2)	1.00 (3/3)
Moisture management	0.50 (1/2)	NULL	0.5 (1/2)
Wound dressing use	NULL	1.00 (1/1)	NULL
Care for physical factor	1.00 (1/1)	NULL	NULL
Care for systemic disorder	0.00 (0/1)	0.00 (0/1)	0.50 (1/2)
Selection of wound dressings, ointments, and negative pressure wound therapy	1.00 (3/3)	0.00 (0/3)	0.75 (3/4)
Wound cleansing	1.00 (1/1)	0.00 (0/4)	1.00 (3/3)
Total	0.73 (8/11)	0.25 (3/12)	0.76 (13/17)

Study II

Characteristics and DESIGN-R 2020 Score Changes

A total of 76 assessment records from 18 PIs were included in the eligible data (Figure 2). A total of 42 records from 14 PIs were assigned to the training data, and 34 records from 4 PIs were assigned to the test data. The characteristics of the patients and PIs are presented in Table 3.

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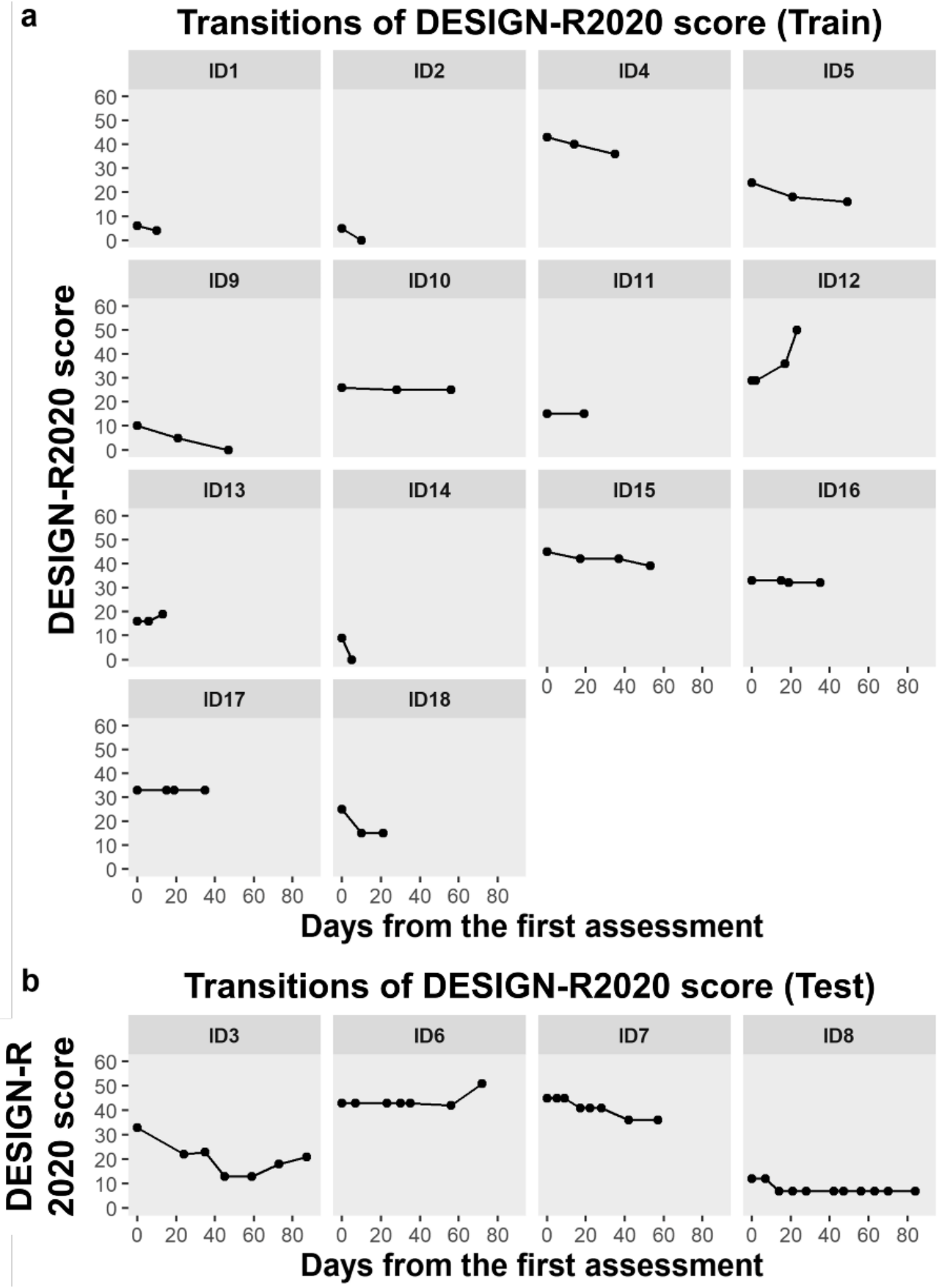
Table . Characteristics of pressure injuries included in Study II.

Characteristics	Training (n=14)	Test (n=4)
Days of follow-up, mean (SD)	29.4 (17.3)	81.2 (23.3)
Age (y)	79.4 (8.4)	85.0 (9.3)
Sex (female), n (%)	6 (43)	4 (100)
Pressure injury location, n (%)		
Sacrum	5 (36)	3 (75)
Coccyx	3 (21)	1 (25)
Others	6 (43)	0 (0)
Pressure injury risk factor, n (%)		
Ability to change posture on bed	9 (64)	3 (75)
Ability to maintain posture in chair	9 (64)	3 (75)
Abnormal bony prominence	6 (43)	1 (25)
Joint contracture	5 (36)	1 (25)
Malnutrition	8 (57)	2 (50)
Wet skin	6 (43)	1 (25)
Vulnerable skin (edema)	4 (29)	2 (50)
Vulnerable skin (skin tear)	6 (43)	1 (25)
Disease, n (%)		
Dementia	5 (36)	3 (75)
Diabetes	3 (21)	0 (0)
Liver disease	2 (14)	0 (0)
Cardiovascular disease	2 (14)	2 (50)
Cerebrovascular disease	5 (36)	1 (25)
Respiratory disease	2 (14)	0 (0)
Cancer	2 (14)	0 (0)

The mean follow-up periods were 29.4 (SD 17.3) days and 81.2 (SD 23.3) days for the training and test data, respectively. Changes in the DESIGN-R 2020 scores for each case are shown in Figure 4.

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Figure 4. Transitions of DESIGN-R 2020 score.



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Determination of the Best Model

The predictors included in the best model and its candidates developed with the training data, and the log marginal likelihoods of the model are shown in Table 4.

Table . Selected predictors and log marginal likelihood in the best model.

Dataset[a]	Predictors included in the best model in each dataset	Log marginal likelihood
Fold 1	Age, DurationForNext, $(DurationForNext)^2$, $(DurationFromDay0)^2$	96.143
Fold 2	Age, DurationForNext, $(DurationForNext)^2$, $(DurationFromDay0)^2$	103.128
Fold 3	Age, DurationForNext, $(DurationForNext)^2$, DurationFromDay0, $(DurationFromDay0)^2$, DESIGN-R2020 score at the first assessment	110.225
Fold 4	Age, DurationForNext, $(DurationForNext)^2$, $(DurationFromDay0)^2$, DESIGN-R2020 score at the first assessment	100.325
Fold 5	Age, DurationForNext, $(DurationForNext)^2$, $(DurationFromDay0)^2$, DESIGN-R2020 score at the first assessment	110.698
All training data	Age, DurationForNext, $(DurationForNext)^2$, DurationFromDay0, $(DurationFromDay0)^2$, DESIGN-R2020 score at the first assessment	116.874

[a]Each fold was composed of 80% of the data randomly selected from all the training data.

The best model included age, DurationForNext and its squared value, DurationFromDay0 and its squared value, and DESIGN-R 2020 at the first assessment scores. Predictors in the candidates of the best model in each fold did not completely match, whereas all candidates included age and $(DurationForNext)^2$ in addition to DurationForNext. The Gelman-Rubin R-hat statistics of all parameters in the best model were less than 1.1, and the traceplot indicated that the MCMC samples were well mixed. A summary of marginal posterior distributions of σ, $\mu\beta\rightarrow$, $\zeta\beta\rightarrow$ of the best model is shown in Table 5. The posterior mean, which is the mean of samples from marginal posterior distributions, of the hierarchical mean parameter of age and DESIGN-R 2020 at the first assessment score was 0.05 and −0.10, respectively.

Table . Summary of marginal posterior distribution of hierarchical parameters in the best model[a].

Parameter	Mean parameter (μ[b]), mean (SD)	Variance parameter (ζ[b]), mean (SD)
DurationForNext	−0.55 (0.44)	0.17 (0.12)
$(DurationForNext)^2$	0.02 (0.02)	0.01 (0.01)
DurationFromDay0	−0.52 (0.22)	0.26 (0.15)
$(DurationFromDay0)^2$	0.02 (0.01)	0.01, (0.01)
Age (y)	0.05 (0.11)	0.04 (0.02)
DESIGN-R 2020 score at the first assessment	−0.10 (0.13)	0.13 (0.09)
Intercept	3.91 (8.11)	0.97 (0.83)

[a]DurationForNext; the number of days from the latest assessment to the next assessment, DurationFromDay0; the number of days from the first assessment to the latest assessment.

[b]The expected a posterior estimation and its standard deviation of samples.

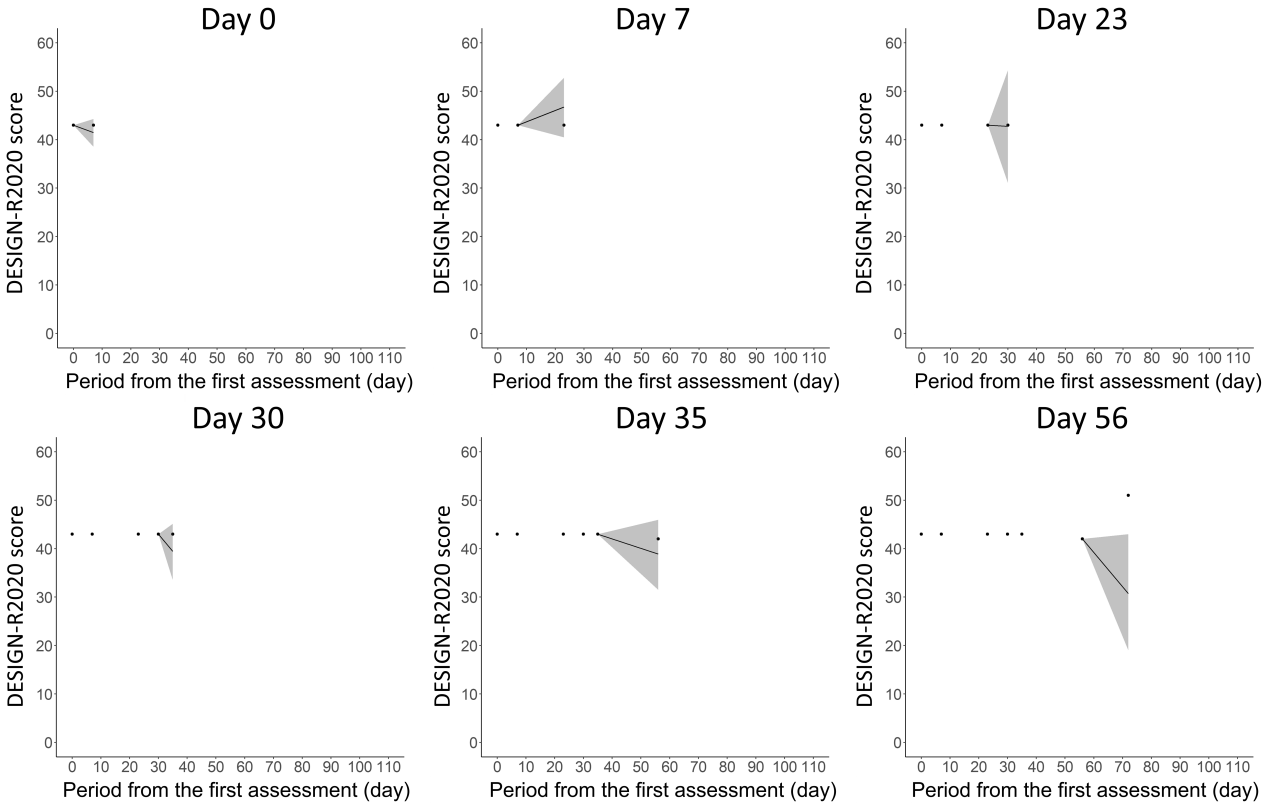
Prediction With the Best Model

Coverage probabilities of the 90% prediction interval among the 4 PIs in the test data were 0.67 (4/6), 0.83 (5/6), 0.86 (6/7), and 0.80 (8/10), respectively. The mean of these coverage probabilities was 0.79 (23/29). An example of the comparison between the actual DESIGN-R 2020 scores and that of 90% predicted intervals in the test data is shown in Figure 5. In this patient, the predictions made from Day 0 to Day 35 included the score at the next assessment in the 90% prediction interval, and the 90% prediction interval for Day 56 did not include the Day 72 score. The worsening of the infection at the time of the last assessment (Day 72) resulted in a 9-point increase in the

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DESIGN-R 2020 score, which was a rare case under expert nurse consultation.

Figure 5. An example of a 90% prediction interval for 1 patient in test data calculated in the best model.



Discussion

Principal Results

The goal is to develop a CDSS that guides home-visiting nurses on appropriate care based on a high-expertise algorithm reflecting a thought of a PI expert and a predictive model that estimates the predictive distribution of the changes in DESIGN-R 2020 to inform nurses whether consultation from an actual expert nurse is needed. This unique idea can develop a CDSS that provides more appropriate care recommendations for patients who require expert wound management in home care settings. Study I developed an algorithm by modifying an existing algorithm with the interviewee's expertise. In Study II, the predictive distribution of changes in the DESIGN-R 2020 score can be reasonably estimated using the patient's age and DESIGN-R 2020 score at the first assessment, and the prediction model was successfully developed.

In Study I, the test of the high-expertise algorithm was designed based on the CDSS validation procedure presented by Rodríguez-González et al [37]. In this study, the referee was the interviewee, and the interviewer prepared the information for the test cases. The referee then judged the closeness of the outputs of the base and high-expertise algorithms to her judgment. Since algorithms should also be assessed quantitatively [38], the closeness and the level of expected healing in the high-expertise algorithm were investigated quantitatively. Furthermore, the test could be regarded as a member check from a qualitative research perspective. Since the base algorithm was developed in 2003, the content of modifications included not only the unique expertise of the interviewee but also the present clinical knowledge. However, we did not distinguish between expertise and evidence because expertise includes the evaluation of evidence and new knowledge [39]. Based on these efforts, the process of algorithm modification was considered internally valid.

In Study I, the agreement and improvement proportions were lower in Round 2 compared with Rounds 1 and 3, particularly for "(8) selection of wound dressings, ointments, and negative pressure wound therapy" and "(9) wound cleansing." Wound dressings and wound cleansing were areas in which the high-expertise algorithm introduced many modifications compared with the base algorithm. In Round 1, relatively few PIs had wound characteristics relevant to these items, whereas in Round 2, many PIs with such characteristics were included, which likely resulted in lower proportions. After further refinements following Round 2, the algorithm was able to provide appropriate recommendations even for PIs with these characteristics in Round 3. The results in Study I showed that the recommendations of the high-expertise algorithm were 75% - 92% consistent with the interviewee's thoughts. Since generally guidelines are applicable to only about 60% - 95% of patients [40], the agreement proportions indicate the high clinical applicability of the developed algorithm. On the other hand, the improvement proportion was not stable. For example, the low improvement proportion for nutritional management indicates that the care recommendations related to nutrition did not contribute substantially to PI improvement. In home care settings, it is often difficult to obtain detailed nutritional information or to modify patients' diets. The system can be

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further improved by adding more cases. Also, we excluded vignettes where both the base and high-expertise algorithms provided appropriate recommendations when calculating improvement proportions because it allowed us to focus on clinically meaningful changes rather than diluting the effect with unchanged cases. However, excluding the vignettes may have slightly inflated the observed mean improvement. In addition, the high expected healing level of 3.25 on a 4-point scale suggests that the algorithm developed in this study has the potential to contribute to PI improvement. By referring to care recommendations based on this algorithm, nurses may be able to provide more effective PI management compared to assessments and care decisions made solely by nurses.

In Study II, we created a model to predict changes in the DESIGN-R 2020 score, while previous studies have predicted a change of wound area or length of wound edge. Although the DESIGN-R 2020 score is the sum of the integer values of 6 subscales making the changes discrete, it includes the pathophysiology of PIs such as infection and necrotic tissue. Nurses select appropriate care based not only on wound size but also on the pathophysiology of PIs, such as infection and necrotic tissue. Because the DESIGN-R2020 score reflects both of these aspects, using changes in this score as the target variable is reasonable. The sampling was appropriate because MCMC samples from the best model were converged to a stationary distribution and the Gelman-Rubin R-hat statistics of all parameters were less than 1.1, indicating adequate convergence.

In addition to predictors related to time, DESIGN-R 2020 score at the first assessment and the patient's age were included in the best model. It is noteworthy that the hierarchical mean parameter of age in the best model showed that the PIs of older patients were more likely to heal slightly sooner. As all the PIs in this study were hard to heal, it is possible that younger patients had some barrier in their general condition, or the care environment was not comparable to that of the older patients. The posterior mean of the hierarchical mean parameter of DESIGN-R 2020 score at the first assessment in the best model was negative. This may suggest that a PI diagnosed as severe at first assessment may take longer to heal, even if the causes of delayed healing were resolved by expert consultation. Unlike in a previous study [18], the location of the PI was not included, because all the PIs in this study were in the trunk or greater trochanter and not in the lower extremities. The best model did not include predictors related to comorbidities or PI risk assessment factor items. These factors may not have affected the healing progress, as they were appropriately addressed by expert nurse consultation. The mean coverage probability of 90% prediction interval was 0.79, which indicates that the model underestimated uncertainty. It means that predicted intervals are narrower than they should be. While this indicates that the best model still has room for improvement, this may adequately estimate the distribution of changes in DESIGN-R 2020 scores at a clinically acceptable level for a longer range than a duration of training data. Other predictors, such as the cause of PI development and delayed healing, and materials used in PI care may improve the performance of the model, allowing for more patient-specific predictions. Also, accessibility to health care resources could also be considered because health care delivery is sometimes difficult in rural areas.

The incorporation of nurse expertise through interviews could also be applied to other chronic disease management domains, such as diabetes and heart failure, where recommendations may support care decisions related to patient self-care education, symptom management, and reporting of abnormalities to physicians. An ethical challenge includes the protection of patient privacy, while a practical challenge may arise from the greater diversity of lifestyle factors compared with PI management, which could make it more difficult to develop a highly accurate CDSS.

Limitations

The small sample size and low variety of PIs may limit both performance and generalizability of the algorithm and the predictive model. Since the expected healing level is determined by 1 expert in Study I, it is not clear how other experts assess the expected healing level for this care algorithm. In addition, we did not split the records from the same PIs into training and test data because they involved the same patient characteristics, and care recommendations vary not only according to the condition of the PIs but also depending on patient characteristics. This may have led the algorithm to perform well for patients with similar conditions.

Study II employed comorbidities reported by home-visiting nurses as predictors that reflect the general conditions indirectly. However, it may have included diseases already well controlled to a level that did not affect the general condition. Hence, the effect of the general condition on PI healing may have been underestimated, and using predictors that directly represent the general condition, such as HbA_{1c} and SpO_2, may improve the model.

Future research should include a prospective evaluation of the high-expertise algorithm in real-world clinical settings. In particular, the effectiveness of the algorithm could be assessed through the monitoring of DESIGN-R 2020 scores, while safety should be evaluated using indicators such as hospitalizations due to PI worsening and the incidence of PI infections. Such a study would provide important evidence regarding the ongoing clinical utility and safety of the algorithm and inform further refinements for broader implementation.

Conclusions

This study was conducted as the first step in the development of a CDSS for home-visiting nurses in PI management. We developed an algorithm that reflected the expert's knowledge in the existing algorithm and showed that the high-expertise algorithm was clinically applicable and close to the wound expert's thoughts. It also determined predictors effective for predicting changes in DESIGN-R 2020 score of PI in home care settings and developed a model to calculate the prediction distribution. This enables the CDSS to inform nurses that it cannot address the patient's management appropriately as a fail-safe mechanism.

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Acknowledgments

We are grateful to Dr. Misako Nagata, an expert in qualitative research, for her helpful advice on interview training.

Funding

This work was supported by the Japan Society for the Promotion of Science Grants-in-Aid for Scientific Research (Grant No. JP20H00560).

Authors' Contributions

Conceptualization: AA, AK, GN, HS
Data curation: AA, AK
Formal analysis: AA
Funding acquisition: HS
Investigation: AA, AK
Methodology: AA, AK, GN
Project administration: GN
Software: AA
Supervision: HS
Writing – original draft: AA, AK
Writing – review & editing: GN, HS

Conflicts of Interest

None declared.

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Abbreviations

CDSS: clinical decision support systems
HBR: hierarchical Bayesian regression model
MCMC: Markov chain Monte Carlo
PI: pressure injury
WOC: wound, ostomy, and continence

Edited by E Borycki; submitted 29.12.24; peer-reviewed by J Yotsuya, K Kuwana, SR Polamuri; revised version received 31.08.25; accepted 26.09.25; published 09.12.25.

Please cite as:
Kitamura A, Ando A, Nakagami G, Sanada H
An Expert Knowledge Algorithm and Model Predicting Wound Healing Trends for a Decision Support System for Pressure Injury Management in Home Care Nursing: Development and Validation Study
JMIR Nursing 2025;8:e65716
URL: https://nursing.jmir.org/2025/1/e65716
doi:10.2196/65716

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Original Paper

Clinical, Operational, and Economic Benefits of a Digitally Enabled Wound Care Program in Home Health: Quasi-Experimental, Pre-Post Comparative Study

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Abstract

Background: The demand for home health care and nursing visits has steadily increased, requiring significant allocation of resources for wound care. Many home health agencies operate below capacity due to clinician shortages, meeting only 61% to 70% of demand and frequently declining wound care referrals. Implementing artificial intelligence–powered digital wound care solutions (DWCSs) offers an opportunity to enhance wound care programs by improving scalability and effectiveness through better monitoring and risk identification.

Objective: This study assessed clinical and operational outcomes across 14 home health branches that adopted a DWCS, comparing pre- and postadoption data and outcomes with 27 control branches without the technology.

Methods: This pre-post comparative study analyzed clinical outcomes, including average days to wound healing, and operational outcomes, such as skilled nursing (SN) visits per episode (VPE) and in-home visit durations, during two 7-month intervals (from November to May in 2020-2021 and 2021-2022). Data were extracted from 14,278 patients who received wound care across adoption and control branches. Projected cost savings were also calculated based on reductions in SN visits.

Results: The adoption branches showed a 4.3% reduction in SN VPE and a 2.5% reduction in visit duration, saving approximately 309 staff days. In contrast, control branches experienced a 4.5% increase in SN VPE and a 2.2% rise in visit duration, adding 42 days. Healing times improved significantly in the adoption branches, with a reduction of 4.3 days on average per wound compared to 1.6 days in control branches (P<.001); pressure injuries, venous ulcers, and surgical wounds showed the most substantial improvements.

Conclusions: Integrating digital wound management technology enhances clinical outcomes, operational efficiencies, and cost savings in home health settings. A reduction of 0.3 SN VPE could generate annual savings of up to US $958,201 across the organization. The adoption branches avoided 1187 additional visits during the study period. If control branches had implemented the DWCS and achieved similar outcomes, they would have saved 18,546 healing days. These findings emphasize the importance of incorporating DWCSs into wound care programs to address increasing demands, clinician shortages, and rising health care costs while maintaining positive clinical outcomes.

(JMIR Nursing 2025;8:e71535) doi:10.2196/71535

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KEYWORDS

home health care; artificial intelligence; AI; digital wound care; wound assessment; operational efficiency; clinical outcomes; healing time; cost saving; skilled nursing visits

Introduction

The demand for home health care and nursing visits has surged due to the persistent rise in the prevalence of comorbidities and the aging population [1,2]. In the United States, 2% of the population have complex chronic wounds, further driving the growing demand for home health care services [3]. Approximately, a third of patients who use home health have at least one wound [4,5], leading to the allocation of a substantial portion of the budget and resources in a home health agency (HHA) for nursing visits being dedicated to wound assessment and care [5]. Nursing visits in HHAs consume a significant proportion of health care delivery costs, primarily due to the time spent by nurses in assessing and managing wounds [6]. Studies have indicated that wound management uses, on average, about 50% to 70% of the nurses' resources [7-11], with over 60% of their time dedicated to changing dressings [12], resulting in an average of extra 3 visits per week [7].

According to the 2019 report from the Centers for Medicare & Medicare Services (CMS), 1.6% of the US population received wound care at a Medicare-certified HHA, totaling 5,266,931 individuals with wounds [13]. This suggests that approximately 15,800,793 patient contacts for dressing changes occur per week, requiring around 7,900,396 clinician hours per week to be spent on wound care visits in HHAs [13]. Research supports the notion that effective wound care management is best achieved through a collaborative health care team [14]. However, the absence of a standardized approach to evaluating wounds and the limited communication platforms for supporting collaboration between clinicians may lead to unnecessary or prolonged visits and extended healing times [15].

Research studies have reported that wounds, especially pressure injuries, pose the highest risk factor for hospitalization, increasing the length of stay by an average of 4.31 days [16,17]. Thus, with 1 in 3 patients who use home health dealing with wounds, a focus on providing higher-quality, more efficient care for patients with wounds has the potential to lead to faster healing and reduced complications for patients, as well as a substantial cost savings and improved reimbursement for HHAs and the health care system.

The increasing number of visits, visit duration, healing time for wounds, and hospital stays have placed a significant burden on the already financially stained health care system, compounded by a shortage of specialized nurses [18]. The majority of HHAs operate below capacity due to clinician shortage, only meeting 61% to 70% of the demand for wound care, leading many to reject wound care referrals [19,20]. This crisis is partly due to inadequate allocation of resources, funding constraints at the organizational level, and the increasing number of nurses leaving the practice or retiring [18]. Thus, addressing the substantial resource demand for managing chronic wounds poses a significant challenge for these agencies [5].

In light of these challenges, it remains crucial to control costs while optimizing outcomes within the health care system. Recognizing the high complexity and resource costs of providing wound care in home health, the CMS allocated the highest base reimbursement for the wound clinical grouping under its Patient Driven Groupings Model value–based payment regime, which was rolled out nationwide in 2020 [13]. Additionally, to address the sustainable health care costs associated with unintended hospital use (such as acute care hospitalizations and emergency department visits), CMS introduced its Expanded Home Health Value-Based Purchasing Model in 2023. This program adjusts an HHA's annual Medicare reimbursement based on the achievement of various quality measures, with the most heavily weighted measure being "unintended hospital use."

Using a digital wound care solution (DWCS) for patients with wounds has been linked to faster healing times [21] and more efficient wound care documentation [22]. DWCSs integrate artificial intelligence (AI) to monitor wound progress and identify potential risks [23], and they are interoperable with organizational systems, allowing efficient and secure data exchange. The seamless data exchange through AI technologies [24] is crucial for establishing a cohesive wound care program that can adopt and scale up digital documentation and objective AI assessment data. Recognizing these benefits, many health care settings have transitioned to incorporating digital technologies to enhance clinician efficiency, capacity, and confidence, ultimately allowing them to deliver a higher quality of care to more who require wound care [21,22,25].

In 2021, CenterWell Home Health (CenterWell), an HHA with 355 branches across 40 states in the United States, launched a comprehensive wound care program to deliver high-quality care. The program involved providing advanced education and training for clinicians in wound management and using the DWCS Swift Skin and Wound (Swift Medical Inc) for quality wound care evaluations. The training program, known as Prevention Intervention, Management, and Education (PRIME), was designed to build the knowledge, skills, and abilities of clinicians in wound care, establishing a network of skilled wound care champions in the field. The DWCS is an evidence-aligned, AI-based technology that captures precise wound images and accurate measurements and provides predictive analytics supporting the wound escalation processes to provide ongoing performance support.

There is a lack of research evaluating the impact of integrating technology into wound care delivery within a home health setting. To our knowledge, this study represents the first attempt to outline the clinical and operational advantages of a wound care program incorporating digital technology in a home health environment. The study's objective was to evaluate the enhancements in clinical outcomes (such as the average time required to heal a wound) and operational outcomes (including the volume of skilled nursing [SN] visits per episode [VPE] and the duration of in-home SN visits) at 14 CenterWell branches

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(initially scoped for this implementation and study). We examined the same 7-month period (from November to May) before (2020) and after (2021) the implementation of the DWCS as part of the comprehensive wound care model in home health. Additionally, the study compared the changes in these clinical and operational benefits with a similar control group of PRIME-certified home health branches that had not yet adopted the digital solution.

Methods

Study Design and Data Sources

This benefits-evaluation study used a pre-post comparative design, using wound care data captured in the Homecare Homebase (HCHB) health information system. HCHB is an electronic medical record (EMR) software developed in 1999. This software is hosted on the cloud and is designed to facilitate home health care frontline workers' abilities to monitor their clinical outcomes and operational activities to enhance the quality of patient care.

Through the HCHB platform, a home health organization can extract a wide range of clinical and administrative data. These include admission and referral data; patient assessment details such as start date of wound care, 60-day episode start and end dates, wound types and stages; as well as the date and time of visits within the 60-day episode. Additionally, it can retrieve information about the discipline and service code of clinicians conducting the visits, discharge dates, hospitalization details, patients' demographics, comorbidities, and payer types. The study's focus was to extract structured data that pertain to the comprehensive management of patients with wounds. This involved filtering the data within the study periods to include records of patients with wounds in the Integumentary Command Center (ICC).

Ethical Considerations

In this study, for the postadoption data, the DWCS used industry-standard protocols; for example, using Health Level 7 to wirelessly transfer encrypted wound care information (wound images and documentation recorded by clinicians at the participating branches using the solution) bidirectionally with HCHB in real time to ensure that outcome data could be monitored and to eliminate double documentation. Wound care data were then accessed from the EMR for tracking and analysis. All communications to the servers follow the Advanced Encryption Standards and comply with the Health Insurance Portability and Accountability Act.

Institutional review board approval was provided by CenterWell HealthCare Center for this quality improvement (QI) descriptive evaluation study. This QI study, which adheres to Tri Council Policy Statement QI policy, was granted an exemption of ethics review (ID:2023-0100) from Pearl IRB, LLC, an independent institutional review board.

Data Abstraction Process and Sample

The anonymous wound care assessment records were collected from the ICC, an entity focused on the comprehensive management of patients with wounds, at 14 CenterWell branches where the DWCS was implemented as part of the comprehensive wound care model. Additionally, records were obtained from 27 control branches at CenterWell that had not yet adopted the DWCS into practice. The 27 control branches were carefully selected to match the criteria of the adoption branches in terms of size; geographical locations; capacity; volume of referrals; and the clinicians' levels of clinical wound care education, training, skills, and expertise. This rigorous selection process aimed to ensure an unbiased comparison when assessing the impact of the DWCS technology on clinical and operational outcomes.

This study compared the change in clinical outcomes by analyzing the median days to heal a wound in the pre- and postadoption periods within the study timeframe for the 14 adoption sites and the 27 control sites. Additionally, operational outcomes were compared, including the number of SN VPE, the associated projected cost-savings, and the duration of in-home SN visits in the same periods for the adoption and control branches.

The study and analysis included wound assessments of all patients with any type of wound that met the following criteria:

1. There were wound records (primary and secondary diagnoses) of any type recorded on admission from both adoption and control branches at CenterWell that were referred to and managed at these sites during the 7-month study period (from November 1, 2020, to May 31, 2021, and from November 1, 2021, to May 31, 2022).
2. For the postadoption period, wounds had to be assessed and managed using the Swift Medical Inc solution at the participating 14 adoption branches in the postadoption period.
3. The records pertained to adult patients aged 18 years or older.

Any wounds outside of the study period were excluded from the analysis. Patients at adoption branches who did not receive wound care using the technology during the study period were not included in the analysis in the postadoption period. This exclusion applied to patients with closed surgical wounds, external fixators, bruising, cellulitis, and extensive diffuse dermatological conditions.

From the 14 adoption branches, we collected and included data from 5239 sixty-day wound episodes involving 3738 unique patients in 2020-2021 (preadoption period) and 3958 sixty-day wound episodes involving 2757 unique patients in 2021-2022 (postadoption period). Similarly, for the 27 control branches, the analysis incorporated data from 5592 sixty-day episodes involving 3859 unique patients in 2020-2021 (preadoption period) and 5429 sixty-day episodes involving 3924 unique patients in 2021-2022 (postadoption period).

The organization's wound care research team (KJ, DG, and KC) independently extracted all required wound patient data for the adoption and control branches based on the wound start data and medical record number from the HCHB EMR during the first week of August 2022. Using the same instrument, filters, steps, and procedures, the eligible wound data were accessed and then deidentified for sharing with the evaluation team (HTM

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and DM) for analysis. Each patient was assigned a study and episode ID number, with no linkage between the medical record number and study ID developed to ensure patient anonymity.

The deidentified data, including essential wound assessment–related variables such as patients' characteristics, episode ID, referral date, branch code, type of wound, classification and anatomical location of wound, wound care start date and effective date of care, start and end dates of episode, wound status, primary diagnosis, visit start date and time, visit end time, duration of visit, service code and description, discipline code, and payor type, were shared in a Microsoft Excel spreadsheet with the evaluation team through a secure platform.

Statistical Analysis

We analyzed wound data in both the adoption and control groups during the pre- and postadoption periods. This analysis encompassed both numeric variables, such as patients' age, and categorical variables, including patients' sex, wound type, payor type, episode status, and comorbidities. In addition, the study calculated several data indictors:

- Home visit utilization, assessed based on the average number of SN visits per 60-day episode: This metric was determined by dividing the number of SN visits (numerator) by the total number of episodes cared for (denominator) at the participating branches during the study period.
- Home visit efficiency, assessed based on average time to complete an SN visit per 60-day episode: It involved calculating the mean time to complete an SN visit, measured in minutes. This calculation was based on the time lapse between the start and end time of each in-home visit per 60-day episode. This analysis considered visits conducted by skilled nurses (registered nurse [RN] and licensed practical nurse [LPN]). These visits included the following specific service description codes: *RN Oasis Admission, SN high Tech Visit-Lasting 1.5 Hours, SN Infusion Subsequent Visit, SN PRN Visit as Needed, SN Rapid Subsequent Visit*, and *SN Subsequent Visit*. As no out-of-home documentation occurs for routine and SN visits, the calculated time encompassed all patient care and documentation activities within a visit. Overall, the findings were summarized using frequencies, means, and SDs.
- Average days to heal a wound: The analysis of average days to heal a wound included any type of wound with an inactive date and considered as "healed," as determined by CenterWell. The study collected the first and last date (inactive date) of the wound and calculated the average days (mean) to heal based on the number of days between the start date and the inactive date of healed wounds. Patients with open wounds who were discharged were not included if the wound was not known to be healed. This analysis segmented the data by wound type (ie, pressure injury, venous ulcer, etc). A Student sample two-tailed *t* test was used to examine the difference in the average number of days to heal a wound across adoption and control branches between the pre- and postadoption periods. The significance of the statistical test was accepted at$P<.05$.

Data analysis was conducted using SPSS software (version 28; IBM Corp).

The analyses showed that the days to heal for both the adoption and control groups were normally distributed, as assessed by Shapiro-Wilk normality test ($P>.05$). Additionally, there was homogeneity of variances, as assessed by the Levene test for equality of variances for both the adoption and control groups ($P=.17$ and $P=.32$, respectively).

Results

Overall Characteristics

The data were collected from 14,278 patients with wounds from both the adoption and control branches, all of whom were recorded in the ICC platform and fulfilled the inclusion criteria. Of these patients, 26.2% (n=3738) were from the adoption branches in the preadoption period and 19.3% (n=2757) were from the adoption branches in the postadoption period. The age of the patients ranged from 23 to 108 years, with approximately half (n=7351, 51.5%) of the participants being female. The included wounds encompassed various types, with surgical wounds and pressure injuries being the most common (Table 1). Overall, there were no statistically significant differences ($P>.05$) between the adoption and control groups in the different time periods, indicating a comparable distribution of wound types across the groups.

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Table 1. Overall characteristics of wound records at the adoption and control branches in the pre- and postadoption periods.

Characteristics	Adoption branches		Control branchers	
	Preadoption period (November 2020 to May 2021)	Postadoption period (November 2021 to May 2022)	Preadoption period (November 2020 to May 2021)	Postadoption period (November 2021 to May 2022)
Unique patient admission, n	3738	2757	3859	3924
Age (years), mean (SD)	73.1 (13.4)	72.3 (13.7)	73.6 (13.2)	74.6 (11.6)
Sex, n (%)[a]				
Male	1854 (49.6)	1331 (48.3)	1863 (48.3)	1879 (47.9)
Female	1884 (50.4)	1426 (51.7)	1996 (51.7)	2045 (52.1)
Wounds episodes managed at participating branches, n	5239	3958	5592	5429
Wound type, n (%)[b]				
Arterial ulcer	41 (0.8)	23 (0.6)	30 (0.5)	31(0.6)
Burn	24 (0.5)	11 (0.3)	37 (0.7)	36 (0.7)
Diabetic ulcer	254 (4.8)	120 (3.0)	326 (5.8)	285 (5.2)
Pressure injury	1445 (27.6)	1081 (27.4)	1535 (27.4)	1483 (27.3)
Skin tear	278 (5.3)	230 (5.8)	416 (7.4)	379 (7)
Surgical wound	1739 (33.2)	1374 (34.7)	1406 (25.3)	1435 (26.4)
Traumatic wound	357 (6.8)	306 (7.7)	505 (9)	489 (9)
Venous ulcer	358 (6.8)	444 (11.2)	457 (8.2)	506 (9.3)
Others[c]	743 (14.2)	369 (9.3)	880 (15.7)	785 (14.5)
Episodes associated with comorbidities, n (%)[b]	2664 (50.8)	2182 (55.1%)	3143 (56.2)	3202 (59)
Episodes not associated with comorbidities, n (%)[b]	2575 (49.2)	1776 (44.9)	2449 (43.8)	2224 (41)
Current episodes, n (%)[b]	396 (7.6)	270 (6.8)	178 (3.2)	225 (4.1)
Discharged episodes, n (%)[b]	2341 (44.7)	1780 (45.1)	2725 (48.7)	2615 (48.2)
Recertified episodes, n (%)[b]	2502 (47.8)	1908 (48.3)	2689 (48.1)	2589 (47.7)

[a]Percentages use the number of unique patient admissions as the denominator.

[b]Percentages use the number of wound episodes as the denominator.

[c]Other types of wounds: abrasion, laceration, blisters, seroma, carcinoma, and hematoma.

Reduction in Utilization of SN Home Care Visits

The data show that the adoption branches experienced a decrease in the average number of SN visits per 60-day episode during the postadoption period as compared to the preadoption period. This led to a decline of 4.3% in the average number of SN VPE from the preadoption period to the postadoption period. On the other hand, the control branches saw a 4.5% increase in the average SN VPE. Consequently, the adoption branches showed an 8.7% improvement in visit utilization compared to the control branches over the same period, as illustrated in Table 2.

Table 2. Comparison of average skilled nursing visits per episode between the adoption and control branches in the pre- and postadoption periods.

Branches	Preadoption period (November 2020 to May 2021)		Postadoption period (November 2021 to May 2022)	
	Visits, n	Skilled nursing visits per episode, n	Visits, n	Skilled nursing visits per episode, n
Adoption	36,433	7	26,825	6.7
Control	36,969	6.6	37,678	6.9

Improved SN Wound Care Visit Efficiency

During the preadoption period, the adoption branches spent an average of 43.2 (SD 40.27) minutes per episode, amounting to 1,573,171 minutes for completing visits. However, in the postadoption period, the average time per episode reduced to 42.1 (SD 37.52) minutes, resulting in a total time spent of 1,128,658 minutes by the adoption branches. This decrease led

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to a 2.5% reduction in the average time required to complete a visit. In total, the adoption group saved 309 days (equivalent to 444,513 minutes) of staff time spent on SN home visits. On the other hand, the control branches experienced a 2.2% increase in the average time to complete the SN visit, from an average of 40.9 minutes (SD 34.20) to 41.8 minutes (SD 36.37). Overall, the adoption branches saw a 4.4% improvement compared to the control group from the preadoption period to the postadoption period, as depicted in Table 3.

Table 3. Comparison of average time to complete a skilled nursing visit between the adoption and control branches in the pre- and postadoption periods.

Branches	Preadoption period (November 2020 to May 2021)		Postadoption period (November 2021 to May 2022)	
	Visits, n	Average time to complete a skilled nursing visit (min)	Visits, n	Average time to complete a skilled nursing visit (min)
Adoption	36,433	43.2	26,825	42.1
Control	36,969	40.9	37,678	41.8

Improved Average Days to Heal a Wound

A significant decrease in the average healing time of wounds was observed at the adoption branches compared to the control branches (P<.001). On average, the adoption branches saw an average reduction of 4.3 days per wound (from 19.7 days to 15.4 days), which was greater than the control group's average reduction of 1.6 days (from 25.9 days to 24.3 days). This corresponds to a 2.7-day improvement compared to the control group, and an overall 15.7% improvement in healing time for the adoption branches (Table 4). Additionally, significant differences were noted in the average days saved between the pre- and postadoption periods for the adoption branches, particularly the reduction in days to heal for pressure injuries, venous ulcers, and surgical wounds (P=.01, P<.001, and P<.001, respectively). In contrast, the average healing time for traumatic wounds, surgical wounds, and diabetic ulcers were increased from the preadoption period to the postadoption period for the control branches. No significant differences were found for any saved days for different types of wounds between the control group between the pre- and postadoption periods (all P>.05; Table 4).

Table 4. Average days to heal a wound between the adoption and control branches in the pre- and postadoption periods.

Type of wound	Adoption branches					Control branches				
	Preadoption period (November 2020 to May 2021)		Postadoption period (November 2021 to May 2022)		*P* value	Preadoption period (November 2020 to May 2021)		Postadoption period (November 2021 to May 2022)		*P* value
	Days to heal, mean (SD)	Episodes, n	Days to heal, mean (SD)	Episodes, n		Days to heal, mean (SD)	Episodes, n	Days to heal, mean (SD)	Episodes, n	
All wounds	19.7 (13.9)	2185	15.4 (15.0)	1856	*<.001*[a]	25.9 (20.4)	2770	24.3 (19.7)	2200	.98
Diabetic ulcer	17.9 (12.6)	106	16.8 (15.4)	55	.68	34.0 (21.1)	326	34.2 (18.3)	261	.98
Pressure injury	18.9 (13.0)	679	15.3 (14.3)	540	*.01*	30.4 (21.2)	735	29.9 (18.6)	695	.88
Skin tear	16.8 (11.6)	72	14.3 (11.7)	80	.14	14.4 (15.2)	116	14.2 (14.6)	110	.92
Surgical wound	20.8 (15.2)	608	15.4 (15.9)	508	*<.001*	18.3 (18.0)	514	21.3 (16.7)	345	*.01*
Traumatic wound	20.8 (13.5)	136	17.9 (15.6)	183	.06	22.9 (19.9)	305	24.0 (19.8)	125	.19
Venous ulcer	18.9 (13.3)	268	13.4 (15.4)	313	*<.001*	31.9 (21.1)	357	29.8 (20.5)	255	.85
Others	21.2 (15.7)	316	17.6 (15.5)	177	.06	28.1 (20.9)	280	30.5 (19.1)	274	.32

[a]P<.05.

Discussion

Principal Findings

To our knowledge, this descriptive, pre-post evaluation study is the first to investigate the impact of adopting digital wound management technology in a home health setting as part of a comprehensive wound care program. Overall, our study recorded a general improvement in clinical and operational benefits among the adoption branches in the postadoption period compared to the preadoption period, surpassing the control branches over the same time frame. For instance, skilled nurses in the adoption branches saved 444,513 minutes, equivalent to 309 days, spent conducting in-home wound care visits after implementing the technology in practice, while the control group added 42 days to the time spent conducting the visits. This finding is crucial for addressing the consequences of the growing shortage of trained nurses in the health care system [26] and the increasing demand to cope with the continuous rise in wound prevalence and the aging population [27].

On average, nurses provide patients with three dressing changes per week [28-30], and according to O'Keeffe [12], this takes up to 66% of the available nursing time. Also, literature has shown that up to 35% of this time is spent on documentation [26,31-34], and 21% is spent on care coordination [26,31]. In

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a previous study, Lindholm et al [35] stated that among a population of 694 patients with wounds, changing wound dressings alone consumed time comparable to full-time employment of about 57 nurses.

The time spent changing a dressing in a typical wound care visit is not only about the physical act of changing the dressing but also always involves other activities such as wound assessment, measurement, and decision-making on the need to change a dressing and the choice of dressing. This comprehensive approach can make the process time-consuming for nurses, as highlighted in studies by Hadcock [36] and Fletcher and Wasek [37], and could be challenging at times [37]. Moreover, the advent of electronic health records was intended to streamline wound care coordination and documentation at home health organizations [38], but studies by Burton et al [39], Sockolow et al [40], and Yang et al [38] have shown that electronic health records may only partially support these processes and can add to the nurses' workload.

The time-saving benefits documented in our study aligns with a previous study that found implementing the Swift Medical Inc solution in an outpatient clinic could potentially save up to 51.7 days of clinicians' time per year compared to traditional wound assessment methods [22]. The observed time saved during home visits may be attributed to the provision of a technology to nurses that helps facilitate effective wound management. The technology allowed for accurate clinical wound information and precise wound images to be captured, enabled online documentation during visits, allowed the electronic exchange of clinical information, and facilitated remote monitoring with experts. This accessibility to best practice wound assessment ultimately led to improved care and cost outcomes.

Further, after implementing the technology, the adoption branches also experienced a 4.3% reduction in the average number of SN visits needed to care for a wound per episode. This reduction in home SN VPE could generate significant cost savings in the home health care setting. Assuming the average hourly rates of LPNs and RNs conducting the SN visits in home health care range from US $26.85 to US $42.85, according to the US Bureau of Labor Statistics [41], CenterWell could potentially save US $600,413 to US $958,201 annually across the organization for every 0.3 reductions in SN VPE, based on a total of 60,898 episodes cared for at the organization in a year. Furthermore, compared to the control group, if the adoption branches had not implemented the Swift Medical Inc solution, they would have conducted an additional 1187 visits during the study period.

Evidence suggests that incorporating technology into wound care management can lead to substantial cost savings by reducing nurses' transportation costs and the utilization of wound care materials with each additional visit [42]. Additionally, Lindholm and Searle [5] demonstrated in a cost-effectiveness study that saving 260 hours of nurses' time per year could result in up to an 80% reduction in management costs. This, in turn, could lead to a reduction in care delivery costs and an increase in practice capacity, allowing for better resource management and reduced workload on clinicians, which may mitigate costs associated with staff burnout, attrition, and recruitment [43]. The time saved could be redirected to managing other patients or engaging in valuable activities [5]. A survey study indicated that clinicians expressed a strong interest in using any saved time to educate current patients on dressing change techniques, thus creating an opportunity for additional time savings that could be allocated to care coordination [37].

It is important to note that despite conducting fewer visits per wound episode and saving time during each visit at the adoption branches, the quality of care provided at these branches remained consistently high. In fact, there was a significant improvement in the average days to heal a wound between the pre- and postadoption periods at the adoption branches. Several research studies have shown that chronic wounds often have extended healing times, which can lead to increased consultation time, treatment supply consumption, dressing changes, and assessment sessions [44-48]. Moreover, prolonged healing times can increase the risk of complications and hospitalization, ultimately adding to the total cost of wound care [44-48]. As a result, time to heal could be the principal driver in reducing total wound care costs [45-48]. Our findings revealed a 15.7% reduction in the average days to heal a wound for the branches that adopted the technology from the preadoption period to the postadoption period ($P<.001$), resulting in a savings of 4.3 days for the adoption branches and only 1.6 days for the control branches. It is projected that if the control branches had adopted the solution and experienced the same improvement as the adoption branches, they would have saved 18,546 days in healing patients with wounds over the same period.

The management of wound care involves a variety of practices including assessment, treatment delivery, utilization of advanced products, services, and supportive tools to improve skills and optimize wound care and management [49-51]. The inclusion of AI technology in wound care can significantly enhance clinicians' ability to manage patient care through precision, efficiency, and interoperability. A study by Chairat et al [24] demonstrated that AI integration can streamline documentation and ensure smooth data exchange across health care systems. Research also has demonstrated that AI algorithms, when applied to wound images captured by smart devices, can achieve over 90% accuracy in identifying wound types and dimensions, streamlining the documentation process and ensuring seamless data exchange across health care systems [24]. Therefore, integrating technology as an essential component of the program is crucial for enhancing wound care, as evidenced by various studies [44,49-52].

Our research indicates that implementing wound care management technology enhances patient outcomes and contributes to cost containment and savings. This aligns with the estimated US $15.7 trillion expansion of the global economy by 2030 attributed to the implementation of AI-based technologies, including assisted intelligence, automation, and autonomous intelligence [53]. Additionally, staying current with wound care knowledge and advancements and integrating technology can significantly improve proficiency in wound care and assist evidence-informed clinicians in delivering effective

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treatment recommendations, irrespective of wound complexity or clinician expertise.

Chronic wounds are often tied to comorbid conditions, increasing the complexity of wound management and placing more burdens on clinicians and patients [46]. Meanwhile, CMS expects HHAs to take on more responsibility in caring for these patients with clinically complex conditions and bridge the referral gap in this population [13].

Hence, it is essential to modernize health care and implement wound management technology to bolster evidence-based practices and enhance clinical management [50], regardless of the wound complexity or the practitioners' experience [50,54-56]. This can be accomplished through the practical implementation of deep learning for automated tracing of wound dimensions, accurate measurements [22], automated wound tissue segmentation [57], and predictive modelling [23], thus enabling real-time decision-making that ensures timely patient-centered care.

As evidenced by our study, the branches that adopted the digital solution demonstrated improvements in managing more complex wounds with comorbid conditions, showing a 1.5% increase compared to the control branches. Additionally, these branches reported a 5% improvement in the rate of healed wounds from the preadoption period to the postadoption period, contrasting with the observed 9% decrease in the overall rate of healed wounds at the control branches. These findings illustrate a modest improvement in the effectiveness of using advanced wound management solutions that have a potentially larger impact if adopted across additional branches within the enterprise. Therefore, integrating AI-powered wound management technology into a comprehensive wound care model enables better wound care delivery and management.

Limitations and Strengths

A major strength of this study is the inclusion of patients who require wound care managed at 41 different branches at one of the largest HHAs in the United States. We also included a control group of 27 PRIME-certified branches, allowing us to compare operational and clinical changes and marginal benefits against them for the same periods. However, while the branches (adoption and control groups) were comparable with regard to demographics, clinical variables, and wound care education and training, generalizing the results warrants caution. Other institutions may not be similar in size, patient demographics, and operational and clinical workflow, so the results should be interpreted within this context.

We used the as-treated analysis approach to gain valuable insight into the impact of implementing the Swift Medical Inc solution in practice. To ensure the accuracy of our findings, we excluded patients who had not undergone assessment using the Swift Medical Inc solution at the adoption sites during the study period. This approach provided a focused understanding of the true impact of the technology on the assessed outcomes.

It is important to note that this study was conducted within a specific time frame of 7 months (from November to May) in both 2020-2021 and 2021-2022. The COVID-19 pandemic significantly disrupted priorities and various aspects of the wound care continuum in 2020, as highlighted by Sen [58]. The increased infection rates of the respiratory pathogen among populations with comorbidities prompted heightened attention to high-risk patients [58] in the preadoption period, and this may have had an unforeseen impact on our findings, either positive or negative.

In addition, due to a lack of data, the study did not assess the sociodemographic variables of patients with wounds, diagnostic methods, nurses' travel costs, cost of used wound supplies, patient costs, or quality of life. Including these variables in exploring the technology's cost-effectiveness would provide valuable insight into the potential savings associated with technology in wound care. A future comprehensive cost-effectiveness study that includes all these variables would be beneficial in informing policy makers and payers about the tangible economic impact of adopting technology for home health to reduce care costs and improve patient outcomes.

Nevertheless, this study presented preliminary data on the impact of adopting a comprehensive wound care management model with the inclusion of technology. Our findings illustrated that HHAs could realize cost savings and clinical and operational improvements by integrating this technology into the wound care program. Therefore, the results may hold significant value for health care providers, administrators, policy makers, and insurance companies.

Conclusion

Incorporating wound management technology into the wound care paradigm can improve operational efficiencies in home health settings by reducing the time required to complete in-home visits and decreasing the volume of SN VPE. These benefits can lead to significant cost savings. In addition, this approach also supports more effective clinical care, leading to faster wound healing, which facilitates the managing of more wound episodes annually, ultimately increasing revenue.

There is a clear need to establish a standardized comprehensive approach that incorporates digital tools as part of the wound care program. Doing so can help address challenges related to wound care assessment, increasing demands, limited human health resources, and increased burnout within the health care setting.

Furthermore, by following Centerwell's example of enhancing clinicians' wound care knowledge and skills with the aid of wound care management technology, other home health care organizations can achieve similar results. This includes reducing the average healing time of wounds by 27% and saving clinicians approximately 530 days annually that would have been spent on conducting more in-home wound care visits.

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Conflicts of Interest

HTM, AC, and RDJF are all current employees of Swift Medical Inc. DM is a former employee of Swift Medical Inc. All other authors have no conflicts to declare.

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Abbreviations

AI: artificial intelligence
CenterWell: CenterWell Home Health
CMS: Centers for Medicare & Medicare Services
DWCS: digital wound care solution
EMR: electronic medical record
HCHB: Homecare Homebase
HHA: home health agency
ICC: Integumentary Command Center
LPN: licensed practical nurse
PRIME: Prevention Intervention, Management, and Education
QI: quality improvement
RN: registered nurse
SN: skilled nursing
VPE: visits per episode

Edited by E Borycki; submitted 21.01.25; peer-reviewed by M Wynn; accepted 23.03.25; published 08.04.25.

Please cite as:
Mohammed HT, Corcoran K, Lavergne K, Graham A, Gill D, Jones K, Singal S, Krishnamoorthy M, Cassata A, Mannion D, Fraser RDJ
Clinical, Operational, and Economic Benefits of a Digitally Enabled Wound Care Program in Home Health: Quasi-Experimental, Pre-Post Comparative Study
JMIR Nursing 2025;8:e71535
URL: https://nursing.jmir.org/2025/1/e71535
doi:10.2196/71535
PMID:40198913

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The Role of an Intraorganizational Digital Community in Shaping Nurses' Professional Identities and Practice: Qualitative Interview Study

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Abstract

Background: In 2017, Israel's health organizations established intraorganizational social media communities, believing that they would serve as a tool that would enable people to share experiences across regional boundaries. However, conducting preliminary studies and analyzing the findings to determine how they affected employees' experience was never part of this effort.

Objective: This study examined the impact of an intraorganizational digital community on nurses' professional identities and practices within a large health care organization.

Methods: Using a qualitative descriptive approach, semistructured interviews were conducted with 20 nurses from various specialties and regions participating in an intraorganizational nurses' community on Facebook.

Results: The findings showed that the intraorganizational community fostered a strong sense of belonging, emotional support, and professional development among its members. Participants talked about having a sense of community, much like being a member of a family, where they could confide in one another, ask for help and advice, and receive support. Enriched professional knowledge, self-efficacy, and pride in the nursing profession were all associated with active involvement in the community. The complex interactions of social media use in a hierarchical health care system were emphatically acknowledged by addressing challenges, including information overflow and concerns about sustaining a professional persona in a public digital domain.

Conclusions: Overall, the study illustrated how crucial it is for health care organizations to actively manage potential negative consequences while using the benefits of intraorganizational digital networks, such as improving supportive relationships and ongoing shared learning. This study contributes to the growing body of knowledge regarding the crossroad between social media and health care, offering insights into developing strategies to promote a supportive and connected nursing workforce. The implications are particularly relevant for organizations seeking to strengthen nurse well-being and professional development through innovative digital tools. Future research should include quantitative studies to assess an intraorganizational platform's influence on outcomes such as nurses' sense of community, professional identity, self-efficacy retention, and job satisfaction.

(JMIR Nursing 2025;8:e81765) doi:10.2196/81765

KEYWORDS

social media; professional identity; intraorganizational digital community; nursing; organizational culture; self-efficacy; sense of community

Introduction

Evolution of Social Media in Health Care Organizations

Social media is reshaping health care organizations' function and communication. Innovative digital platforms enable professionals to exchange information, share experiences, and connect with colleagues across geographic boundaries. This shift raises substantial questions about how these technologies affect nurses' professional identity, daily practices, and sense of community within the workplace. Recent studies indicate that social media is changing health care workers' communication dynamics by enhancing peer interaction and knowledge sharing. Increased use of social networks is associated with enhanced empowerment of both patients and health care professionals. Regarding patients, health-related digital communities enable individuals to interact with others facing similar conditions, access support communities that provide reliable medical information, and become more actively involved in their own care [1].

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Internally, a digital community can help nurture a sense of community; promote professional networking; and exchange fruitful ideas, practices, and organizational professionalism. According to Chen and Wang [1], social media's vast user base also offers valuable data for understanding behavioral and public health trends. The existing literature presents diverse perspectives on these innovations. Some studies suggest that social media can support collaborative research efforts and improve the understanding of health-related issues. These interactive platforms change how patients, health care professionals, and organizations communicate by fostering connections and facilitating information.

Social Theory and the Digital Community

Traditional social science theories enhance our comprehension of digital nurse communities. Social identity theory [2] suggests that being part of a group enhances an individual's self-image. In other words, belonging to a respected group (such as a professional community) can enhance an individual's identity and pride. Engaging in a digital community can strengthen nurses' professional identity by offering validation and a sense of belonging. The idea of digital communities by Rheingold [3] and the theory of communities of practice by Wenger [4] indicate that individuals who interact through digital platforms can cultivate shared values, norms, and knowledge, creating a unified social group even when they are not in the exact physical location.

The dramaturgical theory by Goffman [5] helps understand how people interact and express themselves online. The theory was applied to social networks such as Facebook by Merunková and Šlerka [6], who identified various self-presentation strategies (sharing personal stories, influencer style, valuable content, etc). Their study revealed that, similar to other users, nurses in a work-related digital community seeking to preserve their professional image may be mindful of what they post and consciously manage their online image and privacy.

Because of this awareness of the context and audience, interactions on a nurse's online community are not completely spontaneous; instead, they are influenced by the need to maintain professional standards and an expectation for support. According to Goffman [5], nurses play roles in digital communities in ways similar to offline roles, balancing competence and truthfulness. According to theories of social identity and community of practice, an active intraorganizational social media community can help nurses develop a strong sense of shared identity. On the other hand, the dramaturgical theory by Goffman [5] serves as a reminder that role expectations and image maintenance still influence conduct in such a group. Digital identity management has become a central aspect of professional life for health care employees. In the digital era, professionals are required to navigate the complex boundaries between their personal and professional selves across various online platforms. Recent literature emphasizes that digital identity is dynamic and constructed through ongoing interactions, self-presentation, and audience perception [7]. Health care workers must balance authenticity, privacy, and professionalism, often engaging in "boundary work" to maintain appropriate conduct and protect sensitive information. This process involves critical self-awareness, digital literacy, and adherence to organizational and ethical guidelines for online behavior. Organizations are increasingly called upon to provide training and clear policies to support employees in managing their digital identities responsibly, thereby safeguarding both individual reputation and institutional trust [7,8].

Nurses on Social Media

The public perception of nurses has frequently been influenced by media representations and stereotypes that do not accurately represent their knowledge or independence, which may have a detrimental effect on nurses' professional identities and self-perception [9]. Nurses can use digital communities as a platform to present their public image and express their thoughts. They can criticize old assumptions and bolster their sense of professional worth by sharing their knowledge and achievements. Participation in an intraorganizational digital community can empower nurses by allowing them to acknowledge each other's success and appreciate each other's contribution.

Recent studies have emphasized the significance of such engagement. For instance, nurses are reported to play an essential role in encouraging knowledge exchange on digital health communities, and their social media confidence (knowledge self-efficacy) might significantly affect such conduct [10]. In other words, nursing leadership can stimulate greater involvement and knowledge sharing among their teams by actively facilitating dialogue on a digital community. According to the results of this study, the culture of knowledge sharing can be upgraded by having reliable nurses facilitate interactions in an intraorganizational Facebook group.

Nevertheless, nurses' activities in a digital community raise a question that reveals a conflict between transparency and professional ethics. They must use their digital community activities responsibly for learning and support, enhancing their professional reputation, and increasing public awareness of their profession without breaking their professional boundaries or compromising other participants' privacy [9]. This need can lead to setting standards and guidelines for what nurses can communicate on a digital media community. In reality, health care–providing organizations have social media use standards to guarantee adherence to ethical professionalism and discretion. These guidelines and nurses' ethical standards shape an intraorganizational nurses' community on Facebook [11].

This study aimed to examine the impact of an intraorganizational digital community on nurses' professional identities and practices within a large health care organization. Specifically, the research aims to investigate how participation in a nurses-only intraorganizational Facebook community affects nurses' sense of community, professional growth, and their daily practices.

Methods

Overview

This study used a qualitative descriptive approach to provide an extensive understanding of nurses' experiences with an intraorganizational Facebook community. Participants who

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were most likely to contribute rich information pertinent to the research questions were chosen through a purposive sampling technique [12]. Being a registered nurse within the health care organization in any capacity, from management to staff nurse, and actively participating in the nurses-only intraorganizational digital community were prerequisites for inclusion. Participation was voluntary; ultimately, 10 nurses in managerial positions and 10 nonnurse managers were chosen (N=20). Hence, the sample represented diverse hospitals, units, and regions across the country, making it possible to record a variety of viewpoints. Recruitment continued until the researchers determined that data saturation had been accomplished, which means that no new themes or insights were revealed by further interviews [13].

Participants

The study comprised 20 participants reflecting demographic and training diversity, highlighting the intraorganizational digital community's varied influence on sense of community, professional growth, and burnout. Participants were aged between 33 and 62 years, married, and had children. Educationally, 2 (10%) held PhDs, 11 (55%) had master's degrees, and 7 (35%) held bachelor's degrees. A total of 10 (50%) participants held managerial positions. Participants came from diverse specialties, such as intensive care, palliative care, and psychiatry, with 14 (70%) working in hospitals and 6 (30%) in community clinics.

Including both nonmanagerial and managerial participant groups allowed us to explore how hierarchical position shapes experiences and interactions within the digital community. Notably, many (12/20, 60%) participants described how the usual boundaries between managerial and nonmanagerial staff were softened in the digital space, enabling open dialogue and mutual learning. The digital community often served as a social leveler, fostering egalitarian and supportive interactions that contrasted with traditional workplace hierarchies. This flattening of hierarchy aligns with the concept of "teaming" by Edmondson [14], which emphasizes the value of psychological safety and open communication across authority gradients to promote learning and innovation in organizations. However, some (8/20, 40%) participants remained aware of their hierarchical position, noting that concerns about professional image and credibility could influence their willingness to share openly, especially when managers were present in the discussions.

Only 3 (15%) participants had 10 or more years of experience in their current role, while 13 (65%) had over 20 years of nursing experience. This diversity helped capture a wide range of perspectives on the impact of participating in the digital community.

Data Collection

After obtaining consent, individual interviews were conducted with each participant at times convenient for them, either in a private office or over a secure video connection, to address geographical distance. Each session lasted between 30 and 60 minutes. Using an interview guide, we asked open-ended questions about the nurse's use of digital community (posting, commenting, reading discussions, etc), notable communications within the community, perceived advantages or disadvantages, and any effects on their work or professional views. We urged participants to offer concrete examples and probed further to thoroughly examine themes of interest. We tried to establish a relaxed atmosphere during the interview process, reminding nurses that their candid experiences were respected and that there were no right or wrong thoughts. To guarantee correct verbal information for analysis, the interviews were recorded and transcribed verbatim. Regarding confidentiality issues, any identifiable reference to a workplace, participants' names, and other information that might identify specific patients, individuals, or complicated cases was either eliminated during transcription or substituted with aliases, general descriptions, or codes.

Data Analysis

We examined the transcripts thematically, a structured qualitative approach for deriving and interpreting units of meaning, using aspects of content analysis to classify and condense informational material into themes and categories. Initially, 2 researchers individually reviewed all the transcripts several times to gain a thorough understanding of the data. Subsequently, they conducted an open coding process, analyzing the texts and labeling the concepts or ideas conveyed by the participants. Engaging in ongoing discussions and refinements, we extracted the data into common themes and categories representing the participants' collective experiences. Thematic analysis followed the 6-phase reflexive approach by Braun and Clarke [15]. Coding reliability was ensured through continuous reflexive writing and peer debriefing with 2 experienced colleagues, who discussed and refined categories and themes. Three main themes emerged: sense of community, professional growth, and burnout, a theme not addressed in this paper.

Ethical Considerations

This study was conducted in accordance with the ethical standards of the Declaration of Helsinki and received formal approval from the Helsinki Committee/Internal Review Board of the Meir Medical Center in Israel on August 13, 2024. All participants provided informed consent before participation, understanding the voluntary nature of their involvement and their right to withdraw at any time without consequences. Confidentiality and anonymity were strictly maintained throughout the research process. Data were securely stored, and any identifying information was removed or anonymized to protect participant privacy. The study adhered to the ethical guidelines recommended by the Journal of Medical Internet Research (JMIR) to ensure the integrity and ethical rigor of research involving human subjects and digital platforms.

Results

This section presents the findings with sample quotes from the interviews to demonstrate each theme and its categories.

Theme 1: Sense of Community

The intraorganizational digital community has emerged as a powerful source of emotional support, camaraderie, and professional belonging among nurses. Rather than functioning solely as an information exchange, participants described the community as a "digital family," one that fosters deep

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interpersonal connections and mutual assistance. For example, a nurse recalled a moment of collective solidarity:

> *When a colleague was injured in a road accident that also killed her sister, it was posted, and within an hour, hundreds of nurses expressed their sympathy and offered help…We never felt more united than at that moment.* [P12]

This rapid mobilization of support illustrates how the digital platform enabled nurses to transcend geographical and organizational boundaries, reinforcing a shared identity and sense of unity. Many participants used family-related analogies, highlighting the intimacy and solidarity they experienced within the group. Another nurse shared the following:

> *I won the hospital's monthly excellence award…I received many heartfelt responses…It is a profound feeling that is hard to put into words, especially when all I did was hold my phone and cry.* [P13]

Such expressions underscore the emotional resonance and validation provided by the community, extending beyond professional recognition to personal affirmation. The community also functioned as a social leveler, breaking down traditional hierarchical barriers. Nurses of all ranks interacted as peers, fostering egalitarian dialogue and collaborative problem-solving. One participant described this dynamic as follows:

> *I surf at 2 AM with my first coffee and see a new idea from another ward…like learning from your sister at home how to help your children sleep.* [P10]

This metaphor conveys both the informal, supportive atmosphere and the practical value of peer-to-peer learning. Importantly, the community was perceived as a safe space to vent frustrations, seek advice, or express feelings after a tough day, acting as an always-available peer support network—"much like an always-open extended nursing break room."

However, some participants expressed concerns about authenticity, noting that the overwhelmingly positive tone sometimes inhibited open discussion of negative experiences or controversial viewpoints. As one nurse reflected:

> *I was very pleased, but afterwards I got worried they would link me to posts, perhaps I would be perceived as too lightweight and not serious enough for roles with more responsibility.* [P17]

This highlights the ongoing negotiation of professional image and impression management within the digital space [5]. Recent theoretical contributions further illuminate these dynamics—nurses in digital communities must continuously navigate issues of visibility, authenticity, and boundary work, balancing openness with the need to maintain a professional persona [8]. Thus, while the community fostered a strong sense of belonging and support, it also required members to manage their digital identities thoughtfully within organizational platforms.

Theme 2: Professional Growth and Learning

Beyond emotional support, the digital community served as an informal, dynamic platform for professional development and learning. Nurses consistently reported that participation contributed to their knowledge, skills, and confidence in practice. Sharing knowledge was a central activity, exposing members to new cases, advice, and resources. One participant described the practical impact as follows:

> *I am scrolling at 2 AM on my night shift when I have a minute for coffee, and I get new ideas I want to share with my supervisor.* [P7]

This peer sharing complemented formal training and was perceived as more relevant because it originated from colleagues with direct experience. Such sharing exemplifies a "community of practice" [4], where rapid dissemination of knowledge enhances organizational performance [16]. Another nurse reflected on the tangible benefits:

> *I felt that I genuinely knew more about emergency medicine, and that I would have the tools without having been taught formally how to react in real time.* [P19]

Stories of professional initiative and success circulated within the community, inspiring others to innovate and take leadership. For example:

> *I wrote a post about an innovative approach to patient guidance that we implemented, and the district chief executive nurse called me to say how proud she was.* [P15]

Such recognition reinforced nurses' professional identity and motivated further growth. The community also encouraged self-efficacy, particularly among younger nurses who felt empowered to ask questions and receive guidance from experienced colleagues. As one nurse shared:

> *I never considered myself worthy of all this, but one post about a coffee shop I had established for our team…and today, I cannot go anywhere without people saying…I feel really recognized.* [P16]

Importantly, participation in the digital community required nurses to navigate issues of visibility, authenticity, and professional boundaries in their learning and knowledge-sharing practices. As highlighted by recent theoretical contributions [8], nurses in organizational digital platforms must balance openness and vulnerability with the need to maintain a credible and professional online identity. This boundary work was evident as participants described both the empowerment and the caution that accompanied their engagement in the community.

Despite these benefits, participants acknowledged some limitations. The volume of daily posts sometimes made it difficult to keep up, and not all important information reached every member. However, most considered this a minor issue, as critical messages were also communicated through formal channels.

Discussion

Integrating the Themes: Community and Growth Hand-in-Hand

The 2 primary themes, professional growth and a sense of community, were closely connected when combined. Learning

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and growth processes were enhanced by the dynamic, collaborative, and interactive environment, and vice versa. Nurses were more inclined to share ideas, ask questions, and even acknowledge their lack of expertise because they felt safe and encouraged in the community (theme 1), which are vital behaviors for learning (theme 2). One nurse observed that while she might be reluctant to admit, "I do not know how to do X," in a staff meeting, she witnessed colleagues in the digital community asking the same query openly, which motivated her to do the same without worrying about criticism. A sense of psychological safety characterizes effective learning communities. On the other hand, the community built ties while fostering nurses' professional growth. For example, when a nurse embraced an idea posted on the community and reported success, it bolstered participants' shared sense of improvement and fostered a sense of pride. In this respect, the community was an ideal setting for growth, and every case of progress enriched it.

Interestingly, our findings correspond to other innovative nursing training and practice endeavors. To help nursing students learn about mental health conditions, a recent study [17] used an interactive game-based application. The results indicated that the collaborative, peer-supported strategy improved students' empathy for their peers and involvement. Similarly, our study found that the interactive, peer-driven digital community strengthened practicing nurses' sensitivity to their peers and involvement in professional growth. Both studies found that although the settings differed (students learning through a game vs nurses learning through a digital community), the fundamental concept was the same: a team effort and emotionally supported learning produces more beneficial outcomes than top-down individualized approaches.

Additionally, our study addressed another pressing concern—nurses' professional image and voice [9]. The intraorganizational digital community provided nurses with an enhanced organizational platform, a space to acknowledge achievements, communicate issues that worry them, and share pertinent thoughts and ideas. Such communication can address nurses' internal professional identity.

The community constitutes an informal intraorganizational feedback venue, where nurses' sense of worth develops with their awareness of certain managers participating in the digital community, attuned to their questions, expressing impressions regarding their suggestions and grievances, and possibly communicating supporting responses to their concerns much faster than in the formal arena.

Implications for Practice

Despite a few drawbacks, this study yielded positive advantages of the intraorganizational digital community and introduced meaningful implications for health care organizations.

Organizations should consider supporting designated digital communities for staff to encourage and enhance intraorganizational communication and morale. Our study has shown that a nationwide, open, collegial online space can shatter boundaries between units, specialties, ranks, and geographic locations. This allows faster sharing of best practices and problems and a strong peer and organizational support network.

These findings suggest that nurse managers and leaders should actively engage in such forums and communities. A supportive leadership presence conveys the message that an organization values staff input. In our case, when leaders praised nurses or responded to advice-seeking, suggestions, shared success stories, worries, questions, and other communication within the community, it boosted nurses' morale. Managers' participation enabled the assessment of the level of staff concerns and interests in real time. An intraorganizational digital community can serve as grounds for initiating innovations and a preliminary warning system for identifying staff issues. The success of the digital community in this study gave nurses the sense that this was their space. Hence, although organizations can benefit from participation in the digital community, leaders should respect its informal nature and avoid top-down communication, using a semi-informal tone and engaging in equal participation.

In essence, organizations should embrace the compelling influence of a digital community. When nurses are willing to learn and contribute, they should focus their energy on promoting training opportunities, educational initiatives, and overall improvement efforts.

Theoretical Implications

Theoretically, our findings reinforced and expanded several concepts in the literature. The digital community's influence on professional identity corresponds to social identity theory [2]. Active participation reinforced nurses' identification with fellow nurses and the organization. Regarding the community, nurses used the plural pronoun "we," indicating a strong sense of cohesion. This may have affected their commitment to the organization and improved teamwork in their day-to-day practice, above and beyond the usual boundaries of their work units as a unified community, above and beyond their separate wards or clinics. This suggests that a collaborative and supportive community culture may outweigh conventional team-building practices.

Furthermore, our study clarified the role of digital professionalism, where nurses' conduct in the digital community was ethical and professional. Participants were careful about what they posted, and the interviews yielded no unprofessional outbursts or privacy violations. This implies that nurses' use of social media, especially in a closed, professional setting, was mature, which may result from growing knowledge regarding social media ethical protocol and its repercussions. Additionally, it implied that, in contrast to public social media, intraorganizational digital communities where users could be identified and held accountable for one another might generate more professional behavior. The significance of shared norms and community self-regulation could be emphasized in theoretical models of social media conduct in professional communities.

Unanticipated Findings

Although we expected the digital community to contribute to organization-wide interactions, the degree to which traditional hierarchical barriers seemed to be dissolved within the

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community was a fairly surprising finding. Lower and higher rank nurses interacted on a first-name basis, occasionally resulting in increased openness to work. A staff nurse, for instance, said she felt she could easily and directly contact a nurse in charge regarding a problem because the latter had responded positively to a post she had shared. She might not have done that offline. Nonetheless, although it was not the focus of our study, the disintegration of hierarchy in the digital community was observed and is a noteworthy positive side effect.

Another unexpected finding that emerged from the interviews, although somehow linked to the previous one, is the pace at which the digital community culture influenced changes to day-to-day practice. Among others, following a heated group discussion concerning upgrading shift transfer, several units willingly explored a new shift-change routine. Another unit held a modest social gathering due to a post praising dedicated teamwork during a crisis. These instances demonstrated how the digital community actively changed the workplace atmosphere while also being reflected in it.

In summary, the examined extensive intraorganizational nurses' digital community greatly impacted the nurses' sense of community and professional identity. Active participation yielded stronger connections among nurses throughout the organization, creating a supportive environment that surpassed geographical boundaries and ward or expertise differences. This digital community emerged to strengthen a shared sense of community and pride among nurses and organization members.

The findings revealed that using the digital intraorganizational nurses' community constituted a solid basis for strengthening nurses' professional identity and mutual support and promoting ongoing professional learning and growth. Nurses shared knowledge, gained confidence, and strove to introduce new ideas to their practice. Giving staff a voice online impacted the nurses' work lives, leading to long-term success and job satisfaction, which are crucial in the current health care climate.

Although limited in scope, examining 1 digital community in a single organization, albeit extensive, with a relatively small sample, and exploring only 2 aspects of nurses' work, it is important to note that despite limited generalizability, the study yielded consistent and trustworthy findings. Future research will contribute to reaching a better and more profound picture by examining multiple organizations and diverse intraorganizational digital communities and using a mixed methods approach to assess the impact of digital communities on measurable professional and organizational results.

Although this qualitative study provides rich insights, several potential biases should be noted. Social desirability may have led participants to emphasize positive experiences or avoid criticism, especially given the professional context. Additionally, self-selection bias may have resulted in a sample that was more engaged or favorable toward the digital community. These factors may affect the credibility and transferability of the findings, despite efforts such as reflexive journaling and peer debriefing to enhance trustworthiness. Future research should include more diverse samples and triangulate data sources to address these limitations.

Limitations

As a qualitative study, the findings reflect the subjective experiences and perspectives of a purposive sample within a single organization. Although this approach enables in-depth exploration and rich contextual understanding, it may limit the transferability of the results to other settings. Additionally, social desirability and self-selection biases may have influenced participation and responses, as those with strong opinions or positive experiences may have been more inclined to participate. Reflexive journaling and peer debriefing were used to enhance credibility, but these limitations are inherent to qualitative research. Future studies should consider broader sampling and triangulation across multiple organizations to deepen and validate these insights.

Conclusions and Practical Implications

The findings of this study demonstrate that fostering a strong intraorganizational digital community constitutes a strategic investment in human capital. Such communities build relationships, facilitate knowledge sharing, and strengthen the collective professional identity of nurses. The evidence suggests that digital communities can serve as effective tools for organizational development; professional empowerment; and the creation of a unified, engaged nursing workforce.

Policy and Training Recommendations

The following policy and training recommendations should be considered:

- Health care organizations should formally integrate digital communities into their communication and professional development strategies. These platforms enable rapid information flow, peer support, and collaborative problem-solving, which are essential for organizational resilience and adaptability [14,18].
- Training programs should include dedicated modules on digital professionalism and online identity management, equipping nurses and managers with the skills to navigate visibility, authenticity, and boundary work in digital environments [8].
- Leadership development should emphasize participation in digital communities as equals, fostering psychological safety and modeling constructive engagement.

By implementing these recommendations, health care organizations can leverage digital platforms to enhance staff well-being, morale, and professional growth, ultimately contributing to improved patient care and organizational outcomes.

Acknowledgments

The authors thank all the nurses who participated in the study.

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Conflicts of Interest

None declared.

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Edited by E Borycki; submitted 03.08.25; peer-reviewed by L Ryan, M Tusconi; revised version received 06.11.25; accepted 06.11.25; published 20.11.25.

Please cite as:
Rosenberg E, Cojocaru S
The Role of an Intraorganizational Digital Community in Shaping Nurses' Professional Identities and Practice: Qualitative Interview Study
JMIR Nursing 2025;8:e81765
URL: https://nursing.jmir.org/2025/1/e81765
doi:10.2196/81765

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Determinants of Nurses' Continuance Intention to Use Mobile Health Apps in Clinical Nursing Practice: Structural Equation Modeling to Extend the Expectation-Confirmation Model

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Abstract

Background: Mobile health (mHealth) apps enhance clinical nursing by improving access to resources and patient care. Further benefits include reduced errors, time savings, better communication, cost reduction, and training. Understanding factors driving nurses' continued mHealth adoption is key to its sustained success.

Objective: This study extends the expectation-confirmation model (ECM) to explore the determinants of Iranian nurses' continuance intention to use mHealth apps in their daily clinical routines.

Methods: A cross-sectional, descriptive-analytical study was conducted among 315 nurses from hospitals affiliated with Kashan University of Medical Sciences. The Nurses' Mobile Health Device Acceptance Scale (NMHDA-Scale) was developed by the authors in 2022. The Intention to Continue Using Mobile Health Applications for Nurses questionnaire assesses nurses' future willingness to use mHealth apps in their practice. This questionnaire was designed based on the ECM and the approach by Waltz et al. Its primary aim is to identify the factors that influence mHealth device acceptance, specifically among clinical nurses, as previous studies have not focused on this group and have shown inconsistent relationships between various factors. Participants completed structured questionnaires measuring perceived usefulness, perceived ease of use, social influence, habits, and technology anxiety. Data were analyzed using structural equation modeling in AMOS (version 26). The model tested relationships among confirmation, perceived usefulness, social influence, technology anxiety, and mHealth continuance behavior.

Results: The analyzed sample (n=315) consisted primarily of female (252/315, 80%) and married (243/315, 77.1%) nurses, with a mean age of 35.67 (SD 1.24) years. The analysis revealed that perceived usefulness was significantly influenced by both confirmation (P<.001) and social influence (P<.001). Perceived ease of use was negatively impacted by new technology anxiety (P<.001), indicating that higher anxiety levels reduced perceived ease of use. Additionally, mHealth continuance behavior was positively associated with habits (P=.002), social influence (P<.001), and perceived security risks (P=.008). Contrary to expectations, perceived usefulness did not directly influence mHealth continuance (P=.15), suggesting that other factors, such as habits and social influence, play a more significant role in long-term use.

Conclusions: Sustained mHealth app use by nurses hinges more on social influence and confirmed expectations than perceived usefulness. Although new technology anxiety remains a barrier, habits and social influence are key to long-term adoption. Hospital leaders should prioritize strategies that foster positive social reinforcement, minimize security concerns, and reduce anxiety through training and support when integrating mHealth into nursing workflows. These findings offer critical insights for improving digital health implementation, ultimately enhancing patient care and clinical efficiency.

(JMIR Nursing 2025;8:e68048) doi:10.2196/68048

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KEYWORDS

continuance intention; expectation–confirmation model; habits; mobile health apps; perceived usefulness; user satisfaction; technology anxiety

Introduction

Clinical nurses are responsible for various care interventions, such as administering prescribed medications, taking vital signs, changing wound dressings, and providing supportive and educational interventions to patients [1]. In this context, smartphones offer a new opportunity to improve the quality of care [2]. The use of smartphones in nursing offers several benefits, such as reducing medication errors, improving time management and communication [3], implementing effective cost-saving strategies [4], and improving the quality of education [5,6]. According to a study conducted in 2021, approximately 80% of nurses use their smartphones in the workplace for personal and professional purposes, using them as useful tools to improve the quality of care [7]. Another study conducted in 2018 reported that approximately 62.4% of nursing students use smartphones, with the most commonly used technological resources being medical dictionaries, anatomical atlases, and nursing care guides [8].

Many hospitals are in the process of developing policies regarding the use of smartphones by health care providers in the clinical setting. However, several studies have suggested that nurses may face challenges with accurately determining the appropriateness of smartphone use in the workplace, which may lead to clinical complications [9]. Many studies have examined the continued use of smartphones by users [10,11]. However, these studies have been criticized for their different methodologies and lack of consistency in prioritizing factors related to smartphone use in care teams [12-14]. For example, the study by Muqtadiroh et al [15] revealed a direct relationship between perceived usefulness (PU) and continuance-using factors. In contrast, the study by Wang et al [16] revealed a positive correlation between perceived ease of use (EU) and continuance-using factors. However, another study conducted in 2016 did not support this hypothesis [17].

In the context of technology adoption, continuous use is often associated with the cognitive process of postadoption behavior. This involves the conscious evaluation of technology tools during their use [18]. A prominent theory often used in research on continuance intention is the expectation-confirmation model (ECM). The theoretical framework proposed by Bhattacherjee [19] has received considerable attention in technology acceptance and continuance research [20,21]. The ECM examines the relationships among confirmation, PU, and user satisfaction (SA) with the continuance-using factor [22]. Due to the lack of similar studies with nurses in Iran, the inconsistent findings of previous research, and the strengths of the ECM in elucidating behavioral intentions, this study was designed and conducted to investigate the factors influencing the intention to continue using mobile health (mHealth) apps among nurses in Kashan, with a special focus on the ECM.

Methods

Study Design and Participants

This cross-sectional study was conducted between March 2022 and September 2022 in 6 hospitals affiliated with Kashan University of Medical Sciences. To determine the sample size for structural equation modeling (SEM), based on scientific sources, 5 to 10 samples per item were sufficient to assess the model fit [23]. Given the 33-item scale developed by Mirabootalebi et al [24], 315 clinical nurses were considered as the appropriate sample size. Nurses were selected using systematic sampling. In addition, proportional allocation was used to ensure that the number of nurses selected from each hospital was proportional to the population of nurses in that specific hospital. Sample selection was based on a list provided by the education department of each hospital. In cases where the selected nurses were unavailable or uncooperative, another nurse was randomly replaced (based on the random numbers table).

The inclusion criteria included having at least 6 months of work experience in clinical wards and the use of at least one technology tool in nursing. Exclusion criteria included a failure to complete the data collection scales and withdrawal from further cooperation. After data collection, each scale received was systematically checked for errors, incompleteness, and unanswered items. To ensure the validity of the analysis and an appropriate representation of the data, scales that contained unanswered items or where the response “no comment” was used for all items were excluded from the data analysis. Finally, 368 nurses completed the scales, and after the screening process, data from 315 nurses were considered for data analysis.

Data Collection Scales

The data collection scales included the Nurses’ Mobile Health Device Acceptance Scale (NMHDA-Scale) and the Intention to Continue Using the Mobile Health Application for Nurses questionnaire.

The NMHDA-Scale was developed by Mirabootalebi et al in 2022 [24]. This questionnaire was designed based on the ECM and the approach by Waltz et al [25]. This questionnaire aims to identify influential factors based on the ECM. Previous studies have not focused specifically on clinical nurses and have shown inconsistent relationships between factors. The questionnaire comprises 10 domains, including perceived security risk (PS), new technology anxiety (AN), social influence (SI), EU, confirmation, mHealth continuance (MHC), maturity (MA), PU, habits (HA), and SA. The reliability of the questionnaire was assessed via Cronbach α and McDonald omega coefficients, which were estimated to be 0.877 and 0.879, respectively [24].

The Intention to Continue Using Mobile Health Applications for Nurses questionnaire is designed to measure nurses’ willingness to continue using mHealth apps for nursing care in

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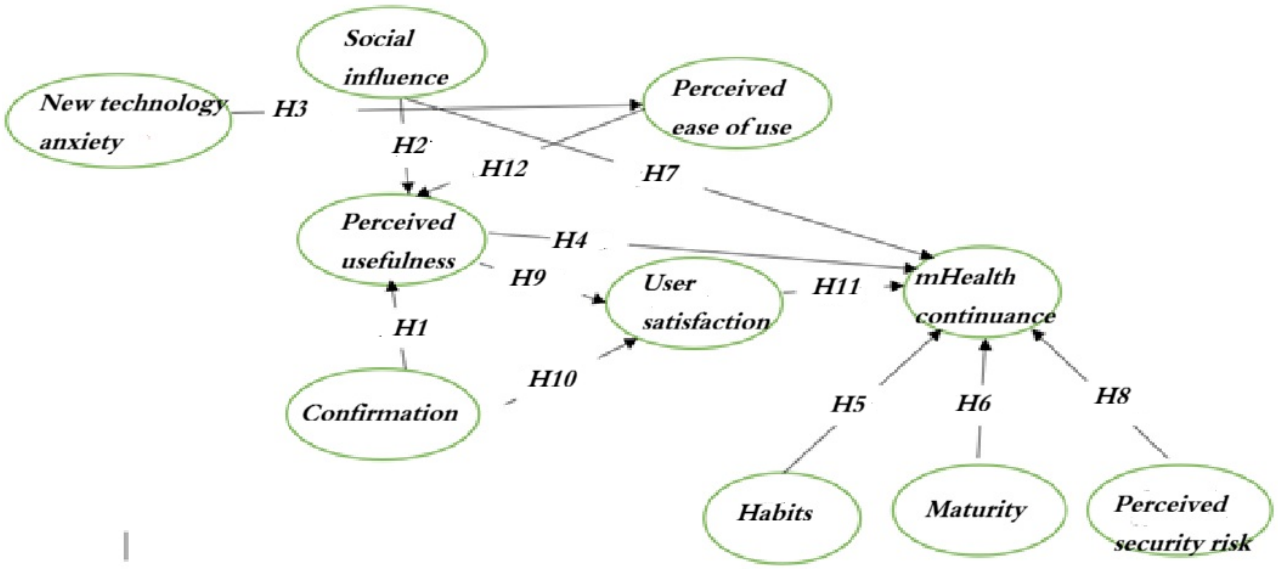
the future. It also includes the willingness to use these tools, efforts to improve nursing care with smartphones, and strategies to integrate them into nursing services. The score of this questionnaire is calculated based on the average score of 3 items. Internal consistency was confirmed via the Cronbach α coefficient, combined reliability (CR), and average variance extracted (AVE) to assess discriminant and convergent validity. The Cronbach α coefficient was greater than 0.8. In this study, a 5-point Likert scale was used to rate each item, with each item receiving a score between 1 and 5.

Research Model

To gain a comprehensive understanding of the postimplementation phase of continued use of information systems (IS continuance), this study developed an ECM research model to explore the key factors that influence the continued use of mHealth in Iran. This model combines Bhattacharjee's ECM [20,21] and model development in other similar studies [13,26-31]. Considering that the relevant literature focuses mainly on the physician population and the need to adapt the factors to the priorities of Iran and the effective personal, organizational, technical, and social factors, the model was developed based on these criteria. This study acknowledges the perspective by Bhattacharjee [19], which offers a theoretical model of IS continuance that distinguishes between acceptance and continuation behaviors. This model draws parallels between people's IS continuance use decisions and their frequent purchase decisions using information and communication technology.

As seen in Figure 1, confirmation refers to the user's perception of the fit between the IS expectations and actual performance [13,28]. MA refers to the user's perception of the quality of the system and reflects the user's perceived level of satisfaction and the need to improve the system [13]. PU is the extent to which a person believes that his or her job performance will improve with a particular system [13,22]. MHC represents the user's intention to continue using technology tools [13]. EU is the extent to which a person intends to exert minimal physical and mental effort when using a particular system [29]. PS refers to the ability of a system to protect information from potential threats and to ensure protection from attacks that could compromise data and services [30]. AN refers to the fear of using new technologies [31]. SA is considered an important component of the use and success of an IS [18]. SI refers to the perceived social pressure that influences behavioral decisions [28]. Finally, HA is proposed as an important construct that influences the continuation or discontinuation of technology use [18].

Figure 1. Research model of the research, including the hypotheses (H) linking the constructs.



The hypotheses of this study are as follows:

- Hypothesis 1 states that confirmation is related to PU.
- Hypothesis 2 states that SI is related to PU.
- Hypothesis 3 states that AN is related to EU.
- Hypothesis 4 states that PU is related to MHC.
- Hypothesis 5 states that HA is related to MHC.
- Hypothesis 6 states that MA is related to MHC.
- Hypothesis 7 states that SI is related to MHC.
- Hypothesis 8 states that PS is related to MHC.
- Hypothesis 9 states that PU is related to SA.
- Hypothesis 10 states that confirmation is related to SA.
- Hypothesis 11 states that SA is related to MHC.
- Hypothesis 12 states that EU is related to PU.

Data Analysis

Data were analyzed using SPSS version 26 (IBM Corp) and AMOS version 24 (IBM Corp). Categorical variables are described as frequencies and percentages, whereas quantitative variables are summarized as the means and SDs. Correlations between variables were assessed using the Spearman-Brown correlation coefficient. SEM was used to examine the relationships between the variables influencing the continuous use of mHealth apps. In accordance with the theoretical model of the study, all variables were analyzed using AMOS software to understand the relationships between the variables, and a structural model was developed. In this study, the Pearson correlation coefficient (r) and regression (R^2) were used to

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determine the relationship with each research variable, with the significance level set at <.05. The structural model test was conducted using path coefficients and R^2 values. The R^2 values indicate the percentage of the variability of the internal variables that can be explained by the external variables, thus demonstrating the predictive power of the model. In addition, model fit criteria were examined, including the root mean square error of approximation (RMSEA), comparative fit index (CFI), Tucker-Lewis index (TLI), χ^2 divided by degrees of freedom (χ^2/df), incremental fit index (IFI), and goodness-of-fit index (GFI). Goodness of fit was indicated by critical values for χ^2/df (<3), CFI and TLI (≥0.9), RMSEA (<0.8), and GFI and IFI (≥0.90) [32,33].

Ethical Considerations

Ethical Statement

The research protocol was submitted to an independent ethics committee to ensure compliance with ethical standards. Any feedback from the committee was addressed prior to the commencement of data collection. All necessary approvals were obtained from the Research Council (number 039, dated 2022) and the Ethics Committee of Kashan University of Medical Sciences (code 40138). The necessary approvals were also obtained from the Vice-Chancellor for Research and Technology of Kashan University of Medical Sciences (IR.KAUMS.NUHEPM.REC.1401.039). This study was conducted in accordance with the principles outlined in the Declaration of Helsinki. We confirm that the research protocol was reviewed and approved by the Institutional Review Board at Kashan University of Medical Sciences.

Informed Consent

The clinical nurses provided consent to participate in the study after being informed about the purpose, procedures, potential risks, and benefits of the research; participation; right to withdraw at any time without penalty; and anonymity of the data collected.

Confidentiality

All data collected from participants were treated confidentially and anonymized. Personal identifiers were removed to ensure privacy, and data were stored securely, accessible only to the research team.

Results

Participant Characteristics

In this study, 400 clinical nurses were included, and data for 315 nurses were analyzed. The mean age of the nurses was 35.67 (SD 1.24) years. Most of the included nurses were female (252/315, 80%) and married (243/315, 77.1%; Table S1 in Multimedia Appendix 1).

Two-Step Path Analysis Approach

According to the questionnaire scores, MHC was rated as high. SA, PS, affirmation, HA, PU, and MA were all rated as average. In addition, EU, SI, and AN received low scores (Table 1). The Pearson correlation coefficient revealed significant correlations between the variables studied (Table 2). Two-step path analysis was used for the SEM. In the first step, reliability assessment and confirmatory factor analysis were performed. The internal consistency of the questionnaire was assessed using the Cronbach α, CR, and AVE and yielded values of 0.851, 0.892, and 0.63, respectively. These results indicate that the reliability of the questionnaire meets the acceptable thresholds for Cronbach α (>0.7), CR (>0.7), and AVE (>0.5). Therefore, the data were suitable for SEM and correlation analysis (Table 1).

Table . Means, SDs, reliabilities, and validities of the model variables.

Variables	Mean (SD)	Cronbach α	CR[a]	AVE[b]
Perceived ease of use	15.6 (4.4)	0.888	0.999	0.62
mHealth continuance	11.1 (2.2)	0.763	0.995	0.61
Maturity	9.6 (2.6)	0.908	0.981	0.61
Perceived usefulness	10 (2.2)	0.763	0.817	0.60
Habits	9.6 (2.8)	0.818	0.821	0.60
Social influence	21.5 (4.4)	0.875	0.791	0.52
New technology anxiety	13.3 (2.2)	0.878	0.991	0.63
Perceived security risk	9 (2.76)	0.901	0.922	0.75
Confirmation	9.6 (2.5)	0.861	0.872	0.75
User satisfaction	9.5 (2.5)	0.855	0.722	0.61

[a]CR: combined reliability.

[b]AVE: average variance extracted.

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Table . Correlation matrix of the model variables.

Variable	EU[a]	SI[b]	AN[c]	HA[d]	PS[e]	CO[f]	MA[g]	PU[h]	MHC[i]	SA[j]
EU										
r	1	0.306	0.699	0.692	0.803	0.737	0.738	0.654	0.323	0.744
P value	—[k]	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
SI										
r	0.306	1	0.370	0.374	0.362	0.370	0.347	0.443	0.633	0.334
P value	<.001	—	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
AN										
r	0.699	0.370	1	0.716	0.715	0.681	0.659	0.602	0.337	0.709
P value	<.001	<.001	—	<.001	<.001	<.001	<.001	<.001	<.001	<.001
HA										
r	0.692	0.374	0.716	1	0.681	0.660	0.641	0.569	0.360	0.643
P value	<.001	<.001	<.001	—	<.001	<.001	<.001	<.001	<.001	<.001
PS										
r	0.803	0.362	0.715	0.681	1	0.740	0.697	0.652	0.220	0.705
P value	<.001	<.001	<.001	<.001	—	<.001	<.001	<.001	<.001	<.001
CO										
r	0.737	0.370	0.681	0.660	0.740	1	0.821	0.741	0.444	0.860
P value	<.001	<.001	<.001	<.001	<.001	—	<.001	<.001	<.001	<.001
MA										
r	0.738	0.347	0.659	0.641	0.697	0.821	1	0.794	0.430	0.838
P value	<.001	<.001	<.001	<.001	<.001	<.001	—	<.001	<.001	<.001
PU										
r	0.654	0.443	0.602	0.569	0.652	0.741	0.794	1	0.546	0.781
P value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	—	<.001	<.001
MHC										
r	0.323	0.633	0.337	0.360	0.220	0.444	0.430	0.546	1	0.408
P value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	—	<.001
SA										
r	0.744	0.334	0.709	0.643	0.705	0.860	0.838	0.781	0.408	1
P value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	—

[a]EU: perceived ease of use.
[b]SI: social influence.
[c]AN: new technology anxiety.
[d]HA: habits.
[e]PS: perceived security risk.
[f]CO: confirmation.
[g]MA: maturity.
[h]PU: perceived usefulness.
[i]MHC: mHealth continuance.
[j]SA: user satisfaction.
[k]Not applicable.

A significance level ≤.05 was used to interpret and accept or reject the hypotheses. We concluded that all hypotheses, except hypotheses 4 and 6, were confirmed. Importantly, a positive path coefficient indicates that the change in the 2 variables is

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in the same and direct direction. Conversely, a negative standard path coefficient indicates that both variables change negatively and vice versa. In other words, when one variable increases, the other variable decreases, or when the independent variable increases, the dependent variable decreases (Table 3).

Table . Statistical assumptions related to the analysis of the measurement model.

Hypothesis	Path	Path coefficient		Critical value	*P* value
		Standard	Nonstandard		
1	PU[a] → CO[b]	0.895	0.852	13.9	<.001
2	PU → SI[c]	0.127	0.133	2.99	<.001
3	EU[d] → AN[e]	0.844	0.952	13.62	<.001
4	MHC[f] → PU	0.574	−0.543	1.4	.15
5	MHC → HA[g]	0.188	0.124	2.24	.002
6	MHC → MA[h]	−0.364	−0.276	−0.905	.37
7	MHC → SI	0.527	0.521	7.7	<.001
8	PS[i]→MHC	−0.234	−0.184	−2.66	.008
9	PU → SA[j]	15.283	5,666	2.697	.007
10	CO → SA	−15.527	5.738	−2.706	.007
11	SA → MHC	0.574	−0.543	1.4	.15
12	EU → PU	1.004	0.065	15.453	<.001

[a]PU: perceived usefulness.
[b]CO: confirmation.
[c]SI: social influence.
[d]EU: perceived ease of use.
[e]AN: new technology anxiety.
[f]MHC: mHealth continuance.
[g]HA: habits.
[h]MA: maturity
[i]PS: perceived security risk.
[j]SA: user satisfaction.

Structural Equation Modeling

In this study, the initial fit of the model was checked. The fit of the adjusted model was then assessed and validated (Table 4 and Figure 2).

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Table . Fit indices for the measurement model and structural model.

Fit indicators	Recommended value	Measurement model		Structural model	
		Before modification	After modification	Before modification	After modification
χ^2/df[a]	1 - 3	2.178	1.89	4.771	2.36
CFI[b]	≥0.90	0.925	0.944	0.744	0.910
GFI[c]	≥0.90	2.178	0.854	0.642	0.832
TLI[d]	≥0.90	0.914	0.935	0.724	0.900
IFI[e]	≥0.90	0.926	0.944	0.746	0.911
RMSEA[f]	<0.08	0.061	0.053	0.110	0.066

[a]χ^2/df: χ^2 divided by the degrees of freedom.

[b]CFI: comparative fit index.

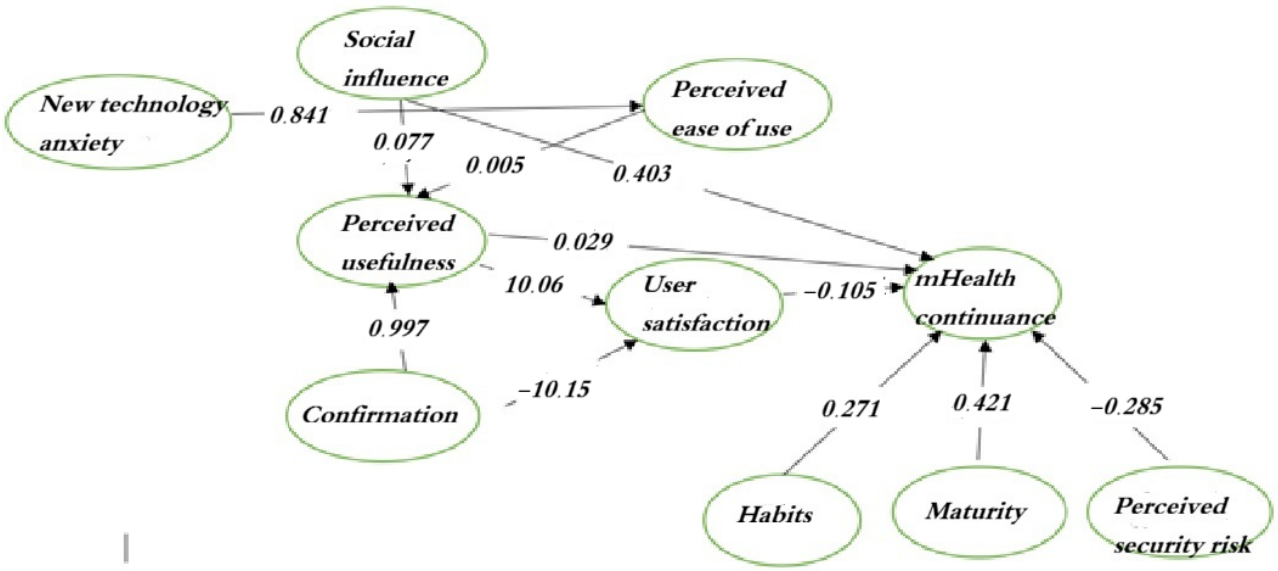
[c]GFI: goodness-of-fit index.

[d]TLI: Tucker-Lewis index.

[e]IFI: incremental fit index.

[f]RMSEA: root mean square error of approximation.

Figure 2. Structural model of the research.



Measurement Model

The measurement model consists of 33 items distributed across 10 variables: PS, AN, SI, EU, confirmation, MHC, MA, PU, HA, and SA. We used 6 model fit criteria to evaluate the overall fit of the model, including the RMSEA, CFI, TLI, χ^2 divided by degrees of freedom (χ^2/df), IFI, and GFI. The statistical results of the model fit are summarized in Table 4.

Structural Model

The results confirmed 6 hypotheses, including hypotheses 1, 2, 3, 5, 7, and 8. In contrast, hypotheses 4 and 6 did not reach statistical significance and were not supported by this study (Figure 1 and Table 4). EU was influenced by AN (P<.001). Furthermore, PU was influenced by confirmation, EU, and SI (P<.001). In addition, MHC was influenced by HA (P=.002), SI (P<.001), and PS (P=.008).

Discussion

Principal Findings

This study investigated the predictors of Iranian nurses' intention to continue using ECM-based mHealth apps in professional practice. The results showed that the use of mHealth services by nurses is optimal, with the majority expressing a willingness to use smartphones for health care services. Therefore, mHealth technology is an important tool for improving health care services. The results of this study show a positive influence of the model constructs on smartphone use. Further development of these constructs could improve technology acceptance in nursing [34].

The empirical results of the SEM confirmed the hypothesized model and showed significant relationships between affirmation and PU. Hsiao and Chen [13] defined the PU factor as the user's understanding of the expected health-related benefits. In

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addition, the results of the study by Lim et al [35] are consistent with the results of our study.

The results of this study show that nurses recognize the impact of mHealth tools on their professional performance. These tools were shown to facilitate data collection, documentation, and analysis of clinical patient data; increase productivity; improve care delivery; promote communication among nursing team members; and support family-centered care.

The SI factor was the second significant variable associated with the PU of mHealth tools. SI encompasses community preferences and values that can significantly influence user perceptions and attitudes. Importantly, technology acceptance is based not only on individual beliefs but also on SIs such as affiliation and perceived popularity [36].

In this study, nurses acknowledged the significant influence of upstream organizations, including the Ministry of Health, senior hospital managers, academics, nurses, and physicians, on recognizing the benefits of mHealth for the delivery of nursing care. The findings of this study support the assertion by Lwoga and Lwoga [27].

The study also found a significant relationship between AN and the EU factor. Sezgin et al [26] also confirmed a significant relationship between the AN and EU factors. Technology anxiety refers to consumers' fears when first encountering a new technology, as well as their willingness and ability to adapt to it. This anxiety can lead to reduced technology acceptance and ultimately hinder users' intention to use the technology [37].

The results of this study can be attributed to the fact that smartphone anxiety can negatively affect the EU factor. Apprehension, fear, and hesitation related to smartphone use can significantly affect EU. Given the busy and responsible nature of the nursing profession, it is understandable that there may be some hesitation due to the fear of making mistakes.

This study did not find a significant relationship between PU and MHC. In other words, the role of PU in influencing nurses' intention to continue using mHealth was interpreted differently than expected in the conceptual model of this study. Despite the importance of PU for nurses' intention to continue using mHealth, it did not have the expected impact. Previous studies have shown a significant correlation between these factors [38,39]. These different results may be due to different research areas, user characteristics, and system applications. Since this factor has been confirmed in other studies, it could be due to reasons such as differences in user demographics, contexts, or mHealth system design. Our focus on nurses in health care and the specific system's usability may explain the differing impact of PU on mHealth use continuation. Furthermore, users' technological proficiency could also influence their perception of usefulness.

The results of this study suggest a significant correlation between HA and mMHC factors. HA refers to the extent to which a person automatically uses mHealth apps. These findings are consistent with those of a 2019 study by Hsiao and Chen [13]. Individual habits are deeply ingrained behaviors that are triggered by situational cues, such as places, people, and past actions. These automatic behaviors are associated with 2 factors, namely (1) smartphone use and (2) the cues that trigger them [39].

The results of this study indicate that the MA factor pathway did not significantly influence MHC. This study proposes an MA model of mHealth through the ECM to provide a comprehensive understanding of the factors that influence people's acceptance of mHealth and how their use progresses from early to advanced stages. The results of the study by Hsiao and Chen [13] are inconsistent with those of our study. They suggested that the lack of nurses' approval may be due to poor quality and dissatisfaction with the technology, leading users to view the system as needing improvement. Studies have shown that poor graphical user interface design and inadequate process design of smartphone systems lead to preventable medical errors [13]. In addition, a lack of understanding of the user interface, user discomfort, and user perceptions of the poor quality of the smartphone system reduce the likelihood of use [13,40]. The development of high-quality user interface designs is critical for mobile learning apps because they can influence user acceptance and usage [41]. In this study, Iranian nurses or users may be in different circumstances than in the study by Hsiao and Chen [13], including differences in experience, technologies used, and even organizational culture, which could be influential because technology at different times and places shows different levels of maturity. In the study by Hsiao and Chen [13], existing apps may have been more developed and therefore more accepted, and this effect of the MA factor may have been noticed more by users.

This study revealed a significant relationship between SI and MHC factors. This finding is consistent with the findings of Chen et al [42]. The study suggests that people are more likely to adopt smartphones for professional use when they observe others doing so, suggesting that influential people play an important role in the perception of new technologies.

The results of this study did not confirm the significant influence of PS on nurses' MHC. PS refers to the user's belief in the safety of the technology [43]. A study by Weichbroth and Łysik [44] revealed that smartphone users are increasingly vulnerable to malicious activities, especially when malware apps are installed on their devices, such as smartphones and tablets. These devices store and protect sensitive information, which serve as a deterrent to their use. These results are consistent with the findings of Natarajan et al [45].

This study did not find a significant influence of PU on SA.

The study by Hsiao and Chen [13] demonstrated a significant relationship between PU and SA. However, Denovan and Marsasi [46] showed that PU positively affects satisfaction and negatively affects attitude. EU is key to satisfaction, as it reflects users' beliefs that a technology or system will be effortless to use. The study by Nuralam et al [47] indicated that PU significantly influences customer satisfaction, though not directly. In addition, Denovan and Marsasi [46] indicated that PU has a significant positive effect on satisfaction and a significant negative effect on attitude.

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This study did not find a significant relationship between confirmation and SA. A significant relationship between approval and SA was confirmed in a related study [13]. This difference can be explained by the measurement tools used and the technology's cultural context.

This study did not find a significant relationship between SA and the continued use of mHealth. In other words, the impact of SA on nurses' intentions to keep using mHealth was interpreted differently than anticipated in the conceptual model of this study. The study by Hsiao and Chen [13] demonstrated a significant relationship between SA and continued usage. This difference may stem from variations in user type (clinical nurses in this study) and app type. Birkmeyer et al [48] and Nie et al [49] also found a correlation between SA and continued use.

This study confirms the significant influence of confirmation on PU. The results of a study in this regard confirmed the existence of a relationship between factor endorsement and PU, essentially confirming the hypothesis of our study [13].

The results of the study by Daneji and colleagues [50] regarding the effects of PU, endorsement, and satisfaction on the intention to continue using massive open online courses also confirmed the relationship between the 2 factors of endorsement and PU.

This study identified factors influencing nurses' work-related smartphone use but has limitations. Specifically, incorporating a qualitative component would have broadened the range of identified factors. Qualitative research, known to enhance quantitative findings, could have provided deeper insights and a more comprehensive understanding [51].

Due to the COVID-19 pandemic and nurses' heavy workloads, this study lacked the time and resources for interviews and other qualitative data collection. Furthermore, the study's location in Kashan limits the generalizability of findings to other cities or countries. Cultural, structural, and environmental variations, including differences in working conditions, technology access, training, and customs, influence nurses' smartphone usage and could lead to different outcomes elsewhere.

To overcome these limitations, future research should prioritize national and transnational validation of the NMHDA-Scale. Furthermore, future studies could explore additional influential factors not examined here.

Strengths and Limitations

This study's strength is that, although many studies have used mHealth measurement tools across various groups, none have used a tool specifically designed and psychometrically validated for nurses. Our study addresses this gap by using a tool designed and psychometrically validated for Iranian nurses.

This study also had some limitations, such as limiting the review to English-language studies, excluding research in other languages.

This study recommends actions across 5 dimensions: management and structure, process, technical, staff, and skills. In management and structure, recommendations include formulating mobile app deployment policies for the health sector, creating supportive policies for nurses, aligning policies at the Ministry of Health level, defining program values and goals early, promoting culture building, and establishing confidentiality and security policies. Process recommendations focus on clarifying tool usage and monitoring procedures. Technically, the study advises formulating security and confidentiality programs, policies, and standards, as well as evaluation and monitoring standards. Regarding staff and skills, recommendations encompass conducting educational needs and feasibility assessments, reviewing and formulating educational topics, identifying effective tools and solutions, and addressing nurses' concerns related to anxiety and security. To effectively address these recommendations, a dedicated committee with relevant expertise should be established within the ministry to conduct investigations and make informed decisions.

Conclusion

Nurses make up a large percentage of hospital staff. Hospitals face potential financial and nonfinancial risks if nurses do not adopt new technologies in their daily work. Since the clinical care of patients depends on the professional skills and experience of nurses, mHealth tools can improve timely access to medical resources for medical staff. As a result, nurses can improve the quality of patient care and streamline their workflow. The results of this study provide valuable insights into the factors that influence nurses' use of smartphones in their professional roles. In addition, the study sheds light on the challenges and opportunities nurses face when using smartphones. Managers of health care organizations who want to encourage continued smartphone use must fully understand the reasons behind this behavior. Therefore, a better understanding of nurses' perceptions of smartphone use is needed to develop new implementation strategies. These strategies should reveal users' attitudes toward smartphones and thus help developers and system administrators improve them and promote their sustainable use.

This study is a useful tool for hospital managers who need to assess the likelihood of success of a new technology. It also helps nurses understand the benefits of use. It focuses on PU, EU, AN, PS, SA, HA, MA, SI, and endorsement. Overall, the results of this study suggest that nurses' intention to continue using smartphones can only be increased if attention is paid to characteristics related to the maturity of the technology and the user's perception of its usefulness.

Acknowledgments

This project was financially supported by the Deputy for Research and Technology, Kashan University of Medical Sciences (KAUMS), Kashan, Iran (grant number 4,01,038). The article processing charge was funded through the Open Access Fund of Neu-Ulm University of Applied Sciences (HNU).

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Conflicts of Interest

None declared.

Multimedia Appendix 1
Demographic characteristics of the sample (n=315).
[DOCX File, 17 KB - nursing_v8i1e68048_app1.docx]

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Abbreviations

AN: new technology anxiety
AVE: average variance extracted
CFI: comparative fit index
CR: combined reliability
ECM: expectation-confirmation model
EU: perceived ease of use
GFI: goodness-of-fit index
IFI: incremental fit index
IS: information systems
MHC: mHealth continuance
mHealth: mobile health
NMHDA-Scale: Nurses' Mobile Health Device Acceptance Scale
PS: perceived security risk
PU: perceived usefulness
RMSEA: root mean square error of approximation
SA: user satisfaction
SEM: structural equation modeling
SI: social influence
TLI: Tucker-Lewis index

Edited by E Borycki; submitted 27.10.24; peer-reviewed by N Trakulmaykee, S Sengoku; revised version received 28.05.25; accepted 28.06.25; published 31.10.25.

Please cite as:
Mirabootalebi N, Holl F, Meidani Z, Rangraz Jeddi F, Tagharrobi Z, Akbari H, Swoboda W
Determinants of Nurses' Continuance Intention to Use Mobile Health Apps in Clinical Nursing Practice: Structural Equation Modeling to Extend the Expectation-Confirmation Model
JMIR Nursing 2025;8:e68048
URL: https://nursing.jmir.org/2025/1/e68048
doi:10.2196/68048

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Fear of Missing Out, Social Media Addiction, and Personality Traits Among Nursing Students: Cross-Sectional Study

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Abstract

Background: The growing use of social media has created concerns about addiction, and thus, it is necessary to explore how personality traits and fear of missing out (FOMO) can be utilized to predict social media addiction (SMA).

Objectives: The purpose of this study was to investigate the connection between personality traits, FOMO, and SMA in university students in Saudi Arabia.

Methods: In this cross-sectional study, data were collected from nursing students using the shortened version of the big five inventory, fear of missing out scale, and SMA scale from May to September 2024.

Results: The study achieved a response rate of 66.7% (414/620), finally including a total of 411 participants. The majority of participants (247/411, 60.1%) had low FOMO scores, while SMA scores showed a different pattern, with a larger proportion (261/411, 63.5%) of participants scoring in the moderate range. In terms of gender differences, male participants exhibited higher levels of FOMO (t=3.86, P<.001) and SMA (t=2.51, P=.013) compared to female participants. Additionally, male participants scored higher in neuroticism (t=3.30, P=.001) and openness (t=1.98, P=.048). Regression analysis revealed that both conscientiousness (β=.357, P<.01) and FOMO (β=.213, P<.01) positively predicted SMA, while neuroticism (β=−.223, P<.01) and being female (β=-.098, P<.05) were associated with lower levels of addiction. The resulting model accounted for 35.8% of the variance.

Conclusions: The study provides evidence that conscientiousness and FOMO are positive predictors of SMA, while neuroticism is negatively correlated with it. Moreover, male participants exhibited higher levels of both FOMO and SMA in comparison to female participants. These findings emphasize the impact of personality traits and FOMO on SMA among university students.

(JMIR Nursing 2025;8:e71502) doi:10.2196/71502

KEYWORDS

social media; personality; fear, neuroticism; conscientiousness; students; nursing

Introduction

The proliferation of social media has revolutionized the way people connect and consume information. Yet, alongside the advantages of social media, several issues have been raised concerning its potential negative effects on a person's well-being [1]. Social media addiction (SMA), also described as problematic social media use, is exemplified by extreme and compulsive usage of social media that negatively impacts an individual's life. Like other forms of behavioral addictions, SMA enmeshes a loss of control over one's usage, social media activities preoccupation, and continued engagement despite adverse outcomes. Numerous studies have investigated the determinants and outcomes of SMA [2-5]. Factors such as personality traits, social influences, and fulfillment of psychological needs have been implicated in the development and maintenance of SMA [2,3]. Moreover, SMA has been associated with a range of negative outcomes, including impaired academic performance, diminished real-life social relationships, and increased risk of mental health problems such as depression and anxiety [4,5].

Fear of missing out (FOMO) refers to the apprehension or anxiety individuals experience when they believe that others are engaging in enjoyable activities or experiences from which they are excluded [6,7]. Research indicates that people with elevated FOMO have a high probability of engaging in excessive social media use, experience higher levels of stress and anxiety, and report lower levels of life satisfaction and well-being [7,8]. Additionally, FOMO has been linked to problematic behaviors such as compulsive smartphone checking, which can further exacerbate feelings of anxiety and dissatisfaction [9].

Personality traits have a considerable role in individuals' susceptibility to FOMO and SMA. Research has identified several personality traits that may contribute to these phenomena [7]. For example, individuals high in neuroticism, considered

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by tendencies toward anxiety and other negative emotions, may be more prone to experiencing FOMO and engaging in excessive social media use as a means of stress-coping strategy [7,9]. Similarly, individuals with high levels of extraversion may also be at increased risk of developing problematic patterns of social media use, as they may seek social validation and affirmation through online interactions [3]. The interplay between FOMO, SMA, and personality traits is complex and multifaceted. Personality traits may influence individuals' susceptibility to FOMO and SMA, while these phenomena, in turn, may exacerbate underlying personality vulnerabilities. For instance, people high in neuroticism may be particularly susceptible to developing SMA as a means of alleviating feelings of anxiety and insecurity correlated with FOMO [9]. Few studies focus on personality types and their relation to FOMO [7,10]. Research suggests that neuroticism is positively correlated with FOMO, as people with higher levels of neuroticism have a high probability of experiencing fear, insecurity, and anxiety related to missing out on rewarding experiences [7]. While extraversion is typically associated with sociability and outgoing behavior, it can also be linked to FOMO, particularly in the context of social comparison and the desire for social validation. Extraverted individuals may be more likely to engage in social media use in order to stay connected with others and seek external validation, leading to higher levels of FOMO [10].

Openness to experience reflects individuals' receptivity to new ideas, experiences, and perspectives. While research on the relationship between openness and FOMO is limited, some studies suggest that individuals high in openness may be more motivated to seek out novel experiences and social interactions, potentially increasing their susceptibility to FOMO [11]. Conscientiousness is characterized by self-discipline, organization, and goal-directed behavior. Although less studied than other personality traits, conscientiousness may play a role in individuals' susceptibility to FOMO, particularly concerning academic and professional goals. High levels of conscientiousness may lead individuals to prioritize staying informed and connected with others, contributing to higher levels of FOMO [10]. Furthermore, research suggests that individuals may use social media as a means of seeking validation and approval from others, leading to heightened feelings of anxiety and insecurity related to missing out on social experiences [11].

The negative consequences of SMA and FOMO on the mental and physical health of university students were reported; studies have shown that the extreme use of social media is linked with symptoms of depression and poor physical activity, exacerbating mental illness [12]. Moreover, SMA has been associated with body image problems, because students compare themselves to unrealistic standards, which results in body dissatisfaction, and therefore, irrational attitudes [13,14]. SMA additionally warps weight perception, which is concerning for the reason that it affects students' lifestyle [15]. Furthermore, continuous exposure to social media may impact health behaviors, for instance, eating habits, which can lead to negative health effects [16]. Thus, the interaction of SMA and FOMO among university students may destroy physical and psychological well-being.

Therefore, it is significant to explore SMA, FOMO, and personality traits among university students, as social media usage is progressively becoming more widespread and might negatively affect mental health, academic performance, and well-being. University students, as they are under the stress of academic and social comparison, are more vulnerable to social media impacts. Understanding how personality influences social media use can help identify students at risk of addiction and the ensuing mental challenges. It is vital to conduct this research to recommend interventions that promote healthier digital habits and improve students' overall well-being. Moreover, among nursing students in Saudi Arabia, little is known about the FOMO and SMA. Thus, this study aims to explore nursing students' personality traits and their relation to the FOMO and SMA in the era of rapid technology.

Methods

Site, Setting, and Design

A cross-sectional study was conducted at the College of Nursing, Imam Abdulrahman Bin Faisal University, located in the Eastern Province of Saudi Arabia, from May to September 2024.

Sampling

The target population for this study comprised students enrolled in the College of Nursing. The inclusion criteria consisted of nursing students from the first to the fifth year. Students who had postponed their courses or withdrawn from the nursing college were excluded. A convenience sampling method was employed due to practical constraints, including limited access to a comprehensive student list and time restrictions. Given that the study aimed to explore associations rather than generalize findings to the entire population, nonprobability sampling was deemed appropriate. While probabilistic sampling enhances generalizability, its implementation was not feasible within the context of this research. The sample size was calculated based on the Raosoft calculator [17], based on the total population of 1129 people, 95% confidence level, and 5% margin. The sample of 287 nursing students was considered representative. Although the calculated sample size was 287, a total of 411 students responded to the survey, and all responses were valid.

Students were contacted via their university email by the registration office. A research pack was sent, which included an information sheet with detailed study information, along with a web-link and barcode to access the study questionnaires. A follow-up email was sent 2 weeks later to remind students to complete the questionnaires. The questionnaires took approximately 30 - 45 minutes to complete.

Study Tools

Fear of Missing Out

The FOMO scale [7] is a self-report instrument designed to measure individuals' tendencies to experience FOMO on rewarding experiences. The questionnaire consists of 10 items, each assessing different aspects of FOMO. Respondents rate their agreement with each item on a scale, typically ranging from 1 (strongly disagree) to 7 (strongly agree). Example items include "I fear others have more rewarding experiences than

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me" and "I fear my friends have more rewarding experiences than me." The Cronbach α coefficient for the FOMO scale has been reported to be around .85, indicating high internal consistency among its items. The scale validity and reliability were measured and confirmed to be appropriate for use in Arabic culture [18]. For this study, the Cronbach α coefficient for the FOMO construct was calculated to be 0.757, while the McDonald ω coefficient was determined to be 0.744.

Personality Traits

The big five personality traits were assessed using a shortened version of the big five inventory, consisting of 44 Likert-scale items. Participants rated their agreement on a scale from 1 (strongly disagree) to 5 (strongly agree). This inventory encompasses five subscales: conscientiousness, extraversion, agreeableness, openness, and neuroticism [19]. Example items include "I see myself as someone who is talkative," "I see myself as someone who tends to find fault with others," and "I see myself as someone who does a thorough job." Validity and reliability assessments for the Arabic version were conducted, revealing Cronbach α coefficients ranging from 0.84 to 0.68 across the subscales [20]. The Cronbach α for the totality of personality traits was calculated to be 0.704, while the McDonald ω was determined to be 0.653.

In addition, the students' sociodemographic data were collected using a form developed by the researchers, which included information such as age, gender, and marital status.

SMA

The social media addiction scale [18] was employed to assess social media usage. This scale, derived from the internet addiction test [21], comprised 14 items tailored to gauge SMA specifically. Respondents rated these items on a 5-point Likert scale, ranging from strongly agree to strongly disagree, with corresponding scores of 5 to 1. Example items include "I often find myself using social media longer than intended" and "I often find life to be boring without social media." The validity and reliability of the social media addiction scale were examined and proven appropriate for use in Arabic culture [18]. The Cronbach α coefficient for the SMA was 0.837, while the McDonald ω coefficient was 0.841.

Ethical Considerations

The study received ethical approval from the Institutional Review Board (IRB) at Imam Abdulrahman Bin Faisal University, under approval number IRB-2024–04-475. The IRB endorsed the study procedures and surveys prior to the initiation of participant recruitment. The participants consisted of nursing students from the College of Nursing at Imam Abdulrahman Bin Faisal University. Prior to participation, students were provided with a comprehensive information sheet that outlined the voluntary nature of the study, as well as their right to withdraw at any time without compromising their academic standing or rights. Participants received a detailed explanation of the study, including its associated risks and benefits. They were assured that their confidentiality and privacy would be upheld in accordance with the study's established guidelines. The information sheet also delineated the research objectives, significance, and potential benefits of the study. Informed consent was obtained from all study participants.

Data Analysis

Data were collected and analyzed utilizing SPSS (version 22; IBM Corp) and Microsoft Excel. Categorical variables were assessed through frequencies and percentages, whereas continuous variables were described using means and standard deviations. The reliability of the scales was evaluated using Cronbach α coefficients. Differences between groups and relationships among variables were analyzed employing *t* tests. Correlation analysis was conducted to examine relationships between various variables. To predict SMA scores, a multiple stepwise regression analysis was conducted, incorporating demographic variables and personality traits, specifically extraversion, agreeableness, conscientiousness, and neuroticism, alongside the FOMO. A *P* value of less than .05 was deemed statistically significant.

Data cleaning and screening were performed utilizing SPSS and Microsoft Excel. The response rate yielded a 66.7% rate of participation, with a total of 414 individuals involved in the study. One participant was eliminated due to zero variance, indicating a lack of engagement, while 2 participants were excluded as outliers based on Mahalanobis distance [22]. The individual personality trait α values were as follows: 0.640 for extraversion, 0.646 for agreeableness, 0.735 for conscientiousness, 0.819 for neuroticism, and 0.614 for openness. Reverse coding was applied where necessary. Both FOMO and SMA scales were categorized into three levels based on the calculated interval of (5 - 1)/3=1.33 [23]. The ranges were delineated as follows: a low score was defined as falling between 1 and 2.33, a moderate score was classified as ranging from 2.34 to 3.67, and a high score was indicated as any value exceeding 3.67.

Results

Table 1 presents the demographic characteristics of the 411 study participants. A significant majority of the participants were female participants (302/411, 73.5%), with a predominant proportion identifying as single (395/411, 96.1%). The age distribution was relatively balanced, with 201/411 (48.9%) participants under the age of 20 years and 210/411 (51.1%) aged 20 or older. Regarding academic standing, 194/411 (47.2%) were first-year students, while 217/411 (52.8%) were enrolled in other academic years

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Table . Characteristics of participants (N=411).

Variable	n (%)
Gender	
Male	109 (26.5)
Female	302 (73.5)
Marital status	
Single	395 (96.1)
Married	16 (3.9)
Age (years)	
<20	201 (48.9)
≥20	210 (51.1)
Education level	
1st year	194 (47.2)
Other years	217 (52.8)

Table 2 presents the distribution of FOMO and SMA scores among participants. The findings indicate that a majority of participants (247/411, 60.1%) exhibited low FOMO scores, while 155/411 (37.7%) fell within the moderate range, and only 9/411 (2.2%) attained high scores. This distribution reflects an overall lower prevalence of FOMO. In contrast, the analysis of SMA scores reveals that 124/411 (30.2%) of participants scored low, 261/411 (63.5%) were categorized within the moderate range, and 26/411 (6.3%) achieved high scores. These results suggest that, although most participants displayed low to moderate levels of FOMO, a notable prevalence of SMA was observed, with a significant proportion reporting moderate to high levels of addiction. Additionally, participants exhibited moderate levels of extraversion, neuroticism, conscientiousness, and openness, while agreeableness recorded the lowest scores.

Table . Distribution of FOMO,[a] SMA,[b] and personality traits scores by frequency and percentage.

Variable	Value
FOMO, n (%)	
Low (≤2.33)	247 (60.1)
Moderate (2.34 - 3.67)	155 (37.7)
High (≥3.68)	9 (2.2)
SMA, n (%)	
Low (≤2.33)	124 (30.2)
Moderate (2.34 - 3.67)	261 (63.5)
High (≥3.68)	26 (6.3)
Personality traits, mean (SD)	
Extraversion	3.1 (0.5)
Agreeableness	2.0 (0.5)
Conscientiousness	2.8 (0.6)
Neuroticism	3.1 (0.8)
Openness	2.6 (0.5)

[a]FOMO: fear of missing out.

[b]SMA: social media addiction.

The analysis demonstrates substantial gender disparities in both FOMO and SMA. Male participants exhibited elevated levels of FOMO (mean 2.43, SD 0.61) in comparison to female participants (mean 2.16, SD 0.63), with a t statistic of 3.86 (P<.001). Likewise, males reported higher levels of SMA (mean 2.82, SD 0.62) than their female counterparts (mean 2.64, SD 0.65), with a t value of 2.51 (P=.013). Nevertheless, the analysis did not identify any significant differences in FOMO or SMA as a function of age or educational attainment (Table 3).

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Table . Group differences in fear of missing out and social media addiction by demographic variables.

Variables	FOMO			SMA		
	Mean (SD)	*t* test (*df*)[a]	*P* value	Mean (SD)	*t* test (*df*)[a]	*P* value
Gender		3.86 (409)	<.001		2.51 (409)	.013
Male	2.43 (0.61)			2.82 (0.62)		
Female	2.16 (0.63)			2.64 (0.65)		
Age (years)		−1.53 (409)	.128		−1.30 (409)	.193
<20	2.18 (0.63)			2.64 (0.63)		
≥20	2.28 (0.64)			2.73 (0.65)		
Education level		−0.93 (409)	.351		−0.24 (409)	.810
1st year	2.20 (0.62)			2.68 (0.63)		
Other years	2.26 (0.65)			2.69 (0.66)		

[a]Two-tailed

Table 4 delineates notable gender differences in specific personality traits. Male participants exhibited significantly higher scores than female participants in both neuroticism and openness. These findings indicate that gender may influence the development of certain personality dimensions among nursing students. Additionally, no significant differences were detected across age groups or educational levels with regard to any of the assessed personality traits.

Table . Group differences in personality traits by gender, marital status, age, and education level.

Variables or categories		Gender		Age (years)		Education level	
		Male	Female	<20	≥20	1st year	Other years
Extraversion	Mean (SD)	3.12 (0.46)	3.06 (0.47)	3.06 (0.47)	3.08 (0.47)	3.05 (0.47)	3.09 (0.47)
	t test (*df*)[a]	1.23 (409)		−0.45 (409)		−0.84 (409)	
	P value	.22		.656		.401	
Agreeableness	Mean (SD)	2.04 (0.47)	1.98 (0.47)	2.02 (0.49)	1.97 (0.44)	2.01 (0.49)	1.99 (0.45)
	t test (*df*)[a]	1.06 (409)		1.13 (409)		0.39 (409)	
	P value	.29		.26		.696	
Conscientious-ness	Mean (SD)	2.8 (0.47)	2.73 (0.57)	2.77 (0.56)	2.73 (0.54)	2.79 (0.57)	2.72 (0.53)
	t test (*df*)	1.2 *(409)*		0.85 *(409)*		1.22 *(409)*	
	P value	.232		.397		.224	
Neuroticism	Mean (SD)	3.25 (0.68)	2.98 (0.76)	2.99 (0.74)	3.11 (0.75)	2.98 (0.76)	3.11 (0.73)
	t test (*df*)	3.3 *(409)*		−1.57 *(409)*		−1.66 *(409)*	
	P value	.001		.111		.098	
Openness	Mean (SD)	2.67 (0.48)	2.56 (0.51)	2.59 (0.50)	2.58 (0.51)	2.58 (0.51)	2.6 (0.50)
	t test (*df*)	1.98 *(409)*		0.12 *(409)*		−0.39 *(409)*	
	P value	.048		.908		.696	

[a]Two tailed

Table 5 revealed the correlations among FOMO, SMA, and various personality traits. FOMO exhibited a positive correlation with conscientiousness, agreeableness, and SMA, suggesting that individuals displaying elevated levels of FOMO tend to be more conscientious, agreeable, and report increased social media usage. Conversely, FOMO demonstrated a negative correlation with neuroticism. SMA displayed positive correlations with conscientiousness, agreeableness, openness, and extraversion, indicating that these personality traits are associated with heightened levels of SMA. In contrast, neuroticism was negatively correlated with SMA, suggesting that individuals with higher levels of neuroticism reported diminished addiction to social media.

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Table . Correlation analysis between fear of missing out, social media addiction, and personality traits.

Variables	Statistical test	Extraversion	Agreeableness	Conscientious-ness	Neuroticism	Openness	SMA
FOMO	*r*[a]	−0.076	0.137	0.261	−0.237	0.077	0.378
	P value	.122	.005	<.001	<.001	.117	<.001
SMA	*r*	0.116	0.308	0.500	−0.389	0.160	1
	P value	.018	<.001	<.001	<.001	<.001	_[b]

[a]r: Pearson Correlation

[b]not applicable

Table 6 demonstrates that the regression model significantly predicts SMA, accounting for 35.8% of its variance (R^2=0.358, *P*<.001). Conscientiousness and FOMO emerged as robust positive predictors, whereas neuroticism and female gender were correlated with lower levels of addiction. Notably, conscientiousness exhibited the most substantial effect among all predictors.

Table . Multiple stepwise regression analysis[a] of predictors of social media addiction.

Predictor	B	SE B	β	*t* test *(df)*[b]	*P* value	95% CI for B
Constant	1.738	0.249	—	6.977 (4, 406)	<.001	1.248 to 2.227
Conscientiousness	0.421	0.051	.357	8.176 (4, 406)	<.001	0.320 to 0.522
Fear of missing out	0.217	0.043	.213	4.996 (4, 406)	<.001	0.131 to 0.302
Neuroticism	−0.193	0.038	−.223	−5.022 (4, 406)	<.001	−0.268 to −0.117
Gender (female)	−0.143	0.061	−.098	−2.349 (4, 406)	.019	−0.262 to −0.023

[a]model summary: R^2=0.358, Adjusted R^2=0.352, F (4, 410)=56.622, *P*<.001

[b]Two tailed

Discussion

Principal Findings and Comparison With Previous Works

The purpose of this study was to investigate the connection between personality traits, FOMO, and SMA in university students, with a specific focus on identifying the main predictors of SMA. The majority of participants had low FOMO scores, whereas SMA scores followed a different pattern, with a larger proportion of participants scoring in the moderate range. In terms of gender differences, male participants exhibited higher levels of both FOMO and SMA compared to female participants. Additionally, male participants scored higher in neuroticism and openness. Regression analysis revealed that both conscientiousness and FOMO positively predicted SMA, while neuroticism and being female were associated with lower levels of addiction.

The results of this study reveal considerable divergence between nursing students' SMA and FOMO scores. Although most nursing students had low FOMO scores, implying that they do not excessively worry about missing out on things online, more participants had moderate SMA scores. This mirrors findings in other countries. For instance, Turkish nursing students reported moderate degrees of SMA, with lower degrees of FOMO [24]. Another Turkish study did not find a significant correlation between the use of smartphones, FOMO, and care behavior, which implies that FOMO may not always be highly associated with SMA among nursing students [25]. In contrast, in China [26] and in Egypt [27], FOMO was significantly linked to increased SMA, especially among university students, opposite to the present findings. The study's results can be explained by Saudi cultural norms prioritizing close family and face-to-face interactions, which reduce the emotional impact of FOMO [28]. However, students still engage in social media due to habits, stress relief, and peer pressure, leading to moderate addiction scores [29]. Social media usage is part of life in Saudi Arabia, and though students may not experience extreme FOMO, they may still be affected by the flow of information and social interaction that sites provide. Therefore, future studies are highly recommended to explore the link between FOMO and SMA among nursing students in different cultures.

Additionally, the study reveals gender differences, with male participants exhibiting higher levels of both FOMO and SMA compared to female participants. A previous study has also confirmed a positive correlation between FOMO and SMA. For example, Brailovskaia et al [30] found that, among 745 social media users in Germany, male participants exhibited higher FOMO and addiction, attributing this to their greater need for social validation. However, Kargın et al [28] found no significant gender differences in FOMO and internet addiction among Turkish nursing students, while Li et al [31] reported similar FOMO levels in both sexes in China among university students. These differences could be attributed to cultural and contextual factors, as in Saudi Arabia, where men may experience more pressure to maintain a social image, potentially explaining their higher FOMO and addiction scores compared to women.

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Furthermore, the study's findings indicate that male participants scored higher in neuroticism and openness. Neuroticism is exemplified by emotional instability and heightened sensitivity to stress and, therefore, anxiety. Young male participants, in particular, may have stronger emotional responses to social media use. These emotional responses may lead them to seek validation or manage negative emotions through social media, which can lead to addiction. The positive relationship between neuroticism and SMA was reported [32,33]. A study by Tekin and Turhan [32] found that individuals with high neuroticism are more likely to experience negative emotions on social media, contributing to compulsive use driven by envy and jealousy. Their tendency to overanalyze and engage in social comparison further increases the desire for social media use, raising the risk of addiction. Additionally, male participants with high openness are more inclined to explore new experiences and engage with dynamic content on social media, driven by curiosity and a desire for trends and self-expression [3]. This ongoing engagement can contribute to addiction-like behavior. Therefore, further research about gender and personality traits is encouraged.

Regression analysis revealed that both conscientiousness and FOMO positively predicted SMA, while neuroticism and being female were associated with lower levels of addiction. This finding is inconsistent with a meta-analysis study by Rajesh and Bangaiah [34], which found a negative relation between conscientiousness and Facebook addiction. Furthermore, among university students in Mexico, while SMA is positively associated with neuroticism, it is negatively associated with conscientiousness [35]. Additionally, conscientiousness, openness to experience, and agreeableness were identified as negative predictors of Facebook addiction among Turkish university students [36]. Moreover, a meta-analysis found that neuroticism was positively associated with internet addiction, while openness, agreeableness, extraversion, and conscientiousness were negatively associated [37]. However, in the United States, among 337 college students, none of the personality traits were found to have a relationship with addiction on Facebook, Instagram, and Snapchat [38]. The current study result can be explained by that conscientious nursing students would use social media to stay organized or updated and thus use it more regularly, while FOMO makes people stay connected and not miss social life, thus increasing addiction vulnerability. Nevertheless, neurotic nursing students would experience negative feelings through the use of social media, and hence reduce their use and weaken their addiction. The lower addiction rates among female participants could reflect more balanced and responsible use, potentially due to different usage patterns or social norms.

Based on the results of this study, there is a vital implication for nursing practice that needs to be considered. Students should be directed to various social, artistic, and sporting activities that aim to support the use of the internet for the benefit of students, provide effective training in social communication and internet awareness, and reduce excessive time spent in social media environments. Psychiatric nurses working in units where primary health care services are provided are known to have an important role in combating addiction, and are also in a key position in the training that will be provided to students in this area. More research should be conducted to identify factors associated with the severity of FOMO.

Likewise, nursing practitioners and educators should be aware of the degree to which social media use is driven by personality traits and how such use impacts mental health. Low conscientiousness or high neuroticism may predispose students to increase SMA as they seek incentives or prevent adverse effects. Being aware of these tendencies may allow nursing educators to provide better care for vulnerable students. Interventions may include integrating digital well-being into nursing education, teaching students how to balance social media use, and promoting healthy coping strategies for managing FOMO. By addressing these issues, nursing schools can not only improve the overall well-being of their students but also equip future healthcare professionals with the skills they need to manage their mental well-being and be an example to patients they will interact with.

Limitations

Several limitations should be acknowledged. First, the data were collected using self-reported questions, which may introduce bias. Second, the responses are subject to recall bias. Additionally, the study measured SMA at a specific point in time, without considering other temporal factors that might influence social media use. Furthermore, the use of a convenience sampling technique may limit the diversity of the sample. Finally, data were gathered only from a nursing college at one university, which may limit the generalizability of the findings.

Conclusion

This study aimed to explore the relationship between personality traits, FOMO, and SMA among Saudi nursing university students. The results indicate that conscientiousness and FOMO are positive predictors of SMA, while neuroticism is negatively associated. Furthermore, male participants tend to have higher levels of both FOMO and SMA than female participants. These findings highlight the influence of personality traits and FOMO on SMA in university students. Thus, strategies that help nursing students in getting the optimum benefits from social media need to be examined and implemented.

Data Availability

The data are available from the corresponding author upon request.

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Conflicts of Interest

None declared.

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Abbreviations

FOMO: fear of missing out
SMA: social media addiction

Edited by T Risling; submitted 20.01.25; peer-reviewed by GS Mendoza-Catalan, N Pavlovic, O Cohen; revised version received 09.04.25; accepted 16.04.25; published 29.05.25.

Please cite as:
Alshowkan A, Shdaifat E
Fear of Missing Out, Social Media Addiction, and Personality Traits Among Nursing Students: Cross-Sectional Study
JMIR Nursing 2025;8:e71502
URL: https://nursing.jmir.org/2025/1/e71502
doi:10.2196/71502

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First Contact With Care Through Clinical Simulation in Nursing Students: Qualitative Study

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Abstract

Background: Clinical simulation with standardized patients provides nursing students with their first approach to care in a safe and realistic environment. This type of experience arouses intense emotions and supports the development of key competencies.

Objective: This study aimed to explore the perceptions of nursing students during their first contact with care through simulation experiences with standardized patients.

Methods: We conducted a qualitative descriptive phenomenological study using focus groups and reflective narratives with a sample of 59 students. A thematic analysis was performed using ATLAS.ti (version 24; Scientific Software Development GmbH).

Results: Three thematic blocks, along with their categories and subcategories, were identified: (T1) first contact with simulation, (T2) learning and competencies, and (T3) preparation for clinical practice.

Conclusions: Clinical simulation has a profound impact on nursing education by offering a safe and realistic environment in which to learn from experience. Emotions, teamwork, and human interaction enrich learning and strengthen professional identity. This approach supports the integration of technical knowledge and relational skills. The results support the inclusion of active and humanized methodologies in training plans.

(JMIR Nursing 2025;8:e81617) doi:10.2196/81617

KEYWORDS

clinical simulation; professional identity; experiential learning; standardized patients; nursing education

Introduction

Background

The education of future nursing professionals requires a progressive, safe, and meaningful approach to the clinical environment. During the first years of the degree, students face the challenge of transforming theoretical knowledge into practical skills that enable them to provide effective and humanized care [1,2]. This transition process, especially in its initial stages, may generate uncertainty, anxiety, and doubts regarding their own competence and professional role [3]. Before their first entry into real clinical scenarios, students must have a first approach to care within a safe environment, which allows them to become familiar with basic procedures and the relationship with the patient [4,5]. In this context, the first contact with basic care represents a formative milestone of great relevance. Activities such as grooming, mobilization, taking vital signs, or feeding a dependent person, although they may seem simple from a technical point of view, involve a high emotional and relational load for the novice student. In turn, these first experiences can awaken insecurities, fears of error or judgment, especially when they have not been previously addressed in a pedagogical context of accompaniment and reflection [6].

Traditional approaches to teaching and learning in nursing have proven to be limited in effectively developing the necessary clinical competencies [7]. Therefore, there is a need to incorporate innovative training strategies that allow students to acquire realistic experiences in a safe environment, free of risk to patients [8]. In this sense, clinical simulation has gained

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relevance as a resource of high educational value, which can significantly improve cognitive learning, psychomotor skills, and emotional development of students, depending on the area and type of implementation [9-12]. Evidence further indicates that simulation-based education produces better learning outcomes than traditional educational methods [13]. Moreover, students who participate in multiple simulation sessions tend to develop a higher level of competence and self-confidence [14].

Simulation-based experience (SBE) can take multiple forms, from structured or virtual scenarios to hybrid modalities, classified by their level of realism [15]. Among these, simulation with standardized patients (SPs; individuals trained to realistically portray specific clinical conditions) offers a highly realistic environment [16]. In this context, it is important to distinguish between the term SP and the actor. According to authors such as Lioce et al [17], an "actor" refers to a person who performs a role in a simulation scenario, who may or may not be specifically trained to standardize a clinical condition. Thus, while a SP combines acting skills with knowledge of the assigned clinical case, the term actor is used in a more general sense.

Numerous studies have shown that the use of SPs contributes to the development of psychomotor skills, improves self-confidence, enhances critical thinking, and strengthens students' communication and interpersonal skills [18,19]. Likewise, by incorporating emotional, ethical, and relational elements, it supports the construction of meaningful and humanized learning [20,21], especially in areas such as basic care, often underestimated in the hierarchy of clinical knowledge, but fundamental in the comprehensive care of the person.

Despite these benefits, most research has focused on advanced students or on high-fidelity contexts associated with critical situations [22]. There is scant evidence on how novice students, in their first year, experience and perceive this first contact with care through clinical simulation [1]. Understanding these initial experiences from the student's own voice is essential to adjust pedagogical strategies, promote adequate emotional support, and facilitate a more conscious, safe, and empathetic transition to real clinical practice [23].

From a qualitative and phenomenological approach, this study aims to understand the perceptions, emotions, and learning of first-year nursing students during their first clinical simulation experience with SPs, focused on basic care. The aim is to give visibility to the subjective and formative impact of this type of experience, as well as to identify elements that favor or hinder the construction of the professional role from the initial stages of training.

Objective

The study aims to explore the perceptions, emotions, and learning experiences of first-year nursing students during their initial clinical simulation encounters with SPs focused on the provision of basic care.

Methods

Design

This was a descriptive phenomenological qualitative study aimed at understanding the perceptions of undergraduate nursing students during their first contact with care through simulation experiences with SPs. The phenomenological perspective allows us to perceive the lived human experience and reveal its meaningful understanding as a person [24]. This design sought to explore students' emotions, expectations, and reactions to their first simulated encounter, as well as their perception of the realism and educational value of the experience. In addition, it allows the identification of learning in communicative, technical, and attitudinal skills, and their impact on confidence and preparation for the real-world clinical environment [25].

Experience or Role of Researchers

The research team consisted of 5 women and 4 men, including 4 professionals with experience in qualitative research design (EGCB, ATR, PDPH, and MCHC). The data were triangulated by 2 external researchers (RJV and MRG). The positioning of the researchers was established in terms of the theoretical framework, their beliefs, previous experience, and personal motivations for participating in the research. The entire team participated in the evaluation of each stage of the research process to reduce researcher bias.

Participants and Sampling

This study was conducted at a university in the Community of Madrid, Spain. In this country, the undergraduate degree in nursing consists of 4 academic years. Specifically, the course Introduction to Practice: Basic Care, which is part of the curriculum, is worth 6 European Credit Transfer and Accumulation System credits and is taught in the first year in the second semester. A purposive sampling strategy was applied with the following selection criteria: (1) being first-year students of the nursing degree, (2) enrolled for the first time in the course Introduction to Practice: Basic Care, (3) not repeating or previously enrolled in the module, (4) having participated in at least 1 complete simulation session with a SP (range: 1-4 sessions), and (5) providing informed consent to participate in the study.

It should be noted that the students have not yet had direct contact with the hospital environment, since clinical internships begin in the second year during the first semester. Therefore, this SBE represented their first structured approach to a clinical situation, albeit in a controlled environment. However, throughout the first course, they have carried out practical training activities in basic skills, such as taking vital signs, patient hygiene, mobilization, and administration of fundamental care, in simulation laboratories with mannequins and other technical resources. These activities allowed them to acquire initial knowledge and skills, as well as a certain familiarity with the simulated clinical environment, which facilitated their participation in more complex scenarios with SPs.

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Data Collection

To capture in-depth the complexity of the experiences during clinical simulations with SPs, a qualitative data collection strategy was implemented, based on a phenomenological approach. This strategy integrated multiple complementary techniques to enrich the understanding of the studied phenomenon from different perspectives. Focus groups (FGs) were conducted within the framework of the simulation sessions and were complemented by field notes prepared by the researchers and reflective narratives written by the participants. This methodological triangulation allowed access to a more holistic and nuanced view of the subjective experiences of the students. The FGs facilitated interaction and the contrast of opinions among participants, favoring the emergence of shared meanings. The field notes, together with the individual narratives, provided additional information of an introspective and observational nature, which contributed to deepening the emotional, cognitive, and attitudinal aspects associated with the simulated experience. Data collection was carried out during April and May 2025.

Each FG consisted of 9 - 11 participants, led by 2 different researchers who assumed the roles of moderator and observer. The moderator posed questions to which each participant responded by speaking in turn, while the observer focused on identifying key points and taking detailed notes. This separation of roles was maintained in all 6 FGs to ensure neutrality and enrich the data collection process. A topic guide was used, which was focused enough to collect information about the study area yet open enough to stimulate discussion and interaction among participants (Textbox 1). However, data collection in qualitative studies is flexible; therefore, during the FGs, the moderator asked about those areas of interest that participants raised in relation to the research question [26,27]. All FGs were audio- and video-recorded with the previous permission of participants. The average duration of each FG was 58 minutes, with 6 FGs being conducted, at which point no new information emerged from the data analysis.

Textbox 1. Interview guide.

Postclinical simulation phase

- What emotions were predominant when facing a “patient” for the first time in a simulated clinical environment?
- Did it change your perception of what it means to provide care?
- Do you think this experience resembles what you might encounter in real clinical practice?
- Do you consider this activity useful for your learning? In what way?
- What aspects would you like to improve before having contact with real patients?
- What elements contributed to the simulation seeming authentic or not?
- How did the presence of the standardized patient influence your way of communicating or behaving?
- Do you think the actor managed to convey emotions or clinical situations in a realistic way?

As a complement to the FGs, field notes were collected by the researchers during the development of the simulations and in the subsequent moments of reflection. These notes recorded nonverbal observations (such as body language, facial expressions, emotional tensions, and spontaneous attitudes), as well as contextual details of the simulated environment, which enriched the interpretation of the discourses collected in the group sessions. A third source of information was also incorporated through written reflective narratives. On a voluntary basis, the participating students were invited to write a personal reflection in the Moodle [SimCapture] virtual environment, responding to a series of open questions aimed at promoting introspection and critical analysis of their experience: “How did you feel during the simulation? What do you think you learned during this experience? How has this simulation influenced your self-confidence in the face of clinical practice?” A total of 43 participants submitted reflective narratives, each providing 1 written response covering the 3 open questions, totaling approximately 3891 words. These narratives allowed access to subjective aspects such as emotions, insecurities, significant learning, and future expectations, providing a complementary view to the group discourses.

The clinical simulation experiences were designed following the SimZones model [28], progressing from lower-complexity zones to more challenging scenarios [15]. In the lower zones (Zone 1 and 2), the focus was on training specific technical skills in a more controlled environment with lower cognitive load. At this stage, teachers adopted an instructional role, directly guiding participants’ learning.

Subsequently, we progressed to Zone 3, where more realistic elements were introduced, such as environmental noise, greater assistance pressure, and the deliberate incorporation of nontechnical skills, such as teamwork, effective communication, and group decision-making. In this phase, the role of the teacher evolved into that of facilitator of inquiry, promoting critical reflection and autonomous learning through structured debriefing strategies.

Table 1 shows the 4 clinical scenarios developed during the simulation, along with the expected learning outcomes and the skills (technical and nontechnical) trained in each.

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Table . Simulated scenario diagram.

Scenario	Learning outcomes	Skills training
A 32-year-old patient, just admitted to the cardiology ward for study, had syncope while at the gym, was seen in the emergency room, and transferred to the ward.	• Accurately identify the patient. • Correctly apply hand hygiene. • Perform the nursing assessment on admission using functional patterns. • Introduce and identify oneself appropriately. • Provide clear information and resolve the patient's doubts. • Perform nursing interventions related to the patient's situation.	• Hand hygiene • Vital signs • Basic ECG[a] • Nursing assessment
A 65-year-old patient with chronic venous insufficiency and an infected ulcer in the right internal malleolus. The wound shows signs of infection, so a dressing and culture are required.	• Perform a focused nursing assessment. • Identify signs and symptoms of infection. • Apply the principles of asepsis and antisepsis in wound care. • Perform correct sample collection for culture. • Develop effective communication with the patient. • Correctly document the procedure in the medical record.	• Infected wound management • Aseptic and sterile wound care techniques • Use of gloves
A 78-year-old patient was admitted to the internal medicine ward for prolonged immobility, presenting with a grade 1 pressure ulcer in the sacral or scapular region. Hygiene of the area and postural changes according to protocol are required.	• Acquire practical skills in hygiene and pressure ulcer prevention. • Perform skin assessment using the Norton Scale. • Identify pressure points or risk of UP[b]. • Promote patient safety in performing postural changes. • Ensure patient comfort during the procedure.	• Patient mobilization • Privacy • Ulcer prevention • Management of grade 1 UP
A 24-year-old patient operated for appendicitis, currently in the postoperative period with severe pain (VAS[c] scale 7/10), is very distressed.	• Develop clinical skills in pain assessment and safe administration of medications. • Improve therapeutic communication with the patient. • Ensure patient safety in the administration of analgesia.	• Medication administration: 5 correct • Patient identification • Pain assessment and management

[a]ECG: electrocardiogram.

[b]UP: pressure ulcer.

[c]VAS: Visual Analogue Scale.

The SPs, who played a variety of roles, were experienced actors with knowledge of caregiving. They were meticulously scripted and skillfully acted out various scenarios, offering participants authentic and immersive experiences to hone both technical and nontechnical skills.

All clinical simulation sessions followed the best practices described by the International Nursing Association of Clinical Simulation and Learning, which encompass 4 key phases [29]: prebriefing, development of the simulated scenario, debriefing, and final debriefing. These phases were meticulously executed and supervised by 2 university professors with expertise in clinical simulation methodology. In particular, during the prebriefing phase, great emphasis was placed on creating a psychologically safe environment following the guidelines proposed by Rudolph et al [30] In addition, the debriefing phase followed the principles of the good judgment model, facilitating an environment in which participants felt empowered to make mistakes, engage in meaningful discussions, and receive constructive criticism. This approach aims to foster reflective learning experiences in which participants and instructors integrate newly acquired knowledge with existing experience [30,31].

Through the simulated scenarios, students not only developed technical and communication skills but also learned how to effectively identify and determine appropriate interventions. The debriefings facilitated reflective thinking and provided constructive feedback, promoting a deeper understanding of the learning experience [32]. As a result, participants are empowered to analyze their actions, identify areas for improvement, and understand the potential impact of their interventions in real-world situations.

Data Analysis

Verbatim transcriptions for each of the FGs, researchers' field notes, and the participants' contributed reflective narratives (RNs) were made. These data were meticulously stored, managed, classified, and organized using the qualitative data analysis software ATLAS.ti (version 24; Scientific Software

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Development GmbH) [33]. The collected data were analyzed using inductive thematic analysis [34], following the steps proposed by Braun and Clarke [35]: (1) repeated and thorough reading of transcripts; (2) initial coding of relevant fragments; (3) grouping of codes into emerging themes; (4) review and definition of main themes, categories, and subcategories; and (5) interpretation of results in relation to the theoretical framework and study objectives.

This method was selected for its flexibility and ability to identify and interpret significant patterns in the qualitative data. An inductive approach was adopted, involving the systematic identification of relevant text segments to address the research objectives. From these segments, a rigorous process of coding and categorization was carried out through 3 analytical levels: first, subcategories were identified that reflected specific nuances of the experiences; second, these were grouped into categories or subthemes that represented broader and more recurrent aspects; finally, higher-order emerging themes were defined that synthesized the general meaning of the discourses.

This interpretative process was iterative and dynamic, allowing for a deeper and more contextualized understanding of the perceptions, emotions, and experiences expressed by the participants. Four researchers with consolidated experience in qualitative research independently carried out the entire thematic analysis process, from initial coding to the construction of themes, categories, and subcategories. Subsequently, a debriefing was held in which individual proposals were compared, and a consensus was reached on the final structure of the analysis. In cases of discrepancies, these were resolved through joint deliberation until informed and consensual agreements were reached within the team.

Rigor and Trustworthiness

The study followed the Consolidated Criteria for Reporting Qualitative Research (COREQ) guidelines [36]. The Guba and Lincoln reliability criteria [37] were applied. Data triangulation was conducted among the researchers involved in the analysis, and the analysis process was reviewed by independent researchers to ensure its credibility. Transcripts were provided to participants with the opportunity to add any relevant information. Importantly, anonymity was preserved during this process, as additions were made using assigned alphanumeric codes, ensuring that individual identities remained confidential. Transferability was ensured by a detailed description of the research setting, participants, context, and methods. Confirmability was achieved by introducing variability in participants' experiences. Each researcher conducted the reading and analysis independently, contrasting and then agreeing on emerging themes, categories, and subcategories.

Ethical Considerations

Ethical approval to conduct the research was obtained from the UNIE University Research Ethics Committee (CEID2025_09). All participants provided written informed consent before participating in this study. To ensure anonymity and confidentiality, each participant in the FGs and RNs was assigned a unique code.

Results

Participants Characteristics

Of the total number of nursing students who met the criteria, 59 (98.33%) of 60 students participated. The majority of participants were female (50/59, 84.75%), compared to 9/59 (15.25%) who were male. The mean age of the participants was 20.4 years (SD 2.75 or 1.83 years; range 17-28 years). The gender discrepancy among students is mainly because the majority of students enrolled in undergraduate nursing programs at Spanish universities are women. The participants were first-year nursing students enrolled in the course Introduction to Practice: Basic Care.

Themes

Three thematic blocks were identified along with their respective categories and subcategories (Table 2): (T1) first contact with simulation, (T2) learning and competencies, and (T3) preparation for clinical practice.

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Table . Themes, categories, and subcategories.

Theme and category	Subcategories
T1[a]: first contact with the simulation	
C1: initial emotions	• Anxiety and nervousness • Fear of error • Feeling of tranquility
C[b]2: evolution of emotions	• Curiosity and motivation • Sense of achievement • Confidence
C3: impact of realism	• Authenticity • Experience as real • Standardized patient
T2: learning and competencies	
C1: theoretical-practical integration	• Application of knowledge • Spontaneous activation • Meaningful learning
C2: learning from error	• Formative value of error • Debriefing • Punitive evaluation • Psychological safety
C3: skills	• Clinical assessment • Critical thinking and clinical judgment • Teamwork
C4: integral perspective	• Integral and humanized perspective • Active listening • Empathy • Trust bonding
T3: preparation for clinical practice	
C1: practical self-confidence	• Tools • Safety in clinical environments • Visualization
C2: professional identity	• Awareness of professional role • Projection into the future

[a]T: theme.

[b]C: category.

Theme 1. First Contact With Simulation

Initial Emotions

The emotional experience of the students during the clinical simulations was intense and diverse, with initial emotions ranging from nervousness to insecurity, surprise, and empathy. Nervousness was a cross-cutting feeling, manifesting itself especially in the wait before entering the stage.

> [You are always nervous to see what you find behind the door. FG1-3]

This anxiety was related to both uncertainty and the desire to do well.

> [I was nervous and scared, but I knew it was to learn. FG4-3]

Another participant in her reflective narratives clearly expressed this combination of excitement and fear.

> [Very excited but nervous. RN17]

However, not all students experienced the stimulation with the same emotional intensity. Some reported greater tranquility, especially when the simulated situation was familiar to them or they perceived that they had mastered the required care.

> [I was calm because it was basic care I had seen in class and I did not feel that I was going on an adventure. FG1-4]

Emotions intensified when facing emotionally charged situations, showing feelings of insecurity and helplessness.

> [The patient was crying and I did not know what to do. FG3-2]

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and

> [I felt bad because I wanted to help but I did not know how. FG3-4]

Evolution of Emotions

As the SBE progressed, a process of positive emotional evolution was evident in many participants, characterized by a transition from initial nervousness to a greater sense of calm, control, and security. This change was not immediate, but the result of progressive familiarization with the simulated environment, the debriefing, and their own reflections. At first, facing a clinical situation in front of observers and peers generated high levels of anxiety and emotional tension.

> [Very nervous at the beginning and more relaxed at the end. FG3-2]

and

> [At the beginning I was very nervous, but little by little I controlled my anxiety. FG5-3]

However, this initial nervousness diminished as they gained confidence in their skills and became more comfortable with the simulated scenario. The safe environment of the simulation, together with the support of the team and emotional self-regulation strategies, such as conscious breathing or concentration, facilitated this transition.

> [Learning to breathe and concentrate helped me not to block. FG4-8]

These experiences not only made it possible to overcome emotional blocks but also gave way to a growing sense of efficacy and competence. Participants reported feeling increasingly able to function in clinical settings, which contributed to a significant gain in self-confidence.

> [At first I was very nervous, but by the end I felt more comfortable. FG5-5]

Progressive emotional adaptation thus became a key process for the development of emotional self-regulation, an essential aspect in nursing practice. Repeated exposure to simulated clinical scenarios allowed students to train their ability to cope with stress and remain calm—fundamental skills in real patient care situations.

> [I am gaining confidence, losing fear; it gives me confidence for the start of my internship. FG6-8]

This reinforces the idea that such experiences prepare them not only on a technical level, but also emotionally.

Impact of Realism

Another key aspect was the emotional impact of the realism of the scenarios, which generated an intense affective response and greater involvement on the part of the students. The authenticity of the simulations (both in the setting and in the clinical elements) led to a feeling of total immersion.

> [For a moment I thought I was in the hospital. FG1-10]

and

> [Seeing the ulcer seemed real, unbelievable. FG2-11]

This realism generated a deep emotional response, which contributed to the real experience of the simulation.

> [It helps me to see myself with that tension inside, with the emotion that I would have in practice. FG2-1]

This immersion was especially reinforced by the presence of the SP, whose performance generated a meaningful connection between the student and the simulated situation. Many noted that interacting with an actor, rather than an inert mannequin or simulator, facilitated emotional involvement and the development of more realistic relational skills.

> [I like talking to patients, so having it be an actor helps me get into the role. FG1-8]

and

> [I have learned that practicing in an environment that simulates a nursing room allows me to better lock in knowledge. By performing the techniques step by step, following an order, I feel that they stick with me in a more lasting way. RN4]

They expressed that this experience made them feel as if they were really attending to a person in a real health care environment.

> [I felt as if I were in the hospital, as if it were a real day. FG6-4]

> [It was like a real patient... it was very real. FG6-10]

In some cases, the actors were able to convey states of vulnerability and anguish that deeply impacted the students, activating empathic responses and emotional containment.

> [It seemed very real to me, the patient was crying and she was able to convey those emotions. FF3-1]

Theme 2. Learning and Competencies

Theoretical-Practical Integration

Clinical simulation emerged as a fundamental tool to support integration between theoretical knowledge and professional practice in training. The students emphasized that, through experiences in simulated clinical scenarios, they were able to understand in greater depth concepts previously learned in an abstract way.

> [I have used the knowledge of what I have been learning, and in the simulation, the things we have learned are clearer. RN22]

This process facilitated a resignification of the academic content, as they were able to experience how theory was translated into concrete actions in clinical contexts closely resembling the reality of health care.

> [You give the theory and until here you do not see it. FG1-6]

Likewise, there was evidence of spontaneous activation of clinical reasoning during practice, where the knowledge acquired was recovered according to situational demands.

> [I remembered what we saw in class. FG6-2]

The practical experience also supported the organization of previous learning, allowing students to connect content from

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different participants that are usually presented in a fragmented way in the curriculum.

> [Here I feel that I put it in value, that I see it in the patient, in an almost real case. FG6-6]

This connection between theory and practice was also manifested in the spontaneous transfer of knowledge during the clinical performance.

> [At that moment I thought about what gloves to put on and suddenly I remembered what we saw in class. FG6-2]

or

> [When I go in there I get the idea that I have to put the thermometer on him because maybe he has a fever because of the infected wound... I start to relate, incredible. FG3-10]

This process was also consolidated during the debriefing sessions, in which students collectively reflected on their actions, strengthening the link between theoretical concepts and their clinical application.

> [Everything studied makes sense. FG5-3]

and

> [I have learned that from theory to practice there is a lot of information and you learn a lot. RN10]

Learning From Error

Another central theme identified in the narratives and the FGs was the formative value of error in the simulated context. The possibility of making mistakes without generating real negative consequences allowed participants to rehearse procedures, recognize failures, and correct them immediately, which was perceived as a unique opportunity for learning.

> [I prefer to make mistakes here than in the hospital. FG6-10]

This protected experience facilitated the acquisition of skills from psychological safety, minimizing the fear of judgment and stimulating self-reflection. Learning did not occur only from one's own mistakes, but also through the observation of peers.

> [The mistakes of my peers and how to act in similar situations. RN27]

The students pointed out that witnessing the actions of others, together with the spaces for shared analysis, allowed them to identify successes and failures that they then incorporated into their own practices.

> [I have also learned from the mistakes I have seen or we have talked about, how to heal a wound by watching a patient talking to me. FG2-6]

Likewise, the relevance of recognizing one's own limits and asking for help when necessary was emphasized, an attitude that promotes safety and prevents errors in real clinical practice.

> [If you don't know how to do something, tell someone else or the teacher. FG3-11]

and

> [Learning to ask for help is part of being responsible with the patient. FG4-7]

In FG6, a student reflected this attitude when she said

> [I did not know what to take, whether alcoholic or aqueous chlorhexidine, and I said I will ask my partner. FG6-5]

The simulation was valued by the students as a safe space for learning, free from the pressure of punitive evaluation.

> [I feel at ease that the simulation does not have a grade, that it is formative, that I am not evaluated. FG2-8]

This safe environment allowed students to experiment, make mistakes, and learn without fear.

> [Nothing happens if I make a mistake, that is good for me because it does not happen to me in clinical practice with a real patient. FG2-6]

In this sense, being able to fail without real consequences was fundamental for the learning process.

> [Being able to fail and not be penalized is a great advantage for learning. FG4-9]

Skills

The skills developed through simulation were multiple and essential for professional performance in real environments. First, students highlighted the organization of the clinical assessment process as a key competency. They recognized that properly structuring the collection of information allowed them to act with greater confidence and avoid omissions.

> [Knowing how to structure the assessment is very important so that I don't forget anything. FG3-9]

They indicated that this skill can be worked on and perfected through simulation.

> [Now I know that I have to follow an order so that I don't miss anything. FG3-10]

and

> [It has helped me to create a mental structure, to keep an order, what is important in day-to-day care. FG6-7]

However, examples also emerged where the absence of this organization affected performance.

> [I was focused on what I had to do. I did not see anything in front of me. I forgot to value the scale and it was in front of me. FG6-6]

The development of critical thinking and clinical judgment was another aspect that emerged during the simulations. Students highlighted the usefulness of these scenarios for learning to prioritize interventions, react quickly, and make decisions under pressure.

> [I learned to react quickly, to prioritize what is most important. FG4-5]

> [The simulation helped me to think quickly and not get carried away by nerves. FG5-2]

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This type of reasoning was enhanced through experiences close to reality, which allowed the integration of multiple clinical variables.

> [It helps to prioritize care, to see the patient as a whole, not in parts. FG6-5]

In addition, some indicated that the practice helped them not only to consolidate previous knowledge, but also to generate confidence to incorporate new elements of care.

> [To reinforce knowledge, to have more confidence to add new ones. FG6-11]

Teamwork was valued as essential to deal with the simulation effectively. Students reflected on the importance of sharing responsibilities, communicating, and coordinating adequately.

> [Working as a team helped me feel that I was not alone and that we could solve it together. FG4-5]

and

> [Thanks to talking with my classmates, it helped me see how important it is to work as a team. RN19]

This collaboration also offered emotional security.

> [We understood each other just by looking at each other, and that made me feel safe. FG6-3]

and

> [I did not know what to do, but seeing my classmates act helped me to follow them. FG6-2]

However, difficulties in coordination and role definition were also identified, especially at the beginning of the simulation.

> [We organized ourselves before going in, but then when we started. we got lost. FG1-8]

The lack of clarity generated confusion and loss of time.

> [We were all talking at the same time and it was chaos. FG6-1]

and

> [We had a hard time deciding who did what. FG6-8]

These experiences reflect the need to strengthen internal planning and communication to improve team effectiveness in simulated clinical situations.

On the other hand, they especially valued the possibility of interacting with actors, as this allowed them to generate more fluid and credible dialogs. This interaction was key to practicing not only verbal content but also tone, body language, and emotional containment of the patient.

> [It helps me to be able to talk to the patient, I think it makes me not feel ridiculous with a simulator. FG1-8]

and

> [There is a lot of difference from doing the practices with an actor that you can ask. FG2-2]

Integral Perspective

Participants agreed that participation in these low-simulation scenarios not only allowed them to hone their technical skills but also to incorporate a broader and more humanized view of care. They noted that the simulations helped them to focus on the patient from a holistic perspective, understanding the person beyond the disease. As one student expressed,

> [To focus on the individualized patient. RN29]

highlighting the change in their approach to more personalized care. Along the same lines, another participant underscored the formative value of these scenarios as a fundamental opportunity to get started in real patient care, allowing them to explore their ability to respond to specific clinical situations.

> [From my point of view, I think these simulations are fundamental to be able to start dealing with the patient, to see how you perform and to be able to improve different technical aspects. RN14]

The experience also facilitated the development of essential communication skills such as active listening and empathy, key elements in the humanization of care and in building a relationship of trust with the patient. In several FGs, the importance of listening without interrupting and putting oneself in the other person's place was highlighted.

> [Listening to the patient without interrupting helped me to understand his situation. FG3-5]

and

> [Putting myself in his place made me better understand what he needs. FG4-8]

This empathic dimension was also reinforced in FG6, where reflections were shared.

> [I think I have learned to listen without interrupting, just letting him tell me how he felt. FG6-7]

or

> [Feeling what the patient is going through made me care for him in another way, more closely. FG6-6]

The simulations also provided a safe environment to rehearse conversations with SPs, which helped improve their communication skills and emotional containment. They were able to practice explaining procedures, adapting to different reactions, and accompanying the patient with serenity.

> [She would talk to me about how she felt and I would try to respond calmly, without rushing, as I would in reality. FG5-6]

and

> [What has helped me most is talking to the patient as if she were on the ward, I would ask her if she was in pain and she would answer me as if she felt it. FG6-4]

A particularly valued aspect was the importance of introducing oneself properly and establishing a relationship of trust from the first contact. This initial gesture was interpreted as a concrete expression of nursing professionalism, which directly influences the patient's perception and well-being.

> [How you have to introduce yourself, how to prepare things, has helped me to understand what a nurse's day-to-day life is like. FG2-2]

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and

> [Introducing yourself with confidence makes the patient relax and trust you more. FG4-4]

Theme 3. Preparation for Clinical Practice

Practical Self-Confidence

The SBE not only served to practice technical and communicative skills, but also to help students project themselves into their future role as nurses, consolidate their professional identity, and gain confidence in their own abilities. One of the most valued effects was the possibility of anticipating future clinical experiences, reducing anxiety, and favoring a smoother transition between the classroom and the hospital. The students expressed that, thanks to the simulation, they felt more prepared and less insecure in real situations.

> [When I get to practice I will say I have already seen it, I have already felt it again. FG1-9]

> [The experience has helped me to reflect on how to do better in the hospital. FG1-1]

and

> [I feel more confident because I have already practiced these situations. FG5-4]

This perception was repeated in the individual narratives.

> [I think it has helped me a lot because when I go to practice, I will already have had a previous experience, however small it may be. RN38]

The students felt that, by facing complex scenarios in a controlled environment, they gained concrete tools to act with greater safety when they have to intervene in a real context.

> [I think that if it happens to me in clinical practice, I would know how to react. FG6-7]

This is also reflected in the reflective narratives.

> [From my point of view, I think that these simulations are fundamental to be able to start dealing with the patient, to see how you manage and to be able to improve different technical aspects. RN5]

highlighting the direct usefulness of simulation as preparation for dealing with real situations. This experience also resulted in an increase in self-confidence in the health care environment.

> [It helps me to feel confident in a health care context. FG6-2]

Along with this sense of familiarity and preparedness, students valued the simulation environment as an opportunity to strengthen self-confidence, decrease fear of error, and develop a sense of self-efficacy. Comments such as

> [After the simulation I feel more confident and eager to continue learning. FG5-4]

and

> [At the end I felt I had done well, and that motivated me a lot. FG5-7]

illustrate the positive impact on their perception of competence. Significantly, some recounted how this experience contributed to progressive growth, which directly impacts their peace of mind and emotional performance.

> [It has given me self-confidence, and I know that I am capable of solving future situations. FG6-7]

The simulation allowed students to identify their emotions, learn to manage them, and experience how they reacted under pressure—an essential aspect of facing the real practice with confidence.

> [I realized that I get nervous, but I can control it if I breathe and concentrate. FG5-3]

and

> [Learning to manage anxiety here helps me for when I have to really take care. FG4-8]

This emotional skill was also highlighted in FG6.

> [I was very nervous, but seeing that I can stay calm gave me a lot of confidence. FG6-2]

and

> [Here I could see how I react under pressure, and that helps me to prepare myself. FG6-8]

On the other hand, thanks to the SBE, many students visualized themselves more realistically in the immediate future in the clinical setting

> [I started by telling her who I was, that I was going to treat her wound...it came out by itself, as if I were already a nurse. FG6-5]

This training offered them a kind of rehearsal that facilitated the transition between the academic and the professional role, favoring a clearer mental representation of what they would experience in their first internships. As one participant expressed,

> [I see myself as if I were in an internship day. RN22]

reflecting how the simulation functioned as a direct projection to the hospital setting.

Professional Identity

The simulation not only facilitated technical learning but also actively contributed to the development of professional identity by allowing students to project themselves as nurses in realistic clinical contexts. This experience had a transforming effect on their self-perception, helping them to visualize themselves practicing the profession.

> [It made me want to see myself as a nurse. FG2-1]

Several participants expressed a strengthening of their professional vocation after the experience.

> [It reaffirms that I have chosen the career I like. FG2-8]

and

> [It has helped me to know that I want to dedicate myself to this. RN39]

The possibility of experiencing the role in a simulated way allowed them to become more aware of what professional practice entails.

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> [When I do the simulation, I see myself in the hospital, really acting as a nurse. FG6-10]

and

> [I see myself more as a nurse every time I participate. FG5-10]

Likewise, students recognized that these practices provided them with a clearer vision of the day-to-day work

> [It is a plus to understand what a nurse does on any given day. FG1-5]
>
> [Having the opportunity to simulate with real patients allows us to see what a nurse does every day. FG3-5]

This perception of anticipated professionalization was also emphasized.

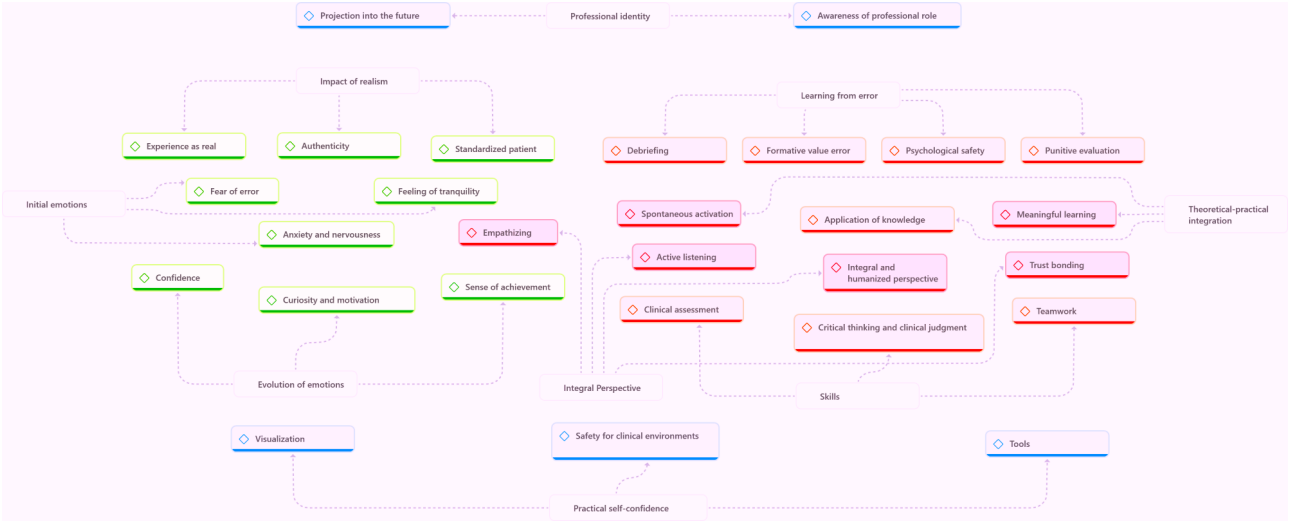
> [Here I feel that I am already practicing, even if it is in an internship. RN31]

The lived experience also allowed participants to project themselves into the future with greater security and confidence in their abilities.

> [To manage future experiences by having the necessary resources and my knowledge. RN16]

Overall, the simulation was experienced as a bridge between the academic and clinical roles, strengthening vocational commitment, identification with the profession, and motivation to continue training as future nursing professionals (refer to Figure 1).

Figure 1. Qualitative data analysis.



Discussion

Principal Findings

The aim of this study was to explore the experiences of nursing students in clinical simulation scenarios focused on the provision of basic care and how these experiences influence their formative, emotional, and professional processes. Clinical simulation, as an active methodology, has proven to be an effective pedagogical tool in the training of health care professionals by providing safe environments where learning is promoted through practice, reflection, and interaction with others [38,39].

Previous studies have supported its usefulness not only in the training of technical skills [5,40], but also in the development of relational and ethical competencies necessary for comprehensive care [17,41,42]. The safe environment provided by the simulation, coupled with the use of strategies such as debriefing and self-regulation techniques, was fundamental in facilitating this emotional transition [43]. These observations are in line with studies [15] that highlight the value of reflective debriefing as a key tool for transforming emotional experience into meaningful learning [44].

From a learning point of view, simulation was consolidated as an effective tool to integrate theory and practice. Students reported a greater understanding of previously abstract concepts and a spontaneous activation of clinical reasoning, as described in research on experiential learning [45,46] and clinical simulation as a catalyst for meaningful learning [47]. Collective reflection during debriefing not only consolidated knowledge but also promoted the critical reconstruction of knowledge from experience [48]. Error, far from being perceived as a failure, emerged as a central formative component. The environment free of real consequences facilitated exploration, self-evaluation, and continuous improvement, confirming previous findings on the value of error in protected contexts. In addition, students highlighted the importance of learning from both their own and their peers' mistakes, thus strengthening observational learning and collective awareness of clinical performance [30,31]. This reflective and collaborative dimension of the simulation, which includes debriefing as a key moment, reinforced self-confidence, facilitated the sharing of emotions, and supported the building of common meanings about the practice of care. Regarding the competencies developed, the simulation favored the strengthening of essential skills such as structured clinical assessment, critical judgment, decision-making, and care prioritization [49], aspects widely supported in the literature as pillars of nursing education [50]. Likewise, teamwork and interprofessional communication emerged as key components, although challenges related to coordination and role assignment

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were also evident, underscoring the need for more specific preparation in collaborative competencies [51].

The results are in line with previous research highlighting the value of simulation as an emotionally meaningful experience, capable of arousing empathy, fostering peer collaboration, and strengthening the student's professional identity [14,52]. In this study, participants highlighted how the realism of the scenarios with SPs, teamwork, and teacher guidance facilitated a deeper understanding of the meaning of caring, beyond the purely technical [16]. The analysis of the verbatim revealed the importance of integrating basic care in clinical simulations, since these not only allow training in fundamental skills, such as hygiene, feeding, or patient comfort, but also constitute a formative space where students explore their emotions, identify their limits, and reflect on their professional role. The process of providing basic care is re-signified by being involved in a simulated context where real people with difficulties, needs, and emotions are represented. This reconstruction of the act of caring allows students to value its relevance and understand it as both a clinical and human act.

In addition, these SBEs become a first approach to the health care environment, especially valuable in the initial courses where students have not yet had access to clinical rotations. Simulation thus acts as a formative bridge that prepares them emotionally and cognitively to face future practices in real contexts with greater confidence and competence [53]. The participants reflected that this experience provides them with security, reduces their fear of the unknown, and strengthens their self-confidence [54] by proving that they are capable of applying their knowledge and managing situations similar to those they will encounter in the clinical setting.

Practical and Research Implications

This study highlights the value of integrating clinical simulation with SPs from the early stages of nursing education. Practically, the findings support the inclusion of SBEs focused on basic care to facilitate the development of technical, emotional, and communicative skills in a safe and realistic environment. These experiences not only enhance students' confidence and preparedness for clinical practice but also contribute to the construction of their professional identity.

From a research perspective, the study provides a foundation for further investigations into the emotional and formative impact of early simulation experiences. Future studies could explore longitudinal outcomes, compare different types of simulation modalities, or evaluate the integration of these methodologies across various nursing curricula. In addition, expanding research to diverse educational contexts could enhance the generalizability and applicability of the findings.

Strengths and Limitations

The strengths of this study lie in its contribution to a deep and experiential understanding of the impact of clinical simulation on the education of nursing students, by exploring not only the development of technical skills, but also emotional, relational, and professional aspects. The research provides an innovative vision of the need to transform traditional teaching models, proposing realistic scenarios that allow for meaningful and reflective learning. In addition, it highlights the usefulness of these simulated experiences to strengthen professional identity and the comprehensive preparation of future nurses.

Among the limitations, it should be noted that the study was carried out with students from a single Spanish university, which restricts the generalization of the results to other educational contexts. In addition, the analysis focused on specific clinical scenarios, so it would be valuable to extend the research with a more diverse sample and with a combination of qualitative and quantitative methods, which would make it possible to evaluate the formative impact of different types of simulation (eg, in the field of mental health). Another limitation is the variability in the number of simulation sessions completed by the participants (ranging from 1 to 4), which may have influenced differences in perceptions and learning experiences. Future studies should control for the number of simulation exposures to analyze its impact more precisely.

Future studies could also consider including second-year students during their first semester of clinical placements. Their participation would allow for valuable comparisons between real clinical practice and simulated practice, further enriching the findings.

Conclusions

This study shows that clinical simulation has a transformative impact on the education of nursing students by providing a safe, reflective, and emotionally meaningful environment for learning. The emotions experienced, the realism of the scenarios, the interaction with SPs, and the cooperation among peers contribute to the development of comprehensive competencies and the construction of professional identity. Simulation facilitates integration between theory and practice, fosters clinical judgment, decision-making, and allows errors to become a learning opportunity. Debriefing reinforces this process by promoting reflection and consolidation of knowledge from experience. In addition, these experiences act as a first approach to the health care environment, especially useful in the initial stages of the career. Students report an increase in their security and self-confidence, as they see that they can apply their knowledge in simulated clinical contexts. Overall, the results support the need to integrate active methodologies such as simulation into the curriculum, addressing not only technical but also human and emotional aspects of care.

Acknowledgments

We would like to thank all the study participants who contributed to this research.

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Data Availability

The datasets generated or analyzed during this study are available from the corresponding author on reasonable request.

Authors' Contributions

Conceptualization was carried out by EGCB, ATR, and MCHC. Methodology was designed by EGCB, ATR, and PDPH. Formal analysis was performed by PDPH and EGCB. Investigation was conducted by ATR. Resources were provided by MRG. Data curation was managed by NNE and AMS. The original draft was prepared by EGCB and ATR. Review and editing were performed by ECS, NNE, and PDPH. Visualization was carried out by MCHC. Supervision was provided by ECS and AMS. Project administration was handled by RJV and MRG, and funding acquisition was secured by RJV.

Conflicts of Interest

None declared.

Checklist 1
COREQ checklist.
[PDF File, 316 KB - nursing_v8i1e81617_app1.pdf]

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Abbreviations

COREQ: Consolidated Criteria for Reporting Qualitative Research
FG: focus group
RN: reflective narrative
SBE: simulation-based experience
SP: standardized patient

Edited by E Borycki; submitted 31.07.25; peer-reviewed by CJV Vuuren, D Cunha; revised version received 13.09.25; accepted 14.09.25; published 08.10.25.

Please cite as:
García Carpintero-Blas E, Del Pozo-Herce P, Hernández-Cediel MDC, Rodríguez-García M, Navas-Echazarreta N, Chover-Sierra E, Martínez-Sabater A, Juárez-Vela R, Tovar-Reinoso A
First Contact With Care Through Clinical Simulation in Nursing Students: Qualitative Study
JMIR Nursing 2025;8:e81617
URL: https://nursing.jmir.org/2025/1/e81617
doi:10.2196/81617

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Gamification as a Tool for Understanding Mental Disorders in Nursing Students: Qualitative Study

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Related Article:

This is a corrected version. See correction statement: https://nursing.jmir.org/2025/1/e83237

Abstract

Background: Gamification has emerged as an innovative pedagogical strategy in the educational field, transferring game tools to the teaching-learning process to improve students' motivation and engagement.

Objective: This study aims to describe nursing students' perceptions of mental disorders using interactive cards as a gamification tool.

Methods: This research was carried out at the Nursing School of a University in Madrid, Spain, with the participation of 50 first-year students enrolled in the nursing degree's general and developmental psychology course. Data were collected through focus groups and reflective narratives with semistructured interview questions between March and April 2024. After data collection, transcripts were generated and subjected to thematic analysis following the Consolidated Criteria for Reporting Qualitative Research (COREQ) checklist.

Results: A total of three themes emerged from the analysis: (1) perception and stigma of mental disorders, (2) emotional connection and personal reflection in learning about mental disorders, and (3) gamification tools and their impact on learning.

Conclusion: Gamification, especially through interactive cards, is valuable for teaching psychology and mental disorders in nursing education. It enables students to gain a deeper clinical understanding of mental illnesses and explore their emotional and social dimensions. This methodology fosters emotional reflection, reduces stigma, and encourages active engagement, contributing to developing more empathetic, reflective, and better-prepared nursing professionals. Its integration into educational programs enhances academic and humanistic competencies essential for mental health care.

(JMIR Nursing 2025;8:e71921) doi:10.2196/71921

KEYWORDS

gamification; mental health; nursing students; cognitive training; qualitative research

Introduction

Over the past decade, gamification has emerged as an innovative educational strategy incorporating game dynamics, rules, and elements into non-game contexts, such as learning environments [1]. Its central aim is to transform traditional educational activities into interactive and engaging experiences, stimulating students' intrinsic motivation and promoting active learning. Gamification introduces game—like components into the

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classroom to foster more dynamic and effective learning processes [2]. This approach is particularly effective when students are internally motivated, as it encourages deeper engagement with their educational journey [3]. It has shown notable success in complex fields such as health care, where integrating theory and practice is essential for developing competent and empathetic professionals [4]. In nursing education, gamification provides a dynamic and immersive framework through which students can engage with real-world challenges, enhancing their clinical, cognitive, and emotional competencies [5,6].

Recent research has highlighted the growing potential of gamification-based mental health interventions to improve emotional well-being and reduce psychological symptoms such as anxiety, stress, and depression [7,8]. These interventions use game design principles to increase users' motivation, active participation, and engagement in their therapeutic processes. This innovative approach is not only transforming the way mental disorders are treated but also how their management is taught to health professionals. As an innovative strategy, gamification has applications in diverse educational contexts [5,6,9] and health interventions focused on people with mental health problems [8,10]. However, despite their advances and growing popularity, there is a notable gap in understanding how these gamified strategies impact both teaching and learning related to mental health.

One of the biggest challenges in nursing education is the understanding of mental disorders [11,12]. These pathologies require an in-depth knowledge of symptoms and an empathic ability to connect with patients' personal and subjective experiences [13]. By implementing game dynamics, such as using interactive cards, students can explore, in a safe and structured way, the inner world of people with mental illness [14]. This methodology helps transform theoretical knowledge into meaningful learning experiences by putting the learner at the center of the process and allowing them to somehow "live" the realities of their future patients [15].

In the specific context of teaching about mental disorders, interactive cards representing various pathologies, symptoms, or clinical scenarios enable students to engage with realistic and meaningful experiences. These cards often include narratives or descriptive vignettes simulating the lived experiences of individuals with conditions such as depression, anxiety, schizophrenia, or bipolar disorder [16]. Through reading and reflection, nursing students are encouraged to recognize the clinical features of these disorders and consider their personal and emotional significance for those affected. This pedagogical strategy supports the development of empathic competencies and enhances students' understanding of mental illness's psychological and social dimensions [17].

In addition, gamification in this context facilitates the development of a comprehensive understanding of the patient [8]. Students can interact more actively and critically with the content by using dynamics such as interactive cards, encouraging deep analysis of the emotions, behaviors, and thoughts that characterize each pathology. This type of tool allows personalization of learning since each student can interpret situations from their perspective, enriching the process by exchanging ideas and experiences with peers [3].

In nursing education, it is essential to move beyond the acquisition of technical skills and to cultivate nontechnical competencies such as empathy, emotional regulation, and effective communication. These attributes are fundamental for delivering holistic and patient-centered care. Gamification serves not only to enhance students' understanding of mental disorders but also to prepare them to engage with patients in an ethical, compassionate, and sensitive manner. Interactive cards, in particular, encourage future nurses to view patients as whole individuals—beyond their diagnoses—by considering their personal histories and social contexts. In this regard, gamified educational tools offer promising avenues for improving both the learning process and the depth of understanding related to mental health care.

This study aims to describe nursing students' perceptions of mental health disorders using interactive cards as a gamification tool.

Methods

Design

An interpretive approach qualitative study [18] was conducted to investigate nursing students' perceptions and experiences during an interactive card gamification activity focused on mental disorders. This paradigm describes how people construct their social reality and knowledge by reconstructing their experiences [19].

Experience or Role of Researchers

A total of 9 investigators (4 women and 5 men) participated in this study, all with PhDs in health sciences and psychology, except for one nurse from the clinical setting with a specialty in mental health (PDP-H). A total of 4 investigators (EGC-B, AT-R, PDP-H, and ACH) had extensive experience conducting qualitative studies in health sciences. One of the investigators (PDP-H) was responsible for recruiting participants. The remaining authors had no prior contact with any of the student participants. The focus groups (FGs) were led by 2 researchers specializing in using gamification tools and active learning methodologies in mental disorders (PDP-H and AT-R). The researchers' positions were established regarding the theoretical framework, beliefs, previous experience, and motivations for participating. The entire team participated in the evaluation of each stage of the research process to reduce researcher bias. Data were triangulated with 3 external researchers (AM-S, RJ-V, and EC-S).

Participants and Sampling

This study was conducted at a university in the Community of Madrid, Spain, where the nursing degree spans 4 academic years. The course General and Developmental Psychology, part of the first-year curriculum, is a 6 European Credit Transfer System (ECTS) credit subject taught in the second semester. It includes both theoretical instruction and the development of subject-related competencies.

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A purposive sampling strategy was used, selecting participants based on their ability to provide relevant insights aligned with the research questions [20]. Inclusion criteria were (1) first-year undergraduate nursing students and (2) an enrollment in the General and Developmental Psychology course at the participating university. Participation was voluntary and offered to all eligible students. Of the 53 students enrolled, 50 chose to participate (n=50). Recruitment continued until data saturation was reached [21], ensuring a comprehensive and information-rich sample.

All participants were first-year students with no formal mental health education; this course represented their initial academic exposure to related topics. While a few had previously experienced basic gamified activities during earlier stages of education, this study marked their first structured encounter with gamification as a pedagogical strategy within higher education.

Teaching Strategy

As part of the educational intervention through gamification, a group activity specifically designed to explore perceptions about eating disorders (EDs), personality disorders (PDs), and emotional instability, such as anxiety and depression, was proposed to students. This intervention was implemented through interactive cards (see Figures 1-4), symbolic tools to facilitate reflection and self-awareness around these mental disorders. During the intervention, a fundamental distinction was introduced between conflict graphs and reframing graphs. These were directly linked to analyzing how students perceive and emotionally process the characteristics and challenges associated with mental disorders.

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Figure 1. Interactive card 1.



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Figure 2. Interactive card 2.



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Figure 3. Interactive card 3.



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Figure 4. Interactive card 4.



Conflict cards represent emotional challenges, internal obstacles, or situations that generate distress, anxiety, or confusion, common elements in disorders such as ED and PD. Through these, students could visually identify problem areas in their emotional lives or associate them with experiences observed in people with mental disorders, fostering a deeper and more empathetic understanding. This process allowed them to reflect on how these internal conflicts might be related to the symptoms and challenges faced by those with mental disorders.

Reframing graphs symbolize a new perspective or emotional solution, providing learners with an optimistic view or path to resolution similar to the therapeutic goals of treatments for mental disorders. This exercise encouraged participants to project how to overcome the challenges represented by the conflict graphs, visualizing possible ways to cope with and manage anxiety, emotional instability, or challenges specific to ED and PD.

The interactive cards functioned as emotional metaphors, enabling students to explore their internal experiences in a tangible and visually expressive manner. This method allowed them to contextualize personal reflections within the broader framework of symptoms and lived experiences associated with

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various mental health conditions. Each student constructed the symbolic meaning of the cards individually, fostering a deeply introspective and subjective approach to emotional analysis. This personalized engagement supported the study's objective of enhancing students' understanding of and sensitivity toward mental disorders' complexities (see Multimedia Appendix 1).

The activity consisted of each group preparing a document that included the following elements:

First, the association of interactive cards with mental disorders; the students were asked to identify and justify which interactive card was associated with each of the disorders presented: eating disorders, personality disorders, anxiety, or depression, justifying this association. This task was intended to promote individual and collective reflection, encouraging participants to explore the symbolic relationship between the interactive cards and the disorders or emotions represented. This phase aimed to get students to deepen their symbolic analysis of the interactive cards and connect the images to their knowledge of mental disorders. The exercise encouraged group discussion, generating different interpretations and a shared understanding of the disorders from an emotional and visual perspective.

Second, the analysis of the abstraction and meaning of the interactive cards was conducted. After addressing the type of disorder and its impact on those who are diagnosed with it, we delved into introspective aspects of the students, such as whether they have ever felt similarly, their fears, problems, and their ideal or desired state. They also reflected on how they believe people with ED experience it and how they would feel if they experienced it personally or if someone close to them had gone through this situation.

The central objective of the gamification activity was to train students in understanding and managing mental disorders through interactive card-based experiences that promoted reflection and emotional analysis. This approach allowed students to develop nursing-specific competencies to address mental health-related situations effectively. For this purpose, a variety of interactive cards representing different mental disorders, such as eating disorders, anxiety, and depression, were used.

Before using the interactive cards, consent was requested from their creator, Alejandro Vera Casas, who approved their use and is knowledgeable about the study and intervention with the students.

Data Collection

To explore diverse viewpoints, FGs were convened along with the researchers' field notes and participants' written reflective narratives, which enriched the analysis. This qualitative methodology allowed for a nuanced and contextualized exploration of lived experiences during the interactive card-based gamification activity on mental disorders [22]. The FGs encouraged interaction among participants, fostering the emergence of varied opinions and perceptions regarding their feelings and learnings [20]. Data collection was conducted between March and April 2024, facilitating a detailed topic analysis [23].

Each group was composed of between 9 and 11 participants, guided by a moderator and accompanied by an observer. The FGs were developed at the university after the gamification activity, with participants seated and facing each other to encourage interaction, data collection, and direct observation. The moderator asked questions, and each participant responded in an orderly manner. The observer complemented the moderator's work, highlighting key points and taking notes. A thematic guide was used, which, although focused on obtaining information specific to the study area, allowed sufficient flexibility to promote discussion and interaction among participants (see Textbox 1). Due to the flexible nature of data collection in qualitative studies, the moderator explored additional themes that emerged from the participants' interventions and related to the research question. All FGs were audio-recorded with the participants' prior permission. A total of 5 FGs were conducted in which no new information emerged from the data analysis, with an average duration of 79 minutes. Before analysis, participants had the opportunity to review the transcripts. In addition, researchers' field notes were used as a secondary source of information.

Textbox 1. Semistructured interview questions.

1. How did you feel about the development of using interactive cards?
2. What has it helped you to relate to mental disorders or learning?
3. What has meant using interactive cards as a gamification tool for your learning?
4. How do you think you could use what you have learned in your professional future?
5. How have interactive cards helped you to integrate content?
6. Has it made it easier to understand?
7. Have you encountered any difficulties while doing the activity?
8. Would you feel comfortable doing the activity in a group or prefer to do it individually? Why?

The results were also triangulated with the 32 individual narratives written by the participants, in which they shared their experiences of managing mental disorders through interactive cards. These narratives included personal reflections and an in-depth analysis of their emotions.

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Data Analysis

Verbatim transcriptions were made for each FG alongside researchers' field notes and reflective narratives. All data were carefully stored, managed, and organized using ATLAS.ti (version 24; Scientific Software Development GmbH), a qualitative data analysis software. An inductive thematic analysis [18] was conducted to identify relevant text segments addressing the research question systematically. The analysis began with open coding of the transcripts, during which researchers identified and labeled meaningful units of text. These initial codes were then grouped into categories based on shared meanings and thematic similarities. The categories were refined and organized into broader thematic groups through an iterative process of constant comparison. This interactive and reflective approach ultimately identified overarching themes that captured participants' experiences, offering a rich and nuanced understanding of their perceptions [24].

A total of 4 researchers (EGC-B, AT-R, PDP-H, and ACH), experts in qualitative research, developed the whole process of obtaining categories and subcategories independently, ending the process with the exchange of both and a consensus on the final decisions of the analysis. In case of divergence of opinions, the theme was identified by consensus among the research team members. In addition, memo writing and analytic discussions were used throughout the process to support reflexivity and maintain analytical rigor.

Rigor and Trustworthiness

The study followed the Consolidated Criteria for Qualitative Research Reporting (COREQ) [25]. The criteria to ensure the reliability of Guba and Lincoln were applied [21]. Data triangulation was used among the researchers involved in the analysis, and the analysis process was subjected to independent researcher review to ensure credibility. Transcripts were offered to participants, who were allowed to add any relevant information. Transferability was ensured by a detailed description of the research setting, participants, context, and method. Confirmability was achieved by introducing variability in participants' experiences. Each researcher conducted the reading and analysis independently, contrasting and agreeing on emerging themes and subthemes.

Ethical Considerations

The study was submitted to the Research Ethics Committee of the Instituto de Investigación Sanitaria Fundación Jiménez Díaz (CEIm-FJD) for review. Although the committee determined that the project fell outside its scope as it did not constitute biomedical research, it found no ethical objections to the documentation provided. All participants gave written consent before participating in this study. To ensure anonymity and confidentiality, a code was assigned to each participant in the FGs and reflective narratives. Participants were recruited through an open call disseminated through institutional channels, including emails and posters. They were informed in detail about the study, its objectives, and procedures, emphasizing that participating or not would not affect their academic career. It was made clear that participation in the study was entirely voluntary, would have no impact on their grades or academic evaluation, and they could withdraw at any time without any consequences on their academic performance or relationship with the university. Strict measures were implemented to ensure neutrality between teaching and research: data collection and interventions were anonymous and did not alter course dynamics, while academic results were managed independently. These actions fully protected students' learning rights.

Results

Participant Characteristics

Of the 53 nursing students who met the inclusion criteria, only 50 participated in the study, representing a participation rate of 94.3% (50/53). A total of 3 students did not attend the gamification activity due to scheduling conflicts, work commitments, or other personal reasons. Most participants were female (44/50, 88%), while 6/50 (12%) were male. The average age of participants was 18.5 years (SD 1.28; range 17-23 years). The gender imbalance reflects broader enrollment trends in nursing programs across Spanish universities, where female students constitute the majority. All participants were first-year nursing students enrolled in the General and Developmental Psychology course.

Themes

From the interactions developed during the gamification activity, three thematic blocks were identified along with their respective categories (see Table 1): (1) Perception and stigma of mental disorders; (2) Emotional connection and personal reflection in learning about mental disorders; and (3) Gamification tools and their impact on learning.

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Table . Thematic analysis overview: themes, categories, and subcategories.

Themes (T)	Categories	Subcategories
T1: Perception and stigma of mental disorders	• Beliefs • Stereotypes and prejudices • Understanding level • Perception of interactive cards	• Myths and initial beliefs • Stigmas in the social environment, unconscious prejudices, and awareness of the impact • Differentiation between disorders, understanding of severity, and identification of symptoms • Emotional impact, learning transformation, open mind, usefulness, and difficulties encountered
T2: Emotional connection and personal reflection in learning about mental disorders	• Personal and social environment • Accompaniment and support networks • Role of mental health professional • Attitudes change	• Influence of family expectations and close environment • Family support, barriers, and support network • Intervention strategies, therapeutic relationship, and more integral vision • Awareness and sensitization
T3: Gamification tools and their impact on learning	• Development of emotional and empathic skills • Learning process assessment • Introspection and self-knowledge • Impact on empathy development	• Improved emotional communication skills to identify emotions • Better understanding, meaningful learning, and integration of knowledge • Personal reflection, identification of experiences and biases, and insecurity • Recognition of other people's emotions, desire to help, and emotional connection.

Theme 1: Perception and Stigma of Mental Disorders

Beliefs

This category explores initial myths and beliefs and changes in students' perception of mental disorders through their interaction with visual material, such as the interactive cards used in the activity. They highlight the pedagogical value of the images and interactive cards in understanding mental disorders more deeply.

> *In future courses, these cards can be employed as a resource to associate the mental pathologies we study.* [FG 1]

When confronted with these resources, self-awareness has been awakened in them that has not only allowed them to rethink their beliefs about mental disorders but also their emotional well-being:

> *I have questioned my own experiences.* [Participant 15]

Stereotypes and Prejudices

Through the activity, participants reflected on how these stigmas affect both how society perceives people with mental disorders and how these people see themselves. The reflections reveal a change in understanding and an increased awareness of the impact of prejudice on the lives of those affected. They have been able to reflect on the role that erroneous beliefs, unconscious biases, and social expectations play in how these people see themselves and how they feel judged by others.

> *We thought it may be a case of personality disorder due in large part to prejudice and lack of confidence.* [FG 5, related to interactive card 1]

Through the interactive cards, the students observed that certain mental disorders, especially the most common ones, tend to be more stigmatized. This recognition allowed them to analyze how social stigma is disproportionately associated with certain disorders, which hinders access to help and adversely affects the well-being of those affected.

> *In the interactive cards, they observe the different types of disorders that are more stigmatized and more common.* [Participant 46]

The free approach to the activity allowed them to deepen their understanding of mental disorders without being constrained by preconceived ideas, which contributed to a more open reflection on the associated prejudices and stigmas.

> *Being a flexible and free-viewing activity, it helps to think about how a person suffering from a disorder might feel.* [Participant 12]

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Understanding Level

Student reflections revealed varying levels of understanding, ranging from the recognition of symptoms to a deeper internalization of the emotions and thoughts associated with different mental disorders. Participants demonstrated the ability to distinguish among various conditions, a crucial step toward comprehending the unique severity and impact. As a student explained,

> *In the image, we see a connection between time and food… we were able to associate different foods with each hour of the day, and it is reflected with an obsession with scheduling, meticulous planning of food intake.* [Participant 16]

This differentiation process enabled students to recognize specific symptoms and interpret how these disorders deeply affect the emotional and cognitive experiences of those who live with them. As one participant reflected,

> *Each time it tends to infinity; that infinity is like associating it with something chronic—of an eating disorder.* [Participant 10]

Such reflections reveal a growing capacity for nuanced understanding that extends beyond surface-level identification, indicating the development of empathetic insight and clinically relevant perspectives.

As students progressed through the activity, they demonstrated an increasingly sophisticated understanding of the varying levels of severity associated with mental disorders—ranging from observable behaviors to more complex emotional and psychological dimensions. They moved beyond simply associating symptoms and behaviors, gaining insight into the emotional toll experienced by individuals living with these conditions, including struggles with control and the anxiety tied to rigid eating patterns. This multidimensional understanding highlights how interactive cards support theoretical learning and foster empathy and emotional connection with the lived reality of mental illness. As a student reflected,

> *Maybe she is aware that she is in that darkness, but she doesn't want to get out because even though she feels bad about herself, she doesn't feel bad—she's comfortable, she doesn't want to get out of there...* [Participant 2]

Perception of Interactive Cards

The participants' perceptions highlight the value of using interactive cards as an educational tool in the study of psychology, particularly in enhancing understanding of mental disorders. The activity was widely appreciated for transforming theoretical content into a more accessible, engaging visual and interactive experience. A participant explained,

> *I found this way of integrating knowledge easier than a more theoretical one. When you see it in an image and have to reflect on its contents, you have to associate all the information you have given us in class to be able to put it into practice.* [Participant 22]

In addition, most participants emphasized the benefits of working in groups, noting that exchanging diverse interpretations and perspectives enriched the learning experience. Group interaction fostered an atmosphere of trust and respect, encouraging deeper reflection and more balanced conclusions. As one student stated,

> *We found it more comfortable to carry out the activity in a group because we were able to deepen our reflection on each interactive card since we had more than one point of view.* [Participant 16]

While participants acknowledged the benefits of the activity, some also highlighted specific challenges—particularly related to the abstract nature of the images, which required considerable interpretative effort. The process of identifying and associating symbolic elements with specific mental disorders was perceived as complex, necessitating an open-minded, analytical, and reflective approach. A student observed,

> *I find it difficult to associate the interactive cards with a disease. I think it is complicated to diagnose, and maybe the signs given by the image have nothing to do with what the author of the photographs really intended.* [Participant 21]

Despite these difficulties, participants recognized the pedagogical value of engaging with ambiguity, noting that it mirrored the interpretive and diagnostic complexities often faced in real clinical settings. The experience thus served as an essential formative exercise, encouraging the development of critical thinking and diagnostic sensitivity. Furthermore, the activity helped to strengthen their connection to the field of psychology, providing early exposure to its multifaceted nature and emphasizing its relevance to their future roles as health care professionals.

Theme 2: Emotional Connection and Personal Reflection in Learning About Mental Disorders

Personal and Social Environment

This category illustrates how personal and social environments significantly influence the emotional and mental experiences of individuals, particularly those living with mental disorders. When engaging with the interactive cards, participants frequently highlighted the distress and anxiety associated with being judged by others and how such judgments shape their self-perception and social behavior. An FG participant reflected,

> *We have felt very distressed and overwhelmed by how you are judged... It seems like a tunnel that looks like a labyrinth... when you are judged, the only thing you do is get lost in your thoughts... generating anxiety.* [FG 2, related to interactive card 1]

Participants also emphasized the powerful impact of societal expectations on self-image. Their feelings of inadequacy or failure to meet imposed standards influence how individuals view themselves and present themselves in social contexts. The metaphor of "mirrors" represented the weight of external expectations, underscoring how individuals may feel lost or disconnected when constantly comparing themselves to idealized social norms. As a participant stated,

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> *We interpret that the person may find themselves at a loss or judge by others' expectations... This influences the way he/she shows him/herself to society.* [Participant 38]

These insights underscore the importance of understanding the relational and societal dimensions of mental health, highlighting how external judgment and social pressure can exacerbate emotional distress and contribute to the internal struggles faced by those with mental disorders.

Other participants highlighted the influence of society in the understanding of mental illnesses, recognizing how these pathologies affect not only the people who are affected from them but also their close environment.

> *We believe that interactive cards have allowed us to understand how mental illness affects people and how it can have an impact on the environment, the society.* [FG 4]

Through various interpretations, the effects of mental health in the social context are valued, highlighting the importance of understanding the connections between self-image, food, and social perceptions.

Accompaniment and Support Networks

Participants reflect on the importance of accompaniment and support networks in the context of mental disorders. They highlight the challenges faced by people who lack family or social support and the crucial role of these networks in the recovery process. They acknowledge that the recovery process is not linear and that relapses may occur. However, they stress that, despite difficult moments, accompaniment and support can help the person to continue on the road to recovery:

> *You can fall because you are not in a good moment... there can be relapses, but in the end, everything leads to the same place, which follows the path.* [Participant 9, related to interactive card 2]

A central theme in this category is the lack of support faced by many people with mental disorders. Several participants pointed out that those without support networks, whether family or social, tend to experience more difficulties in their recovery process. Lack of resources and isolation can negatively affect self-esteem and self-image, making it challenging to follow appropriate treatment.

> *She knows that what surrounds her is darkness; many people who have a mental pathology have no family, no resources, no means, in the end, that has an impact on the follow-up and her own self-esteem and self-image.* [Participant 26]

Participants also reflect on the obstacles and barriers in readapting to a healthy routine, identifying relapses as moments in which external support is essential.

> *In addition, we consider that houses dirt roads could represent the 'stops, relapses or downs' of the process to readapt to a stable and healthy routine of meals.* [Participant 8, related to interactive card 2]

Role of Mental Health Professional

Students reflected on the role they will assume as future mental health professionals, emphasizing the integration of the knowledge acquired during their training to enhance care for individuals with mental disorders. They identified their understanding of eating disorders, personality disorders, and trauma as essential foundations for their future clinical practice. As a participant expressed,

> *In our professional future, we could use this knowledge to address similar cases in the field of psychology... integrating the acquired knowledge of eating, personality disorders, and addressing trauma into our professional practice.* [Participant 48]

The 2 central pillars frequently mentioned as critical to effective intervention were: establishing a strong therapeutic alliance and implementing evidence-based strategies. Participants acknowledged the need to combine empathy with scientifically supported methodologies to promote patients' emotional well-being and recovery.

> *This would include implementing evidence-based intervention strategies and establishing a strong therapeutic relationship to promote my patients' emotional well-being and recovery.* [Participant 15]

Furthermore, students highlighted the value of adopting a holistic perspective in mental health care. Rather than focusing solely on visible symptoms or first impressions, they advocated for a more comprehensive approach that considers emotional, social, and psychological dimensions in an integrated manner. As stated in one FG,

> *Not to be so rigid with opinions and try to see beyond what we can appreciate at a glance, that is, not to stay only with the initial but to devote time and effort to see everything in a more holistic way.* [FG 1]

These reflections demonstrate the development of a professional identity rooted in empathy, critical thinking, and a commitment to evidence-based, person-centered care.

Attitudes Change

Participants reported a shift in their attitudes toward greater empathy, particularly as they began to understand the anxiety and distress caused by the uncertainty surrounding recovery from EDs. The lack of a clear resolution to the struggle often leads to heightened emotional distress for affected individuals. This insight made students more aware of the profound emotional burden these disorders entail. As an FG participant reflected,

> *What we interpret from this image is that it represents a person who has hit rock bottom... the weight that food generates in his mind causes him nightmares.* [FG 3, related to interactive card 3]

These reflections contributed to a notable change in how students perceive individuals with EDs, fostering a recognition of the diversity and complexity of their experiences and the importance of a nuanced and empathetic understanding. Several participants also expressed a deepened appreciation for the severity of EDs and other mental health conditions, with some

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indicating a desire to explore the topic further to support those affected better. A student shared,

> *I have felt overwhelmed in general with the four interactive cards, as it considers mental pathologies as something serious and difficult, and I have to integrate myself into the subject to try to understand it.* [Participant 36]

Through reflection and analysis of the lived experiences represented in the interactive cards, students developed a more empathetic and comprehensive perspective on the ongoing struggles and emotional challenges faced by individuals with mental disorders. This attitudinal shift underscores the value of sensitizing future health care professionals to the seriousness of mental illness and promoting an informed, compassionate approach to understanding and care.

Theme 3: Gamification Tools and Their Impact on Learning

Impact on Empathy Development

Students' perceptions suggest that the activity functioned as a meaningful catalyst for deepening their understanding of mental disorders and enhancing their capacity for emotional recognition and connection with affected individuals. Many participants described experiencing a strong sense of identification through empathically placing themselves in the position of those living with such conditions. As an FG participant expressed, this involved, "putting themselves in the shoes of people suffering from different disorders, having identified eating disorders, anxiety, depression, and personality disorder" (FG 3).

Testimonials also revealed a profound sense of empathy and compassion, particularly when engaging with the images used in the activity. This emotional response often translated into a genuine desire to offer support:

> *"I feel empathy and compassion when viewing the images; it generates in me a desire to help and support those suffering from eating disorders, depression, and anxiety.* [Participant 12]

Such responses suggest that the activity encouraged emotional resonance and identification with the challenges faced by others, but also inspired a meaningful commitment to action.

Introspection and Self-Knowledge

The results reveal that the activity has been a significant means of personal reflection for the students. The tool used has allowed them to express their emotions and share experiences in an intimate and personal way. On the one hand, it has helped them to reflect on themselves, highlighting the importance of self-knowledge in their emotional process:

> *They allow us to express our emotions and to pour ourselves out in a personal way.* [FG 2]
>
> *Besides that, it has helped us to reflect on ourselves.* [FG 3]

A participant mentioned that he identified with insecurities that he had experienced throughout his life, which highlights the relationship between the activities and the personal experiences of each individual:

> *I find the interactive cards overwhelming as well as reflective, and they have caused me anguish, concern or even physical discomfort, since in some I have felt identified with insecurities that have arisen throughout my life.* [Participant 8]

This suggests that the activity not only allows the expression of emotions but also invites them to confront and identify their personal experiences and biases. Likewise, the activity promoted reflection on the mental and emotional health of some participants, leading them to question their personal experiences:

> *The interactive cards generate intense emotions in me such as sadness, fear or discomfort, recalling my own struggles and challenges.* [Participant 12]
>
> *It helps to express feelings, emotions that we do not know how to explain and shape, such as anxiety.* [FG 1]

These findings suggest that the process of inspection and self-knowledge generated through the activity constitutes a valuable resource for emotional development.

Learning Process Assessment

They highlight the effectiveness of the activity in broadening the understanding of mental disorders and fostering critical reflection on them. Several noted that the activity allowed them to "broaden the mind and see beyond what is depicted on the interactive cards" (FG 5), promoting deep inquiry and reflection on the various layers of meaning in the images. They recognized that an image does not have a single meaning and that, like mental disorders, perceptions can vary significantly depending on the point of view. This experience helped them challenge the idea that a person with a mental disorder can be pigeonholed into a single experience or interpretation.

> *They allowed me to understand that an image does not have to have only one meaning...a single thing can represent a great variety of sensations and impressions depending on one's point of view.* [Participant 12]

It emphasizes that each representation can evoke a variety of sensations and impressions depending on the observer's viewpoint. Testimonials also reflect the importance of approaching sensitive topics with care and respect. A participant emphasized the ability to "draw conclusions with a careful and thoughtful approach" (P27), suggesting that the activity focuses on theoretical understanding and the ethics of communicating about sensitive topics. This critical reflection is crucial for developing respectful and conscientious professional practice in the mental health field.

Likewise, it was mentioned that the activity is an excellent way to integrate the knowledge acquired in class:

> *...good activity to integrate the knowledge obtained in class, adding the sensations that each disorder can arouse in the viewer and therefore further ingraining the knowledge of the various disorders.* [FG 1]

Integrating theoretical knowledge with practical, emotional experiences reinforces the understanding of the various disorders and facilitates a deeper connection with the material studied.

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Finally, the interactive cards' interpretation helped participants gain a "graphic view of the different mental disorders" (Participant 32) and the topics covered in the course, which translates into more meaningful and visual learning. They suggest the activity is a valuable resource to enhance learning and foster a more holistic and empathetic understanding of mental disorders.

Development of Emotional and Empathic Skills

Students reflected on how the activity significantly contributed to developing emotional skills for addressing mental disorders. Interactive cards were seen as an educational tool and a potential aid in clinical settings, facilitating patient openness and expression. An FG participant noted:

> *Through the interactive cards, the patient can become more open and share deeper aspects of their personal experience, such as when asked to draw themselves.* [FG 1]

The value of creative dynamics in therapeutic processes was emphasized, particularly in enabling patients to express experiences and emotions that may be difficult to articulate verbally. Furthermore, participants recognized the potential of these tools for early detection and assessment:

> *The interactive cards can be valuable tools for early detection of mental health problems and for assessing the emotional state of patients.* [FG 2]

These reflections underscore the broader applicability of the activity, not only in education but also in clinical practice and mental health research.

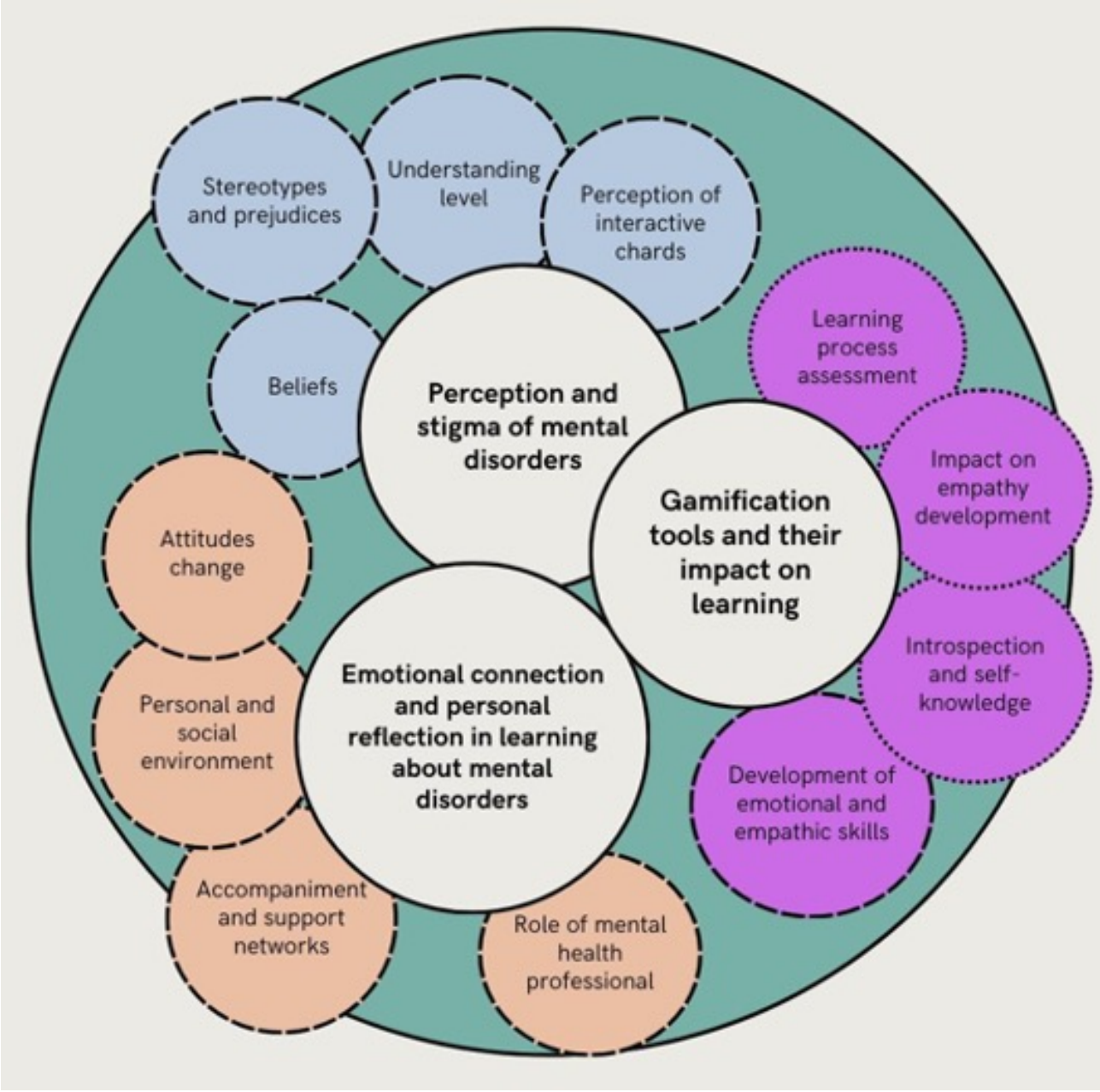
This perspective underscores the value of interactive cards within individual clinical contexts and as valuable tools in broader educational and research initiatives to deepen the understanding of mental disorders. Participants emphasized adopting a biopsychosocial framework when analyzing the interactive cards. This approach involves dedicating time and effort to constructing shared meanings beyond superficial interpretations. As an FG participant noted, it is vital "not to stay only with the initial but to dedicate time and effort to see everything in a more holistic and integrated way with a common meaning elaborated (FG 4).

Such an integrated perspective is essential for developing critical competencies in psychology. Encouraging students to consider emotional, psychological, and social dimensions together fosters a more comprehensive and empathetic understanding of patients' lived experiences. Ultimately, it cultivates reflective, thoughtful, and patient-centered mental health professionals.

These results reflect the complexity of understanding mental disorders through gamification as a learning tool. Figure 5 allows us to establish the following themes: the first theme deals with the perception and stigma of mental disorders. The second theme deals with emotional connection and personal reflection in learning about mental disorders. The third theme deals with gamification tools and their impact on learning. All of them are interrelated with each other through the ATLAS-TI program.

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Figure 5. Qualitative data analysis.



Discussion

Principal Findings

This study explored nursing students' perceptions of the approach and management of mental disorders through gamification experiences, using interactive cards as an educational tool. Gamification is presented as an innovative pedagogical approach that transforms the learning process, providing students with an active and participatory experience that encourages critical reflection and meaningful learning [1,3,26,27]. Results suggest that using interactive cards not only stimulates students' critical reflection on mental disorders but also allows them to challenge their theoretical knowledge, thus promoting growth in their self-confidence and ability to cope with complex situations in the mental health field [28-30].

These findings can be interpreted within the experiential learning framework, as the gamified activity immerses students in realistic scenarios that demand active decision-making, emotional involvement, and reflection. By confronting stigmatizing beliefs and exploring different perspectives through role-play and interaction, students engage in a process that aligns with transformative learning theory, fostering a change in their mental models and attitudes toward individuals with mental health disorders [31]. In this way, gamification serves as a motivational tool and becomes a vehicle for deep personal and professional growth [26-29].

Currently, gamification is gaining ground in clinical practice as an innovative strategy in the treatment and prevention of certain mental disorders. Several studies have shown that gamified interventions can improve patient engagement and motivation, facilitating treatment adherence in disorders such as depression and anxiety [7,8,32]. These tools allow patients

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to perform self-care, emotional regulation, and coping skills exercises in an interactive way, which can reduce symptoms and improve overall well-being. In addition, gamification in mental health can be tailored to each patient's needs, personalizing the experience and promoting active, hands-on learning of life skills [8,32]. However, despite the proven benefits of mental health, gamification is still being implemented progressively in the academic training of health sciences students. These benefits highlight the importance of the intervention carried out in the present research, which addresses and studies the treatment of mental health disorders such as eating disorders, emotional instability, and personality disorders from a gamified approach.

Implementing these strategies in the classroom could facilitate the understanding and managing of these mental illnesses, promoting the development of practical skills and greater empathy in future nursing professionals. Currently, nursing students require alternative and innovative methods to maintain a high level of engagement in their learning process. Gamification has demonstrated significant benefits in the development of cross-cutting clinical competencies, favoring essential qualities such as resilience, confidence in teamwork, effective communication, resource management, and taking responsibility in collaborative roles [3,27]. These innovative approaches promote more dynamic learning and reinforce key skills needed in the clinical setting, with encouraging results [28,33]. Furthermore, gamification, by using game dynamics in educational contexts, motivates students to engage more deeply with the study material [3,26,34].

The research findings highlight that gamification, by incorporating emotional and realistic elements, maximizes the positive impact on students' professional and personal development [29]. Students' interest was stimulated by interactive cards representing different mental disorders. They could participate through FGs in in-depth and diverse discussions, which enriched their understanding of the topic and helped them develop essential interpersonal skills and emotional intelligence [3]. These skills include empathy, active listening, and effective communication, which are fundamental to establishing therapeutic relationships with patients [15,30,35].

Through the collaborative exploration of interactive cards, students were able to identify and critically analyze the signs and symptoms associated with eating disorders and emotional instability. This process facilitated the recognition of clinical manifestations and deepened their understanding of the emotional and social contexts that shape each mental health condition. By engaging with the complexities of mental disorders from multiple perspectives, students developed a more nuanced and empathetic appreciation of the lived experiences of individuals affected by these conditions [36].

Participants emphasized the importance of understanding the underlying motivations behind the behaviors of people with mental disorders. This reflects a more holistic and balanced approach that moves beyond a narrow focus on risk factors to acknowledge the role of protective factors. Such insights support the development of a comprehensive perspective on mental health, reinforcing the need for multidimensional assessments that integrate emotional, social, and clinical considerations in practice [36].

This level of insight is fostered through educational strategies that immerse students in emotionally meaningful and reflective learning experiences, aligning with the principles of experiential learning, as students are immersed in simulated, meaningful scenarios that demand reflection, analysis, and decision-making. Furthermore, the activity design fostered dialogical and collaborative learning spaces—through FGs and discussions—that facilitated the development of interpersonal skills such as empathy, active listening, and therapeutic communication [31]. Taken together, these processes also resonate with the principles of transformative education, as the students not only engaged in active, experience-based learning but also reported having questioned their preconceived ideas and developed a more nuanced and compassionate understanding of mental illness.

One of the key advantages of gamification lies in the positive perceptions students hold toward educational games, which enhance motivation and promote learning across cognitive and affective domains. When implemented in team-based formats, gamification also improves communication and social interaction among participants. It offers opportunities to build interpersonal connections, foster mutual respect, and develop teamwork and collaboration skills while simulating real-world professional challenges [26,27,37]. By sharing reflections and experiences, this collaborative learning process contributes to developing practical competencies. It positively influences students' perceptions of their field and future career aspirations [30,33].

The findings of this study highlight that gamification not only improves nursing students' competencies and confidence but also has a transformative impact on their career aspirations. Through gamification, students develop a deeper understanding of the complexity of managing mental disorders, which helps them approach mental health with a more empathetic and proactive attitude. Gamification is therefore established as a valuable tool in training future nursing professionals, promoting a holistic and positive approach to mental health care that will benefit students and patients.

Practical and Research Implications

The practical implications of this study highlight the importance of integrating gamification tools, such as interactive cards, into health sciences education, specifically in the training of nursing students. This approach improves understanding of mental disorders and fosters the development of emotional competencies and key skills, such as empathy, effective communication, and critical reflection, essential for providing comprehensive and humanized care. Incorporating these tools can also enhance students' ability to engage with patients more compassionately and informally, improving patient outcomes. Incorporating these tools can also enhance students' ability to engage with patients more compassionately and informally, improving patient outcomes. Likewise, the implementation of these strategies can be extended to clinical settings, where interactive tools could be adapted for patient education or used as support in therapeutic contexts. In addition, these activities

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promote collaborative learning, creating a space for open discussion and exchange of perspectives among students, which enhances their preparedness to address complex situations in professional practice. This approach is also aligned with the principles of experiential learning, where students learn through direct practice and reflection on their experiences, reinforcing understanding and retention of key concepts.

In terms of research, this study opens the door to future explorations that evaluate the longitudinal impact of gamified tools on understanding and empathy toward mental disorders. It would be relevant to investigate how this approach influences the development of professional competencies over time. In addition, it is suggested that studies be conducted in different cultural and educational contexts to determine the transferability of the findings and compare the effectiveness of gamification versus traditional teaching methodologies. Research should also focus on developing and customizing gamified tools adapted to the specific needs of the students and disorders studied. Finally, exploring emerging technologies, such as virtual or augmented reality, could maximize immersion and enrich student learning in this field.

Strengths and Limitations

This study highlights 2 fundamental aspects. First, it proposes an innovative perspective on transforming the university educational model, advocating using gamification tools, such as interactive cards, to enrich understanding and reflection on mental disorders. Second, gamified strategies stimulate student interest and participation and facilitate more profound and meaningful learning.

Regarding the study's limitations, it is relevant to mention that it was conducted with nursing students from a university in Spain, which restricts the generalizability of the findings to other contexts or institutions. This study reflects students' perceptions of using interactive cards as a gamification tool to explore mental disorders. It would be valuable to extend qualitative research in a broader framework, incorporating a variety of gamification tools and complementing it with quantitative studies that measure the effectiveness of these innovative educational strategies.

Conclusions

This qualitative study has shown that gamification, used as a teaching strategy, can be an effective tool to improve the understanding of mental disorders among nursing students. Participants highlighted a higher degree of empathy, motivation, and commitment to learning, as well as a better internalization of content related to mental health. The results also reveal that nursing students face difficulties when participating in gamification activities related to mental disorders, mainly due to their limited prior experience in this field. In this context, implementing graphics as a gamified resource was shown to be an effective strategy to address these difficulties. These graphics, used as metaphors, provided an interactive and reflective framework that facilitated learning, allowing students to explore their emotions less directly and express them symbolically.

This visual approach helped participants reflect on their internal conflicts and project their goals and aspirations while developing self-assessment skills by identifying emotions, conflicts, and possible solutions. In this way, gamification serves to transmit knowledge and as a catalyst for students' personal and emotional growth in the mental health field. From a practical point of view, these findings suggest that including gamified dynamics—especially those with visual and symbolic components—in nursing training programs can facilitate a more meaningful, empathetic, and participatory approach to studying mental disorders.

As future lines of research, it is proposed to replicate this study with more extensive and more heterogeneous samples and to complement the qualitative approach with quantitative studies that evaluate the impact of gamification on variables such as academic performance, knowledge retention, or the development of emotional competencies. It would also be relevant to explore teachers' and clinicians' perceptions of integrating gamified methodologies in teaching content related to mental health.

Acknowledgments

The authors thank all students who participated in the study.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Detailed descriptions of each interactive card.
[DOCX File, 1718 KB - nursing_v8i1e71921_app1.docx]

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Abbreviations

COREQ: Consolidated Criteria for Reporting Qualitative Research
ED: eating disorder
FG: focus group
PD: personality disorder

Edited by G Strudwick; submitted 30.01.25; peer-reviewed by E Echaniz, K Erenli; revised version received 18.04.25; accepted 28.04.25; published 20.06.25.

Please cite as:
Del Pozo-Herce P, Tovar-Reinoso A, García Carpintero-Blas E, Casaux Huertas A, Ruiz de Viñaspre-Hernández R, Martínez-Sabater A, Chover-Sierra E, Rodríguez-García M, Juarez-Vela R
Gamification as a Tool for Understanding Mental Disorders in Nursing Students: Qualitative Study
JMIR Nursing 2025;8:e71921
URL: https://nursing.jmir.org/2025/1/e71921
doi:10.2196/71921

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Supporting Web-Based Teaching and Learning of Virtual Care Skills and Competencies: Development of an Evidence-Informed Framework

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Abstract

Background: Professionals across caring disciplines have played a significant role in the development of virtual care, which uses remote technologies to offer support and services from a distance. As virtual care becomes increasingly essential, instructors must ensure that students are equipped with both interpersonal abilities and digital competencies, merging traditional hands-on methods with web-based learning. Despite its growing importance, there is a lack of comprehensive frameworks to guide the design and delivery of web-based learning experiences that foster the development of virtual caring skills and competencies among students in caring professions.

Objective: This study aims to develop an evidence-informed framework to support web-based teaching and learning of virtual caring skills and competencies.

Methods: We present a synthesis of our research resulting in an evidence-informed framework. We integrated findings from an evidence synthesis, surveys, and semistructured interviews with students and educators, and consultations with key stakeholders.

Results: Principles of this framework include (1) connection and interaction; (2) compassion, empathy, and care; (3) vulnerability; (4) a client-centered focus; (5) inclusivity and accessibility; and (6) flexibility. The framework's four main domains are (1) virtual caring skills; (2) teaching and learning methods; (3) barriers to teaching, learning, and providing virtual care; and (4) facilitators of teaching, learning, and providing virtual care.

Conclusions: This framework was developed by and for students and educators to aid in planning, promoting, and enhancing virtual caring skills development. It can be used to better equip students to provide virtual care, thereby positively impacting client care and outcomes. This framework can support educators, students, decision makers, and practice partners to build learning experiences aimed at preparing students to provide virtual care effectively.

(JMIR Nursing 2025;8:e75868) doi:10.2196/75868

KEYWORDS

virtual care; telehealth; telemedicine; education; distance; clinical competence; empathy; patient-centered care; educational technology; curriculum; health education

Introduction

Background

Professionals across caring disciplines, including educators, doctors, nurses, social workers, and allied health professionals, have played a crucial role in the global response to COVID-19 pandemic. The rapid shift toward virtual care, where care is provided remotely through information technologies, has placed an unparalleled burden on these caring professionals [1,2]. With virtual care practices now essential for health care delivery, it is imperative to educate current students in caring professions and expose them to the requisite interpersonal and technological competencies for effective virtual care. However, there are no comprehensive frameworks to support the development and implementation of web-based learning opportunities that help students in caring professions develop the required virtual caring skills and competencies.

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Caring Professional Education

Caring professions, such as education, medicine, nursing, social work, and other allied health professions, are dedicated to supporting the health, well-being, development, education, and social needs of individuals and communities. These professions prioritize humanitarian objectives over material needs. Traditionally, education in caring professions relied on conventional methods such as face-to-face lectures, experiential in-class learning, and seminar formats. These educational approaches were often complemented by work-integrated learning placements, where students engaged with seasoned educators and practicing health professionals to acquire essential hands-on skills, dispositions, and competencies (eg, K-12 classrooms, hospital settings, and counseling centers) [3,4]. The landscape of education has evolved in caring professions due to advancements in technology and the emergence of virtual care. The integration of technology into education has opened new avenues for learning and skill development through web-based platforms, simulations, and virtual reality, for example, which supplement traditional teaching methods. The shifts to web-based and blended learning models have placed growing emphasis on fostering competencies related to virtual care, including effective communication through digital platforms, ethical considerations in telehealth, and leveraging technology to enhance client experiences and outcomes. While web-based education and some aspects of virtual care existed prior to the COVID-19 pandemic, the pandemic required everyone, irrespective of profession, location, or preference, to find new and inclusive ways of integrating web-based education and virtual care.

Impact of COVID-19 Pandemic

The COVID-19 pandemic necessitated an abrupt shift and expansion to virtual teaching, learning, and caring, prompting caring professional degree programs to adopt alternative strategies for providing students with necessary training experiences and learning opportunities [1,5,6]. This sudden transition placed unprecedented demands on higher education institutions to effectively instruct core competencies crucial to care provision and on caring professionals to ensure the meaningful implementation of virtual care in practice [1,4]. Despite long-standing literature emphasizing the need to support educators in meeting students' requirements [7,8], this need has become even more critical in the context of the COVID-19 pandemic [9].

This global crisis brought about significant changes in educational and care delivery methods, underscoring the importance of equipping caring professionals with the necessary skills to navigate current challenges and future uncertainties. Many educators in the caring professions encountered challenges in integrating effective web-based learning experiences, grappling with both technological and pedagogical hurdles as they prepared students for virtual work environments [10-13]. The pandemic prompted higher education institutions to reassess web-based education delivery within the caring professions and identify essential technological competencies for success in today's digital economy. The onset of COVID-19 pandemic emphasized the necessity for a structured, evidence-based approach to develop and implement educational technologies in web-based teaching and learning contexts [2,10,14,15].

While some promising adaptations and strategies have been reported globally by higher education institutions [12,16-18], there is currently no empirical framework specifically designed for the web-based teaching and learning environment of caring professional education. Recent research underscores the need for such a framework to better understand the conditions fostering productive e-learning opportunities and to establish structured educational goals and methodologies that support the development of students' virtual caring skills [11,19-21].

While there is a pressing need for educators to promote the development of both interpersonal and digital skills essential for providing virtual care, incorporating digital technologies into web-based classrooms and virtual caring professional practice can increase the expenses, time commitment, energy, and effort needed to provide students with substantial educational experiences. Despite practical and educational hurdles associated with emerging technologies, faculty members can overcome these barriers by adopting a deliberate and strategic approach to their work. To our knowledge, no comprehensive frameworks have been developed or evaluated to outline the necessary conditions to create effective practices to foster productive e-learning opportunities to support the development of virtual care skills and competencies for students in caring professions.

Research Aims

The main aim of this research was to develop an evidence-informed framework supporting the teaching and learning of virtual caring skills and competencies. This framework can be used by (1) educators for planning, implementing, and evaluating teaching and learning strategies aimed at developing virtual caring skills and competencies; (2) students to assess their strengths and areas needing improvement in virtual caring skills and competencies; (3) institutional decision makers to inform key strategies related to teaching and learning virtual caring skills and competencies; and (4) employers to gain insight into the broad range of virtual caring skills and expertise that caring professionals can contribute to the workforce.

Methods

Data Sources

We used an integrated knowledge translation approach [22] to develop our framework using a collaborative research model where researchers and knowledge users, including educators and students, worked together. Our multidisciplinary team included 2 students and 4 faculty members from diverse caring professions within the same institution. Together, we codeveloped the research questions, successfully secured research funding, and actively participated throughout the framework development process. In using this approach, which involved shared power and coproduction of knowledge, we aimed to generate more relevant and actionable findings with greater uptake across policy and practice. Our research used a mixed methods pragmatic approach [23], incorporating (1)

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evidence synthesis, (2) surveys involving students and educators, (3) semistructured interviews with students and educators, and (4) consultations with key stakeholders.

Evidence Synthesis

We conducted a systematic review to identify web-based learning opportunities aimed at helping students in caring professions to develop and apply virtual caring skills and competencies in virtual caring environments. Our synthesis encompassed evidence from 38 studies, curriculum details, study outcomes, barriers and facilitators to technology integration, impacts on students, and effects on professional practice [24]. The findings from our review guided the formulation of surveys for students and educators, followed by subsequent semistructured interviews.

Surveys

Based on the results of our systematic review, we developed 2 surveys, 1 for students and 1 for educators, from caring professions within the same institution. These surveys included demographic items and questions about experiences with and perceptions of web-based teaching and learning technologies, instructional methods, and virtual caring skills. Items included closed and open text responses. Survey data were analyzed using descriptive statistics, with variations in distributions across the dataset summarized and presented in tables and graphs [25]. Inferential statistics were used to investigate potential relationships between demographic variables and satisfaction, preparedness, and the likelihood of using web-based teaching and learning technologies for developing virtual caring skills [25]. Open text responses were analyzed with interview data. There were 93 student and 82 educator survey respondents. The complete survey results are available in a separate publication [26,27].

Interviews

Students and educators in caring professions who agreed to be interviewed were purposively sampled based on survey results to ensure representation across disciplines, genders, and levels of experience. Semistructured interview guides consisted of open-ended questions designed to explore each participant's experiences and perspectives on web-based learning aimed at developing virtual caring skills and competencies. Interviews were conducted on the web via Zoom (Zoom Video Communications, Inc) and typically lasted between 20 and 45 minutes. All interviews were digitally recorded and transcribed verbatim for subsequent analysis. Data collection continued until all willing participants had completed their interviews. A total of 9 students and 8 educators participated in the semistructured interviews, which were thematically analyzed using an inductive approach to identify common interactive themes across the data [28,29]. The detailed findings from these interviews are published elsewhere [24].

Mixed Methods Analysis

Expanding upon our previous efforts and advancing from our prior research, we embarked on a process of cross-referencing our findings across different stages of the study using a mixed methods metamatrix [30]. This integration technique allowed us to comprehensively analyze all gathered data collectively. The implementation of a metamatrix enabled us to develop a robust visual framework, aiding in identifying patterns across various data types and establishing a clear documentation trail [30].

Consultations With Knowledge Users

Consultations with students and educators occurred iteratively throughout data collection, analysis, and framework development stages. During these consultations, which included presentations at national and international teaching and learning conferences, knowledge users were presented with emerging themes to solicit feedback on the relevance, gaps, and applicability of the framework. The feedback from knowledge users was collated by graduate student team members, shared with the broader research team, and integrated into the final framework.

Ethical Considerations

The institutional review board that granted the ethics approval for this study is the University of Calgary Conjoing Health Research Ethics Board (REB22-0748). Prior to participation, all participants were provided with a comprehensive consent form that provided a detailed explanation of the study, outlined the voluntary nature of the study, and reinforced participants' right to withdraw at any time, as well as any associated risks and benefits. All participants were assured that their confidentiality and privacy would be upheld in accordance with the ethics application. Informed consent was obtained from all study participants and no compensation was provided for participation.

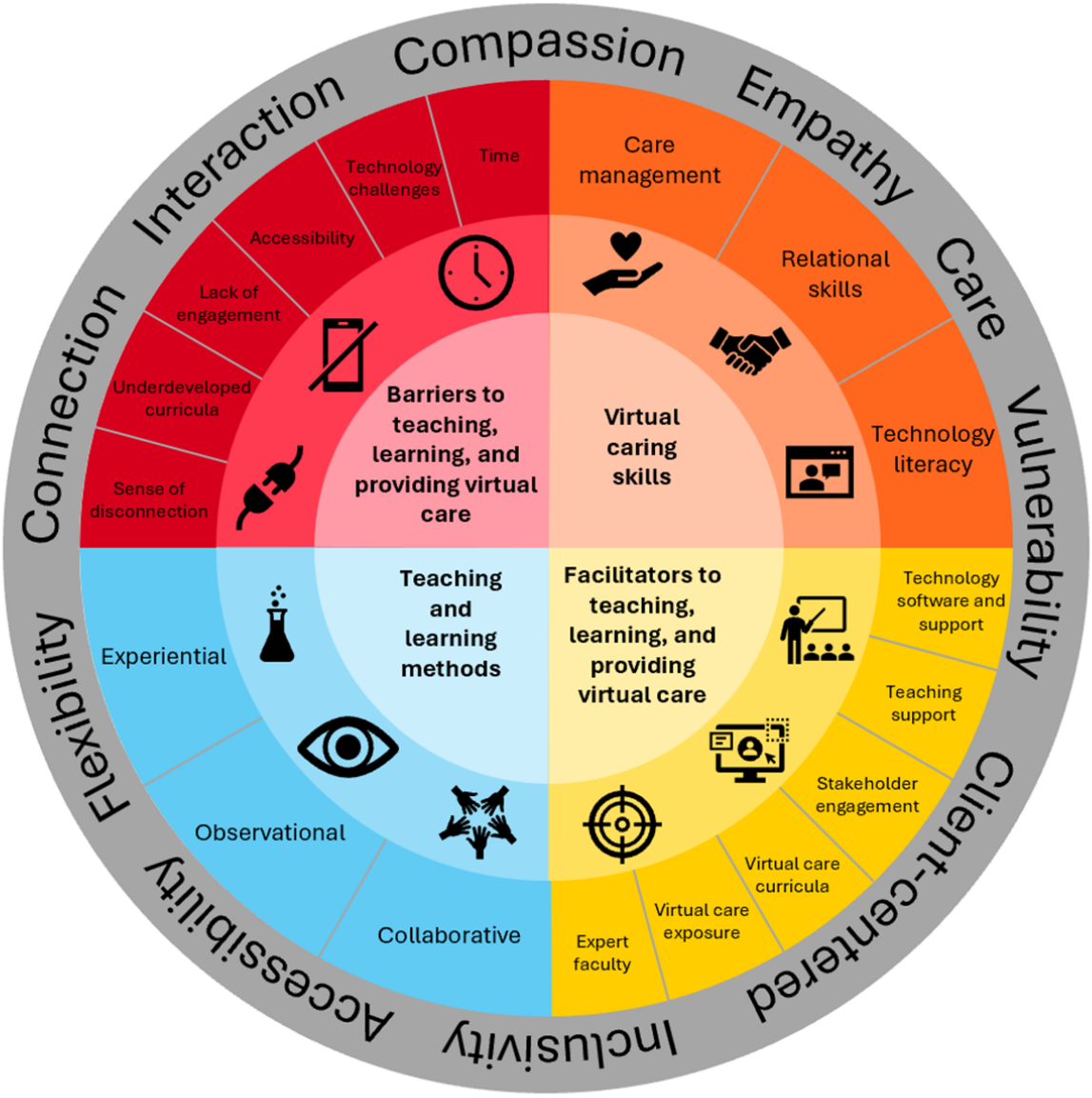
Results

Overview

The framework developed through this research process (Figure 1) is structured around 10 principles (outer ring) and consists of 4 major domains (center of framework), which are further divided into 18 subdomains. These subdomains encompass key considerations when teaching and learning virtual caring skills in web-based environments.

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Figure 1. Virtual Caring framework.



Principles for Teaching and Learning Virtual Caring Skills

Connection and Interaction

Establishing connections and fostering interactions in virtual environments are crucial for building relationships, as the absence of such connections can noticeably diminish engagement. In virtual settings, dedicating time to understanding the perspectives and concerns of individual students, educators, colleagues, and clients becomes imperative, highlighting the crucial skill of fostering connections for caring professionals. Particularly in the context of virtual learning and caregiving practices, students and educators emphasize the importance of prioritizing personal connections with clients over technical and hands-on skills when delivering virtual care. Various methods, including in-class activities, group work, breakout rooms, allowing time for questions, sharing experiences, role-playing, and using multimodal content, can enhance engagement and interaction. Educators can exemplify effective interaction strategies applicable to providing virtual care.

Compassion, Empathy, and Care

Creating learning experiences that prioritize compassion, empathy, and care, particularly in virtual settings, demands emotional labor and deliberate planning. Effectively integrating web-based teaching and learning technologies requires emotional bravery from educators to foster students' proficiency in virtual caring skills. Designing learning activities that center on social and emotional learning becomes crucial for promoting individual well-being. When it comes to teaching, learning, and offering virtual care, embracing and authentically displaying compassion, empathy, and care are fundamental elements.

Vulnerability

In adapting to new virtual environments, both students and educators should be open to exploring unfamiliar approaches, acknowledging that outcomes may not unfold as anticipated.

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The progress of virtual care may be hindered through a lack of willingness to embrace vulnerability or adopt novel strategies to provide care. Establishing safe and courageous learning and caring spaces is essential. Professionals in the caring field must cultivate a supportive atmosphere within virtual environments, breaking down barriers and nurturing relationships to advance virtual caring initiatives that meet clients' needs.

A Client-Centered Focus

Recognizing the importance of client-centeredness is crucial in virtual caring practices. In web-based learning and interactions, students and clients must perceive a sense of genuine care that prioritizes their well-being. A client-centered approach involves assessing individual client needs and adapting strategies to effectively address these within the virtual environment. This perspective not only informs the questions caring professionals may ask in these situations but also shapes the care provided to future remote clients. The pandemic has heightened our collective awareness of the intricate nature of human experiences, emphasizing the value of adopting a more holistic approach to the teaching and practice of virtual care.

Inclusivity and Accessibility

The advent of educational technology has enhanced inclusivity and accessibility in learning and caring, introducing innovative modes of engagement that are particularly beneficial for individuals who are members of marginalized groups. The transformative influence of online and virtual platforms in educational technology has significantly broadened the scope of inclusivity, accessibility, and equity in learning and caregiving. This technological advancement has expanded educational and caregiving opportunities to people residing outside urban areas, or managing diverse life responsibilities, or experiencing physical challenges, providing access that was previously limited. However, accessibility can still be hindered by challenges such as poor internet connectivity, limited web-based or computer literacy or access to appropriate electronic devices, and a lack of physical spaces conducive to web-based learning or accessing web-based care. As virtual caring continues to gain prominence in society and increases accessibility for some, it is important to recognize and support those who may find this mode of caregiving inaccessible.

Flexibility

Flexibility emerges as a fundamental principle in acquiring and applying virtual caring skills. The inherent nature of web-based learning provides crucial flexibility, allowing individuals to grasp content and skills at their preferred pace and schedule. This proficiency seamlessly extends to their virtual caring practice, empowering both students and clients to engage more effectively and customize their experiences according to their distinct needs and interests. Demonstrations of flexibility can manifest in various aspects, including accessibility, choice of topics, meeting times, and personalization of care.

Four Major Domains

Virtual Caring Skills

Care Management

Effectively managing virtual care requires the cultivation of critical thinking, organizational prowess, advocacy, adaptability, client education, assessment, documentation, and problem-solving skills—all crucial proficiencies for students pursuing careers in caring professions. Profound skills are required to organize client care effectively, conduct thorough client assessments, and advocate for accessing resources within virtual care environments. Caring professionals must excel in asking pertinent questions, discerning when to delve deeper, and adapting skillfully when necessary. These competencies enable them to navigate the complexities of virtual care delivery and ensure comprehensive and compassionate support for clients.

Relational Skills

In virtual care settings, fundamental relational skills—including effective communication, relationship building, ensuring psychological safety, and conveying empathy—play a crucial role in providing care. Emphasis must be placed on observing nonverbal cues and voice tone and practicing active listening when operating in virtual contexts. Although establishing rapport and building relationships with clients may present challenges in virtual environments, it remains an essential aspect of care. Nurturing psychological safety and expressing empathy during virtual care delivery can contribute significantly to clients feeling comfortable and at ease throughout the care process.

Technology Literacy

Proficiency in technology is vital for delivering virtual care. Students must acquire the skills and confidence to navigate diverse virtual care technology platforms. Being able to operate smoothly within these technological platforms enables students and professionals to redirect their focus to the client and their well-being. Additionally, a comprehensive understanding of the legal and ethical dimensions associated with providing virtual care, including aspects such as thorough documentation and privacy concerns, is of utmost importance.

Teaching and Learning Methods

Collaborative Learning

Collaborative web-based learning plays a pivotal role in fostering the development of virtual caring skills among students in caring professions. Through dynamic mechanisms such as class discussions, group work, and interdisciplinary collaboration, students engage in a rich educational experience that extends beyond individual perspectives. Collaborative learning environments provide a platform for students to share diverse insights, cultivate empathy, and refine their communication skills. In the context of caring professions, this collaborative approach can enable students to understand various dimensions of care, incorporating holistic perspectives from multiple disciplines. Moreover, the virtual nature of these interactions not only mirrors the evolving landscape of care provision but also equips students with digital communication

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and teamwork skills crucial for contemporary professional practice.

Experiential Learning

Experiential web-based learning opportunities offer another avenue for nurturing virtual caring skills among students in caring professions. Engaging in virtual simulations, role-play, and case study scenarios allows students to immerse themselves in realistic yet controlled environments that mirror the challenges and dynamics of their future professions. This hands-on approach not only deepens their understanding of theoretical concepts but also hones their ability to navigate complex situations with empathy and sensitivity. Additionally, virtual practicum experiences can further provide students with authentic interactions with virtual clients. These immersive encounters enable students to apply their knowledge and skills in a safe and supervised web-based setting, fostering the development of virtual caring skills within the context of genuine client interactions.

Observational Learning

Observational learning in web-based settings plays a pivotal role in shaping the development of virtual caring skills among students in caring professions. By actively observing faculty members and engaging in virtual settings that simulate professional work, students gain valuable insights into the nuances of compassionate and effective care delivery. This learning approach allows them to witness real-world scenarios, model empathetic behavior, and internalize best practices in virtual care. Through this observational process, students not only grasp the theoretical underpinnings of their field but also cultivate a deeper understanding of the practical application of virtual caring skills. By emulating the actions and techniques demonstrated by experienced professionals in the web-based environment, students can refine their own approach to virtual care, laying the foundation for a compassionate and ethically grounded professional practice in the digital realm.

Barriers to Teaching, Learning, and Providing Virtual Care

Technological Challenges

Certain technological challenges pose significant obstacles to teaching, learning, and delivering virtual care. These challenges encompass issues such as streaming disruptions, navigating unfamiliar technologies, and the inherent unreliability and unpredictability of technology. Caring professionals must acquire the skills not only to use technology themselves but also to guide clients in navigating unfamiliar technological terrain. Moreover, they need to adapt to and address technology failures as they arise. The hurdles associated with technology can have repercussions on both student learning and their capacity to deliver exceptional, appropriate, and timely care to clients.

Limited Access to Virtual Caring Equipment, Internet, and Technology

The teaching, learning, and delivery of virtual care can be impeded by challenges such as limited accessibility, inadequate equipment, client web-based literacy, and insufficient internet connections. Scarce access to mobile devices and reliable internet connections not only affects student learning but also restricts the scope of care they can extend to clients, leading to diminished interactivity. These concerns are particularly significant when teaching and delivering virtual care to clients in rural and remote areas, underscoring issues related to unequal access to web-based resources and broader accessibility challenges for clients.

Sense of Disconnection

Delivering care in virtual settings may limit the capacity to form personal connections with clients or offer specific therapeutic services that rely on in-person interactions. For instance, therapeutic touch is a caring skill that is typically used in face-to-face interactions. The absence of a personal connection and the difficulty in fostering a sense of community with clients can pose a substantial obstacle to effective care provision. Moreover, delivering appropriately personalized care over the phone presents additional challenges due to the inability to convey messages through body language.

Time Constraints

The constraints of time pose significant challenges in the domains of teaching, learning, and delivering virtual care. Both students and clients may struggle to maintain prolonged engagement on the web, while educators face additional demands, especially when facilitating experiential learning for virtual care practices. These constraints underscore the need for efficient and focused approaches to ensure meaningful educational and caring interactions within the limitations of web-based environments.

Underdeveloped Virtual Caring Curricular Content

There is a noticeable gap in the availability of content for educators seeking to teach students about virtual caring. Faculty require more resources to adequately prepare students for engaging in virtual caring practices. Often, curricula are constrained and overloaded, with virtual care content treated as an afterthought. Virtual caring skills and competencies, considered specialized practices, may not be conventionally integrated into broader, generalist-focused curricula. However, with the advent of COVID-19 pandemic, virtual care has emerged as an essential skill set for many caring professions. The absence of dedicated curricula on virtual caring could potentially hinder students in caring professions from effectively providing virtual care in their future practices.

Lack of Engagement

Interruptions, decisions regarding the use of cameras, and difficulties in connecting with students, educators, colleagues, and clients can diminish levels of engagement. Active participation from clients in education and care settings is required to achieve intended outcomes. In virtual settings, the prevalence of interruptions and uncertainties about whether cameras should be on or off may prompt questions about presence and limit clients' and caregivers' overall sense of engagement. Negotiating these challenges is essential for fostering a more conducive web-based environment for providing virtual care.

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Facilitators of Teaching, Learning, and Providing Virtual Care

Technology Software and Support

Acquiring knowledge and purposefully using technology and virtual caring software can enhance the facilitation of teaching, learning, and delivering virtual care. Conducting orientation and skill development sessions to familiarize individuals with the technology can be beneficial. Despite the potential assistance of virtual care technology, without a thorough comprehension of its efficient and effective utilization, students and educators may encounter difficulties in establishing meaningful caring connections with clients.

Teaching Support

Support for teaching in web-based settings—from teaching and learning departments, colleagues, faculty members, or external networks—can significantly contribute to skill development in virtual care instruction. Continuous development and exchange of best practices serve as valuable avenues for fostering ongoing growth in confidence and competence when using virtual caring technology. Leveraging a collaborative approach ensures a sustained and progressive enhancement of teaching skills related to virtual care in web-based environments.

Stakeholder Engagement

Effective development of virtual caring skills relies on support and engagement from various stakeholders, including care providers, clients, students, educators, and institutions. The diversity of perspectives these stakeholders bring to virtual caring experiences is invaluable, and leveraging these viewpoints can enhance the effectiveness of teaching and learning about virtual care. Collaborating with and incorporating insights from these diverse stakeholders are essential for a comprehensive approach to virtual caring skill development.

Expert Faculty

Facilitating the learning of virtual caring skills necessitates the presence of expert faculty proficient in web-based education and experienced in delivering virtual care. These experts play a crucial role in modeling and promoting web-based etiquette, fostering psychological safety within the virtual classroom, and structuring interactive activities that contribute to a shared and enriching learning experience.

Virtual Care Curriculum

Recognizing virtual care as a current reality underscores the importance of integrating it into professional educational programs focused on teaching caring skills. Enhancing the effectiveness of teaching, learning, and delivering virtual care involves aligning virtual caring expectations, competencies, and learning objectives within the curriculum. Strategies can include developing a dedicated virtual care course or incorporating threaded virtual care topics throughout a curriculum.

Virtual Care Exposure

Gaining familiarity with virtual care through activities such as shadowing virtual care providers, practicing virtual caring skills with clients, watching web-based demonstrations, or engaging in role-play and simulated virtual care environments can significantly contribute to developing virtual care proficiency and deepening one's comprehension of the diverse scope of this mode of practice. Increased exposure to virtual care experiences can enhance the effectiveness of web-based learning.

Discussion

Principal Findings

The findings from this multiphase and multifaceted study resulted in the development of an evidence-informed framework to support teaching and learning virtual caring skills and competencies. The components of this Virtual Caring framework are based on our previous research including an evidence synthesis, surveys, and interviews, and the framework was refined through stakeholder consultations. The Virtual Caring framework highlights key principles for virtual care, virtual caring skills, teaching and learning methods, and barriers to and facilitators for teaching, learning, and providing virtual care.

Teaching, learning, and providing virtual care can benefit greatly from incorporating key principles such as connection, interaction, compassion, empathy, care, vulnerability, client-centered approaches, inclusivity, accessibility, and flexibility. Creating a caring environment and cultivating relationships with clients in health care can facilitate shared decision-making, thereby improving client outcomes [31]. In a qualitative study exploring health care providers' experiences in building rapport in telehealth settings, caring professionals emphasized that building rapport with clients is essential for fostering positive, productive interactions with clients and their families [32]. Additionally, establishing meaningful connections and interactions in virtual environments is essential for nurturing a sense of community and trust among students [33]. Felton et al [33] stated that trust is fundamental in the educator-student relationship and crucial for students to feel psychologically safe. They recommended *trust moves* to help foster the trust of students, including strategies such as getting to know the students, demonstrating mastery of the content, engaging respectfully, and showing sensitivity to diverse identities [33].

Infusing compassion, empathy, and care into virtual interactions ensures that the human element remains integral in digital spaces, promoting a more client-centric and supportive care environment. Recognizing vulnerability as a strength rather than a weakness encourages open communication and collaboration, thereby deepening connections between care professionals and clients. Adopting a client-centered approach ensures that virtual care is tailored to each individual's unique needs and preferences, promoting the effectiveness and personalization of interventions. In a scoping review examining barriers and facilitators to telehealth implementation in populations at risk for health disparities, Baily et al [34] indicated that client-centered approaches serve as facilitators in delivering telehealth care and can help mitigate health disparities. Moreover, Health Canada [35] has underscored the importance of a client-centered and community-centered focus to achieve the quadruple aim in telehealth. Inclusivity and accessibility principles can ensure that virtual care remains accessible to everyone, regardless of diverse backgrounds, life

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situations, or abilities. Finally, flexibility enables adaptation to the evolving landscape of virtual care, accommodating the dynamic needs of both learners and clients. By embracing these principles, educators, learners, and care providers can create virtual care environments that are not only effective and efficient but also empathetic, client-centered, and inclusive.

To effectively provide virtual care, students in caring professions require specific skills. Robust care management skills are paramount to ensuring that caring professionals can organize, coordinate, and optimize the delivery of care in the digital landscape. This includes proficiency in using virtual platforms for scheduling, monitoring client progress, and facilitating communication among the care team. Relational skills are equally important, enabling care providers to establish and maintain meaningful connections with clients through virtual channels. This involves cultivating effective communication, active listening, and empathy to create a supportive and trusting virtual care environment. Noddings [36,37], an education scholar, discussed the centrality of relationships and caring in education, emphasizing the importance of listening carefully and responding to expressed needs without assuming what students may require. The theoretical writings of Noddings [36,37] are applicable across various caring professions and can guide professionals in delivering client-centered care that is supported by relational skills. Additionally, technology literacy is foundational in virtual caring, equipping care providers with the competence to navigate and leverage digital tools effectively. Combining these skills enables the delivery of high-quality virtual care that is not only technologically proficient but also rooted in the principles of empathy, communication, and client-centeredness.

Collaborative, experiential, and observational learning form a robust triad that supports students in developing essential virtual caring skills. Through collaborative learning, students engage in collective exploration and discussion, fostering a diverse range of perspectives and insights that contribute to a holistic understanding of virtual care. Experiential learning, which includes virtual simulations and practical scenarios, allows students to actively apply theoretical knowledge in realistic contexts, enhancing their problem-solving abilities, and deepening their virtual caring skills. In a study examining the impact of virtual telehealth simulation on prelicensure community health nursing students, significant increases in knowledge, attitude, and confidence were observed following simulation-based education [38]. Students also rated the learning experience highly and found the content important to their learning [38]. Although virtual simulations have gained popularity in health care, this experiential learning modality may also prove valuable in other caring professions, such as social work [39]. Observational learning can further complement these approaches by providing students with the opportunity to witness seasoned professionals in action. This allows them to model empathetic behavior, effective communication, and other crucial skills in virtual care settings. Moreover, students need to see their educators as caring professionals who provide an environment conducive to their learning. This combined approach not only enhances students' proficiency in using digital platforms but also cultivates the interpersonal and technical competencies required for successful and compassionate virtual care practice.

Several challenges can pose significant barriers to the effective teaching, learning, and provision of virtual care. Technological challenges can impede the seamless delivery of virtual care services and teaching and learning experiences. According to Ortega et al [40], limited access to the internet or technological devices can exacerbate disparities, preventing some individuals from participating in web-based learning or accessing virtual care. This limitation can create a pervasive sense of disconnection, stemming from the absence of face-to-face interactions, which affects both student engagement in learning and clients' perception of care. Time constraints further compound these issues, as professionals and learners may struggle to balance virtual care demands with other responsibilities. Moreover, maintaining engagement poses a challenge, as the virtual environment may not always capture the same level of attention and participation as in-person settings. Additionally, the underdeveloped nature of virtual caring curricula poses a barrier. Educators grapple with the task of aligning educational materials with the dynamic and evolving landscape of virtual care, potentially leaving gaps in essential skills and knowledge. Addressing these challenges is crucial for ensuring that virtual care education is inclusive, effective, and capable of meeting the diverse needs of both learners and care recipients.

The effective facilitation of teaching, learning, and the provision of virtual care hinges on several key factors. First and foremost, technology software and robust technical support are crucial in creating seamless virtual care experiences. Access to reliable platforms and assistance in navigating digital tools ensure that caring professionals and students can confidently engage in virtual care settings. Teaching support also plays a critical role. Educators benefit from training in web-based pedagogy and virtual care methodologies, which enhances the quality of instruction and fosters an environment conducive to optimal learning outcomes. Moreover, active stakeholder engagement is essential. Collaboration with care organizations, policy makers, and industry experts helps align virtual care education with real-world practices and expectations. Expert faculty with specialized knowledge in virtual care enriches the learning experience by offering valuable insights and mentorship. Exposure to diverse virtual care scenarios through simulation or practicum further enhances preparedness. Learners can apply theoretical concepts in practical settings and adapt to the complexities of digital care delivery [41]. In concert, these elements create a supportive framework that empowers both educators and learners to navigate the nuances of virtual care with confidence and proficiency.

Practice Implications

As workforce needs continue to shift, our Virtual Caring framework can support the development of virtual caring skills and competencies across various caring professions. We created this framework to serve as a tool for educators, students, and decision makers, enabling the systematic and intentional integration of virtual caring skill development into caring professions education. We anticipate that our framework will

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be useful to several target audiences across multiple organizational levels, including educators, students, decision makers, and practice partners. For example, educators and students can use this framework to facilitate discussions on teaching and learning strategies, establish plans for enhancing virtual caring skills, and promote critical reflection and career growth in virtual care practices. Institutional decision makers and teaching and learning centers can leverage the framework to guide the development of programs tailored to nurturing virtual caring skills among professional students. At a broader level, institutional, regional, national, and international associations can use the framework to amplify conversations and develop strategies aimed at fostering widespread cultural shifts in integrating virtual caring skills into caring professions education. Despite potential resource constraints in higher education institutions related to virtual care technology and teaching support, our framework offers a structured approach for administrators to strategically plan virtual caring initiatives that address the growing demands of caring professions. Additionally, educators can identify opportunities for collaboration with other caring professional programs, potentially creating synergies that enhance program offerings. Thus, our Virtual Caring framework catalyzes advancing the integration of virtual caring competencies across caring professions education, ensuring preparedness and responsiveness to evolving workforce needs.

Strengths and Limitations

This research reflects the global state of evidence on web-based learning opportunities designed to develop and apply virtual caring skills and competencies among students in caring professions. Our research, while underpinned by global literature, primarily focused on the perceptions and experiences of caring professions students and educators from one Canadian university, aiming to provide insights across various disciplines. The inclusion of participants from a range of disciplines strengthened this study, allowing for a deeper exploration of the complexities involved in web-based learning for developing virtual caring skills. The triangulation of data from different phases of this study into an evidence-informed framework strengthens the findings.

While our research followed a systematic and rigorous approach, this study is not without limitations and caveats. Despite a comprehensive and systematic literature search, some relevant literature might have been missed. Additionally, variations in web-based teaching and learning methods regarding virtual caring skills posed challenges for direct comparisons, yet they also provided valuable insights into different approaches, benefits, and associated challenges. Moreover, although the literature informing this work is globally representative, the data collection from student and educator surveys and interviews was conducted at one research-intensive university in Canada, potentially limiting the generalizability of our findings to other institutions. However, stakeholder consultations at 3 different national and international events provided a broader perspective and validated the relevance of the framework beyond the study's specific context.

Future Research

Our study also underscores the need for further research with robust study designs to better understand how to effectively support the development and implementation of web-based learning opportunities that help students in caring professions in developing the required virtual caring skills and competencies. Existing research on teaching virtual caring skills in web-based settings may not be robust [41]; however, the need for caring professionals to develop virtual caring skills and competencies is clear [24,26]. Our comprehensive framework designed to facilitate the development and integration of web-based learning opportunities aimed at nurturing essential virtual caring skills across caring professions is novel. Rigorous evaluation of the use and impact of this framework is needed [41]. Future longitudinal studies could also investigate the sustained impact of virtual caring skills development over time.

Conclusions

This evidence-informed Virtual Caring framework was developed by educators for educators, specifically to support web-based teaching and learning of virtual caring skills and competencies among caring professional students. It serves as a tool for planning, promoting, and enhancing the development of virtual caring skills in web-based educational settings. Institutions can use this framework to inform their efforts in refining current strategies or developing new approaches aimed at fostering virtual caring skills development among their students.

Conflicts of Interest

None declared.

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Edited by E Borycki; submitted 11.04.25; peer-reviewed by A Gaudino, B Henry, C madu, P Koppel, SM Shaffi; accepted 01.05.25; published 03.07.25.

Please cite as:
Nowell L, Dolan S, Johnston S, Jacobsen M, Lorenzetti DL, Oddone Paolucci E
Supporting Web-Based Teaching and Learning of Virtual Care Skills and Competencies: Development of an Evidence-Informed Framework
JMIR Nursing 2025;8:e75868
URL: https://nursing.jmir.org/2025/1/e75868
doi:10.2196/75868

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The Intention of Primary Health Nurses to Participate in Internet Plus Nursing Service: Cross-Sectional Survey

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Abstract

Background: "Internet Plus Nursing Service" (IPNS) offers innovative solutions for China's growing home health care demands. Understanding primary care nurses' participation intentions is crucial for service optimization.

Objective: This study evaluates primary health nurses' intention to participate in IPNS—a technology-mediated home care model combining mobile health platforms with in-person visits—and examines how digital readiness, safety perceptions, and organizational factors influence participation decisions, to guide policy optimization for scalable digital home health care delivery.

Methods: A cross-sectional survey was conducted in Jiangsu Province, China (December 2023-December 2024) using the validated Participation Intention of Nurses on IPNS Scale. Convenience sampling enrolled 3952 nurses from 13 prefecture-level cities in Jiangsu—the second-tier administrative divisions in China that typically encompass both urban and rural areas, each with independent health care systems governed by municipal health authorities. Statistical analyses included *t* tests and ANOVA with SPSS 22.

Results: A total of 3952 surveys were completed. The participation intention scale yielded a mean (SD) total score of 66.13 (7.89) across respondents. Subscale analysis revealed mean (SD) scores of 18.57 (2.68) for participation attitude, 18.87 (2.49) for subjective norms, and 25.67 (3.48) for perceived behavioral control. Significant demographic predictors of participation intention were identified through statistical analysis. Male nurses demonstrated stronger intention ($t_{72.974}$=−23.139, P<.0001), as did those over 30 years old ($F_{39,51}$=27.215, P<.0001) and bachelor's degree holders ($t_{2185.018}$=−4.994, P<.0001). Workplace characteristics also showed significant associations, with nursing management department staff ($F_{39,51}$=45.877, P<.0001) and those with less organizational workloads ($F_{39,51}$=9.829, P<.0001) displaying greater intention. Professional factors including higher positional rank ($F_{39,51}$=37.32, P<.0001), more advanced titles ($F_{39,51}$=30.176, P<.0001), and over 11 years of experience ($F_{39,51}$=5.242, P=.001) predicted stronger participation intent. Finally, nurses earning 5000 - 10,000 RMB (a currency exchange rate of RMB 1=US $0.71 is applicable) monthly showed significantly higher intention scores ($F_{39,51}$=16.141, P<.0001).

Conclusions: Policymakers should prioritize 3 interventions: (1) develop IPNS-specific safety protocols and legal safeguards, (2) optimize workload allocation through intelligent scheduling systems, and (3) establish tiered incentive mechanisms targeting middle-income nurses and experienced practitioners.

(JMIR Nursing 2025;8:e72846) doi:10.2196/72846

KEYWORDS

cross-sectional studies; home health care; internet-based nursing; participation intention; primary health nurse

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Introduction

"Internet Plus Nursing Service" (IPNS) has gradually gained attention in China as a new model for extending nursing services. This model combines traditional health care with digital technology, allowing registered nurses to use online platforms, such as mobile apps or systems affiliated with hospitals, to offer integrated care to patients who have been discharged or those with limited mobility. Through this service, nurses visit patients' homes to provide a wide range of care, including wound management and chronic disease treatment. The entire process, from scheduling appointments to tracking services in real-time and documenting visits, is managed digitally. This shift enables nursing services to move from conventional medical institutions to community and home environments, marking a stark departure from traditional home nursing methods that often depend on phone calls or require patients to visit health care centers for service arrangements. In recent times, there has been a notable increase in demand for this "online application, doorstep service" model in China. To qualify for IPNS, nurses must have at least 5 years of clinical experience and hold a senior professional title, and they must be verifiable through the national nurse registration systems [1].

With China's aging population and changing disease patterns, there is an increasing demand for home health care. By 2020, over 264 million people aged 60 years and above lived in China, accounting for 18.7% of the total population, an increase of 5.4% since 2010 [2]. The World Health Organization predicts that by 2050, China will have the largest elderly population in the world [3]. Additionally, around 260 million people in China are living with chronic diseases, and this number continues to rise [4]. The country also has 85 million disabled people, more than half of whom require long-term care at home [5]. Although China has over 4.7 million registered nurses, with 1.15 million working in primary health institutions, the nurse-to-population ratio is only 3.56 per 1000 people. This indicates a significant gap in the availability of nursing services.

Home-based health care has seen extensive implementation in high-income countries like the United Kingdom and the United States, largely driven by rapid advancements in information technology. This transformation has led to the emergence of IPNS, which plays a crucial role in enhancing the quality and efficiency of care. The main goals of IPNS include facilitating patient recovery, minimizing waste of medical resources, and reducing health care costs [6,7]. The evolution of health care policy in the United Kingdom, from the establishment of the National Health Service to its recent digital transformation, showcases a continuous adaptation to the changing public health landscape [8]. In recent years, the UK government has prioritized digital health technologies to tackle challenges such as an aging population and the increasing prevalence of chronic diseases, aiming to improve service efficiency and patient experiences [8,9]. In both the United States and the United Kingdom, IPNS is primarily delivered through mobile health and telenursing. Mobile health provides health information and services via mobile devices, significantly enhancing patients' ability to manage their own health, especially in the context of chronic disease management [10]. Patients can utilize dedicated apps to record and monitor their health data, which supports more effective self-care [11]. Additionally, wearable devices and environmental sensors enable health care providers to remotely monitor patients' physiological parameters in real time. The data analytics generated from these technologies assist clinicians in creating personalized treatment plans, ultimately leading to improved therapeutic outcomes [12].

In response to the challenges posed by an aging population and a shortage of nursing personnel, IPNS has been piloted across China with support from "Internet Plus" technology and national policies. However, it is still in the early stages of development. The IPNS model, also known as "Sharing Nurse," was first introduced in Shandong Province in 2016 and has since expanded to other regions, including Beijing, Shanghai, and Guangzhou [13]. In 2018, the State Council issued the "Opinions on Promoting the Development of 'Internet Plus' Medical and Health Care," emphasizing that "Internet Plus" health care is a critical component of the "Healthy China" initiative [14]. Subsequently, the National Health Commission issued the "Pilot Work Plan for 'Internet Plus Nursing Service'" to increase the supply of nursing services through IPNS and meet patients' diverse health care needs more effectively [15]. IPNS is part of the broader movement toward integrating "Internet Plus" technology into health care, supporting the development of both "Healthy China" and "Digital China."

IPNS allows patients to receive care at home without visiting health care institutions, addressing the challenge of the "last mile" in health care delivery. Nurses are essential to the success of IPNS, and their willingness to participate will directly influence the implementation and expansion of the service. Previous research has explored nurses' perceptions of IPNS, but little is known about primary health care nurses' intentions to participate. This study seeks to fill this gap by assessing the participation intentions of nurses in primary health institutions, aiming to provide recommendations for policy development and strategies to recruit more nurses into IPNS.

Methods

Design and Setting of the Study

This cross-sectional survey was conducted in Jiangsu Province, China, between December 2023 and December 2024. Registered nurses from 13 prefecture-level cities in Jiangsu were recruited using stratified convenience sampling, encompassing both urban and rural administrative divisions. Recruitment ensured representation from different types of primary health care institutions. The inclusion criteria for participation were (1) being a registered nurse working at a primary health care institution, (2) having at least 1 year of clinical experience, and (3) agreeing to participate in the survey. The exclusion criteria were (1) being away from nursing-related duties for more than 12 months and (2) experiencing significant personal or family events within the past 6 months, such as bereavement or divorce.

Of the 4016 nurses who initially completed the survey, 64 were excluded from analysis: 19 had missing responses exceeding 20%, 17 met the exclusion criteria, and 28 provided straight-line responses. The final sample consisted of 3952 nurses.

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Survey Questionnaire

The data were collected using a self-designed questionnaire that included sociodemographic information and the "Participation Intention of Nurses on Internet Plus Nursing Service Scale," developed by Su et al [16]. Guided by the Theory of Planned Behavior by Young et al [17], we conceptualized IPNS participation intention as driven by 3 latent constructs: attitude—personal evaluation of participation outcomes, subjective norms—perceived social expectations, and perceived control—self-efficacy assessments. This theoretical orientation informed our scale development and item formulation. The questionnaire was administered online via a platform.

Sociodemographic Information

Sociodemographic variables included age, gender, educational background, department, organizational workload, position, professional title, years of experience, personal income, marital status, and number of children.

Participation Intention of Nurses on Internet Plus Nursing Service Scale

The "Participation Intention of Nurses on Internet Plus Nursing Service Scale" was specifically designed to measure nurses' intentions to participate in IPNS. The scale comprises 3 subscales: participation attitude (5 items), subjective norms (5 items), and perceived behavioral control (7 items). The participation attitude subscale includes items related to the development concept (A1-A2), values (A3-A4), and economic outlook (A5). The subjective norms subscale addresses work-related (B1-B3) and family-related (B4-B5) influences. The perceived behavioral control subscale evaluates self-perception (C1-C2), environmental perception (C3-C5), and technological perception (C6-C7).

Each item is rated on a 5-point Likert scale, with responses ranging from 1 (strongly disagree) to 5 (strongly agree). The total score on the scale ranges from 7 to 85, with reverse scoring applied to items 10, 12, and 13 (where original scores of 1=5, 2=4, 3=3, 4=2, and 5=1 were transformed before summation). Higher scores indicate a stronger intention to participate in IPNS. The internal consistency of the scale was confirmed with a Cronbach α of .871 in this study, indicating good reliability.

Data Collection and Analysis

The survey was distributed online from December 2023 to December 2024. Categorical data were summarized using frequencies and percentages, while normally distributed continuous data were reported as mean (standard deviation). To assess differences in participation intention based on demographic characteristics, independent *t* tests and one-way ANOVA were employed. Post hoc testing using the least significant difference method was applied where applicable. A *P* value of less than .05 was considered statistically significant. Data analysis was performed using SPSS version 22 (IBM Corp.).

Ethical Considerations

For privacy protection, in compliance with relevant regulations, participants were informed of the scope and purpose of personal privacy information collection, with only information essential for the study collected after obtaining their consent, and additional consent from legal guardians secured for those from special groups. Regarding data confidentiality, participants' personal identification information was separated from core research data and anonymized with codes; the data were stored on encrypted servers, transmitted via encrypted channels, accessible only to authorized researchers, and archived or destroyed in accordance with regulations after the study. For participant compensation, reasonable compensation (RMB 1-2 [US $ 0.71~1.42]) was provided based on participants' time and effort invested, with reimbursement available for additional expenses incurred, and the compensation was independent of study results with a compliant funding source. Ethically, the study was approved by the Ethics Committee of Nanjing Medical University First Affiliated Hospital (approval number: 2023-SRFA-247).

Results

Sociodemographic Information and Work-Related Characteristics of Primary Health Care Nurses

A total of 3952 primary health care nurses participated in the study. Of these, 68 (1.8%) were men and 3884 (98.2%) were women. The ages of the participants ranged from 21 to 56 years, with a mean (SD) age of 32.35 (8.57) years. The average (SD) years of clinical nursing experience was 11.6 (6.9) years. Regarding educational background, 1128/3952 (31.1%) held an associate's degree, while 2724/3952 (68.9%) had a bachelor's degree.

The distribution of departments in which the nurses worked was as follows: 1452/3952 (36.7%) worked in internal medicine, 1248/3952 (31.6%) in surgery, 564/3952 (14.3%) in nursing management, 408/3952 (10.3%) in gynecology and pediatrics, and 208/3952 (5.3%) in other departments.

Regarding the perception of organizational workload, 84/3952 (2.1%) nurses felt their workload was excessive, 2194/3952 (55.5%) considered their workload heavy, and 1674/3952 (42.4%) felt their workload was normal.

With respect to professional titles, 2656/3952 (67.2%) were general nurses, 768/3952 (19.4%) were specialist nurses, 388/3952 (9.8%) were head nurses, and 140/3952 (3.5%) were directors of nursing. Regarding seniority, 2164/3952 (54.8%) were primary nurses, 800/3952 (20.2%) were intermediate nurses, and 988/3952 (25%) were senior nurses.

In terms of income, 2460/3952 (54.7%) nurses earned less than 5000 RMB per month, 1516/3952 (38.4%) earned between 5000 and 10,000 RMB per month, and 276/3952 (6.9%) earned more than 10,000 RMB per month; a currency exchange rate of RMB 1=US $0.71 is applicable. Details can be found in Table 1.

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Table . Participation intention to Internet Plus Nursing Service (IPNS) of primary health care nurses (N=3952).

		Participation intention scores				
Items	Participants, n (%)	Mean (SD)	*t* test *(df)*	*F* test *(df)*	*P* value	Post hoc
Gender			–23.139 (72.974)	N/A[a]	<.001	N/A
Female	3884 (98.3)	64.23 (8.33)				
Male	68 (1.8)	79.35 5.27)				
Age (years)			N/A	27.215 (39, 51)	<.001	B>A C>A
A <30	1676 (42.4)	63.34 (8.75)				
B 30 - 40	972 (24.6)	65.30 (8.69)				
C >40	1304 (33)	65.38 (7.88)				
Education background			–4.994 (2185.018)	N/A	<.001	N/A
Associate's degree	1228 (31.1)	63.46 (9.01)				
Bachelor's degree	2724 (68.9)	65.96 (8.24)				
Departments			N/A	45.877 (39, 51)	<.001	A>B-E
A Nursing management	564 (14.3)	67.52 (8.32)				
B Internal medicine	1452 (36.1)	62.74 (5.18)				
C Surgery	1248 (31.6)	63.40 (9.08)				
D Gynecology and pediatrics	408 (10.3)	63.64 (8.73)				
E Others	208 (5.3)	63.57 (7.66)				
Organization workload			N/A	9.829 (39, 51)	<.001	C>B>A
A Excessive	84 (2.1)	60.58 (10.85)				
B Heavy	2194 (55.5)	64.44 (8.89)				
C Normal	1674 (42.4)	66.77 (7.81)				
Position				37.32 (39, 51)	<.001	D>C>A-B
A Nurse	2656 (67.2)	63.73 (8.28)				
B Specialist nurses	768 (19.4)	62.83 (4.80)				
C Head nurse	388 (9.8)	65.66 (10.14)				
D Director of nursing	140 (3.5)	68.05 (6.12)				
Professional titles			N/A	30.176 (39, 51)	<.001	C>B>A
A Primary	2164 (54.8)	63.90 (8.47)				
B Intermediate	800 (20.2)	64.86 (7.96)				
C Senior	988 (25.0)	66.30 (8.78)				
Years of working			N/A	5.242 (39, 51)	.001	C>A-B D>A-B
A 1-5	1176 (29.8)	64.02 (9.19)				
B 5-10	776 (19.6)	63.89 (7.75)				
C 11-20	756 (19.1)	64.78 (8.70)				

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		Participation intention scores				
Items	Participants, n (%)	Mean (SD)	*t* test *(df)*	*F* test *(df)*	*P* value	Post hoc
D >20	1244 (31.5)	65.14 (8.13)				
Personal income (RMB[bc] per month）			N/A	16.141 (39, 51)	<.001	B>A B>C
A 1-5000	2160 (54.7)	63.80 (8.42)				
B 5000-10,000	1516 (38.4)	65.27 (8.63)				
C >10,000	276 (6.9)	63.65 (8.09)				
Total	3952 (100)	66.13 (7.89)				

[a]N/A: not applicable.

[b]RMB: Renminbi (Chinese Yuan), the official currency of China.

[c]A currency exchange rate of RMB 1=US $0.71 is applicable.

Intention to Participate in IPNS

The mean (SD) total score on the Participation Intention Scale was 66.13 (7.89). The mean (SD) score for the participation attitude subscale was 18.57 (2.68). Major primary health care nurses viewed IPNS as a new opportunity for self-actualization (3256/3952, 82.4%), perceiving it as a way to enhance their professional image (3136/3952, 79.4%), increase the value of nursing (3272/3952, 82.8%), and improve their income (3120/3952, 78.9%). However, more than half of the nurses expressed concerns, believing that the risks of IPNS outweighed its benefits.

The mean (SD) score for the subjective norms subscale was 18.87 (2.49). Most nurses reported they would participate in IPNS based on the recommendations of hospital leaders (3344/3952, 84.6%), colleagues (3200/3952, 81.0%), experts (3260/3952, 82.5%), or relatives (2858/3952, 72.3%). However, 1708/3952 (43.2%) participants noted that IPNS might require significant amounts of their time, which could be a barrier to their participation.

The mean (SD) score for the perceived behavioral control subscale was 25.67 (3.48). A large proportion of nurses reported feeling satisfied with serving more patients (2844/3952, 71.9%) and had a positive perception of IPNS policies (2836/3952, 71.8%) and associated risks (2776/3952, 70.2%). Additionally, 2604/3952 (65.9%) nurses expressed confidence in the technological aspects of IPNS. However, 2092/3952 (52.9%) nurses expressed concerns that a change in their physical location might negatively impact the quality of care they could provide. The details are presented in Table 2.

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Table . Participation intention to Internet Plus Nursing Service (IPNS) of primary health care nurses (N=3952).

Dimensions/item	Strongly disagree, n (%)	Partially disagree, n (%)	Neither agree nor disagree, n (%)	Partially agree, n (%)	Strongly agree, n(%)
A. Participation attitude					
A1. I think “Internet+ nursing service” is a new thing and a path of self-realization	28 (0.7)	68 (1.7)	668 (16.9)	1824 (46.2)	1432 (36.2)
A2. I think participating in the “Internet+nursing service” can shape my personal image and expand my influence	28 (0.7)	80 (2.0)	708 (17.9)	1692 (42.8)	1444 (36.5)
A3. I think participating in “Internet+nursing service” has more advantages than disadvantages and can enhance the professional value of nursing	14 (0.4)	20 (0.5)	660 (16.7)	1808 (45.7)	1464 (37.0)
A4. I think there are more risks than the benefits of participating in “Internet+care services”	72 (1.8)	460 (11.6)	1392 (35.2)	1264 (32.0)	764 (19.3)
A5. I think I can participate in the “Internet+nursing services” to get more benefits	58 (1.5)	160 (4.0)	672 (17.0)	1768 (44.7)	1352 (34.2)
B. Subjective norm					
B1. I will participate in the “Internet+Nursing Service” due to the support and guidance of my hospital leaders	28 (0.7)	53 (1.3)	580 (14.7)	1952 (49.4)	1392 (35.2)
B2. I will participate in the “Internet+nursing Service” for the recommendation of my colleagues in my hospital	28 (0.7)	80 (2.0)	644 (16.3)	1860 (47.1)	1340 (33.9)
B3. I will participate in “Internet+nursing Services” due to the views of experts in related fields	37 (0.9)	24 (0.6)	668 (16.9)	1908 (48.3)	1352 (34.2)
B4. I will participate in the “Internet+nursing Service” due to the advice of my relatives and friends	45 (1.1)	156 (3.9)	908 (23.0)	1712 (43.3)	1176 (29.8)
B5. I am worried that participating in “Internet+nursing services” will take up a lot of my family life time and increase my burden	168 (4.3)	624 (15.8)	1452 (36.7)	1016 (25.7)	692 (17.5)
C. Perceived behavioral control					

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Dimensions/item	Strongly disagree, n (%)	Partially disagree, n (%)	Neither agree nor disagree, n (%)	Partially agree, n (%)	Strongly agree, n(%)
C1. I think participating in the "Internet+nursing service" can enable me to serve more patients in need and make me feel happy	14 (0.4)	64 (1.6)	636 (16.1)	1792 (45.3)	1460 (36.9)
C2. I am confident that I can provide good services for patients independently through the "Internet+nursing service"	32 (0.8)	92 (2.3)	1016 (25.7)	1812 (45.9)	1032 (26.1)
C3. I understand the relevant policies of government departments on carrying out "Internet+nursing service," and I will consider participating in this service	21 (0.5)	36 (0.9)	1080 (27.3)	1756 (44.4)	1080 (27.3)
C4. I think the change of physical location when participating in "Internet+nursing services" will affect the quality of nursing services provided	28 (0.7)	468 (11.8)	1364 (34.5)	1336 (33.8)	756 (19.1)
C5. I understand the risks I may encounter in participating in "Internet+nursing services"	16 (0.4)	128 (3.2)	1048 (26.5)	1784 (45.1)	992 (25.1)
C6. I can get the training on how to participate in the basic technology of "Internet+nursing service"	23 (0.6)	60 (1.5)	1288 (32.6)	1560 (39.5)	1044 (26.4)
C7. I think it is easy to master the registration, certification, audit, login, and other links that you must pass before participating in the "Internet+nursing service"	16 (0.4)	36 (0.9)	920 (23.3)	1832 (46.4)	1148 (29.0)

Variations in Participation Intentions Based on Demographic Characteristics

Significant differences in participation intentions were observed based on several demographic factors. Male nurses ($t_{72.974}$=−23.139,, P<.0001), nurses aged over 30 years ($F_{39,51}$=27.215, P<.0001), those with a bachelor's degree ($t_{2185.018}$=-4.994, P<.0001), those working in departments with nursing management ($F_{39,51}$=45.877, P<.0001), those with a lighter organizational workload ($F_{39,51}$=9.829, P<.0001), those holding higher positions ($F_{39,51}$=37.32, P<.0001) or professional titles ($F_{39,51}$=30.176, P<.0001), those with over 11 years of experience ($F_{39,51}$=5.242, P=.001), and those with a personal income between 5000 and 10,000 RMB per month ($F_{39,51}$=16.141, P<.0001) were more likely to express a positive intention to participate in IPNS. Similar results are found in the subscales (Tables 1 and 3-5).

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Table . Participation attitude to Internet Plus Nursing Service (IPNS) of primary health care nurses (N=3952).

Items	Participants, n (%)	Participation attitude scores				
		Mean (SD)	*t* test *(df)*	*F* test *(df)*	*P* value	Post hoc
Gender			–19.831 (72.645)	N/A[a]	<.001	N/A
Female	3884 (98.3)	18.95 (2.75)				
Male	68 (1.8)	23.35 (1.79)				
Age (years)			N/A	57.442 (39, 51)	<.001	B>A C>A
A <30	1676 (42.4)	18.49 (2.76)				
B 30 - 40	972 (24.6)	19.27 (3.00)				
C >40	1304 (33)	19.54 (2.57)				
Education background			–5.59 (2303.484)	N/A	<.001	N/A
Associate's degree	1228 (31.1)	18.66 (2.85)				
Bachelor's degree	2724 (68.9)	19.19 (2.76)				
Departments			N/A	37.083 (39, 51)	<.001	A>B-E E>B-D
A Nursing management	564 (14.3)	20.04 (2.46)				
B Internal medicine	1452 (36.1)	18.69 (3.07)				
C Surgery	1248 (31.6)	18.45 (3.03)				
D Gynecology and pediatrics	408 (10.3)	18.92 (2.05)				
E Others	208 (5.3)	19.07 (2.33)				
Organization workload			N/A	11.296 (39, 51)	<.001	C>B>A
A Excessive	84 (2.1)	17.6 (3.45)				
B Heavy	2194 (55.5)	19.06 (2.94)				
C Normal	1674 (42.4)	18.05 (2.54)				
Position			N/A	53.939 (39, 51)	<.001	D>C>A-B
A Nurse	2656 (67.2)	18.68 (2.68)				
B Specialist nurses	768 (19.4)	19.00 (1.70)				
C Head nurse	388 (9.8)	19.57 (3.47)				
D Director of nursing	140 (3.5)	20.34 (1.68)				
Professional titles			N/A	44.857 (39, 51)	<.001	C>B>A B>A
A Primary	2164 (54.8)	18.68 (2.75)				
B Intermediate	800 (20.2)	19.19 (2.53)				
C Senior	988 (25.0)	19.66 (2.98)				

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Items	Participants, n (%)	Participation attitude scores				
		Mean (SD)	*t* test *(df)*	*F* test *(df)*	*P* value	Post hoc
Years of working			N/A	16.208 (39, 51)	<.001	C>A-B
A 1-5	1176 (29.8)	18.74 (2.84)				D>A-B
B 5-10	776 (19.6)	18.74 (2.61)				
C 11-20	756 (19.1)	19.09 (2.95)				
D >20	1244 (31.5)	19.44 (2.73)				
Personal income (RMB[bc] per month)			N/A	20.218 (39, 51)	<.001	B>A B>C
A 1-5000	2160 (54.7)	18.77 (2.71)				
B 5000-10,000	1516 (38.4)	19.30 (2.92)				
C >10,000	276 (6.9)	18.49 (2.58)				
Total	3952 (100)	18.57 (2.68)				

[a]N/A: not applicable.

[b]RMB: Renminbi (Chinese Yuan), the official currency of China.

[c]A currency exchange rate of RMB 1=US $0.71 is applicable.

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Table . Subjective norms to Internet Plus Nursing Service (IPNS) of primary health care nurses (N=3952).

Items	Participants, n (%)	Subjective norm Mean (SD)	*t* test *(df)*	*F* test *(df)*	*P* value	Post hoc
Gender			–19.573 (72.614)	N/A[a]	<.001	N/A
Female	3884 (98.2)	19.01 (2.75)				
Male	68 (1.8)	23.35 (1.79)				
Age (years)			N/A	50.727 (39, 51)	<.001	B>A C>A
A <30	1676 (42.4)	18.58 (2.64)				
B 30 - 40	972 (24.6)	19.29 (3.02)				
C >40	1304 (33)	19.57 (2.69)				
Education background			–7.48 (2347.998)	N/A	<.001	N/A
Associate's degree	1228 (31.1)	18.59 (2.79)				
Bachelor's degree	2724 (68.9)	19.31 (2.76)				
Departments			N/A	34.444 (39, 51)	<.001	A>B-E
A Nursing management	564 (14.3)	19.97 (3.17)				
B Internal medicine	1452 (36.1)	18.77 (3.05)				
C Surgery	1248 (31.6)	18.48 (2.67)				
D Gynecology and pediatrics	408 (10.3)	18.99 (1.86)				
E Others	208 (5.3)	18.69 (2.40)				
Organization workload			N/A	10.977 (39, 51)	<.001	C>B>A
A Excessive	84 (2.1)	18.12 (3.28)				
B Heavy	2194 (55.5)	19.24 (2.91)				
C Normal	1674 (42.4)	19.93 (2.58)				
Position			N/A	49.007 (39, 51)	<.001	D>C>A-B
A Nurse	2656 (67.2)	18.77 (2.61)				
B Specialist nurses	768 (19.4)	18.43 (1.36)				
C Head nurse	388 (9.8)	19.76 (3.45)				
D Director of nursing	140 (3.5)	20.14 (2.42)				
Professional titles			N/A	57.380 (39, 51)	<.001	C>B>A
A Primary	2164 (54.8)	18.73 (2.63)				
B Intermediate	800 (20.2)	19.10 (2.63)				
C Senior	988 (25)	19.86 (3.09)				
Years of working			N/A	16.178 (39, 51)	<.001	C>A-B D>A-B
A 1-5	1176 (29.8)	18.74 (2.78)				
B 5-10	776 (19.6)	18.86 (2.47)				
C 11-20	756 (19.1)	19.21 (3.05)				

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Items	Participants, n (%)	Subjective norm Mean (SD)	*t* test *(df)*	*F* test *(df)*	*P* value	Post hoc
D >20	1244 (31.5)	19.47 (2.78)				
Personal income (RMB[bc] per month)			N/A	38.478 (39, 51)	<.001	B>A B>C
A 1-5000	2160 (54.7)	18.73 (2.60)				
B 5000-10,000	1516 (38.4)	19.69 (2.94)				
C >10,000	276 (6.9)	18.59 (3.02)				
Total	3952 (100)	18.87 (2.49)				

[a]N/A: not applicable.

[b]RMB: Renminbi (Chinese Yuan), the official currency of China.

[c]A currency exchange rate of RMB 1=US $0.71 is applicable.

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Table . Perceived behavioral control to Internet Plus Nursing Service (IPNS) of primary health care nurses (N=3952).

Items	Participants, n (%)	Perceived behavioral control scores				
		Mean (SD)	*t* test *(df)*	*F* test *(df)*	*P* value	Post hoc
Gender			–25.773 (74.867)	N/A[a]	<.001	N/A
Female	3884 (98.2)	26.27 (3.58)				
Male	68 (1.8)	32.65 (1.98)				
Age (years)			N/A	6.171 (39, 51)	.002	B>A C>A
A <30	1676 (42.4)	25.26 (3.85)				
B 30 - 40	972 (24.6)	26.74 (3.61)				
C >40	1304 (33)	26.27 (3.41)				
Education background			–1.984 (2167.088)	N/A	.047	N/A
Associate's degree	1228 (31.1)	26.21 (3.91)				
Bachelor's degree	2724 (68.9)	26.46 (3.53)				
Departments			N/A	46.408 (39, 51)	<.001	A>B-E
A Nursing management	564 (14.3)	27.6 (3.29)				
B Internal medicine	1452 (36.1)	25.94 (3.71)				
C Surgery	1248 (31.6)	25.71 (3.86)				
D Gynecology and pediatrics	408 (10.3)	25.43 (2.67)				
E Others	208 (5.3)	25.31 (3.49)				
Organization workload			N/A	22.801 (39, 51)	<.001	B>A C>A
A Excessive	84 (2.1)	24.87 (4.62)				
B Heavy	2194 (55.5)	26.53 (3.76)				
C Normal	1674 (42.4)	26.79 (3.41)				
Position			N/A	17.95 (39, 51)	<.001	D>A-C
A Nurse	2656 (67.2)	26.28 (3.59)				
B Specialist nurses	768 (19.4)	26.40 (2.53)				
C Head nurse	388 (9.8)	26.33 (4.25)				
D Director of nursing	140 (3.5)	27.57 (2.83)				
Professional titles			N/A	26.882 (39, 51)	<.001	C>B>A
A Primary	2164 (54.8)	25.50 (3.64)				
B Intermediate	800 (20.2)	26.38 (3.86)				
C Senior	988 (25)	26.78 (3.42)				
Years of working (years)			N/A	1.82 (39, 51)	.141	N/A
A 1-5	1176 (29.8)	26.54 (4.02)				
B 5-10	776 (19.6)	26.28 (3.30)				

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Items	Participants, n (%)	Perceived behavioral control scores				
		Mean (SD)	*t* test *(df)*	*F* test *(df)*	*P* value	Post hoc
C 11-20	756 (19.1)	26.48 (3.80)				
D >20	1244 (31.5)	26.23 (3.40)				
Personal income (RMB[bc] per month)			N/A	1.484 (39, 51)	.227	N/A[a]
A 1-5000	2160 (54.7)	26.29 (3.69)				
B 5000-10,000	1516 (38.4)	26.48 (3.64)				
C >10,000	276 (6.9)	26.57 (3.50)				
Total	3952 (100)	25.67 (3.48)				

[a]N/A: not applicable

[b]RMB: Renminbi (Chinese Yuan), the official currency of China.

[c]A currency exchange rate of RMB 1=US $0.71 is applicable.

Discussion

Principal Findings and Comparison With Previous Works

European countries have been leading the way in implementing innovative practices in IPNS, showcasing various models that enhance patient care while tackling the challenges of an aging population and limited health care resources. For instance, the Netherlands and Sweden have successfully integrated digital health solutions into their health care systems, enabling remote monitoring and telehealth consultations that effectively manage chronic diseases. A meta-analysis revealed that residents in Western European regions, where digital health infrastructure is more advanced, showed significantly higher awareness and willingness to engage in IPNS [18]. These innovations not only improve access to care but also empower patients to take an active role in managing their health. Beyond remote consultations, European nations have leveraged mobile applications to facilitate communication between patients and health care providers, ensuring timely interventions and support. A notable example comes from Germany, where a study demonstrated the successful implementation of a web-based platform that enabled seamless communication between palliative care teams and patients, ultimately enhancing the quality of care provided [19]. Additionally, countries like Denmark have embraced a holistic approach to IPNS by integrating social care with health services, addressing the broader needs of patients and improving overall health outcomes. The effectiveness of these innovative practices is highlighted by the positive feedback from both patients and health care professionals. As these countries continue to refine their models, there is a growing emphasis on ensuring that all patients can benefit from these advancements in health care delivery [20].

This study is, to our knowledge, the first to assess the participation intentions of primary health care nurses in IPNS using a professional scale. Nurses in primary health institutions are crucial for the success of IPNS, as their attitudes toward participation directly influence the effectiveness of the program. In general, the study found that primary health care nurses exhibited a medium-high level of intention to participate in IPNS.

A majority of nurses showed a positive attitude toward participating in IPNS, viewing it as an opportunity for professional development and self-actualization. They believed that IPNS could enhance the value of nursing, improve their personal image, and increase their income. However, despite the positive outlook, more than half of the nurses expressed concerns that the risks associated with IPNS, such as medical risks, personal safety risks, and user information security risks, might outweigh its benefits. These findings are consistent with the results of previous studies, which highlighted concerns regarding the risks of internet-based health care services [21]. To address these concerns, it is crucial to improve relevant laws and regulations, enhance the monitoring of the service process, and establish robust safety protocols to ensure both the nurses' and patients' security. Strengthening emergency response mechanisms and clarifying legal protections will help mitigate perceived risks and improve nurses' willingness to participate.

In terms of subjective norms, most of the nurses expressed a willingness to participate in IPNS based on the recommendations of hospital leaders, colleagues, and family members. The guidance from hospital leaders and experts emerged as a major factor shaping nurses' willingness to participate, with most nurses acknowledging its substantial impact on their decision-making. This finding underscores the importance of leadership and organizational support in driving the adoption of new health care models like IPNS. Furthermore, a significant portion of nurses (n=1708; 43.2%) indicated that time constraints might hinder their participation. Time management challenges, including the time required for traveling and completing service-related tasks, could potentially reduce nurses' engagement with IPNS [22]. To mitigate these issues, health care institutions and internet platforms should consider providing sufficient support to reduce time burdens. This could include flexible scheduling, allowing nurses to manage their work hours more efficiently, and utilizing big data to optimize care delivery logistics [23].

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Regarding perceived behavioral control, the majority of nurses expressed positive perceptions of the policies, risks, and technology associated with IPNS, which indicates a favorable attitude toward this new model. However, more than half of the respondents were concerned that the change in the physical location of nursing activities (from the hospital to patients' homes) could negatively impact the quality of care. This concern is understandable given the limited resources available in home settings, such as inadequate medical equipment and medications [24]. Moreover, the regulations in China currently stipulate that nurses should perform their duties at their registered workplace, which is inconsistent with the flexible practice model of IPNS. This regulatory mismatch raises concerns about potential "illegal medical practice" and could discourage nurses from participating in IPNS [25]. To address these concerns, there is a need for clear legal frameworks that support multisite practice, as well as regulations that ensure home environments meet the necessary standards for delivering safe and effective nursing care.

Despite the considerable conveniences brought by the widespread adoption of IPNS, this innovative care model has also raised significant safety concerns and implementation challenges. Nurses providing home-based care often encounter risks to their personal safety and face difficulties in safeguarding patient privacy. Research indicates that nursing professionals generally exhibit a high level of risk awareness regarding IPNS, with over 51% of frontline nurses recognizing moderate-to-high risk levels associated with this service [20]. Additionally, critical issues such as cybersecurity vulnerabilities of service platforms and inconsistent service quality standards have emerged. The current absence of comprehensive policies and uniform regulations has led to disparities in quality, which negatively affect patient trust and participation rates. These challenges highlight the urgent need to improve safety protections for nursing staff, establish robust service standards, and strengthen policy frameworks to ensure the sustainable development of IPNS. In response, several high-income countries have implemented institutional safeguards to ensure service quality and safety in digital nursing services. For example, Germany and Switzerland have created specific legislative and policy frameworks that clearly outline nurses' responsibilities and safety standards in telenursing contexts, providing protections comparable to those in traditional care models [21]. Finland has successfully integrated information technology with nursing services through a centralized digital platform that facilitates remote patient monitoring and personalized care delivery [20]. Furthermore, many European nations have established dedicated regulatory bodies to oversee and evaluate the implementation of internet-based nursing services, ensuring compliance with national health care standards.

The study also revealed that male nurses were more likely to participate in IPNS than female nurses. From a socioeconomic standpoint, male nurses in China frequently encounter stronger traditional pressures to serve as the main family providers, potentially motivating them to pursue supplementary earnings through flexible work arrangements like IPNS [26]. This phenomenon is further compounded by deeply ingrained cultural stereotypes in Chinese society that traditionally link men with outdoor occupations while associating women with indoor caregiving roles, which may subtly shape their willingness to participate in such work opportunities. These intersecting factors of economic necessity and unconscious gender role expectations create a complex backdrop for understanding male nurses' engagement with alternative income sources in China's health care landscape. In contrast, female nurses may be more concerned about personal safety, particularly when providing care in patients' homes, as this setting could expose them to potential risks. While male nurses generally perceived lower physical vulnerability. These gender differences suggest that targeted interventions may be needed to address the specific concerns of female nurses, such as implementing safety measures like one-click alarm systems to ensure nurses' personal security during home visits [27].

Nurses with more than 11 years of experience and those over 30 years old showed a higher willingness to participate in IPNS. These nurses likely have greater confidence in their clinical skills and emergency response abilities, which makes them more comfortable with the challenges of providing care in home settings. This finding is consistent with previous research that suggested that experienced nurses tend to be more adaptable to new working environments [28]. Consequently, experienced nurses could play a central role in the expansion of IPNS, particularly in managing complex cases and addressing potential challenges that arise in home care situations.

Furthermore, nurses with higher educational qualifications (bachelor's degree or above) were more likely to participate in IPNS. This could be attributed to their broader knowledge base and openness to adopting new technologies and models of care [29,30]. Nurses in nursing management roles also exhibited a higher intention to participate, likely due to their leadership positions and a deeper understanding of the potential benefits of IPNS for the health care system. The high level of interest in IPNS among nurses in management positions could also reflect their desire to improve nursing services in response to the growing demand for home health care.

In terms of organizational workload, nurses with lighter workloads were more likely to participate in IPNS. This finding aligns with previous studies that have shown that high workload pressures discourage participation in supplementary health care programs [13]. To encourage more nurses to engage in IPNS, health care institutions must balance the workload of primary health care nurses and ensure that their participation in IPNS does not lead to burnout or excessive strain. Offering training and incentive programs could also help increase nurses' motivation to participate in this emerging model of care [31].

Finally, nurses with a personal income between 5000 and 10,000 RMB per month expressed the highest intention to participate in IPNS. This group of nurses, who are typically more established in their careers, may be more motivated to participate in IPNS as a means of supplementing their income and improving their financial stability. For nurses with higher incomes, the opportunity to participate in IPNS may be less appealing due to the additional workload it entails, while nurses with lower incomes may feel less confident in their ability to provide care in a new and potentially challenging environment.

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Limitations

This study has several limitations. First, the sample was limited to nurses from Jiangsu Province, which may affect the generalizability of the findings. Second, while we examined key sociodemographic factors, the study did not assess several important psychosocial and organizational determinants that may influence participation intentions, including job satisfaction, perceived meaningfulness of work, professional autonomy, competence beliefs, or perceived social impact of IPNS services—all of which have been shown to affect health care professionals' engagement in innovative practices. Additionally, the study did not explore whether measured intentions translated into actual IPNS engagement, as this likely depends on contextual, organizational, and policy factors that require further investigation. Further research should employ longitudinal designs with more diverse national samples while incorporating comprehensive assessments of both structural and individual psychological factors to better understand IPNS participation dynamics.

Conclusions

This study highlights the medium-high level of participation intention among primary health care nurses in IPNS and identifies several demographic and work-related factors that influence their willingness to participate. These findings underscore the importance of addressing concerns related to time, safety, and the regulatory framework to increase nurse engagement in IPNS.

Policymakers should adopt a comprehensive strategy to improve IPNS participation by implementing strong safety measures such as real-time GPS tracking and emergency alerts, along with clear legal guidelines to define liability and safeguard nurses during home visits. To enhance efficiency and reduce burnout, artificial intelligence–powered scheduling tools should be used to intelligently distribute workloads based on travel distance, case difficulty, and nurse expertise. Additionally, a tiered incentive program should be introduced, offering middle-income nurses financial rewards like bonuses or tax breaks while providing experienced nurses with career advancement opportunities and leadership roles in IPNS initiatives.

These efforts should be supported by continuous nurse feedback channels and public education campaigns to ensure long-term success, fostering a system that tackles safety risks, workload challenges, and financial concerns while ensuring fair service access in both urban and rural communities. This well-rounded approach will not only increase nurse involvement but also elevate the overall quality and availability of IPNS for patients.

Policymakers and health care institutions should focus on creating supportive environments, providing adequate training, and offering incentives to encourage more nurses to participate in this promising model of home health care.

Acknowledgments

The authors would like to thank the nursing staff of primary medical institutions for their assistance in participant recruitment and data collection.

This study was supported by the Young Scholars Fostering Fund of the First Affiliated Hospital of Nanjing Medical University (PY2023042). Project of "Nursing Science" Funded by the 4th Priority Discipline Development Program of Jiangsu Higher Education Institutions (Jiangsu Education Department [2023] No.11). Research Project of Nursing Discipline by the Chinese Medical Association Press in 2022 (CMAPH - NRG2022045) Scientific. Research Projects of the Chinese Nursing Association in 2023 (ZHKYQ202307).

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Conflicts of Interest

None declared.

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Abbreviations

IPNS: Internet Plus Nursing Service

Edited by D Dordunoo; submitted 19.02.25; peer-reviewed by B Yang, S Udod; revised version received 17.07.25; accepted 26.08.25; published 01.10.25.

Please cite as:
Xu B, Li S, Chen K, Ding L, Liu L
The Intention of Primary Health Nurses to Participate in Internet Plus Nursing Service: Cross-Sectional Survey
JMIR Nursing 2025;8:e72846
URL: https://nursing.jmir.org/2025/1/e72846
doi:10.2196/72846

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The Effectiveness of a Question-Embedded Movie Clips Learning Program in Nursing Students: A Quasi-Experimental Pretest-Posttest Study

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Abstract

Background: Technological innovations make significant impacts on nursing education. New teaching strategies are constantly emerging, offering students a dynamic and interactive educational experience. The Question-Embedded Movie Clips Learning program used in this study was developed based on the drill and practice learning principle, aiming to facilitate nursing students' skills and build their confidence before entering real clinical settings.

Objective: This study aims to investigate the comparative effect between the newly developed Question-Embedded Movie Clips Learning program and the current practice of mind mapping exercises on students' learning outcomes and study satisfaction.

Methods: This study adopted a quasi-experimental design using a pretest-posttest approach with nonequivalent groups. The study sample consisted of 132 third-year nursing students who enrolled in one of two class sections of the psychiatric nursing course at a university in Thailand. By flipping a coin, the first study section (n=62) was assigned to the intervention, and the second section (n=70) was assigned to the control group. During the 2-hour class sessions, students received identical learning structure and sequence, except for group exercises of either the Question-Embedded Movie Clips Learning program or the mind mapping. The data were collected through the pretest-posttest questionnaire, the perceived satisfaction with the learning experience scale, and the open-ended reflective questions.

Results: A statistically significant increase was observed in the learning outcome scores of both the intervention group (t_{61}=–30.48, 95% CI –10.59 to –9.28; P<.001) and the control group (t_{69}=–27.04, 95% CI –8.19 to –7.07; P<.001); all t statistics reported are based on 2-tailed tests. There was, however, a statistically significant difference in the outcome scores between the 2 groups. Even after controlling for pretest scores, students in the experimental group had a significantly higher adjusted mean score than those in the control group ($F_{1,129}$=67.67, P<.001).

Conclusions: The study has provided empirical evidence that using the Question-Embedded Movie Clips Learning program along with traditional instruction in teaching therapeutic relationships and communication significantly improves learning outcomes.

(JMIR Nursing 2025;8:e71111) doi:10.2196/71111

KEYWORDS

web-based; embedded questions; video clips; therapeutic communication; nurse-patient relationship; nursing students

Introduction

Background

An important skill set for nurses is interpersonal skills and communication. Mental health, in particular, is a branch of nursing that applies the therapeutic use of self and relationships as a means of bringing about positive health changes in patients. Despite being crucial for nursing care, many nursing students find learning interpersonal skills to be a challenge and struggle to establish therapeutic relationships with patients. As not all attributes of these complicated skills can be taught in lecture classrooms, nursing students express having difficulty learning them through conventional instruction and show preferences for more innovative, interactive, and practice-based strategies [1,2]. Nursing educators, therefore, need to shift from familiar teacher-centered teaching toward student-centered learning to provide an impactful educational experience.

Among studies aiming to identify the best teaching methods for clinical skill acquisition, there seems to be a consensus emerging about the importance of active learning and student engagement. Cumulative evidence strongly supports the benefit of incorporating instruction that is self-directed, reflective, immediate, stimulating, and experientially immersive to produce a constructive impact on students' learning outcomes [3].

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Pedagogical strategies that carry labels such as student-directed education, process-oriented instruction, or experiential and authentic learning are increasingly being explored by nurse educators. As a result, innovative teaching, including simulation-based learning, flipped classrooms, artificial intelligence–based training, and web-based learning platforms with augmented or virtual reality are gradually being embraced as methods to prepare nursing students to meet professional demands [4,5].

Learning therapeutic communication effectively involves tailoring instruction to different learning styles and using a variety of teaching methods. By acknowledging and supporting learning preferences, student engagement and desirable learning outcomes can be ensured. Recent review studies highlighted the preference of kinesthetic and multimodal to be the most dominant learning style among undergraduate nursing students [6-8]. Several studies have also explored the issue of learning styles among Thai nursing students. A descriptive study examined the learning styles of 177 Thai nursing students using the Felder and Solomon index and found that most students (89.8%) were sensing learners who prefer to learn from observation, action, and problem-solving in gradual stages [9]. The result corresponded with studies reporting the majority of Thai nursing students' preference for multimodal learning of visual, auditory, read or write, and kinesthetic learning [10-12] with participative learning style being most prevalent [13]. Accordingly, this study incorporates movie-based case studies, embedded practice questions, and group work for learning strategies. Movie clips were used as real-world examples to promote critical thinking and reinforce practical skills through problem-solving. Additionally, group work and in-class presentations can promote active involvement, peer discussions, and knowledge sharing.

In Thailand, 7 studies on the use of innovative teaching strategies were found particularly relevant to teaching nursing students therapeutic communication. Two studies using standardized patient simulation reported positive effects on students' learning outcomes and satisfaction with mental health and psychiatric nursing courses [3,14]. Another 3 studies used computer-assisted instruction to create online lessons and found that students had higher scores on learning achievement, perceived efficacy, and communication skills compared to students in the control group, who received conventional lectures [15-17]. Two of the studies explored using integrated digital technologies to provide an immersive learning experience for teaching therapeutic relationships and management of psychiatric patients in specific situations. The first study used augmented reality applications on smartphones and reported a high level of student satisfaction after the study [18]. The other study that used a virtual reality learning program found that students had higher scores on attitudes and confidence in managing patient aggression [19].

The current format for teaching interpersonal skills and therapeutic communication is text-based lectures combined with mind mapping group exercises. From the 2020-2022 academic year, mind mapping has been used as the standard teaching method for this topic. While exam results are satisfying for all learning requirements, the majority of nursing students who have completed the course feel that they have insufficient knowledge to effectively engage in therapeutic relationships with the patients. These difficulties in transferring theoretical knowledge into clinical practice are viewed as major obstacles in nursing education [20]. As lectures can make learning relatively superficial and transient, active learning strategies are needed. Though innovative strategies are being adopted by Thai nurse educators, the methods are restricted to tutorial and simulation use; other training strategies such as drill and practice and problem-solving instructions have not yet been studied for their effectiveness. To overcome the limitation of traditional text-based teaching, the Question-Embedded Movie Clips Learning (QEMCL) program used in this study was designed based on drill and practice, as well as instructional game principles. The aim of the study is to examine the effectiveness of the QEMCL program on nursing students' satisfaction and learning outcomes on the therapeutic use of self and communication skills.

Theoretical Framework

This study used the Classroom Action Research framework based on the Plan-Do-Check-Act cycle to make continuous teaching improvements. The cycle begins with the "PLAN" stage, which deals with preparing class lessons. The "DO" stage involves teaching the lesson, engaging in learning activities, and assigning work. The "CHECK" is to assess learning outcomes and make recommendations for improvements, and the "ACT" stage is the use of the improved teaching strategies in the classroom. Presenting the findings, or outcomes, of this learning project correlates with the "CHECK" stage, which aims to check whether what had been planned in the first stage has been achieved. The recommendations of this study are related to the "ACT" stage, which aims to improve the learning outcome of the lesson [21].

Literature reviews on studies examining the effectiveness of educational interventions for medical and nursing students' therapeutic communication skills have been widely conducted [22-25]. These reviews, however, primarily focused on summarizing educational programs, while only a few studies included a description of a theoretical framework. A more recent systematic review found that employing Jonassen's constructivist learning environments (CLEs) [26] can effectively promote the therapeutic communication education of nursing students and, therefore, was recommended for nurse educators [27]. The CLE instructional design postulates that students learn best by solving practical problems to integrate new knowledge into what they already know. Adopting this approach, this study was planned in accordance with CLE elements by providing problem-based case scenarios with the use of videoclips as cognitive tools and lecture clips as related information resources. A modeling instructional method was used, with the movie character acting as a role model illustrating the use of therapeutic communication techniques. With the constructivist approach, the teaching method of this study was designed to encourage critical thinking, problem-solving, and collaborative learning among nursing students.

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Methods

Ethical Considerations

This study was approved by the ethics committee of Khon Kaen University (no. HE 662147). The participants consisted of nursing students from the Faculty of Nursing at Khon Kaen University. Students were offered the opportunity to join the study voluntarily, with the assurance that their participation would not affect their academic standing or grades. Informed consent was obtained from all study participants. Participants were assigned code numbers for all data entry purposes. The participant-to-code number list was then destroyed after all study data had been collected. No compensation was provided to participants for participating in this study.

Sample and Setting

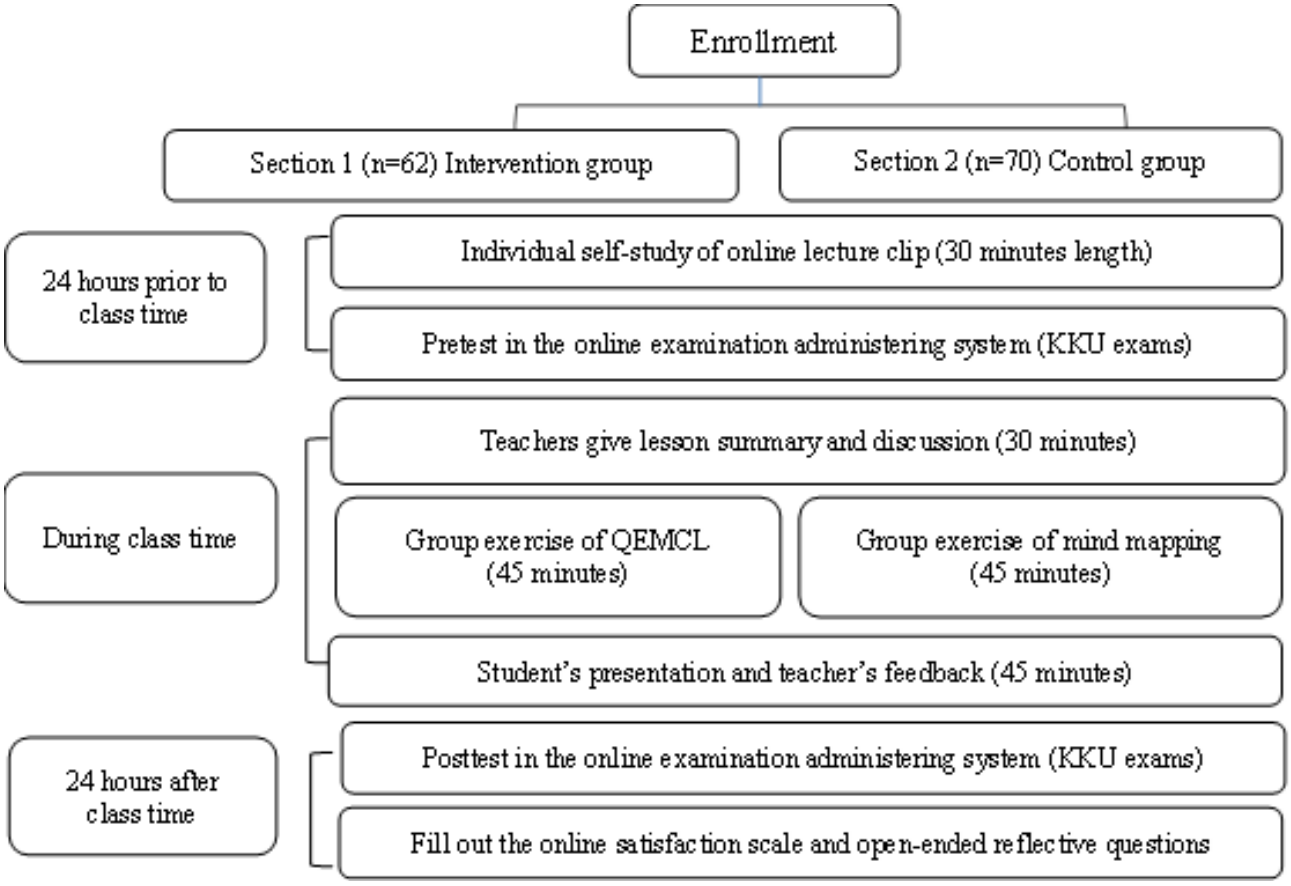
Using the effect size of computer-based education on nursing knowledge from an earlier study [28], the power analysis yielded at least 59 participants, with an effect size of 0.43, a significance level of 0.05, and a power of 0.9. The inclusion criteria were (1) being enrolled in the psychiatric nursing course, (2) having access to a device (smartphone, tablet, or computer) that can perform online tasks, and (3) agreeing to participate in the study. The exclusion criteria were retaking the psychiatric nursing course. There were 132 third-year nursing students enrolled in one of two sections of the psychiatric nursing course at Khon Kaen University for the 2023 academic year who met the inclusion and exclusion criteria. For practical reasons and to ensure a comprehensive analysis, all 132 students were recruited to participate in the study on a voluntary basis.

Recruitment and Data Collection

The recruitment process started 2 weeks prior to the class date. By flipping a coin, students in the first study section (n=62) were assigned to the intervention, and those in the second section (n=70) were assigned to the control group. In the process of informed consent, students were informed about their potential placement in either an intervention or an active comparison group. Adobe Acrobat Sign was used to obtain online digital signatures of students' informed consent. By using codes, students' identities were not directly disclosed to ensure privacy and confidentiality. All students gave their permission to be part of the study and signed their consent to participate. To ensure structural consistency, both groups received a 30-minute self-study online lecture, took the pretest within 24 hours prior to the class session, and participated in a 2-hour class session. The class time for both groups was on the regular learning schedule that runs along the academic semester, so there was no interference with students' other learning that potentially affected their focus and willingness to engage. During the class sessions, students received identical learning materials and sequences, except for group exercises of either the QEMCL program or mind mapping. Class sessions for both sections were held on the same day, scheduled during consecutive time periods (8 - 10 AM for the first study section and 10 - 12 PM for the second study section), and led by the same instructor. Students in both groups took the posttest and filled out the satisfaction scale and open-ended reflective questions within 24 hours after class (see Figure 1). All tests were scheduled at the same time using the university's online examination administering system.

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Figure 1. The flowchart of the research procedure. KKU: Khon Kaen University; QEMCL: Question-Embedded Movie Clips Learning program.



Instruments

There were 3 instruments used for data collection. The first was the QEMCL program, which is an interactive web-based learning program using question-embedded short movie clips that illustrate therapeutic relationships and communication techniques. This program is composed of short clips from 3 movies, each highly acclaimed for educational use: *Good Will Hunting* [29], *Ordinary People* [30], and *The Prince of Tides* [31]. Researchers selected 7 - 8 sequential clips from each movie, corresponding to the typical number of psychotherapy sessions. Each clip had 7 - 8 questions embedded in it, making a total of 53 - 62 questions per movie. The questions were organized to foster students' reflective activities, encourage them to identify with characters, and stimulate their clinical judgment. Interactive functions provided in the program to enhance active practice and skill development include immediate feedback with short contextual explanations, real-time scoring, and summative tests with certificates of accomplishment. The content validity of study questions was evaluated by 3 experts in the field, yielding an index of item-objective congruence (IOC) of 0.85. The program had an index of process and output efficiency (E1/E2) of 85/82.6. Details of the QEMCL program development and the evaluation of its efficiency have been reported elsewhere [32].

Only *Good Will Hunting* was selected for this study as the intervention group class exercise due to its coherent run-time and the 2-hour class period limitation. There were 7 selected scenes—Scene 1: First meeting; Scene 2: It's your turn to move; Scene 3: Super philosophy; Scene 4: Regrets; Scene 5: What do you want to do?; Scene 6: It's not your fault; and Scene 7: Do what your heart tells you. These scenes were chosen as they capture the essence of how phases of the therapeutic relationship can be constructed through therapy sessions [33]. Scene 1 portrayed the initial phase of the relationship with the important concept of mistrust along with the power of therapeutic authenticity and genuine connection. Scene 2 represented the identification phase where the therapist shows unconditional positive regard, respect, and empathy that creates a safe environment for therapeutic engagement. Scenes 3 through 5 depicted the working phase in which the therapist employs a delicate balance of self-disclosure, compassion, and directness to challenge the client's defense mechanisms. Scenes 6 and 7 portrayed how the therapist was working toward the termination phase, where masterful uses of active listening, nonjudgmental acceptance, and inducing emotional catharsis are illustrated to help the client explore his experiences, gain insights, overcome his emotional wounds, and find his purpose in life.

As *Good Will Hunting* is an American film, language barriers can be a concern. Additionally, the portrayal of American culture, including its values and beliefs, may be unfamiliar to students from different backgrounds. To overcome these challenges, the Thai subtitles were provided so that students could follow the story efficiently and be able to focus on the characters' behaviors and intentions. Although cultural differences undoubtedly shape language styles, the interpretation of meaning should not be reduced to stereotypical thinking, but instead to develop awareness, respect, sensitivity, and curiosity to understand value orientations. To facilitate culturally

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responsive learning, students were asked, as part of group exercises, to identify the scenes they thought showed some aspect of American culture, analyze the different styles of communication, and propose alternative approaches from another cultural perspective. Using these teaching activities, the film can be a valuable resource in helping students recognize culturally influenced behavior and apply the communication strategies depicted in the movie to their own nursing practice.

The second instrument was a 30-item multiple-choice structured pretest-posttest questionnaire developed by the researchers. This questionnaire consists of 3 subscales measuring students' learning outcomes of memorization, understanding, and applied knowledge. The possible score range was 0 to 30 points. The reliability of the questionnaire was confirmed using the test-retest method with an intraclass correlation coefficient of 0.84. The third instrument was a 10-item scale designed by the researchers to assess students' perceived satisfaction with the learning experience. Each item featured a 5-point Likert scale ranging from strongly satisfied to strongly dissatisfied with a possible score from 0 to 50. This measure consists of 3 subscales of the learner's usability, learning content, and the system and function. The pilot test of this scale yielded a Cronbach α coefficient for internal consistency of 0.83. Finally, 2 open-ended reflective questions were used to evaluate students' intention to recommend learning exercises to others as well as their perceived benefits and limitations of the exercises.

Statistical Analysis

Data were analyzed with descriptive statistics, chi-square test, *t* test, and analysis of covariance (ANCOVA) using Stata 16.1. To check for ANCOVA assumptions, the homogeneity of regression slopes was examined. A nonsignificant interaction between pretest scores and groups (P=.21, 95% CI –0.52 to 0.11) was found, suggesting that the slopes of regression lines for the control and intervention groups were the same. For the homogeneity of variances, Levene test results indicated that the variances were equal across the 2 groups ($F_{1,130}$=0.7, P=.4). Additionally, the normality of residuals was confirmed by the q-q plot, the kernel density histogram, and the Shapiro-Wilk test (w_{132}=0.98, P=.12).

Results

Before analyzing the outcome differences, descriptive statistics of each variable were performed. Table 1 presents the results of the homogeneity test for students' general characteristics. The average ages of students in the intervention and control groups were 21.61 (SD 0.75) and 21.53 (SD 0.58), respectively. There were higher percentages of women than men in both the intervention group (60/62, 97%) and the control group (63/70, 90%). No significant difference, however, was observed in either mean age (t_{130}=–0.72, two-tailed, 95% CI –0.32 to 0.15; P=.47) or proportion of gender (χ^2_1=2.4, P=.12).

Table . Demographics of the participants in the intervention and control groups.

Variable	Control group (n=70)	Intervention group (n=62)	Statistic test
Age (years), n (%)			t_{130}=–0.72[a], 95% CI –0.32 to 0.15; P=.47
21	36 (51)	31 (50)	
22	31 (44)	27 (44)	
23	3 (4)	1 (2)	
24	0 (0)	3 (5)	
Mean (SD)	21.61	21.53	
Gender, n (%)			χ^2_1=2.4, P=.12
Male	7 (10)	2 (3)	
Female	63 (90)	60 (97)	

[a]Independent 2-tailed *t* test.

As shown in Table 2, the learning outcome scores and students' satisfaction of both groups were compared. The average pretest scores of the intervention group (n=62) and the control group (n=70) were not statistically different (t_{130}=0.3, 95% CI –0.51 to 0.67; P=.77). The *t* statistics reported elsewhere are based on 2-tailed tests. Compared to the control group, the intervention group had a larger increase between pretest and posttest, with significantly different posttest scores (t_{130}=–8.23, 95% CI –2.75 to –1.68; P<.001). The overall satisfaction scores of both the intervention and control groups were high, with each item ranging from 4 to 4.8. There was, however, a significant difference in student satisfaction scores between the 2 groups (t_{130}=–2.93, 95% CI –3.24 to –0.63; P<.001). The students in the intervention and control groups were most satisfied with the learner's usability (mean 4.52, SD 0.5; mean 4.31, SD 0.51), system and function (mean 4.24, SD 0.51; mean 4.05, SD 0.55), and learning content (mean 4.11, SD 0.44; mean 3.92, SD 0.43), respectively.

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Table . Comparison of the learning outcome and student satisfaction.

Variable	Control group (n=62), mean (SD)	Intervention group (n=70), mean (SD)	Independent *t* test[a]
Learning outcome			
Pretest	15.43 (1.83)	15.34 (1.60)	t_{130}=0.3, 95% CI –0.51 to 0.67; *P*=.77
Posttest	23.06 (1.41)	25.27 (1.68)	t_{130}=–8.23, 95% CI –2.75 to –1.68; *P*<.001
Paired *t* test[a]	t_{69}=–27.04, 95% CI –8.19 to –7.07; *P*<.001	t_{61}=–30.48, 95% CI –10.59 to –9.28; *P*<.001	
Student satisfaction	40.76 (3.67)	42.69 (3.93)	t_{130}=–2.93, 95% CI –3.24 to –0.63; *P*<.001

[a]Two-tailed.

To avoid any potential difference in the respondents' levels of knowledge at the beginning of the study, tests of ANCOVA were conducted to examine the comparative effects of the QEMCL and mind mapping strategies on student posttest scores, with students' pretest scores as the covariate. The results indicate that there was a significant difference in learning outcomes between the 2 groups, with $F_{1,129}$=67.67, *P*<.001. As shown in Table 3, after controlling for pretest scores, the posttest scores were related to the group variable. Students in the QEMCL group had a significantly higher adjusted mean score (mean 25.27, SD 0.19) than those in the mind mapping group (mean 23.06, SD 0.18). Moreover, the partial eta square (η^2) values provided information about the effects of the pretest and the groups on the posttest scores. The effect size of the group on the posttest was 0.3441, meaning the group variable explained 34.2% (160/465) of the posttest learning outcome after removing the variation explained by the pretest. On the other hand, the effect size of the pretest was 0.0165, which means approximately 1.7% (5.11/310.11) of the posttest variance was explained by the pretest.

Table . Results of ANCOVA[a] test for mean scores of learning outcomes.

Variable	Partial sums of squares	Degrees of freedom	Mean square	*F* test	Significance	Partial eta-square
Model	166.72	2	83.34	35.26	.000	0.3534
Groups	160.00	1	160.00	67.67	.000	0.3441
Pretest score	5.11	1	5.11	2.16	.144	0.0165
Residual	305.00	129	2.36	—[b]	—	—
Total	471.72	131	3.60	—	—	—

[a]ANCOVA: analysis of covariance.

[b]Not applicable.

As for the question about the students' intention to recommend learning exercises to other students, 62 (100%) students of the intervention group (n=62) indicated that they would recommend the QEMCL program to others, while 59 (84%) of those in the control group (n=70) did so for the mind mapping activity. In the intervention group (n=62), 54 (87%) students stated that the QEMCL program was highly beneficial to their learning, and 8 (13%) stated that it was somewhat beneficial. In the control group (n=70), only 46 (66%) and 23 (33%) students, respectively, gave the mind mapping exercise the same ratings. No students stated that either learning activity was of small benefit or no benefit at all to their learning.

Table 4 presents key quotations excerpted from the open-ended responses regarding the perceived benefits and limitations of the learning exercises. The benefits included (1) improving learning efficiency, (2) thought provoking, (3) enhancing understanding, and (4) inspiring self-directed learning. The limitation was an inadequate application feature. Students' reflections on learning experiences also revealed significant implications that teachers should design interactive learning programs. Specifically, students defined the benefits of the program associated with its capacity to foster deep learning and enhance memory content, reduce anxiety, and increase motivation, as well as the simplicity of use. Reported program limitations were associated with the small number of movies and with technical problems.

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Table . Students' reflections on learning experience.

QEMCL[a]	Mind mapping
Perceived benefits	
Improving learning efficiency	
• "Repetitive learning through the exercise helps me to see the same thing from different angles and start to recognize a pattern, and that, for me, brings out clarity." [ID#0128] • "The clips provided context of when, why, and how to use particular communication techniques." [ID#0156]	• "It turns the boring and hard to understand textbook lessons into beautiful artworks that is a lot easier to pay attention to." [ID#0205]
Thought provoking	
• "You don't know what to say to your patients, until you hear it from the experts. It can, at least, get you start before you can find your own (words)." [ID#0154] • "The movie gets me prepared of all the possible challenging situations I might face during the encounter with patients. Especially the violent behaviors at the beginning. Yeah, I think that's what I get the most from the movie, how to get past all the mistrust before being able to work on real problems." [ID#0134]	• "Comparing your work with those of other groups helps to correct the misunderstandings and highlight importance issues." [ID#0252]
Enhancing understanding or disputing the misunderstanding	
• "I don't think I can ever understand (the concept of) "abreaction" from reading. Even after seeing it from the movie, it's still hard to describe in words." [ID#0151] • "The movies give me a realistic picture of therapeutic relationship." [ID#0107] • "Depression or aggressiveness, they all sound the same to me from the lecture, until I saw the clips and had to answer the question, then, I could tell them apart." [ID#0115] • "I used to think that I have to always say smart things, give recommendations for patients to solve their problems, you know, being a superior one for them to depend on. But Dr. McGuire did the opposite, he had so many chances to tell Will what is the right thing to do, but he didn't. Instead, he asked and waited for the answer from Will, even when Professor Lambeau asked him to tell Will what to do. That makes me realized that I was wrong, and I need to figure out what is actually the purpose of therapeutic communication." [ID#0134]	• "By trying to identify key concepts, sorting them into categories, and linking them together to get a comprehensive picture, the class content has been simplified so that it is easy to understand and memorize." [ID#0221] • "Pictorial illustrations make abstract concepts perceptible and manageable." [ID#0256] • "Mind maps help connect concepts and makes the dispersed detailed become one conforming theme." [ID#0260]
Promoting culturally responsive learning	
• "I think grabbing patient's neck is not an acceptable manner for the therapist to do, but that might happen to anybody when you lost the temper, even for therapist, whether he's an American or Thai." [ID#0107] • "I feel that the way Will talk to Dr. McGuire is not what I normally see in Thai patients. It's almost like talking back to someone you should pay more respect to." [ID#0142]	—[b]
Inspiring self-directed learning	
• "Immediate feedback and scoring make me learn faster, it's like you have a personal tutor." [ID#0124]	• "You can keep the (mind map) work for review before exam." [ID#0229]
Perceived limitations	
Limited application features	
The complexity of the infrastructure • "Some of the provided explanations are too short. It'll be better to elaborate to some extent. Or even better, add the function that we (students) can ask for more explanation if needed." [ID#0157]	—

[a]QEMCL: Question-Embedded Movie Clips Learning.

[b]Not applicable.

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Discussion

Principal Findings

The results of this study showed increased posttest scores for both the QEMCL (intervention) and mind mapping exercise (control) groups. The implementation of both learning methods is, therefore, supported for improving students' learning outcomes on therapeutic use of self and communication. However, there was a significant difference between the posttest scores of the 2 groups after controlling for the effect of pretest scores. The difference was in favor of the experiment group, indicating a higher learning achievement by the QEMCL group ($P<.001$). The effect size of 0.3441, as measured by partial eta square, was quite large, with 34.4% (160/465) of the difference in variance explained by overall learning. This magnitude of effect is consistent with previous meta-analysis studies, which have shown positive computer-based education effects on knowledge ranging from 0.24 to 0.43 [28,34]. The results suggest that QEMCL can be used as a teaching tool to improve upon traditional teaching strategies.

Both groups showed significant differences between pretest and posttest scores, suggesting that the 2 approaches are both powerful instructional tools for nurse educators. This finding is in line with previous studies that support the benefit of using mind mapping and film-based learning strategies. The focus on classification and memorization makes the mind mapping exercise particularly beneficial to students' ability to process and absorb new knowledge [35]. As students create mind maps, they learn to retrieve keywords, conceptualize learning content, and organize their thinking to generate comprehensive illustrations [36,37]. Moreover, students' enjoyment of generating artistic drawings facilitates their emotional engagement and memory retention [38,39]. Similarly, the movie clips in the QEMCL program enable students to envision themselves engaging in therapeutic relationships with patients. The exercise provides visual tools that help students learn by watching the clips, and then analyzing and exchanging their thoughts with others. This art-based learning method has been described as a Visual Thinking Strategy (VTS). By stimulating visual areas of the brain, the VTS allows students to describe, analyze, and interpret information through observing and discussing mind map images and movie scenarios [40].

Though the learning outcome effects were significant within both the intervention and control groups, the difference in learning outcomes between the 2 groups was also significant, suggesting the superiority of the QEMCL over mind mapping. This finding can be explained as follows: a picture may be worth a thousand words, but it cannot tell the whole story. Stories make the nurse-patient relationship and the context of using therapeutic techniques become apparent. Movie plots depict how clinical situations change and unfold over time. The mind mapping exercise may be able to stimulate visual thinking, but the QEMCL goes further by using storytelling to reinforce critical thinking. This narrative pedagogy helps students to think through and interpret situations they encounter from multiple perspectives and to understand clinical reasoning as a complex process [41,42]. With *Good Will Hunting*, the therapeutic relationship between Will Hunting and Dr Sean Maguire became vividly presented to students [ID#0107, 0115, and 0151]. The students learn how the therapist gets through the initial phase of the relationship with challenging situations from the patient's mistrust [ID#0134]. Movie clips illustrate the effective use of techniques that open up opportunities for students to imitate and become accustomed to therapeutic communication [ID#0154 and 0156]. In addition, the clips provided thought-provoking ideas for students to reconsider prior misunderstandings and work on gaining new knowledge [ID#0134]. Finally, the clips directly expose students to diverse communication styles, teaching them to respect diversity and adapt their ways to suit culturally specific gestures [ID#0107 and 0142].

Previous studies support that dynamic visual media, such as videoclips, improve the processing and understanding of information by engaging both hemispheres of the brain. As the left side processes the dialogue, plot, rhythm, and lyrics, and the right side processes the visual images, sound effects, and harmonic relationships, videoclips capture students' attention and stimulate thinking more quickly and more effectively than direct statements, setting out concepts, or straight course material [43]. Furthermore, compared to the noninteractive mind mapping exercise, interactive features of QEMCL such as stopping and replaying videoclips, getting feedback, and tracking personal progress allow students to personally distribute their attention and cognitive resources across the videos. The selected scenarios with embedded questions encourage students to think critically, correct their misunderstandings, and develop their own communication strategies. This participatory instructional strategy creates a constructive learning environment in which students are active participants who engage in problem-based and transformative learning. Students can advance at their own pace and in harmony with their unique cognitive skills and needs [44]. The QEMCL is, then, promising to facilitate procedural learning of discrimination, concept application, and rule-using, which are subskills of Bloom's psychomotor domain [45].

Considering themes emerging from students' reflection, those in the mind mapping group used keywords such as identifying key concepts, sorting those concepts into groups, placing them in classified orders, and linking them together to get a comprehensive picture. Those in the QEMCL group, on the other hand, used terms such as identifying proper concepts in a given scenario, differentiating among similar concepts, distinguishing principles applied in particular situations, clarifying the rationale for the choice of action, and discriminating between possible responses in various situations. Bloom's taxonomy categorizes 6 levels of cognitive complexity: knowledge, comprehension, application, analysis, synthesis, and evaluation [45]. Students' reflections indicated that the mind mapping exercise helped them memorize class content as organized structures and details, suggesting cognitive learning outcomes mostly at the knowledge level. Students in the other group stated that the QEMCL provides vivid examples of how to interpret patient behaviors and select different responses for the best probable outcome based on details unique to specific situations. Such reflection indicates that their learning outcomes were at the comprehension and application levels. This explanation is consistent with their higher posttest scores on

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the subscale of understanding (mean 8.53, SD 0.9; mean 7.41, SD 0.88) and applied knowledge (mean 8.77, SD 0.97; mean 7.47, SD 0.97), while the control group scores higher on the memorization subscale (mean 8.17, SD 1.05; mean 7.97, SD 0.9).

Limitations

First, the knowledge test questions were identical for pre- and posttest, which could allow for familiarity with the questions. To minimize the testing effect, alternative measures with equivalent difficulty of the outcome variable should be used for repeated assessment. Second, even though the pretest score was statistically controlled as a covariate variable, other potential confounding variables such as prior academic performance in relevant courses should also be considered to ensure the validity of the results. Third, students in the second section who have the class from 10 AM to 12 PM may experience fatigue, reduced concentration, or cognitive overload, as they already had another class compared to those in the first section who had the class from 8 to 10 AM. Finally, the findings of this study have limited generalizability because the sample included nursing students from only one university. Therefore, further studies using nationwide systematic sampling are highly recommended.

Conclusions

As instructional approaches are designed for varying purposes, identifying the best teaching strategies to promote nursing students' engagement in academic and clinical settings has always been a challenge for nursing educators. While conventional text-based or lecture-based classroom environments facilitate students' learning by listening, the mind mapping and the QEMCL exercises provide visual thinking tools that help students organize class content. The mind mapping exercise can help students organize their thoughts in a way that is easy to refer back to and build upon, while the QEMCL puts students in contact with realistic hypothetical situations and allows them to learn through observation, accumulating practical experience they will be able to integrate into real situations. Nursing education should not only promote students' theoretical thinking but also improve their implicit knowledge and clinical skills. Incorporating computer-based drills and practice lessons with traditional class structures appears to be an effective pedagogical methodology, especially for lessons with limited class time. With the readiness of the university's online support system and the simplicity of the application, the current learning program was implemented as planned with all students following study instructions. Given the easy identification of and access to appropriate material in this age of online learning, the use of the QEMCL program should be encouraged. Based on the current findings, we can conclude that QEMCL is both an enjoyable and effective teaching tool, yielding significantly higher learning gains than mind mapping exercises.

Acknowledgments

The authors would like to thank all the nursing students who participated in the development phase and the testing phase of the current web-based learning program. The authors received no financial support for the research, authorship, and publication of this article.

Authors' Contributions

CC led the development of the study by drafting the protocol and the initial data collection tools. Both CC and JS contributed to the data collection and the statistical analysis. CC was responsible for drafting the manuscript while JS provided critical feedback about the study design, data collection, analysis, and reporting. Both authors have contributed to the preparation and review of the paper and agreed on the final version.

Conflicts of Interest

None declared.

Checklist 1
CONSORT-eHEALTH checklist (V 1.6.1).
[PDF File, 1259 KB - nursing_v8i1e71111_app1.pdf]

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Abbreviations

ANCOVA: analysis of covariance
CLEs: constructivist learning environments
IOC: item-objective congruence
QEMCL: Question-Embedded Movie Clips Learning
VTS: Visual Thinking Strategy

Edited by E Borycki; submitted 10.01.25; peer-reviewed by T Pummanee; revised version received 13.05.25; accepted 18.05.25; published 08.07.25.

Please cite as:
Choenarom C, Samputtanon J
The Effectiveness of a Question-Embedded Movie Clips Learning Program in Nursing Students: A Quasi-Experimental Pretest-Posttest Study
JMIR Nursing 2025;8:e71111
URL: https://nursing.jmir.org/2025/1/e71111
doi:10.2196/71111

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Effectiveness of m-Learning in Enhancing Knowledge Retention for Nurses' Lifelong Learning: Quasi-Experimental Study

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Abstract

Background: The current information and communication technologies, digital literacy, and ease of access to communication and information devices by nurses provide them with new ways and intention to access information for technical-scientific updating, ensuring the quality and safety of health care. Mobile learning (m-learning) offers a flexible and accessible alternative for continuing professional education, overcoming barriers such as time constraints and financial burden.

Objective: This study aimed to evaluate the effectiveness of m-learning in nurses' knowledge retention of chronic obstructive pulmonary disease self-management, using a Massive Open Online Course with integrated virtual clinical simulation.

Methods: A quasi-experimental pre- and posttest study was conducted, with no control group, among 168 nurses from a Portuguese hospital. The intervention included an asynchronous online course with 13 modules. Knowledge retention was assessed by comparing the mean scores before and after the course.

Results: The results indicated a significant increase in knowledge retention. The participants' average score increased from 59.97% in the initial assessment to 84.05% in the final assessment (P<.001). Nurses with a master's degree exhibited a higher level of basic knowledge than those with a bachelor's degree. The course completion rate was 93.45%, reflecting significant engagement attributed to gamification and clinically relevant content.

Conclusions: This study confirms the effectiveness of m-learning in improving knowledge retention in nursing. This strategy is a valuable approach to lifelong learning, promoting quality and safety in delivering health care. m-learning is useful in nurses' lifelong learning, offering flexibility and more effective support for clinical practice. Integrating virtual simulation and gamification boosted motivation and reduced drop-out rates, highlighting the potential of m-learning in lifelong learning in health care.

(JMIR Nursing 2025;8:e72957) doi:10.2196/72957

KEYWORDS

m-learning; nursing; continuing education; knowledge retention; COPD; MOOC; clinical virtual simulation; chronic obstructive pulmonary disease; Massive Open Online Courses; mobile learning

Introduction

Background

Available information and communication technologies (ICT), digital literacy, and easy access to communication and information devices provide nurses with new opportunities for technical and scientific updating. These advancements are directly linked to the safety and quality of care [1]. However, nowadays, there are still barriers to accessing lifelong learning [2], such as the need to balance family and professional life and the associated financial burden [3,4]. On the other hand, the decrease in human resources and their turnover and the increase in workload in health institutions are obstacles to nurses' continuing training [5,6].

The use of ICT-based platforms by health care institutions as a strategy for providing lifelong learning to nurses enables large-scale access with no geographical and time limits [7-9].

The World Health Organization defines a digital health intervention as the specific use of digital technology to achieve health-related objectives. An example of these interventions is managing training and educational content and making it available to health professionals in digital format [10]. Digital education includes computer-based offline and online education, open and massive online courses, serious games and gamification, augmented reality environments, virtual reality, virtual simulations of clinical cases, psychomotor skills training, and mobile learning (m-learning), among others [11].

e-learning, electronic learning or web-based learning often complement traditional teaching models, encompassing

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knowledge through digital technologies. These educational approaches promote access to training for health professionals [10,12].

The technological development has leveraged changes in education and fostered the use of mobile technologies in the acquisition of knowledge and its mobilization for clinical practice [13]. Current distance education contexts demand the use of mobile devices in addition to traditional computers [14].

We have been witnessing the progressive introduction and incorporation of e-learning as a pedagogical strategy coupled with the growing access to portable distance communication devices, such as smartphones and mobile internet networks. Within this new reality, m-learning has emerged as a new opportunity to promote nurses' access to digital education as a critical resource for lifelong learning. m-learning is the management and provision of education and training content in electronic format for health care professionals [10]. It allows users to access educational content via mobile devices, regardless of time and location [15]. Evidence shows that m-learning is at least as effective as traditional learning [11].

Massive Open Online Courses (MOOCs), made available by higher education institutions [16], certified and integrated into the in-service training programs of health institutions, are emerging as important contributors to incorporating m-learning in the continuing training of health professionals. Moreover, MOOCs can contribute to developing nurses' skills, specifically in training for self-management of noncommunicable chronic diseases such as chronic obstructive pulmonary disease (COPD).

Massive Open Online Courses

MOOCs are based on the definition of various concepts such as e-learning, mass communication, knowledge sharing, and openness [17]. MOOCs comprise quality content and aim at a large target audience, overcoming many of the in-class barriers [9]. With over 20 years of existence, these courses stand out for their creative methodology for conveying information and implementing innovative pedagogy and tools [18]. The MOOCs' primary goal in the health field is to improve the health status of the general population while promoting the safety and quality of the care provided [8].

In recent years, the number of MOOCs has grown exponentially, in line with the increase in the number of people with access to the internet [19,20]. In 2021, around 220 million people enrolled in online courses, representing twice the number of students enrolled in 2020 [21].

This reality explains the upward trend in using MOOCs, as they are easy to access and tend to be free [22]. The size of the global MOOC market was US $9.45 billion in 2023, estimated to reach US $39.72 billion by 2032 [23].

MOOCs comprise several characteristics, such as openness, which means the possibility of enrolling and withdrawing from the course; autonomy, referring to the pace of learning and goal attainment; diversity, which allows adaption to different time zones; and interactivity, where the effects of learning picture the sharing between participants [8].

MOOCs have been perceived as an innovative method enabling useful and effective online learning compared to face-to-face training [8]. Its success relies on the number of trainees that can be enrolled swiftly; its ability to respond to individual learning styles by using multiple tools for interaction between participants; its flexibility [2] and the guarantee of quality learning associated with cost savings in professional training.

In nursing education, the use of MOOCs has fostered the creation of broader learning opportunities for individuals and health institutions [24].

A MOOC must be designed considering the needs of the participants [25] and increase motivation and engagement. Continuous training that aims to respond to nurses' needs and is perceived as positive for the quality and safety of the care provided is more attractive and likely to better capture nurses' intention to attend and complete the course [26].

MOOCs used to develop professional competencies show higher enrollment and completion rates compared to more generic content [27,28].

The number of drop-outs in trainees from MOOCs before completion has been under analysis. In a study with 9 million students, only 5% to 18% of participants completed the course [29]. Another study reported a MOOC completion rate of less than 10% [30]. More recently, MOOC drop-out rates have ranged from 10% [31] to 85% [32].

The advantages and personal and professional gains for individuals who attend MOOCs are irrefutable, considering the impact on learning and overall knowledge pertaining to the development of skills, attitudes, confidence, and commitment [33].

Incorporating gamification features into MOOCs and using virtual patients for clinical decision training could help increase the involvement and motivation of participants to complete MOOCs [6,17,34]. MOOCs should integrate virtual patient simulators, recreating gamified environments, which are predictors of realism, fun, and motivation for participants, and reduce the drop-out rate [4,35], thus increasing MOOC completion rates [36,37].

However, little is known about the effectiveness of using m-learning for nurses' lifelong learning. Therefore, this study sought to assess the effectiveness of an m-learning strategy on nurses' knowledge retention.

Methods

Study setting

A quasi-experimental pre- and posttest study was conducted without a control group, using a nonprobabilistic convenience sampling technique. All nurses from the Internal Medicine Department of a central hospital in northern Portugal who voluntarily agreed to participate in the study were considered eligible. Thus, all 193 nurses from the Internal Medicine departments were eligible to participate.

The primary outcome of the study was the nurses' level of knowledge, analyzed using a continuous variable expressed as

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a percent (0 - 100). The calculation of the average level of knowledge before and after attending the MOOC resulted from computing the relative weight of each module included in the intervention. Knowledge retention was calculated by testing the differences between the average percent obtained before and after the intervention.

Intervention

The development of the MOOC was supported by the theme of self-management of COPD, considering the need expressed by the professionals within the study context and according to the Global Initiative for Chronic Obstructive Lung Disease (GOLD). The GOLD initiative reveals that COPD is now one of the 3 leading causes of death in the world, and 90% of these deaths occur in low- and middle-income countries. Many people suffer from this disease for years and die prematurely because of it or disease-associated complications. Globally, the burden of COPD is expected to increase in the coming decades due to continued exposure to COPD risk factors and an aging population [38].

This study used the Adult Learning Theory of Malcolm Knowles (1913 - 1997), since for effective learning, adults—nurses in this case—have to perceive the usefulness of the knowledge provided and how to mobilize it for their daily practice [39].

This study included a training program available in MOOC format, called self-management of COPD (Ecare-COPD). This program has been subject to continuous validation, with special highlight for its adequacy and scientific and pedagogical relevance [6]. This MOOC was made available on NAU, an e-learning platform, created and administered by the Scientific Computing Unit (FCCN) of the Foundation for Science and Technology (FCT). This model supports training and enables the design of training programs in Portugal using the MOOC format.

This MOOC was organized into 13 modules, 12 of which are formative and include lessons on a topic. Each lesson includes a theoretical overview of the topic, one or more supporting videos (lasting about 5.06 min) and bibliographical references.

In addition, in module 13, which was not assessed, each participant was able to practice clinical decision-making through four clinical scenarios using the Body Interact virtual patient simulator [35,40-43]. In this module, each participant had the opportunity to mobilize the previously acquired knowledge using the game methodology.

Data Collection

Sociodemographic variables and variables characterizing the professional category of the participants were used to characterize the sample.

The level of knowledge was assessed using a set of items, including 29 multiple-choice questions and 24 true or false statements, on the clinical area of COPD. The assessment items were determined by the experts who developed the contents of the training program and validated by a group of experts in the field of the training program.

It should be noted that the evaluation questions were pretested with 10 nurses. At this stage, only editing corrections were deemed necessary and no question was amended. Knowledge assessment was performed through an initial knowledge assessment of the participants after registering on the NAU platform. All participants were able to attend the training program despite the initial assessment. Each participant was asked to complete a knowledge assessment at the end of each module.

Data Analysis and Processing

The statistical analysis was performed using SPSS Amos (version 29.0; IBM Corp) and SPSS (version 29.0; IBM Corp) software. Descriptive statistics and inferential analysis were used to analyze the different variables under study. The Student *t* test was used to test for differences between means. The results are reported according to APA standards, with Cohen *d* effect magnitude (0.2 low; 0.5 mean and 0.8 high) and *P* values set at <.05.

Ethical Considerations

Ethical approval was granted by the Ethics Committee of CHUPorto/ICBAS (reference number 2021.010). All participants received an informed consent form and the anonymity and confidentiality of the data collected was guaranteed. We have also ensured that participants have the option to participate and will not suffer any damage or loss in case they do not complete the training program.

Results

This study included 168 nurses from the medicine department of a hospital in northern Portugal, representing 87% (n=193) of the total nursing staff in the department. The remaining 13% (n=25) of potential participants were absent due to temporary work incapacity, extended health-related leave, and parental leave.

Of the participants, 69.6% (n=117) were female, 11.3% (n=19) were male, and 19% (n=32) preferred not to answer. The mean age of nurses was 32.96 (SD 9.37; 24-59) years; average professional experience as a nurse of 10.12 (SD 7.50; 0-37) years, and an average experience of 6.43 (SD 6.22; 0-26) years in the Medicine Department of this hospital in the north of Portugal. Further, male nurses were older (t_{131}=−2.674; *P*=.004; Cohen *d*=0.67; men=37.94 and women=32.70), had longer professional experience (t_{132}=−3.401; *P*<.001; Cohen *d*=0.86; men=15.17 vs women=9.26), and had longer experience in the medical department (t_{131}=−2.615; *P*<.005; Cohen *d*=0.66; men=10.17 vs women=6.11). In this study, 74.4% (n=125) of the nurses held a bachelor's degree in nursing, 11.9% (n=20) held a master's degree, and 13.7% (n=23) opted not to disclose this information. Regarding professional categories, 66.1% (n=111) were general nurses, 19.6% (n=33) were specialist nurses, 1.2% (n=2) were nurse managers, and 13.1% (n=22) did not provide any information.

Regarding attendance at the training program, data analysis revealed that out of 168 participants, 157 successfully achieved an evaluation score exceeding 50%, thereby qualifying for a certificate of participation and completion. Among these, 99.36% (n=156) were issued certificates, while 0.63% (n=1)

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had still not received their certificates at the time of data extraction. In addition, 6.54% (n=11) of enrolled participants did not complete the training program despite completing their registration.

The participants completed an initial knowledge assessment, achieving an average score of 59.97% (SD 19.37; 0-97). The final knowledge retention assessment was calculated by determining the relative weight of each module. Participants scored on average 84.05% (SD 24.29%; 0-100) in the final assessment.

Descriptive statistics for the evaluation of the 12 modules included in the training program are described in Table 1.

Table . Descriptive data for the assessment of the 12 modules of the formative program.

Modules assessed	Participants (N=168), mean (SD; range)
Module 1	92.01 (17.81; 33-100)
Module 2	80.70 (27.49; 0-100)
Module 3	98.11 (8.58; 33-100)
Module 4	88.28 (14.33; 40-100)
Module 5	92.48 (14.04; 40-100)
Module 6	83.33 (24.97; 0-100)
Module 7	88.85 (16.60; 25-100)
Module 8	58.97 (49.35; 0-100)
Module 9	67.95 (46.82; 0-100)
Module 10	83.44 (37.29; 0-100)
Module 11	91.28 (16.09; 20-100)
Module 12	87.90 (32.72; 0-100)

Statistically significant differences in knowledge retention were found between the mean initial assessment score of 59.97 (SD 19.37) and the final assessment score of 84.05 (SD 24.29; t_{167}=16.697; P<.001), with a large effect size (Cohen d=1.28).

An analysis of the relationships between sociodemographic and professional characteristics revealed a statistically significant difference in knowledge retention between the mean initial assessment scores of 69.15 (SD 12.77) among nurses with a master's degree, while those with a bachelor's degree had a mean score of 62.52 (SD 13.62; t_{143}=−2.037, P=.02, Cohen d=0.49). These findings demonstrate that nurses with a master's degree have a higher baseline knowledge on this subject compared to those nurses with a bachelor's degree.

These study results confirm that the implemented pedagogical strategy significantly enhances knowledge retention among nurses within this specific context.

Discussion

Principal Findings

This study included a sample of 168 nurses from the medicine department of a hospital in northern Portugal who achieved an average score of 59.97% on the initial knowledge assessment. Throughout the training program, participants underwent final knowledge assessments at the end of each module, resulting in an overall average score of 84.05%. These findings demonstrate that the pedagogical strategy using ICT delivered through a MOOC and incorporating virtual clinical simulation significantly enhanced knowledge retention among nurses (P<.001, Cohen d=1.28).

Numerous studies on educational programs support these findings, highlighting their effectiveness in improving knowledge outcomes [44-47].

The positive impact of interventions involving simulation on knowledge acquisition is also well documented, although primarily in studies with nursing students. These findings underscore the value of active learning strategies [48], which play a critical role in motivating trainees to acquire knowledge [49,50]. This evidence reinforces the rationale for integrating virtual clinical simulation and virtual patients into the MOOC's content.

This study also revealed that nurses holding a master's degree exhibited a higher level of knowledge in the initial assessment of this area compared to those with a bachelor's degree. These findings suggest that the second study cycle facilitates the consolidation of cognitive and instrumental skills and equips nurses with the ability to manage complex situations, such as empowering patients to self-manage chronic conditions such as COPD. Consequently, a master's degree is expected to enable nurses to deliver specialized and targeted interventions that address the actual needs of the population, implement evidence-based complex interventions, and promote the quality and safety of care.

The training program was conducted in a MOOC format and incorporated multimedia resources (eg, videos) and brief summaries of the latest evidence on COPD. These features enhance the perceived usefulness of a MOOC [51], fostering greater engagement and commitment to the learning process [52] while increasing participants' intention to enroll in similar courses in the future [53].

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These factors may help to explain the low drop-out rate observed in this training program (6.55%), which is notably lower than those reported in previous studies [6,29-32,54].

As previously mentioned, the alignment of the MOOC with the participants' professional roles [27,28], specifically its focus on developing competencies to empower individuals with COPD to improve self-management of the disease, likely contributed to higher enrollment and completion rates.

In addition, the flexibility provided to participants to complete the training program [55] may have further supported the high completion rate by accommodating the professionals' needs to balance personal, family, and work responsibilities.

The use of simulation is increasingly significant in pre- and postgraduate programs [56]. High-fidelity simulation enables recreating a situation or event in which a virtual patient represents or responds to physiological parameters, providing high realism and dynamism for those involved [57]. This helps to optimize engagement in the learning process. High-fidelity simulation, which can include simulation with virtual patients, improves learning satisfaction, confidence, and self-efficacy among nursing students [58-60].

Virtual patient simulation has been used effectively to improve learning, specifically knowledge, self-confidence, practical skills, student satisfaction, and critical thinking [35,61]. It contributes to transforming learning environments into more interactive and creative scenarios, facilitating participants' learning and achieving goals [62]. The integration of simulation with virtual patients, along with the gamification component of the training program, played a pivotal role in promoting adherence and achieving higher completion rates. Using simulation with virtual patients is an effective strategy for fostering active learning and stimulating intrinsic motivation to learn. This approach enabled the recreation of clinical decision-making environments and scenarios that participants were familiar with, allowing them to identify opportunities to enhance their decision-making skills when addressing daily challenges, in line with the findings from previous studies [4].

Limitations

This study had some limitations. The first limitation concerns the study's methodology, mainly because of the absence of a control group. This prevented attributing knowledge gains to the developed intervention. Further randomized controlled studies are suggested to confirm the results.

Also, since the sample was restricted to one medicine department in a single hospital institution, it hindered the generalizability of the results. Future research should include samples from different healthcare contexts.

In addition, the study was limited only to one intervention related to COPD self-management; thus, further investigation including other areas and dimensions of nursing practice is needed to examine the impact of implementing a pedagogical strategy in the continuous training of nurses.

In addition, future studies should focus on the longitudinal monitoring of the sample, particularly to assess knowledge retention on the subject under study.

Conclusions

The adopted training program improved knowledge retention. Therefore, it is an alternative for optimizing nurses' lifelong learning according to the program features, which have highly contributed to the completion rate (93.45%).

The obtained results provide relevant information to health institutions and their managers concerning the characteristics of a pedagogical strategy for the continuous training of nurses. These results align with the professionals' needs and attest to the quality and safety of care.

Similarly, the results of this study should enable higher education institutions responsible for designing MOOCs to reflect on their content and reformulate or improve them.

Acknowledgments

This study was supported by National Funds through FCT – Fundação para a Ciência e a Tecnologia, I.P., within CINTESIS, R&D Unit (reference UIDB/4255/2020 and reference UIDP/4255/2020).

Conflicts of Interest

None declared.

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Abbreviations

COPD: chronic obstructive pulmonary disease
GOLD: Global Initiative for Chronic Obstructive Lung Disease
ICT: information and communication technologies
m-learning: mobile learning
MOOC: Massive Open Online Course
WHO: World Health Organization

Edited by E Borycki; submitted 21.02.25; peer-reviewed by SA Mukhtar, S Bezerra; revised version received 10.05.25; accepted 18.05.25; published 17.07.25.

Please cite as:
Cunha DJ, Machado P, Padilha JM
Effectiveness of m-Learning in Enhancing Knowledge Retention for Nurses' Lifelong Learning: Quasi-Experimental Study
JMIR Nursing 2025;8:e72957
URL: https://nursing.jmir.org/2025/1/e72957
doi:10.2196/72957

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Readiness and Acceptance of Nursing Students Regarding AI-Based Health Care Technology on the Training of Nursing Skills in Saudi Arabia: Cross-Sectional Study

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Abstract

Background: The rapid advancements in artificial intelligence (AI) technologies across various sectors, including health care, necessitate the need for a comprehensive understanding of their applications. Specifically, the acceptance and readiness of nursing students as future health care professionals to adopt AI-based health care technologies, along with the factors influencing these attitudes, are critical for facilitating the effective integration of AI in health care settings.

Objective: This study aimed to assess the readiness and acceptance of nursing students regarding the use of AI-based health care technologies in the nursing skills training in Saudi Arabia.

Methods: A descriptive cross-sectional research design was used. A convenience sampling technique was applied to recruit 322 participants. Data were collected between June and September 2023 using a self-administered questionnaire that included the technology readiness index (TRI) and the technology acceptance scale.

Results: Approximately 92.2% (297/322) of participants exhibited positive attitudes toward AI, and 74.8% (241/322) demonstrated innovativeness, indicating a generally favorable perception of AI. However, more than half of the students (59% [190/322] and 59.3% [191/322], respectively) reported feelings of discomfort and negative perceptions regarding AI use. Regarding TRI, 69.6% (224/322) of participants showed moderate readiness, while 30.4% (98/322) exhibited a high level of TRI. A substantial majority (320/322 99.4%) expressed acceptance of AI-based technologies in their training, with only 0.6% (2/322) reporting nonacceptance. Older students (aged >22 y) exhibited significantly higher levels of AI acceptance and readiness compared to younger students (P<.001). In addition, female students demonstrated significantly greater readiness and acceptance levels than male students (P=.003). Further, third-level students reported the highest mean scores in both acceptance and readiness (66.77 and 16.69, respectively; P=.002), while first-level students had the lowest (60.59 and 15.15). Among course groups, students enrolled in Maternal and Child Health Nursing reported the highest mean scores (65.19 and 16.30), whereas those in Community Health Nursing reported the lowest (57.50 and 14.38; P<.001).

Conclusions: The findings indicate that nursing students demonstrated a generally positive level of readiness and acceptance toward the use of AI and related technologies in education and training. However, these levels remained moderate overall, highlighting the need to enhance awareness and deepen students' understanding of AI's potential to improve training effectiveness and health care quality.

(JMIR Nursing 2025;8:e71653) doi:10.2196/71653

KEYWORDS

artificial intelligence; technology; readiness; acceptance

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Introduction

Artificial intelligence (AI) refers to the development of computer systems capable of performing tasks that typically require human intelligence. AI is currently one of the most transformative forces globally, with a particularly significant impact on the health care sector. It holds the potential to revolutionize various aspects of health care, from hospital operations and clinical trials to pharmaceutical development. These applications aim to improve health care delivery and reduce costs for both institutions and patients [1]. In this context, readiness refers to individuals' preparedness to adopt and effectively use new technologies. In the context of education, the emergence of new behavioral change is closely linked to the student's level of readiness. Readiness plays a critical role in enabling nursing students to adapt to future advancements in health care technologies. It is particularly essential for the effective integration of AI into nursing education and clinical practice, as it equips students to navigate a technology-driven health care environment. Therefore, assessing nursing students' readiness and attitudes is important for the successful integration of AI into their future professional roles [2].

The AI market in health care, valued at US $15.4 billion in 2022, is projected to grow at a compound annual growth rate of 37.5% from 2023 to 2030. This rapid expansion is driven by several key factors, including the increasing volume of digital patient health data, a rising demand for personalized treatment, and the need to reduce health care costs [3]. Over the past 5 years, the impact of AI technologies on nurse educators, nursing students, and practicing nurses has been the focus of extensive research, highlighting the transformative potential of AI in nursing education and clinical practice [4,5]. To effectively disseminate knowledge about AI algorithms and their applications, which are expected to play a significant role in both medical and nursing fields, it is recommended that medical and nursing schools integrate AI into their curricula [6-8]. A systematic review and meta-analysis by Amiri et al [9] examined the attitudes and knowledge of medical, dental, and nursing students toward AI in health care. The findings revealed a moderate level of knowledge (3736/8491, 44%) and a generally positive attitude (5519/8491, 65%), suggesting a promising level of acceptance of AI technologies among health care students.

In situations where clinical coaching opportunities are limited, the integration of innovative technologies significantly enhances nursing education by supporting professional skill development and effective training [10,11]. Nurse educators must become both knowledgeable and confident in the use of emerging AI health technologies. In addition, practicing nurses require an urgent need for upskilling to effectively integrate AI health technologies into clinical practice [12]. While technological advancements in nursing have been substantial, the impact of AI is particularly transformative. Examples include medication-dispensing robots, companion robots for individuals with special needs, and AI systems used for population health management and care coordination [13]. Registered nurses must understand the role of AI in modern health care delivery. Therefore, nursing education must clearly define the competencies required for integrating AI into practice to ensure its optimal use and value [14].

An Egyptian study conducted at Cairo University revealed that fourth-year nursing students held moderate attitudes toward AI [15]. A systematic mapping review of 22 articles indicated that virtual reality simulations are used for diverse educational purposes, including procedural skills training, emergency response training, and psychomotor skills development [16]. In addition, a scoping review of 131 papers on AI technologies showed that AI is already impacting nursing roles, workflows, and nurse-patient interactions, suggesting that AI-powered solutions have the potential to improve nursing practice. However, nurses must proactively ensure that person-centered, compassionate care remains in the integration of AI [17].

Student nurses' attitudes and intentions regarding AI use are influenced by their perceptions of its role in nursing practice [18]. To successfully integrate AI into clinical settings, it is essential to understand nurses' attitudes and behaviors toward both current and anticipated AI applications.

Evaluating their current level of AI knowledge is crucial to identify future training needs [19]. Although nursing attitudes significantly affect AI acceptability and adoption, research in this domain remains limited [18]. Thus, this study aims to assess the readiness and acceptance of nursing students in Saudi Arabia regarding the use of AI in the nursing skills training. This investigation seeks to provide valuable insights into the factors that influence nursing students' preparedness and acceptance to embrace AI in their education. Despite a growing global interest in integration of AI in health care, there remains a significant knowledge gap in Saudi Arabia, where only a limited number of studies have explored this area. Addressing this gap is essential to effectively align health care education within international best practices and emerging technological trends. Given the global shift toward integrating AI into both health care and nursing education, it is particularly important to understand nursing students' readiness and acceptance of this technology. Ultimately, this study will contribute to ensuring that future nursing graduates are equipped to adopt AI technologies in clinical settings, thereby enhancing the quality of patient care in line with international standards.

Methods

Study Design and Settings

This study used a descriptive cross-sectional research design and was conducted at 3 universities in Saudi Arabia among undergraduate nursing students. Data collection took place between June and September of the 2023 academic year.

To ensure accessibility, data were collected using a self-administered online survey developed in Arabic via Google Forms. The survey link was disseminated through various social media platforms, including WhatsApp (Meta), Instagram (Meta), and Facebook (Meta), by coinvestigators at each participating university. Participants were instructed to complete only one version of the survey to maintain data integrity and prevent duplicate responses.

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Sample Size

A convenience sampling technique was used to collect the data from a total of 322 undergraduate nursing students enrolled in 3 Saudi universities. These universities were initially selected using a multistage probability sampling technique. The required sample size was calculated using the open-source calculator OpenEpi, Version 7, based on a total population of 1983 nursing students. The sample size calculation was based on an expected frequency of 50%, a 5% margin of error, and a 95% confidence level, resulting in a minimum sample size of 322 students. Proportional allocation was used to determine the number of participants from each university: (100 students from Al-Baha University (population =618), 44 students from Al-Jouf University (population =265), and 178 students from Al-Shamal Faculty of Nursing (population =1100).

Tool of the Study

The questionnaires used for data collection were divided into 3 sections. Section one collected sociodemographic data from nursing students, including age, gender, academic level, and specialty training course. Section 2 consisted of the Technology Readiness Index (TRI), a tool originally developed by Parasuraman and Colby [20] and adapted for this study. This section included 16 items designed to measure technology readiness across four dimensions: for optimism (4 items), innovativeness (4 items), discomfort (4 items), and insecurity (4 items). Each item was rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Optimism and innovativeness reflect positive predispositions toward technology, while discomfort and insecurity represent negative tendencies. To calculate the overall total TRI Score, the negatively worded dimensions (insecurity and discomfort) were reverse coded by subtracting each item score from 6. The final TRI score was computed using the formula: TRI = (Innovative+Optimism+(6-Insecurity) + (6-Discomfort))÷4). The score ranges from 1.0 to 5.0, with higher scores indicating greater technology readiness. For interpretation, readiness levels were categorized as follows: low (<2.0), moderate (<3.5), and high (>3.5).

Section three focused on the technology acceptance model (TAM), originally developed by Davis [21] and adapted by the researcher of this study. This section included 16 items grouped into 3 key constructs to measure technology acceptance: Perceived usefulness (6 items), perceived ease of use (6 items), and intention to use (4 items). All items were rated on a 5-point Likert scale ranging from 1 = extremely unlikely to 5 = extremely likely. To calculate the average perception score, the total score of all TAM items was summed for each participant. This raw score was then converted into a percentage by dividing it by the maximum possible score and multiplying by 100. The average percentage was computed across all participants to determine the overall mean perception score. Perception levels were categorized as follows: low (<65%), moderate (65% to <80%), and high (≥80%). For interpretive purposes, scores <40% were considered not accepted, while scores >40% were considered accepted.

To ensure clarity for comprehension for all nursing students, the survey was initially translated into Arabic and then back-translated into English to verify accuracy and consistency. Content validity was evaluated by a panel of five experts, all holding PhDs in nursing. The experts were requested to evaluate the relevance and clarity of each item, provide suggestions for improvement, and determine whether the items appropriately reflected the objectives of the study. Reliability of the instruments was assessed using Cronbach α. For TRI, which consisted of 16 items, the reliability coefficient was α =. 820. For TAM, also comprising 16 items, the reliability coefficient was α=.782.

Pilot Study

A pilot study was carried out on 10% of the study sample (N=32) to assess the clarity, feasibility, and applicability of the survey tools. Participants in the pilot study were excluded from the final sample to avoid bias. The average time to complete the survey ranged from 15 to 20 minutes. The study was conducted across three universities: Al-Baha University (n=618), Al-Jouf University (n=265), Al-Shamal Faculty of Nursing (n=1100).

Ethical Considerations

Ethical approval for this study was obtained from the Research Ethics Committee, Faculty of Nursing, Al-Baha University (approval number 44127970). In addition, official permission letters were secured from the Faculty of Nursing in each sitting Al-Baha University, Al-Jouf University, and Al-Shamal Faculty of Nursing to conduct the study and collect data. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki. Participation in the study was entirely voluntary, with no academic consequences for students who chose to participate. Anonymity and confidentiality were strictly maintained by not collecting names or any personally identifiable information. All data was securely stored and used exclusively for research proposals. Before participation, written informed consent was obtained from all participants.

There were no consequences or effects on grades for not participating; participation was completely voluntary. Participant anonymity was guaranteed by withholding names or any other personally identifying information. All data was safely stored and used solely for this study. Every participant gave their written informed consent.

Statistical Analysis

Data were analyzed using IBM SPSS software, version 20.0. The Kolmogorov-Smirnov test was used to assess the normality of data distribution. Quantitative variables were summarized using range (minimum and maximum), mean, and SD. Statistical significance was determined at *P* value <.05. For inferential statistics, the student's *t* test was used to compare between 2 independent groups for normally distributed data, while a one-way Analysis of Variance (*F* test) was applied to compare means among more than 2 groups. To identify which group differed significantly, post hoc analyses were conducted using the Tukey HSD test.

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Results

Table 1 presents the demographic characteristics of the study participants. The age of participants ranged from 18 years to over 22 years. Approximately half of students (154/322, 47.8%) were aged between 18 and 22 years, while a low percentage (49/322, 15.2%) were older than 22 years. Regarding gender, 47.2% (152/322) of the participants were male, and 52.8% (170/322) were female. In terms of academic level, the majority of students were in their second year (133/322, 41.3%) and third year (103/322, 32.0%). A smaller percentage was in their first year (27/322, 8.4%), while (59/322, 18.3%) were in their fourth year. In addition, nearly half of the participants (150/322, 46.6%) were enrolled in administrative nursing specialty training, while one quadrant (82/322, 25.5%) was in adult nursing specialty training. On the other hand, the lowest percentage (14/322, 4.3%) of participants was in Psychiatric nursing specialty training.

Table 2 illustrates the TRI findings among the nursing students. The majority of students reported high levels of optimism (297/322, 92.2%) and innovativeness (241/322, 74.8%), reflecting positive attitudes regarding the use of technology. Conversely, more than half of the participants reported moderate feelings of discomfort (190/322, 59.0%) and insecurity (191/322, 59.3%), indicating some negative feelings regarding technology. In addition, approximately 69.6% (224/322) of the participants reported moderate TRI, while 30.4% showed high TRI. Furthermore, the mean TRI score across all participants was 3.30 (SD =0.46), suggesting moderate levels of readiness to use technology in nursing skills training.

Table 3 presents participants' levels of acceptance regarding various dimensions of technology use. A majority (187/322, 58.1%) exhibited high acceptance in terms of perceived usefulness of technology, while 29.2% (94/322) showed moderate acceptance and 12.7% (41/322) reported low acceptance in this domain. Regarding perceived ease of use, about half of the participants reported low acceptance, whereas 25.2% (81/322) and 18.6% (60/322) showed moderate and high acceptance, respectively. Concerning the intention to use or adapt the technology, 40.7% (131/322) showed high acceptance, while 34.8% (112/322) and 24.5% (79/322) reported moderate and low acceptance, respectively. Overall, 34.8% (112/322) of the participants demonstrated high technology acceptance, 40.1% (129/322) had moderate acceptance, and 25.2% (81/322) showed low acceptance.

reveals that the vast majority of students (320/322, 99.4%) reported overall acceptance of using technology, while only a small fraction (2/322, 0.6%) indicating no acceptance.

Table 4 compares nursing students' acceptance and readiness to use AI and modern technology. The results indicate that students exhibited higher acceptance of technology and AI, with SD of 61.80±9.08 , 65.34 (SD 10.27), and 67.37 (SD 10.49), respectively, while their readiness scores were comparatively lower at (15.45 SD 2.27,16.33 SD 2.57, 16.84 SD 2.62). A significant difference was observed with respect to age: students older than 22 years showed a greater acceptance and readiness compared to younger students aged 18 - 20 or 20–22 years, with statistical significance (P<.001). In addition, women show a high level of acceptance and preparedness to use technology and artificial intelligence, with a statistical significance of (0.003). The mean for females was (16.38 SD 2.38, 65.51 SD 9.50) compared to males (15.55 SD 2.55, 62.21 SD 10.21). Our findings reveal that third-level students exhibited the greatest acceptance and readiness (66.77 SD 10.04, 16.69 SD 2.51), while first-level students exhibited the lowest (60.59 SD 10.44, 15.15 SD 2.61), showing a statistical significance of (P=.002). Moreover, students participating in the Maternal and Child Health Nursing course exhibited the highest levels of acceptance and readiness (65.19 SD 9.41, 16.30 SD 2.35), while those in the Community Health Nursing course displayed the least acceptance (57.50 SD 7.93, 14.38 SD 1.98), with a statistical significance of (P<.001).

Turkey HSD Post hoc showed that students >20 years had significantly higher AI readiness and acceptance compared to those aged 18 - 20. Third-year students had significantly greater AI readiness and acceptance than first- and second-year students. Students in the administrative nursing specialty showed significantly higher AI readiness and technology acceptance than those in other specialties.

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Table . Distribution of the studied nursing students according to demographic data (n=322).

Demographic data	Values, n (%)
Age (years)	
18 - 20	154 (47.8)
20 - 22	119 (37.0)
>22	49 (15.2)
Sex	
Male	152 (47.2)
Female	170 (52.8)
Academic level	
First-year	27 (8.4)
Second year	133 (41.3)
Third year	103 (32.0)
Fourth year	59 (18.3)
Specialty	
Maternal and child nursing	26 (8.1)
Psychiatric nursing	14 (4.3)
Community nursing	26 (8.1)
Critical nursing	24 (7.5)
Administrative nursing	150 (46.6)
Adult nursing	82 (25.5)

Table . Distribution of the studied nursing students according to overall artificial intelligence readiness items (n=322).

Artificial intelligence readiness	Low (<2), n (%)	Moderate (2–3.5), n (%)	High (≥3.5), n (%)	Score range	Total score, mean (SD)	Average score (1–5), mean (SD)
Optimism	1 (0.3)	24 (7.5)	297 (92.2)	4–20	17.88 (2.63)	4.47 (0.66)
Innovativeness	3 (0.9)	78 (24.2)	241 (74.8)	4–20	16.02 (3.37)	4.01 (0.84)
Discomfort	80 (24.8)	190 (59)	52 (16.1)	4–20	9.81 (3.98)	2.45 (1.0)
Insecurity	100 (31.1)	191 (59.3)	31 (9.6)	4–20	9.08 (3.45)	2.27 (0.86)
Overall	0 (0)	224 (69.6)	98 (30.4)	16–80	15.99 (2.49)	3.30 (0.46)

Table . Distribution of the studied nursing students according to overall technology acceptance items (n=322).

Technology acceptance	Low (<65%), n (%)	Moderate (65% –80%), n (%)	High (≥80%), n (%)	Score range	Total score, mean (SD)	Average score (1–5), mean (SD)
Perceived usefulness	41 (12.7)	94 (29.2)	187 (58.1)	6–30	26.09 (4.09)	4.35 (0.68)
Perceived Ease of Use	181 (56.2)	81 (25.2)	60 (18.6)	6–30	21.64 (4.53)	3.61 (0.75)
Intention to use	79 (24.5)	112 (34.8)	131 (40.7)	4–20	16.22 (2.98)	4.05 (0.74)
Overall	81 (25.2)	129 (40.1)	112 (34.8)	16–80	63.95 (9.96)	4.0 (0.62)

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Table . Relation between total score for overall (Artificial Intelligence Readiness, Technology acceptance) with demographic data (n=322).

Demographic data	n	Artificial Intelligence readiness, mean (SD)	Technology acceptance, mean (SD)
Age (years)			
18 - 20	154	15.45 (2.27)	61.80 (9.08)
20 - 22	119	16.33 (2.57)	65.34 (10.27)
>22	49	16.84 (2.62)	67.37 (10.49)
F[a] (*P*)[b]		7.952[c] (<.001[c])	7.952[c] (<.001[c])
Sex			
Male	152	15.55 (2.55)	62.21 (10.21)
Female	170	16.38 (2.38)	65.51 (9.50)
t[d] (*P*)		3.005[c] (.003[c])	3.005[c] (.003[c])
Academic level			
First-year	27	15.15 (2.61)	60.59 (10.44)
Second year	133	15.59 (2.30)	62.37 (9.20)
Third year	103	16.69 (2.51)	66.77 (10.04)
Fourth year	59	16.04 (2.57)	64.15 (10.29)
F (*P*)		5.077[c] (.002[c])	5.077[c] (.002[c])
Specialty			
Maternal and child nursing	26	16.30 (2.35)	65.19 (9.41)
Psychiatric Nursing	14	15.93 (2.80)	63.71 (11.21)
Community Nursing	26	14.38 (1.98)	57.50 (7.93)
Critical nursing	24	15.02 (2.86)	60.08 (11.44)
Administrative nursing	150	16.74 (2.19)	66.95 (8.78)
Adult nursing	82	15.33 (2.57)	61.30 (10.29)
F (*P*)		7.552[c] (<.001[c])	7.552[c] (<.001[c])

[a]F: F for One way ANOVA test

[b]*P*: *P* value for comparison between the studied categories

[c]Statistically significant at $P \leq .05$

[d] t:Student *t*-test

Discussion

Principal Findlings

This study examined the readiness and acceptance of nursing students in Saudi Arabia regarding the use of artificial intelligence-based health care technology for nursing skills training. The findings indicate that most students are optimistic about incorporating AI into their education, with 69.6% reporting moderate readiness to adopt AI-related technological interventions. These results align with previous research showing that nurses generally hold positive attitudes and intentions toward the utilization of AI technologies in their practice and education [14,18]. Therefore, it is essential to incorporate specific courses on AI, promote student engagement with emerging technologies, and encourage faculty members to stay current with advancements in AI and its applications in nursing care [22].

Moreover, the study demonstrated that more than half of the participants (59% [190/322] and 59.3% [191/322]) experienced moderate discomfort and insecurity regarding the use of AI technologies. This highlights the need for increased efforts to educate nursing students about the efficacy and value of AI in training. In addition, participants demonstrated moderate techno-readiness toward adopting AI technologies. Sensitization initiatives should emphasize the benefits of AI, such as improving patient safety, enhancing the quality of clinical decision-making, and increasing efficiency in healthcare processes, including patient monitoring [15]. Furthermore, the moderate levels of techno-readiness highlight the need to increase nursing students' exposure to technology in order to enhance their attitudes and perceptions of its value in nursing practice.

The overall technology acceptance among participants indicated that the majority exhibited moderate to high levels of acceptance. The findings reflect generally favorable attitudes

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toward the usefulness of technology, with more variability in perceived ease of use and intention to adopt it. While 58.1% of participants showed high acceptance regarding the perceived usefulness of technology, a notable proportion reported moderate to low acceptance. These findings highlight the need to foster greater engagement and raise awareness about the benefits and value of integrating technology into nursing education. As noted by Swan [14], such awareness is vital for facilitating positive shifts in perceptions and attitudes [22,23]. Additionally, perceived usefulness and ease of use of technological interventions, such as AI, have been consistently identified as strong predictors of willingness to adopt these technologies in nursing practice [14,17,20]. The results further indicate that most participants perceive the ease of use of AI technology as moderate to high. These findings are consistent with a study conducted in Nepal, which reported their moderate levels of digital literacy among nursing students [24]. However, they contrast with the findings of Stellesfson et al [25], who observed insufficient e-health literacy among college learners. This insufficiency is largely attributed to current curricula that often do not adequately incorporate the use of technologies such as AI in nursing and clinical education.

Additionally, the results indicate that the vast majority of participants (99.4%) accepted the use of technology, with only a small percentage (0.6%) reporting no acceptance. This underscores the importance of integrating innovative curricula at the undergraduate level to enhance nursing students' exposure to emerging technologies such as AI. Early and structured exposure is crucial for building technological competency and fostering positive attitudes towards the use of AI in clinical practice [15]. Moreover, the study found no statistically significant differences in technology readiness and acceptance based on demographic variables such as age, gender, academic level, and specialty. This suggests that training programs should adopt a universal approach, targeting all nursing students equally. Such an inclusive strategy simplifies implementation, enhances cost-effectiveness, and supports the use of varied teaching methods to promote AI literacy. Educators can incorporate various methods such as role-plays, debates, panel discussions, and hands-on activities to enhance understanding of AI's value and applications.

Furthermore, increasing students' clinical exposure to AI technologies may positively shape their perceptions and encourage proactive engagement. Such shifts in perception are vital for fostering continuous learning and the development of essential nursing competencies in an AI-integrated environment. Nonetheless, several limitations should be acknowledged. First, the cross-sectional design restricts the ability to detect causal relationship between variables, making it challenging to determine the directionality of these correlations and understand how they might evolve over time. Second, the use of self-reported measures may introduce bias, as participants might provide socially desirable answers or may not accurately recall their experiences. Furthermore, while online survey distribution offers convenience, it may inadvertently exclude certain student groups, particularly those with limited access to or familiarity with digital platforms, thus potentially affecting the representativeness of the sample.

Conclusion

The findings indicate that nursing students demonstrated a generally positive readiness and acceptance regarding the use of AI and technology in education and training. However, this readiness and acceptance were at a moderate level, highlighting the need for enhanced awareness and a deeper understanding of AI's potential to improve training efficiency and the quality of healthcare delivery. To address this gap, nursing education programs should integrate AI-related content into their curricula, thereby fostering students' familiarity, competence, and confidence in using emerging technologies in clinical and educational contexts.

Acknowledgments

The researchers acknowledge the participants for participating in the study.

Data Availability

The data used to support the research results are accessible to the corresponding author upon request.

Authors' Contributions

Conceptualization: KA, TAM.
Data curation: RAA.
Formal analysis: RAA.
Investigation: KA.
Methodology: KA, ANA, BS.
Project administration: KA, MSAH.
Resources: ASG, HHA.
Software: TAM, ANA.
Supervision: KABS, TAM.
Validation: ANA, FAAR.
Visualization: HHA, MSAH, TAM, FAAR, BS.
Writing – review & editing: All authors.

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Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence
TAM: Technology Acceptance Model
TRI: technology readiness index

Edited by A Abd-alrazaq; submitted 23.01.25; peer-reviewed by A seda, J Qaddumi, K Zaben; revised version received 21.05.25; accepted 22.05.25; published 30.07.25.

Please cite as:
AL-Olaimat K, Salameh B, Abdulhalim Alqadi R, Alruwaili A, Hakami M, Huwaydi ALanazi H, Maharem T, Abdelkader Reshia FA Readiness and Acceptance of Nursing Students Regarding AI-Based Health Care Technology on the Training of Nursing Skills in Saudi Arabia: Cross-Sectional Study
JMIR Nursing 2025;8:e71653
URL: https://nursing.jmir.org/2025/1/e71653
doi:10.2196/71653

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Assessing the Use of Welfare Technology in Social Care for Older Adults Through Assistant Nurses' Perceptions of Upskilling and Care Delivery Outcomes: Cross-Sectional Study

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Abstract

Background: The implementation of welfare technologies, a broad array of technologies that have the potential to maintain or improve individuals' safety, independence, and participation, has increased rapidly in recent years, offering new ways of delivering care. However, studies of welfare technology use in the social care sector are scarce.

Objective: This study aims to explore the use of different types of welfare technologies, training in the use of these technologies, and to identify their associations with outcomes for care recipients and frontline care workers in the social care of older adults.

Methods: A cross-sectional survey was conducted based on a nationwide randomized sample of assistant nurses employed in social care for older adults in Sweden (N=1163; response rate 23%). Dependent variables were outcomes for care recipients (continuity of care, participation, and reduction in loneliness) and upskilling for frontline care workers. The exposure variables were types of welfare technologies and training in the use of such technologies. Associations between exposure and dependent variables were assessed through logistic regression models.

Results: According to the perceptions of care workers, interactive technologies were significantly positively associated with continuity of care (odds ratio [OR] 1.58, 95% CI 1.15 - 2.18), participation (OR 2.01, 95% CI 1.48 - 2.74), and reduction in loneliness among care recipients (OR 1.92, 95% CI 1.41 - 2.62). In addition, there was a significant positive association between interactive technologies and upskilling of care workers (OR 2.44, 95% CI 1.58 - 3.79). Despite the benefits of welfare technology, the effects can also be negative, as shown by the findings on the use of digital documentation (OR 0.69, 95% CI 0.49 - 0.96), digital locks or cameras or sensors (OR 0.62, 95% CI 0.46 - 0.84), and the lower likelihood of participation. Training in the use of welfare technology was significantly associated with outcomes for care recipients (continuity of care: OR 2.02, 95% CI 1.53 - 2.66; participation: OR 1.91, 95% CI 1.45 - 2.51; reduction in loneliness: OR 1.74, 95% CI 1.31 - 2.30), as well as upskilling of care workers (OR 4.59, 95% CI 3.28 - 6.42). The interaction analyses showed that participants who had not received any training but used digital documentation reported favorable views on continuity of care and upskilling, whereas those who had received training expressed concerns about participation and addressing loneliness.

Conclusions: The potential outcomes of welfare technology use in social care for older adults can vary with the types of technologies used. Care workers hold positive perceptions toward interactive technologies to improve care delivery outcomes and skill development. The findings on training and improved outcomes suggest that investing resources to promote training can reinforce positive experiences. While training had a positive impact, the interaction effects of digital documentation and training were mixed.

(JMIR Nursing 2025;8:e65641) doi:10.2196/65641

KEYWORDS

effects of technology in social care; care users; skill development; training; assistant nurses; care providers; digitalization; older adults; geriatric; care; continuity of care; social care; loneliness; older adult care

Introduction

Background

The use of digital services has increased rapidly in recent years to address health care and social welfare challenges [1], such as the care needs of aging populations and the shortage of frontline care workers [2]. Welfare technology, a term used in the Nordic context, covers a broad array of technologies that have the potential to maintain or improve individuals' safety, independence, and participation, thereby promoting their quality of life [3,4]. The efficient use of care workforce resources is another expected outcome of welfare technology; for example, automation reduces the need for face-to-face appointments for

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minor issues and frees up resources for tasks that really require human contact [4,5]. Hence, new ways of delivering both traditional and emerging types of welfare services offer potential benefits for care recipients as well as care workers [2]. Due to these constant changes, up-to-date knowledge is needed about the effects of digitalization on social care practices. In Sweden, assistant nurses are the main workforce providing social care for older adults. For the sustainable deployment of technology, it is essential that these frontline workers perceive its use as beneficial both for themselves and for their care recipients. In this study, we explored associations between welfare technologies and potential benefits for care recipients (eg, continuity of care, participation, and lower levels of loneliness) and frontline care workers (eg, upskilling).

Theoretical Perspectives

The perceived usefulness is an important component of theoretical models on technology acceptance in voluntary or mandatory settings [6-8]. It refers to the extent to which an individual believes that using technology enhances work performance. In social and health care contexts, the usefulness of welfare technology includes work performance as well as quality of care [8-11], which are broad and interrelated concepts. For instance, technology can improve workflow efficiency and simultaneously enhance care delivery, thereby influencing both aspects.

In the context of social care for older adults, continuity of care can be defined as the degree to which a series of discrete care events are perceived as coherent, connected, and consistent with the needs of older adults and personal context [12,13]. Digital care records, an example of welfare technology, provide quick access to the updated information, often entered by multiple care providers. This minimizes the risk of errors and enables timely referrals, thereby facilitating continuity of care [14], which is an indicator of quality of care. This implies that the types of welfare technologies contributing to continuity of care are perceived as useful.

Another indicator of perceived usefulness could be participation, an expected outcome of welfare technology in social care. Participation refers to the care recipients' involvement in an area of life, such as social participation or being involved in care planning [2,3,15]. For example, if care recipients have access to their digital care records, they can participate in planning their own care [2,14].

Continuity of care and participation can be seen as instrumental indicators of quality of care. The perceived usefulness of welfare technology in addressing social issues such as loneliness provides a broader perspective. The risk of loneliness or social isolation increases with the advancement of age, owing to life situations emerging from health conditions or living arrangements. Although technology cannot replace face-to-face interactions, it can provide complementary functions that contribute to overcoming the barriers (eg, mobility challenges) of social interactions [16]. Thereby, technology may have the potential to address loneliness or social isolation among older adults.

The implementation of welfare technologies stipulates discussion on changes in work complexity and required skills. Work complexity encompasses nonrepetitive tasks, greater autonomy, and skill development [17]. Job designs with higher complexity levels present workers with new challenges and stimulate the acquisition of new skills, defined as upskilling [17,18]. The upskilling approach suggests that technology use has altered the occupational structure, leading to more complex work [17]. This implies a hypothesis on a positive association between the use of welfare technologies and the upskilling of frontline workers. However, a problem arises when the use of welfare technology is perceived to collide with professional identity [19]. Adequate training equips professionals with the skills required to use new technology and facilitates understanding of the justification for technology. These attributes of training contribute to positive experiences with, and the reinforcement of, technology use [9,11,20]. Consistent with previous research, we hypothesize that training is positively associated with upskilling and care delivery outcomes.

Prior Research

A systematic review including studies on primary health care has shown mixed findings, which might be due to the multidimensional aspect of continuity of care [21]. Similarly, a study performed in Swedish primary health care has shown that an association between welfare technology and continuity of care could be understood in many ways [14]. For example, the use of digital records and communications increases the likelihood of informational continuity, whereas interrelation continuity (ie, between the patient and a single care provider) improves for some but not all patients [14,21].

A systematic review including studies on user feedback from older adults and their formal or informal caregivers has shown that welfare technologies can improve independence and self-management among older adults [10]. Here, independence refers to not depending on others for assistance [10], hence potentially improving the likelihood of participation in daily life activities [15]. According to the views of professionals in Swedish municipal social care for older adults, welfare technology could be an enabler of care recipients' participation via access to their care plans [2]. Another systematic review has shown that technology contributes positively to improving social interaction between older adults and their formal or informal caregivers and to reducing loneliness among older adults [10]. Specifically, technology such as video calls and social media facilitated communication with others. However, interaction with robots is also appreciated by older adults for reducing loneliness [10]. During the pandemic, the majority of social care workers in a Welsh study perceived that technology benefited efforts to address loneliness or social isolation among older adults [16]. Despite receiving training in the use of technology and support in accessing it (eg, they could borrow tablets and have smart home devices and assistive technology such as Amazon Alexa installed), telephone calls remained the most common means of social interaction [16].

The level of education and occupational requirements are often used as broad measures of workforce skills [17]. However, using years of schooling as a proxy for skill has been criticized for its

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static nature. In contrast, job requirements are shaped by the nature of work tasks, which are dynamic and subject to change over time. Consequently, an individual's ability to perform these tasks is influenced not only by formal education but also by prior experience and adaptability [17]. This underscores the need for continuous skill development to address the evolving complexities of work, particularly in the context of digitalization. Previous research has shown that digital competency is crucial to understanding the relevance of technology in clinical contexts in providing high-quality patient care and building positive experiences of technology use [1,20]. However, inadequate training in the use of technology may slow down the learning process [5].

In summary, there are high expectations regarding the potential benefits of using welfare technologies and providing training in their use. However, studies on the use of welfare technology in the social care sector are scarce, and therefore, there is limited empirical evidence to support that such expectations are being borne out [1]. This lack of empirical evidence on the desired benefits contributes to resistance to the deployment of technology [2]. Moreover, previous research has primarily focused on the potential benefits of a single type of welfare technology, such as digital communication [1,16,21]. A particular type of technology may have a positive effect on one indicator of quality of care but a negative effect on another. This suggests a need to understand the potential outcomes of different types of welfare technologies in the same context.

Objective

This study aims to explore the use of different types of welfare technologies, training in the use of these technologies, and to identify their associations with outcomes for care recipients and frontline social care workers.

Methods

Study Design, Setting, and Population

A cross-sectional study design was used. In Swedish social care for older adults, assistant nurses make up the main workforce and comprise the population of this study. Assistant nurses aged ≥18 years and employed in social care for older adults in Sweden for a minimum of 5 years were selected through the Swedish Occupational Register. High turnover and short-term employment are common in social care for older adults. A 5-year experience requirement ensures that participants have adequate experience of social care of older adults to provide informed and critical perspectives on the use of welfare technology. A total of 70,696 eligible participants were identified. This study forms part of a larger project investigating the working environment of assistant nurses in social care of older adults, which is based on an earlier project examining working conditions in Swedish social care for older adults [22]. To enhance the potential for conducting subgroup statistical analyses, a representative sample size of 5000 participants was determined in collaboration with Statistics Sweden.

In Sweden, care for older adults is a public responsibility. A fundamental value in social care for older adults is to ensure that they live an independent, dignified life, including good mental health and well-being (5 chapter 4 § Social Services Act). The municipalities (N=290) are responsible for social care. Provision of basic home health care (up to nurse level) is also the responsibility of municipalities in all but one region. Both public and private providers can offer publicly funded social care. The implementation of welfare technology is shaped by a top-down approach. Local variations can be expected in the extent of deployment of welfare technologies due to the decentralized system. The sector of social care of older adults is characterized by a predominantly female workforce, and assistant nurses typically hold an upper secondary education.

Data Collection and Sources

Data were collected from December 2023 to February 2024 through a survey questionnaire. The survey assessed working conditions in social care for older adults and included 46 items. It was adapted from a previous questionnaire on working conditions [22]; however, the dependent and exposure variables used in this study were newly developed. To construct items related to technology, training, and upskilling, the project team drew on the Swedish national report on eHealth and technology [23]. These items have been used in the national survey, thereby enhancing the likelihood of face validity.

Data collection was conducted in collaboration with Statistics Sweden and a research firm connected to the university. The population register was used to distribute invitations to potential participants' postal addresses. Each participant received an invitation letter with study information, a web link, and a QR code providing access to the online questionnaire. To increase response rates, 2 reminder mailings were sent, including both a paper version of the questionnaire with a prepaid return envelope and the web link. The research firm administered the web-based survey using its proprietary platform and applied a template questionnaire structure tailored to question types and scales. Paper-based responses were scanned, and the data were transferred into the dataset using the research firm's software. Quality assurance procedures included matching scanned responses with the original paper forms to ensure data accuracy.

In the next step, survey data were linked to the national register, the Longitudinal Integration Database for Health Insurance, and the Labor Market by Statistics Sweden to obtain data on sociodemographic variables.

Ethical Considerations

Invited participants received information about the study and the confidentiality of their responses. Potential participants were informed that the survey would take approximately 30 minutes to complete, and that participation was voluntary, with the option to respond selectively to individual items. They were also informed that, upon accepting the invitation, their sociodemographic data would be obtained from national registers. Written informed consent was obtained from all participants. The research group received deidentified data, with the key securely stored at Statistics Sweden. The national ethical board granted ethical approval for this study (registered number 2023-04427-01).

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Variables

Dependent Variables

Outcomes for care recipients, measured by the perceptions of care workers, were continuity of care, participation, and reduction in loneliness and social isolation (hereafter referred to as loneliness). These indicators were measured with three questions: (1) Has the use of welfare technology contributed to the continuity of care for care recipients? (2) Has the use of welfare technology contributed to increased participation of care recipients? and (3) Has the use of welfare technology contributed to reduced loneliness and social isolation among care recipients? The response alternatives were: no, not at all; yes, to some extent; yes, to a relatively high extent; yes, to a high extent. These variables were modeled as dichotomous (no, not at all: 0; yes: 1).

The upskilling index was developed based on 2 questions: (1) Has the use of welfare technology contributed to the development of competence in care? (2) Has the use of welfare technology contributed to new competence? The response alternatives were: no, not at all; yes, to some extent; yes, to a relatively high extent; yes, to a high extent. These variables were modeled as dichotomous (no, not at all: 0; yes: 1).

Exposure Variables

Types of welfare technologies were measured by asking, "What kind of welfare technology do you use in your work (fill in all the options you use)?" The response options were (1) digital locks to get access to the care recipient's home, (2) cameras or sensors for supervision, (3) digital medication (eg, medicine dispensers, robots, reminders), (4) digital support for care recipient in grocery shopping, (5) digital support for care recipient in training and activity (eg, VR, animal robots, and apps), (6) digital communications between you and care recipient (eg, video calls), (7) digital communication between you and your colleagues, and (8) digital documentation and planning (eg, using apps to register visits to care recipients or to document notes made at the visit). The Swedish National Board of Health and Welfare conducts annual data collection on types of welfare technology used in social care and municipal health care [23]. These data informed the development of response categories on types of welfare technology. Moreover, the selected welfare technologies are consistent with the findings of a recent exploratory study [24].

Training in the use of welfare technologies was measured from a single item: Have you received any special training to improve your skills in using welfare technology? The response options were (1) yes, I have received training on using a specific type of welfare technology; (2) yes, I have received training for more general technical skills related to my professional role; and (3) no, I have not received training on using welfare technology. In regression, this was modeled as a dichotomous variable (no: 0; yes: 1).

Covariates

Age, sex, level of education, workplace (care home and home care), and work experience were the covariates. Potential covariates were selected based on a theoretical model [6], previous research [8], or possible differences in care routines at the care home and in-home care.

Data Analysis

Characteristics of the study participants were presented in absolute and relative frequencies (Table 1). The continuous variable was reported as mean and SD. To increase the sample size (and thereby statistical power), types of technologies were grouped into 5 categories. Digital locks and cameras or sensors were combined into a category. Digital support in grocery shopping, digital support for care recipients in training and activity, and digital communications with care recipients require the care recipients to actively interact with the technology; therefore, these technologies were grouped under the category interactive technology.

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Table . Characteristics of the study participants.

Characteristics	Values (N=1163)[a]
Age (years), mean (SD)	51.9 (9.6)
Sex, n (%)	
Male	80 (6.9)
Female	1083 (93.1)
Education, (n%)	
Primary or lower secondary	24 (2.1)
Upper secondary ≤2 years	459 (39.5)
Upper secondary 3 years	501 (43.1)
Postsecondary <3 years	124 (10.7)
Postsecondary ≥3 years	55 (4.7)
Workplace, n (%)	
Home care	382 (32.8)
Care home	752 (64.7)
Work experience (years), n (%)	
≥15	902 (77.6)
10 - 14	146 (12.6)
<10	110 (9.5)
Welfare technologies, n (%)	
Digital locks	619 (53.2)
Cameras or sensors	387 (33.3)
Digital support in medicine	362 (31.1)
Activity and training	110 (9.5)
Digital support in grocery shopping	169 (14.5)
Digital communication between care provider and care recipient	103 (8.9)
Digital communication between colleagues	271 (23.3)
Digital documentation and planning	852 (73.3)
Not using welfare technologies	64 (5.8)
Training in the use of welfare technologies, n (%)	606 (52.1)
Continuity of care, n (%)	603 (51.8)
Patient participation, n (%)	511 (43.1)
Reduction in loneliness or social isolation, n (%)	420 (36.1)
Upskilling, n (%)	810 (69.6)

[a]Missing data were 2.5% for workplace and 0.4% for work experience. A total of 51 participants lacked complete information on welfare technologies, training, and dependent variables. Missing values for dependent variables were 9% for training, 11% for continuity of care, 10% for participation, and 8% for upskilling.

Logistic regression models were used to analyze the associations between independent and dependent variables. The proportion of missing data ranged from 0.4% to 11% (Table 1), with 51 participants lacking complete information on exposure and dependent variables. Given a relatively low level of missingness, we conducted a complete case analysis. Multivariate model building was done in 4 steps (Multimedia Appendix 1). At the first step, covariates age, sex, education, workplace, and work experience were entered. At the second step, types of welfare technologies were entered. At the third step, training in the use of welfare technologies was entered. At the fourth step, interaction between training in the use of welfare technologies and types of welfare technologies was entered. Only those interactions that significantly contributed to the model were considered. Results are presented as OR with 95% CI.

The deviance statistic (−2LL), Cox and Snell's R^2 (R^2_{CS}), and Nagelkerke R^2 (R^2_N) tests were used for model building [25].

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The deviance describes the unexplained variance in the model, so the smaller the value of deviance, the better the model fits the data. R^2_{CS} and R^2_N are approximations of the R^2 statistic for multiple linear regression, which describes the variance in the dependent variable explained by the model. R^2_{CS} and R^2_N are calculated differently and may provide divergent estimates, thus both were included. The variance inflation factor was used to check potential multicollinearity among independent variables. The variance inflation factor of less than 10 was observed for all variables and deemed acceptable [25].

The interaction between digital documentation and planning (hereafter referred to as digital documentation) and training significantly contributed to the regression model (Multimedia Appendix 1). To evaluate the interaction effect of digital documentation and training, we predicted the probabilities for the outcome using the full model, setting the values of nonfocal variables to their mean values, and visualized the results with 95% CI. A significance level <.05 was used. The final multivariate models, including associations between independent and dependent variables, are presented in the Results section, whereas interaction effects are illustrated as figures. SPSS V.29 (IBM Corp) for Windows and Statistical software R version 4.4.1 (R Development Core Team) were used to conduct all analyses.

Results

Characteristics of the Study Participants

A sample of 5000 individuals received an invitation, of whom 1163 participated in the study. The mean age of the study participants was 51.9 (SD 9.6) years, and 1083 out of 1163 (93%) participants were women (Table 1). Only 24 out of 1163 (2.1%) participants had primary or lower secondary education. However, upper secondary education was common among the participants, of whom 459 (39.5%) completed up to 2 years and 501 (43.1%) completed 3 years. Among the 1163 participants, 179 (15%) had postsecondary education. Of the 1163, 752 (64.7%) participants worked in care homes, and 382 (32.8%) worked in home care. The work experience of at least 15 years was reported by 902 out of 1163 participants (77.6%); 146 participants (12.6%) had 10 - 14 years, and 110 participants (9.5%) had less than 10 years of experience. Among the 1163 participants, 852 reported use of digital documentation (73.3%) and 619 reported use of digital locks (53.2%). Of 1163 participants, 110 (9.5%) indicated that they used technologies for activity or training, and 103 participants (8.9%) reported digital communication with care recipients. A total of 606 participants out of 1163 (52.1%) had been trained in the use of welfare technologies. In response to the question regarding the use of welfare technologies, 603 out of 1163 (51.8%) participants were positive regarding continuity of care, 511 participants (43.1%) regarding participation, 420 (36.1%) regarding reduction in loneliness, and 810 (69.6%) regarding upskilling (Table 1).

Continuity of Care

In the multivariate model, interactive technologies were statistically significantly associated with the higher odds of continuity of care (OR 1.58, 95% CI 1.15 - 2.18) (Table 2). In contrast, digital locks and cameras or sensors (OR 0.79, 95% CI 0.58 - 1.08), digital support in medicine (OR 1.29, 95% CI 0.96 - 1.75), digital documentation (OR 1.33, 95% CI 0.95 - 1.85), and digital communication with colleagues (OR 0.99, 95% CI 0.72 - 1.38) were the types of welfare technologies with no significant association with continuity of care. However, training in the use of welfare technology was significantly associated with continuity of care (OR 2.02, 95% CI 1.53 - 2.66).

The interaction analysis has shown that the participants who did not have training but used digital documentation had a higher probability of positive perceptions regarding continuity of care. Although perceptions on continuity were positive among participants who had training, the use of digital documentation had no significant effect (Figure 1).

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Table . Models for binary logistic regression exploring associations between welfare technologies, training, and potential outcomes for frontline care workers and care recipients.

Variables	Continuity of care	Participation	Reduce loneliness	Upskilling
Covariates, OR[a] (95% CI)				
Age (years)	1.02 (1.00 - 1.03)[b]	1.00 (0.99 - 1.02)	0.99 (0.98 - 1.02)	1.03 (1.01 - 1.05)[b]
Female	0.58 (0.32 - 1.02)	1.17 (0.68 - 2.02)	0.98 (0.57 - 1.69)	0.48 (0.23 - 0.99)[b]
Workplace care home	1.07 (0.79 - 1.43)	1.03 (0.77 - 1.38)	1.31 (0.97 - 1.76)	0.97 (0.67 - 1.39)
Work experience (years), OR (95% CI)				
≥15	Ref.[c]	Ref.	Ref.	Ref.
10 - 14	1.86 (1.18 - 2.91)[b]	1.63 (1.06 - 2.49)[b]	1.61 (1.06 - 2.46)[b]	1.46 (0.85 - 2.50)
<10	2.25 (1.28 - 3.96)[b]	1.39 (0.82 - 2.38)	1.96 (1.16 - 3.31)[b]	1.75 (0.89 - 3.44)
Education, OR (95% CI)				
Upper secondary <2 years	Ref.	Ref.	Ref.	Ref.
Upper secondary 3 years	0.94 (0.69 - 1.28)	0.88 (0.66 - 1.20)	0.96 (0.71 - 1.31)	1.32 (0.91 - 1.91)
Postsecondary	0.98 (0.66 - 1.48)	0.90 (0.61 - 1.33)	0.93 (0.62 - 1.38)	1.24 (0.75 - 2.05)
Types of technologies, OR (95% CI)				
Digital locks and cameras or sensors	0.79 (0.58 - 1.08)	0.62 (0.46 - 0.84)[b]	0.77 (0.57 - 1.05)	1.05 (0.73 - 1.49)
Digital support in medicine	1.29 (0.96 - 1.75)	1.17 (0.87 - 1.56)	1.13 (0.83 - 1.51)	1.59 (1.08 - 2.35)[b]
Interactive technologies	1.58 (1.15 - 2.18)[b]	2.01 (1.48 - 2.74)[b]	1.92 (1.41 - 2.62)[b]	2.44 (1.58 - 3.79)[b]
Digital documentation	1.33 (0.95 - 1.85)	0.69 (0.49 - 0.96)[b]	0.73 (0.52 - 1.02)	2.08 (1.45 - 2.99)[b]
Digital communication with colleagues	0.99 (0.72 - 1.38)	1.01 (0.73 - 1.38)	0.82 (0.59 - 1.14)	1.28 (0.83 - 1.97)
Training, OR (95% CI)				
Training in the use of welfare technologies	2.02 (1.53 - 2.66)[b]	1.91 (1.45 - 2.51)[b]	1.74 (1.31 - 2.30)[b]	4.59 (3.28 - 6.42)[b]
−2LL[d]	1260.596	1297.035	1267.204	938.650
R^2_{CS}[e]	0.075	0.069	0.058	0.175
Nagelkerke R^2_N[f]	0.100	0.092	0.079	0.260

[a]OR: odds ratio.

[b]Statistical significance at the $P<.05$ level.

[c]Ref.: reference.

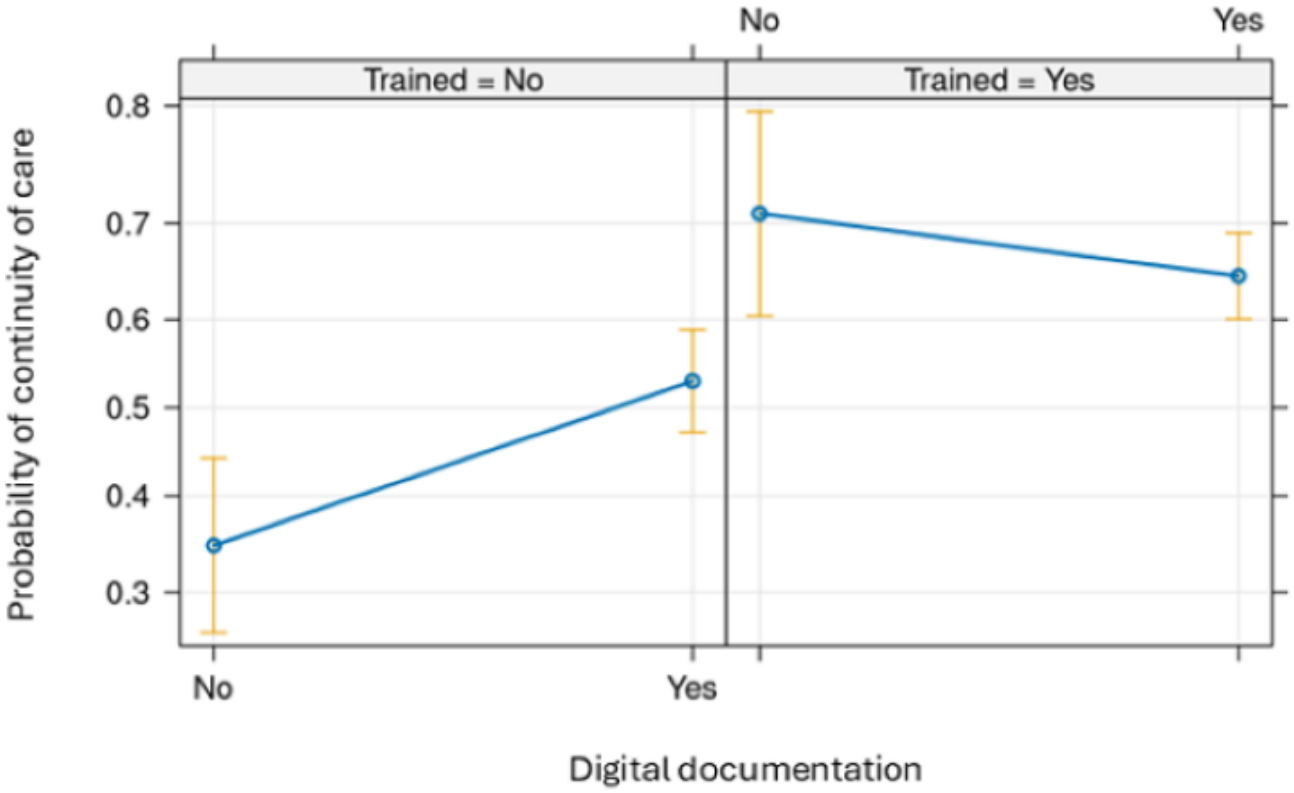
[d]−2LL: deviance.

[e]R^2_{CS}: Cox and Snell R^2.

[f]R^2_N: Nagelkerke R^2.

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Figure 1. Predicted probability of continuity of care as a function of digital documentation and training in welfare technology.



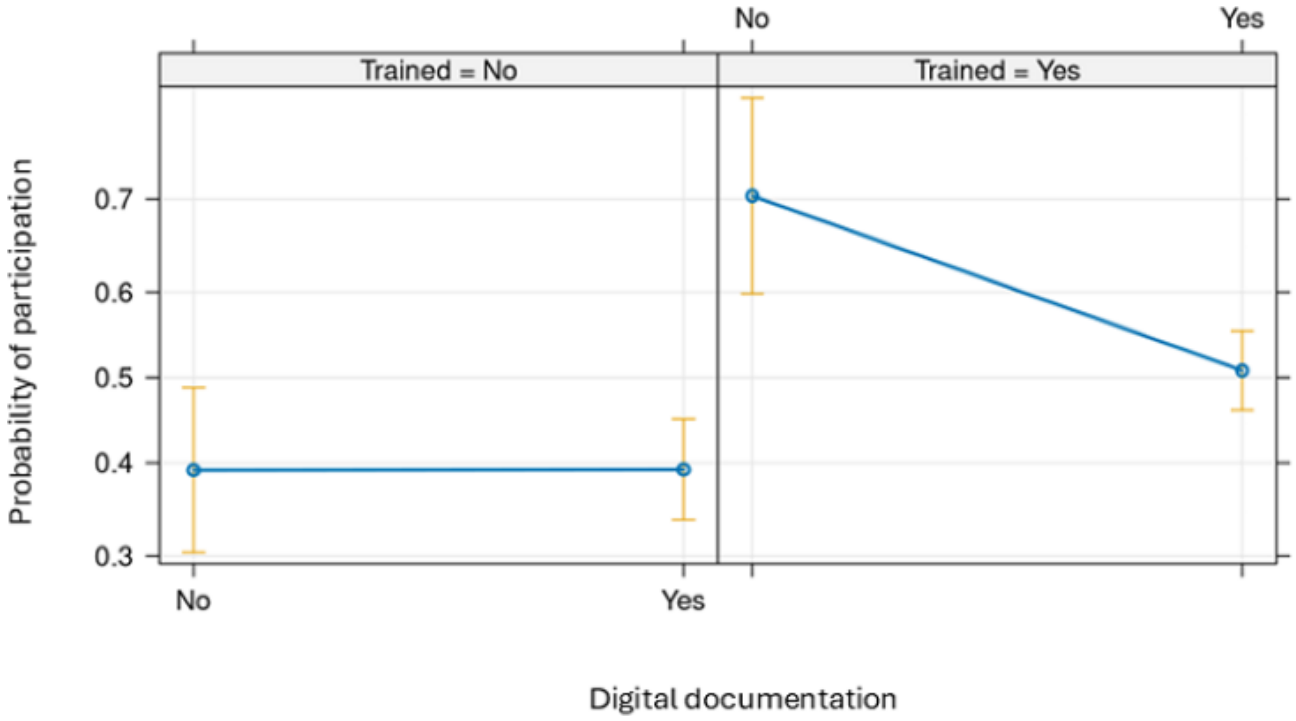
Participation of Care Recipients

In the multivariate model, use of digital locks and cameras or sensors (OR 0.62, 95% CI 0.46 - 0.84) and digital documentation (OR 0.69, 95% CI 0.49 - 0.96) were significantly associated with a lower OR of participation (Table 2). Conversely, the use of interactive technologies was significantly associated with participation (OR 2.01, 95% CI 1.48 - 2.74). The types of welfare technologies that were not significantly associated with participation were digital support in medicine (OR 1.17, 95% CI 0.87 - 1.56) and digital communication with colleagues (OR 1.01, 95% CI 0.73 - 1.38). Nevertheless, there was a significant association between training in the use of welfare technology and participation (OR 1.91, 95% CI 1.45 - 2.51).

Training was positively associated with perceptions of participation; however, this effect was attenuated when combined with digital documentation. Among those who had no training, digital documentation had not shown any effect on participation, while among care workers who had training, it was associated with a decreased probability of positive perceptions (Figure 2).

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Figure 2. Predicted probability of participation as a function of digital documentation and training in welfare technology.

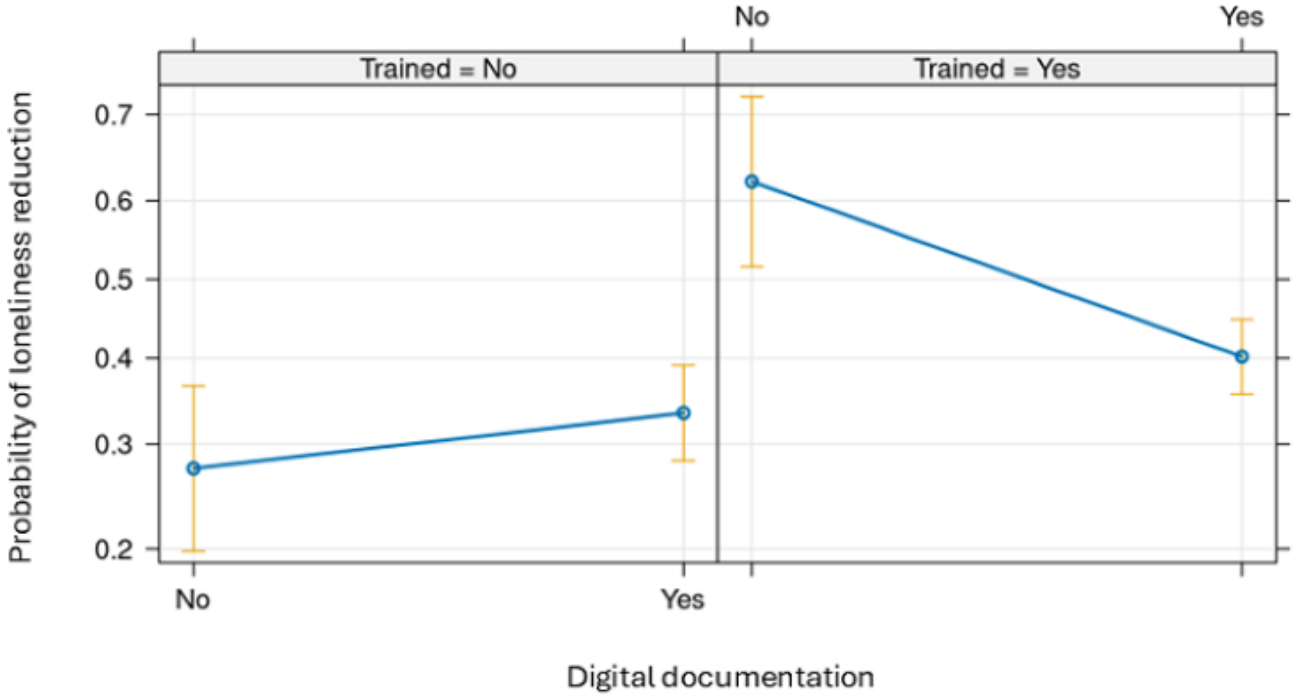


Reduction in Loneliness

Care workers' perception of addressing loneliness among care recipients has shown a statistically significant association between the use of interactive technologies and reduced loneliness among care recipients (OR 1.92, 95% CI 1.41 - 2.62) (Table 2). All other technologies included in this study had no significant association with loneliness such as digital locks and cameras or sensors (OR 0.77, 95% CI 0.57 - 1.05), digital support in medicine (OR 1.13, 95% CI 0.83 - 1.51), digital documentation (OR 0.73, 95% CI 0.52 - 1.02), and digital communication with colleagues (OR 0.82, 95% CI 0.59 - 1.14). Care workers who received training in welfare technology had positive perceptions of its use for the reduction in loneliness of the care recipients (OR 1.74, 95% CI 1.31 - 2.30).

Among those who had training, digital documentation has shown a significantly decreased probability of positive perception on reduction in loneliness (Figure 3). However, the association between digital documentation and the probability of outcome was not significant in the group with no training.

Figure 3. Predicted probability of reduction in loneliness as a function of digital documentation and training in welfare technology.

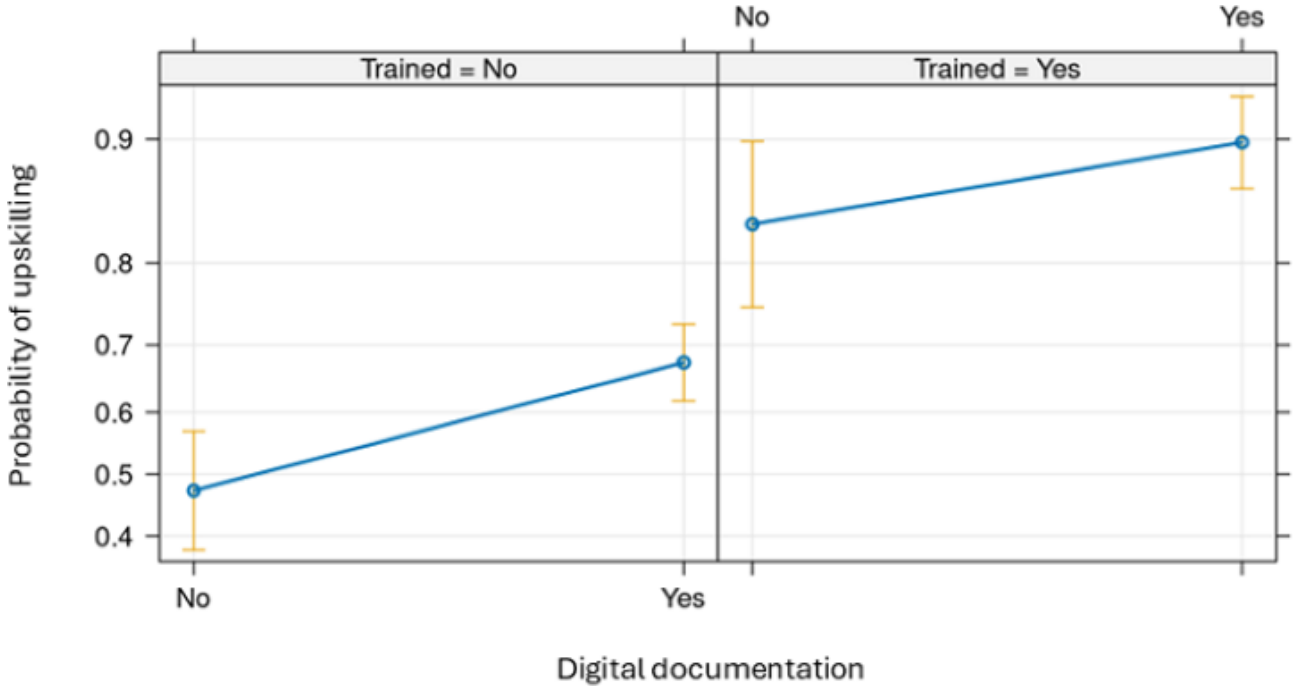


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Upskilling

In the multivariate model (Table 2), types of welfare technologies significantly associated with higher ORs of upskilling among care workers were digital support in medicine (OR 1.59, 95% CI 1.08 - 2.35), use of interactive technologies (OR 2.44, 95% CI 1.58 - 3.79), and digital documentation (OR 2.08, 95% CI 1.45 - 2.99), whereas digital locks and cameras or sensors (OR 1.05, 95% CI 0.73 - 1.49) and digital communication with colleagues (OR 1.28, 95% CI 0.83 - 1.97) were the technologies not significantly associated with upskilling. Nevertheless, training in the use of welfare technology was significantly associated with upskilling among care workers (OR 4.59, 95% CI 3.28 - 6.42) (Table 2). Digital documentation has shown a higher probability of upskilling, but the effect was significant only in the group that did not have training (Figure 4).

Figure 4. Predicted probability of upskilling as a function of digital documentation and training in welfare technology.



Discussion

Principal Findings

Based on the perceptions of assistant nurses, this study explored associations between types of welfare technologies and outcomes for care recipients as well as for care workers and whether training in the use of welfare technologies was associated with these outcomes. We found that the use of interactive technologies was associated with the continuity of care, participation, and reduction in loneliness among care recipients, and upskilling of frontline care workers. However, not all types of technologies had similar effects. For example, the use of digital documentation was associated with upskilling but negatively associated with participation. In addition, the use of digital locks and cameras or sensors was negatively associated with participation only. Furthermore, while digital support in medicine was associated with upskilling among care workers, no significant associations were seen for care recipients. Training in the use of welfare technologies was independently associated with all the dependent variables, yet the interaction of training and use of digital documentation had mixed effects.

Comparison With Prior Research

This study's findings on interactive technologies are broadly in line with those of studies highlighting the importance of technologies supporting communication to improve quality of care [26], participation [24], and to reduce loneliness among care recipients [10]. Interactive technologies require care recipients to take an active role; for example, training, grocery shopping, video conferencing, and contributing to the involvement and empowerment of care recipients. Care workers perceive that such technologies provide a range of options that can be customized to meet the specific needs or preferences of care recipients. In addition, these technologies facilitate joint activities between care workers and care recipients while also having an important role in keeping care recipients engaged [24]. Hence, technologies supporting a sense of connection and time spent with care recipients are perceived as important by formal and informal caregivers for improving quality of care, job satisfaction, and acceptance of technology [5,9,26].

The introduction of technology in the workplace changes job design, fostering the acquisition of new skills [18]. Care workers perform various combinations of tasks, using different types of welfare technologies, each requiring different levels of skill. This diversity makes it difficult to establish a clear reference point for skill development [17]. Moreover, the lack of studies on types of technologies and upskilling limits our ability to make comparisons with previous research. Our study shows a positive association between types of welfare technologies and upskilling. However, the use of digital locks and communication tools among colleagues did not reach statistical significance. These technologies do not demand high-level skills. Furthermore, care workers often perceive digital locks as tools of convenience [24] and likely explain our findings.

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The associations between training in the use of welfare technologies and improved outcomes contribute to the empirical evidence supporting the idea that training can contribute to the positive experiences with using technology [9,11] and skill development among care workers [18]. Training endows essential skills in the use of technology and enhances critical reasoning in relation to technology use and quality of care, hence potentially contributing to upskilling.

Previous research has shown that digital documentation enables faster access to necessary information that can help reduce errors and promote collaborative care [11,14]. These attributes of digital documentation contribute to informational continuity according to the views of Swedish primary health care nurses [14], and this is consistent with our findings on continuity, but only among those who did not have training and use digital documentation. Nevertheless, multidimensional aspects of the concept of continuity of care and critical reasoning likely explain a nonsignificant effect of digital documentation on the probability of continuity among those who received training. For example, digital records may not ensure interrelation (patient and single provider) continuity of care. Moreover, the administrative character of digital documentation does not align with the fundamental value of patient-provider interaction in nursing care [9,14] and likely explains our findings on the combined effects of training and use of digital documentation on a lower likelihood of participation and in addressing loneliness among care recipients. An exploratory qualitative study can offer insights into the combined effects of training and digital documentation on diverse perceptions of care delivery outcomes.

Assistant nurses sometimes perceive digital documentation as time-consuming and monotonous [24]. Such repetitive work is often perceived as low in complexity and therefore seen as offering limited opportunities for upskilling [17]. However, the interaction analyses have shown a positive association between digital documentation and upskilling in our study. In repetitive work, the repeated use of specific skills can lead to greater fluency and precision, suggesting that such tasks may still offer learning potential [18].

Potential Implications

Training provision improves skills and fosters capacities to adapt to workplace innovations [17,18]. In line with this understanding, our findings on training and improved outcomes suggest that investing resources to promote training can reinforce positive experiences, thereby sustaining social care practices.

This study shows that care workers hold more positive perceptions toward technologies that promote the active involvement of care recipients. Nevertheless, consistent with previous research, such technologies remain among the least commonly implemented in older adult care settings [4]. Their broader adoption could play an important role in enhancing care recipient engagement and social participation. To fully understand the potential of these technologies, future research should incorporate the perspectives and lived experiences of care recipients themselves.

Strengths and Limitations

A strength of this study is that it is based on a survey including a randomized national sample exploring the potential benefits of welfare technology for care recipients as well as for care workers. The study sample included both public and private providers.

This study has a few limitations, including that the cross-sectional study design limits the ability to draw a temporal relation between the exposure and outcome. The low response rate (23%), particularly among younger age groups (aged <44 years), may pose a risk of selection bias, limiting the generalizability of our findings. There is no consensus on the definition of continuity of care and participation, which may lead to slightly different interpretations of concepts. As noted, this research project and the questionnaire are based on an earlier project. However, questions related to welfare technology were new, which can influence internal validity. National reports and experiences of the research team informed the development of the questionnaire. Moreover, studies in the Nordic context have used a similar approach [4]. Therefore, the problem is minimal.

Participants with missing data on welfare technology may have different opinions; however, they are few (n=51). The survey was not limited to welfare technology, and the items related to technology were placed at the end. This is likely that the participants have other reasons to stop the survey, for example, tiredness. Receipt of training was measured by a single item that is limited to cover components of training. Moreover, local variations can be expected in the content and form of training. Finally, the amount of variance our models explained in their respective outcomes was not substantial; this was particularly the case for outcomes for care recipients. This is perhaps not surprising given the many factors that might potentially influence outcomes for older adults with complex care needs.

Conclusions

This study contributes by identifying how the type of welfare technology and training has an impact. We found that the potential outcomes of welfare technology in social care for older adults can vary with the types of technologies used. Specifically, care workers hold positive perceptions that the use of interactive technologies is associated with the continuity of care, participation, and reduction in loneliness among care recipients, suggesting the importance of patient-provider interaction. Despite the benefits of welfare technology, the effects can be negative, as shown by the findings on the use of digital documentation, digital locks and cameras or sensors, and the lower likelihood of participation. Nevertheless, care workers hold favorable views regarding the use of welfare technologies contributing positively to their skill development.

Training in the use of welfare technologies was positively associated with the perceived usefulness of these technologies in continuity of care, participation, reduction in loneliness of care recipients, and upskilling of care workers. While training had a positive impact, the effects of digital documentation were mixed in relation to training. Notably, participants who had not received any training but used digital documentation reported favorable views on continuity and upskilling, whereas

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participants with training expressed concerns about participation and addressing loneliness. Future research should explore how specific training components interact with digital documentation to better understand their combined influence on care outcomes.

Acknowledgments

This study was accomplished within the context of the Centre for Ageing and Health (AgeCap), University of Gothenburg. We are grateful to Dr Hans Ekbrand for his insightful feedback and assistance in the interaction analysis. The study was supported by the Swedish Research Council for Health, Working Life and Welfare (grants 2023-00174 and 2013-2300). The funding organization has no role in the development of study design, analysis, or manuscript writing.

Data Availability

The datasets analyzed during this study are not publicly available due to ethical reasons, such as anonymity. However, the dataset and Swedish questionnaire used are available on reasonable request to the corresponding author.

Authors' Contributions

LD and MN contributed to the design of the study and the interpretation of the results. LD obtained funding and was responsible for the data collection. MN was responsible for the statistical analysis and drafting of the manuscript. LD constructively reviewed the manuscript. MN and LD finalized the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Model building for binary logistic regression exploring associations between welfare technologies, training, and potential outcomes for frontline care workers and care recipients
[DOCX File, 43 KB - nursing_v8i1e65641_app1.docx]

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Abbreviations

OR: odds ratio

R^2_{CS}: Cox and Snell R^2

R^2_{N}: Nagelkerke R^2

Edited by E Borycki; submitted 22.08.24; peer-reviewed by J Pani, K Duan, Y Arakawa; revised version received 29.06.25; accepted 15.07.25; published 26.08.25.

Please cite as:
Naseer M, Dellve L
Assessing the Use of Welfare Technology in Social Care for Older Adults Through Assistant Nurses' Perceptions of Upskilling and Care Delivery Outcomes: Cross-Sectional Study
JMIR Nursing 2025;8:e65641
URL: https://nursing.jmir.org/2025/1/e65641
doi:10.2196/65641

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Original Paper

Exploring Educators' Perceptions and Experiences of Online Teaching to Foster Caring Profession Students' Development of Virtual Caring Skills: Sequential Explanatory Mixed Methods Study

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Abstract

Background: Professionals in caring disciplines have been pivotal in advancing virtual care, which leverages remote technologies to deliver effective support and services from a distance. Educators in these caring professions are required to teach students the skills and competencies needed to provide high-quality and effective care. As virtual care becomes more integral, educators must equip students in these fields with both interpersonal and technological skills, bridging traditional hands-on learning with digital literacy. However, there is a gap in evidence exploring educators' perceptions and experiences of teaching caring profession students about virtual caring skills within online environments.

Objective: This study aims to better understand caring profession educators' online teaching experiences to foster student development of virtual caring skills and competencies.

Methods: We used a sequential explanatory mixed methods approach that integrated a cross-sectional survey and individual interviews with educators from caring professions to better understand caring professional educators' online teaching experiences to foster student development of virtual caring skills and competencies. The survey's primary objectives were to examine the various elements of existing e-learning opportunities, delve into educators' perspectives and encounters with these opportunities, and identify the factors that either facilitated or hindered online teaching practices to support students in developing virtual caring skills and competencies. The individual interview guides were based on survey findings and a systematic review of the evidence to gain deeper insights into educators' experiences and perspectives.

Results: A total of 82 survey participants and 8 interview participants were drawn from educators in the fields of education, medicine, nursing, and social work. Various instructional methods were used to help students develop virtual caring skills, including reflections on learning, online modules, online discussion boards, demonstrations of remote care, and consultation with clients. There was a statistically significant difference between educators' level of experience teaching online and their satisfaction with online teaching and learning technologies (P<.001) and between educators' faculties (departments) and their satisfaction with online teaching and learning technologies (P=.001). Participants identified barriers (time constraints, underdeveloped curriculum, decreased student engagement, and limited access to virtual caring equipment and technology), facilitators (clearly defined learning objectives, technology software and support, teaching support, stakeholder engagement, and flexibility), and principles of teaching virtual caring skills in online environments (connection, interaction, compassion, empathy, care, and vulnerability).

Conclusions: Our study identifies the barriers, facilitators, and principles in teaching virtual caring skills, offering practical strategies for educators in caring professions. This study contributes to the growing body of educational research on virtual caring skills by offering educator insights and suggestions for improved teaching and learning strategies in caring professions' programs.

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As educational practices evolve, future research should explore how traditionally in-person educators can effectively teach virtual caring skills across diverse contexts.

(JMIR Nursing 2025;8:e64548) doi:10.2196/64548

KEYWORDS

health care education; virtual care; telehealth; online teaching; mixed methods study; student; teaching; virtual caring skills; cross-sectional survey; interview

Introduction

Background

Professionals in caring fields, including educators, physicians, nurses, and social workers, have played a crucial role in the ongoing development of virtual care where remote information technologies are used to ensure quality and effective care. The shift to virtual care has paved the way for innovative approaches to delivering care services, such as online teaching; remote health care and social services; and remote assistance for individuals, families, and communities to improve their social functioning, all from a distance. These virtual interactions demand digital literacy skills and comfort with technology, skills that traditionally may not have been intentionally integrated into formal education.

As virtual caring practices become integral to care provision, it is imperative that educators support caring profession students in acquiring the interpersonal and technological competencies necessary for providing virtual care. Traditionally, educators in caring professions relied on face-to-face lectures and seminar-style instruction with work-integrated learning placements, where students gained hands-on skills and collaborated with experienced educators and practicing health professionals in settings such as K-12 classrooms, hospitals, and counseling centers [1,2].

The shift to virtual teaching and care settings has challenged caring profession educators to incorporate alternative strategies for providing essential educational experiences to students [3-5] and placed added responsibilities on caring professionals to implement virtual care effectively in practice [2,3]. While the literature has long emphasized the need to support educators in meeting students' requirements [6,7], this need has become even more critical with the increasing prevalence of virtual care environments [8,9].

Higher education institutions have an opportunity to re-evaluate their approach to delivering online education in caring professions and identify the essential technological competencies necessary for success in today's virtual world. Given the significant transformation in education and care delivery, it is imperative that caring professionals possess the requisite skills and competencies to adapt and thrive in these new virtual environments. However, many caring profession educators face challenges when creating effective online learning experiences to prepare students for new virtual work environments, including limited bandwidth, the lack of technological devices, unfamiliarity with technological platforms, a lack of connection with students, and a lack of student engagement [10-13]. Learning new technologies can be cumbersome and frustrating [14], and technical issues can disrupt interactions that typically occur face-to-face [15-19]. These challenges underscore the necessity for a structured, evidence-based approach to developing and implementing educational technologies in online teaching and learning contexts to support virtual caring skill development [10,20-22].

The authors recently completed a systematic review from which they identified innovative online education initiatives that harnessed learning technologies for the education of caring professionals and demonstrated a growing emphasis on assisting students in cultivating effective virtual caring practices suitable for today's virtual environments [23]. The systematic review [23] highlighted a pressing need for greater emphasis on assessing and training educators to immerse students in digital technologies, thus fostering the development of both interpersonal and digital skills essential for delivering virtual care. More research is needed regarding educators' experiences and perceptions of teaching virtual caring skills.

This Study

Adding to the limited body of literature would potentially enhance the understanding of best practices in online instruction to promote the development of virtual caring skills. Therefore, we conducted this study to answer the following research questions: (1) How do caring professions' educators *describe* the online instructional methods used that support student development of virtual caring skills and competencies? (2) What are caring professions' educators' *experiences and perceptions* of online learning opportunities for helping students develop virtual caring skills and competencies? and (3) What are the *facilitators and barriers* to creating and engaging in online teaching that supports students' development of virtual caring skills and competencies?

Methods

Design

We adopted a sequential explanatory mixed methods study design [24] to gather, analyze, and integrate quantitative and qualitative data. We used a cross-sectional survey and conducted individual interviews to gain insights into the online teaching experiences of educators in caring professions in supporting students to develop virtual caring skills and competencies. The integration of the 2 research phases became apparent when the design of the interview guide was informed by the survey findings, enabling us to delve deeper into the results obtained from the survey. Furthermore, integration occurred as we used the qualitative findings to better understand the quantitative findings, ultimately forming interpretations from the integrated findings.

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Sample and Participants

Voluntary participation was sought from educators in caring professions, including education, medicine, nursing, and social work (including those cross appointed to arts and veterinary medicine) across a midsized research-intensive institution in western Canada. Any self-reported educators from the abovementioned faculties were included in the study. No completed surveys or interviews were excluded.

Data Collection

We crafted a survey using established methods as outlined by Rattray and Jones [25]. The survey's primary objectives were to examine the various elements of existing e-learning opportunities, delve into educators' perspectives and encounters with these opportunities, and identify the factors that either facilitated or hindered online teaching practices to support students in developing virtual caring skills and competencies. The survey encompassed a combination of Likert scale, closed-ended, and open-ended questions, covering demographics, experiences, instructional methods, satisfaction levels, technology use, effectiveness, and readiness. To ensure the survey's validity, both in terms of face and content, we conducted a pilot study with a sample of 10 educators who did not participate in the study. Their suggested edits were incorporated into the survey before its dissemination.

To distribute the survey securely, we used an online platform, Qualtrics (Qualtrics International Inc). Our recruitment efforts spanned various channels such as email, Twitter (subsequently rebranded as X), Instagram (Meta Platforms), and Facebook (Meta Platforms), mirroring the methods used in prior studies [26,27]. Completion of the survey was considered as an indication of informed consent. In addition, we invited all survey participants to share their email addresses if they were interested in participating in a follow-up interview.

To gain deeper insights into educators' experiences and perspectives, we developed a semistructured interview guide based on the findings from a systematic review [23] and the responses received in the survey. We reached out to all survey participants who provided their email addresses and conducted interviews lasting between 30 and 60 minutes via the Zoom (Zoom Communications) platform. Before each interview, we confirmed oral consent, and the sessions were audio-recorded and transcribed verbatim.

Data Analysis

The closed-ended survey responses were obtained from Qualtrics and subsequently imported into the SPSS (version 28; IBM Corp) statistical software package for analysis. Descriptive statistics were calculated to summarize the characteristics of the study sample, including factors such as age, gender, faculty affiliation, length of time in current position, and previous experience with online teaching and learning technologies. Variations in data distribution were summarized and visually presented through tables and graphical representations, following the guidelines outlined by Polit and Beck [28]. In addition, 1-way ANOVA and Kruskal-Wallis *H* tests were conducted to analyze differences in satisfaction and likelihood to use online teaching and learning technologies in the future to support students in developing virtual caring skills. These analyses were conducted as deemed appropriate, following the recommendations of Polit and Beck [28]. To enhance readability and facilitate subsequent post hoc analyses, participant-reported ages were collapsed into 4 categories: ≤39, 40-49, 60-59, and ≥60 years. Team members with experience in statistical analysis met and contributed to ensure the accuracy of these findings.

For the analysis of open-ended survey responses and interview transcripts, each was assigned a unique identifier and imported into NVivo (version 14; Lumivero) to manage qualitative data. Our qualitative data analysis followed a thematic approach using an inductive process, aligning with the methods proposed by Braun and Clarke [29] and Nowell et al [30]. To gain a comprehensive understanding of the data, 2 researchers (LN and SJ) independently reviewed the entire qualitative dataset. Consensus coding was completed as both researchers coded the same transcripts and compared results on a one-to-one basis. Each researcher assigned sections of text to relevant codes, and the coding was then merged and discussed. Regular monthly meetings were held to establish and ensure a shared understanding of initial codes.

Larger team meetings, involving all authors, were conducted to collectively scrutinize and further refine emerging patterns in the qualitative data, ultimately confirming the identified themes and subthemes. Throughout the analysis process, written memos and meeting minutes were maintained to document our approach and decisions. Adhering to research and reporting standards, we followed the Standards for Reporting Qualitative Research outlined by O'Brien et al [31] when reporting this study.

Data Integration

Integration occurred at 2 points in this study. First, the quantitative findings were used to inform the qualitative interview guide. Following an independent analysis of all qualitative and quantitative data, the data were integrated using a joint display as an analysis tool. During this analysis, qualitative data were used to explain and corroborate quantitative findings [32]. Quantitative findings were compared to qualitative themes to examine similarities and differences. Through this methodology, we were able to develop interpretations regarding educators' perceptions and experiences.

Ethical Considerations

We obtained approval from our local Conjoint Health Research Ethics Board (REB22-0748) to carry out this study. Educators were offered the opportunity to join the study voluntarily, with the assurance that their involvement in the survey would remain anonymous and would not affect their university employment status or career advancement. Completion and submission of the online surveys implied consent. Before participating in interviews, all respondents gave informed verbal consent. Interviews were administered by a graduate student who had no prior supervisory relationship with the participants. To protect participant anonymity, distinct identifiers were assigned to each participant, and the data were aggregated accordingly. No compensation was provided to participants for participating in this study.

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Rigor

We used several techniques to ensure the rigor of our study. Regular team meetings provided opportunities for debriefing, introspection, and deliberate questioning of our interpretations, as suggested by Morse [33]. We maintained a comprehensive audit trail that included codebooks, meeting minutes, and shared files to document all study-related decisions, following the guidelines proposed by Carnevale [34]. While 2 researchers were responsible for coding all qualitative data, the broader research team assessed and deliberated on decisions related to themes and subthemes. We revisited the raw survey and interview data to further validate our findings and ensure that they authentically represented the voices of the educator participants.

Results

Participant Demographics

A total of 82 educators started the survey, and 72 (88%) completed the entire survey. The 10 (12%) participants who did not complete the entire survey completed up to the final 5 survey items. We included all responses provided by participants in our final analysis as they yielded valuable insights and contributed to our overall study findings. Of the 82 survey participants, 19 (23%) agreed to be contacted for a follow-up interview of which 8 (10%) responded and completed an interview. Table 1 provides participant demographics for the survey and interviews.

Table 1. Participant demographics.

Demographic and demographic subcategory	Survey (n=82), n (%)	Interview (n=8), n (%)
Age (y)		
<39	11 (13)	0 (0)
40-49	25 (30)	1 (13)
50-59	29 (35)	3 (38)
>60	16 (20)	4 (50)
No response	1 (1)	0 (0)
Gender		
Men	18 (22)	2 (25)
Women	58 (71)	6 (75)
Gender diverse[a]	6 (7)	0 (0)
Faculty		
Education	21 (26)	3 (38)
Medicine	34 (41)	3 (38)
Nursing	16 (20)	2 (25)
Social work	7 (9)	0 (0)
Other (joint appointments)	4 (5)	0 (0)
Experience[b]		
Beginner	35 (43)	3 (38)
Intermediate	24 (29)	2 (25)
Expert	23 (28)	3 (38)

[a]Gender diverse included gender fluid, nonbinary, queer, and individuals who prefer not to disclose. Some categories were collapsed due to the need to maintain anonymity, particularly with small numbers in particular subcategories.

[b]Beginner=taught <4 online courses; intermediate=taught 5-7 online courses; expert=taught ≥8 online courses.

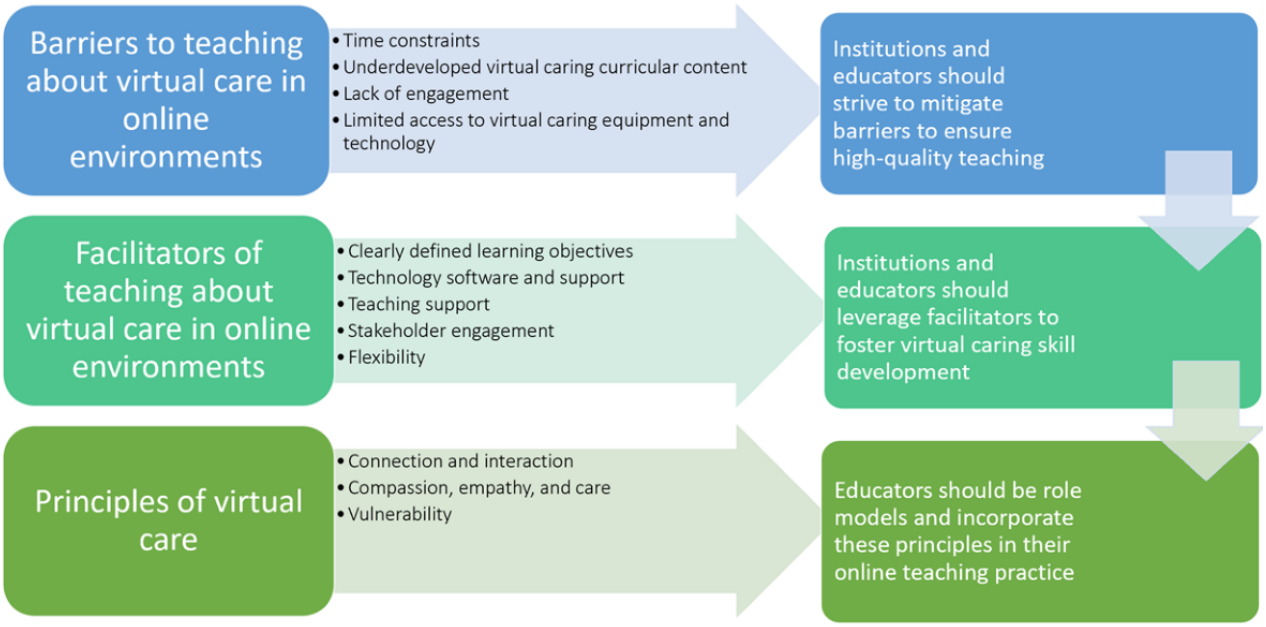
Quantitative Results

Overview

Educator survey respondents (n=82) indicated that a variety of online instructional methods were used to help students develop virtual caring skills in a *select all that apply* survey item (Figure 1). The most frequently reported online instructional methods included using reflections on learning (50/82, 61%), online modules (35/82, 43%), and online discussion boards (49/82, 60%). Educators reported using demonstrations of remote care (23/82, 28%) and consultation with clients (21/82, 26%). Respondents that used the option of *other* (7/82, 9%) described using verbal check-ins, synchronous meetings, simulations, social media, and flipped classrooms. Some respondents indicated that they have not used any online instructional methods to develop virtual caring skills (17/82, 21%).

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Figure 1. Overview of themes, subthemes, and implications.



Satisfaction With Online Teaching and Learning Strategies

Survey participants (n=80) reported their level of satisfaction with online teaching and learning strategies, with 71 (89%) participants indicating that they were either satisfied or somewhat satisfied with the approaches used in their classrooms. However, a notable proportion, approximately 11% (9/80) of the participants, reported dissatisfaction.

Likelihood of Using Online Teaching and Learning Technologies

Among educators who responded to the question (n=70) about the likelihood of using online teaching and learning technologies to support students in developing virtual caring skills in the future, 53 (76%) indicated that they were very likely or somewhat likely to engage in this modality. Conversely, 17 (24%) educators responded that they were not likely to use online teaching and learning for the development of virtual caring skills in the future.

We conducted 1-way ANOVA tests to explore potential differences in satisfaction and likelihood to use technology scores among groups based on gender, age, faculty, years of experience in current position, or experience with online teaching and learning technologies. Table 2 summarizes the ANOVA test results.

In the survey, an expert was defined as an educator who had designed and taught ≥8 classes. There was a statistically significant difference between educators' level of experience teaching online and their satisfaction with online teaching and learning technologies ($F_{2,77}$=11.465; P<.001), with a large effect size (η^2=0.23) [28]. A Bonferroni post hoc analysis demonstrated that educators with expert experience with teaching using technology reported significantly higher satisfaction (mean 2.82, SD 0.39) compared to those at beginner (mean 2.06, SD 0.69) or intermediate levels (mean 2.21, SD 0.59). No statistically significant difference was found between those at beginner and intermediate levels. A statistically significant difference was found between educators' faculties (departments) and their satisfaction with online teaching and learning technologies ($F_{4,75}$=5.119; P=.001), with a large effect size (η^2=0.21). A Bonferroni post hoc analysis found that educators from the faculty of education (mean 2.75, SD 0.44) rated their satisfaction with online teaching and learning technologies significantly higher than faculty from medicine (mean 2.12, SD 0.64) or nursing (mean 2.07, SD 0.70). There were no statistically significant differences found between social work and the remaining faculties. Notably, all other comparisons via 1-way ANOVA tests yielded no statistically significant results.

Through Levene tests, two 1-way ANOVA test pairings were found to have unequal variances: (1) faculties and likelihood of using online teaching and learning technology and (2) years of experience and likelihood to use online teaching and learning technology. The Kruskal-Wallis H test, a nonparametric equivalent, was used to examine those relationships. A Kruskal-Wallis H test demonstrated that there was a statistically significant difference in the likelihood of using online teaching and learning technologies and the different faculties (H_4=13.44; P=.009), with a mean rank likelihood of 52.0 for the faculty of social work, 43.2 for the faculty of nursing, 36.8 for the faculty of education, 34.6 for other faculties, and 27.0 for the faculty of medicine. A pairwise comparison revealed that educators from the faculty of social work had a significantly higher likelihood of using online teaching and learning technologies than the faculty of medicine when considering the Bonferroni correction for multiple tests, P=.01. This was the only significant relationship found in the pairwise comparison after applying the Bonferroni correction. Kruskal-Wallis H test demonstrated that there was no statistically significant difference in the likelihood of using online teaching and learning technologies and years of experience (H_5=3.956; P=.56).

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Table 2. ANOVA test results.

Variable comparison	Descriptive statistics		ANOVA		
	Participants, n (%)	Mean (SD)	*F* test (*df*)	η^2	*P* value
Gender and satisfaction (n=80)			1.38 (2, 77)	0.04	.26
Men	18 (23)	2.11 (0.68)			
Women	56 (70)	2.39 (0.65)			
Gender diverse	6 (8)	2.17 (0.75)			
Age (y) and satisfaction (n=80)			0.31 (3, 74)	0.01	.82
0-39	10 (13)	2.40 (0.52)			
40-49	25 (31)	2.24 (0.66)			
50-59	29 (36)	2.28 (0.80)			
>60	14 (18)	2.43 (0.51)			
Faculty and satisfaction (n=80)			5.12 (4, 75)	0.21	.001
Education	20 (25)	2.75 (0.44)			
Medicine	34 (43)	2.13 (0.64)			
Nursing	15 (19)	2.07 (0.70)			
Social work	7 (9)	2.71 (0.49)			
Other	4 (5)	2.00 (0.82)			
Experience (y) and satisfaction (n=80)			0.99 (5, 74)	0.06	.43
<1	5 (6)	2.20 (0.84)			
1-5	28 (35)	2.39 (0.63)			
6-10	21 (26)	2.43 (0.68)			
11-15	12 (15)	2.33 (0.65)			
16-20	5 (6)	1.80 (0.84)			
>20	9 (11)	2.11 (0.60)			
Online experience and satisfaction (n=80)			11.46 (2, 77)	0.23	<.001
Beginner	34 (42)	2.06 (0.69)			
Intermediate	24 (30)	2.21 (0.59)			
Expert	22 (28)	2.82 (0.39)			
Gender and likelihood to use (n=70)			1.68 (2, 67)	0.05	.20
Men	14 (20)	2.07 (0.92)			
Women	52 (74)	2.38 (0.80)			
Gender diverse	4 (6)	1.75 (0.96)			
Age (y) and likelihood to use (n=70)			0.28 (3, 36)	0.01	.84
0-39	6 (9)	2.50 (0.55)			
40-49	22 (31)	2.18 (0.91)			
50-59	26 (37)	2.35 (0.89)			
>60	14 (20)	2.29 (0.73)			
Online experience and likelihood to use (n=70)			1.92 (2, 67)	0.05	.16
Beginner	27 (39)	2.11 (0.89)			
Intermediate	22 (31)	2.23 (0.81)			
Expert	21 (30)	2.57 (0.75)			

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Qualitative Findings

Overview

Figure 1 offers a summary of 3 overarching themes and their associated 12 subthemes, which were identified when analyzing the qualitative data. It also highlights potential recommendations for supporting online teaching to enhance the development of virtual caring skills. The subsequent sections delve deeper into the exploration of these findings.

Barriers to Teaching About Virtual Care in Online Environments

Educators identified several barriers that were encountered for online teaching and learning related to the development of virtual caring skills, including time constraints, underdeveloped virtual caring curricular content, a lack of engagement, and limited access to virtual caring equipment and technology. Despite these barriers, participants often highlighted their adaptability in addressing the needs of their students and teaching contexts.

Time Constraints

Participants reported time constraints as a concern, citing challenges such as the increased duration of virtual interactivity and the need to adapt clinical experiences for online platforms. Educators discussed time constraints as a limiting factor for teaching duration and described the need for adjustments. One participant shared the following:

> *Another barrier is always time, right?...For it not to be just text heavy and kind of interactive, you need time, and you don't necessarily have that.* [P6, interview, education educator]

In some cases, the concern expressed was for students who could not be online for extended durations:

> *Clinical online, it's eight hours online. We made a decision that was too much for the students to be online.* [P1, interview, nursing educator]

In addition to teaching time constraints, educators noted that additional time was required when offering experiential learning in practice:

> *Timing was always an issue. It seemed to take longer to do virtual appointments than in person.* [P8, interview, medicine educator]

The shift to virtual teaching and learning spaces prompted educators to be mindful of time constraints and their impacts. Despite these challenges, all participants adjusted to better cater to the needs of their students and those they would be caring for in practice.

Underdeveloped Virtual Caring Curricular Content

Educators reported difficulties in identifying key content related to virtual caring. As noted by a nursing educator, virtual caring content was often missing from the curriculum due to curricular overload:

> *Actually, I would say one of the things that I feel that is missing from the clinical practice for [this context] is the education part. We do a little bit of in the clinical, but to do the total education...we have to do it that way because there's no time to include absolutely everything.* [P1, interview, nursing educator]

Virtual caring skills and competencies were often considered a specialized practice and were therefore not traditionally incorporated into more generalist-focused curricula. However, the onset of the COVID-19 pandemic made virtual care a crucial competency for many caring professions. An educator from the faculty of education noted how students tried to balance the unknown of virtual care expectations with how they may be expected to practice virtually when they graduated:

> *...but [students] don't necessarily know what they're getting into because you're asking them to look at an area that is somebody else's whole specialization, and yet we expect all teachers to know this information.* [P3, interview, education educator]

These responses demonstrated the challenges educators faced due to the lack of virtual caring curricular content, potentially negatively impacting students' ability to provide virtual care in their future practice.

Lack of Engagement

Educators expressed concerns regarding the lack of student engagement they encountered in online settings when teaching about virtual care. They cited interruptions, decisions about cameras being on or off, and struggles connecting with students and colleagues as factors negatively impacting student engagement levels. The online environment posed a complex challenge, with frequent connectivity issues and interruptions. One interview participant noted the following:

> *We had cats and dogs. We had children interrupting...every time a student would come in [to the Zoom call], the doorbell [chime] would ring and [their] dog would go berserk. [They'd] be constantly shutting mute on, and then have to do something about that dog. So, [they]'d disappear from the screen and then come back.* [P1, interview, nursing educator]]

The debate over whether students should have their cameras switched on or switched off during virtual learning was raised, particularly in terms of establishing a sense of presence:

> *To providing an ethic of care is the cameras on cameras off issue...the preference for students to have their cameras off makes for a very difficult teaching environment...I can't see your face; I can't see your reaction.* [P3, interview, education educator]

Beyond visible student presence in a virtual class, educators also raised a concern about how virtual caring challenged their own engagement and sensory perceptions:

> *I can't sense what's going on for them...You can't feel the energy in the room, right? You can't see body language. You can't see nonverbal communication...These are professions where we rely on all of our senses. And in a virtual environment, they're not all there.* [P6, interview, education educator]

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One survey respondent identified the following:

> *I can't see faces or check in with people who might show signs of confusion the same way I can in person. You can't "read the room" online.* [P23, survey, medical educator]

Limited Access to Virtual Caring Equipment and Technology

Educators expressed concerns about the limited access to virtual caring equipment and technology, which had a detrimental impact on interactivity. For one educator in medicine, the lack of equipment was an ongoing challenge:

> *I would say that the interaction suffered. We struggled with not having enough private computer space in the hospital. We struggled with not having cameras for the learners, and microphones, and that went on for quite a while.* [P8, interview, medicine educator]

For a nursing educator, the lack of student internet access was a challenge in teaching virtual care and creating environments for students to practice their virtual caring skills:

> *And there was one student who had to do [Zoom] on [their] cell phone, and she was using her minutes on her phone. It was getting too expensive. It was so much better if [they] just didn't use [their] cell phone...there were other students, their internet would go down.* [P1, interview, nursing educator]

Teaching and providing virtual care in rural and remote areas brought attention to the privilege of internet access and resources as well as the challenges faced by clients:

> *There are limitations in some of the other countries about their access to Wi-Fi…many people do not have access to Wi-Fi at home. Therefore, the scheduling is important. I think many centers then also have interruptions of their Wi-Fi and are constantly on and off, on and off, and that creates some problems for them. And finally, there's a few centers that the reason for that happening is that they lose electricity.* [P5, interview, medicine educator]

> *Remote learning in rural areas, it all depends on bandwidth...At the beginning, I didn't realize the reason why people weren't turning their cameras on...Tech is always a barrier...whether it's bandwidth, whether it's Zoom not working, whether our own internet.* [P6, interview, education educator]

The challenges, such as lack of equipment and poor internet accessibility, directly impacted educators' ability to teach students virtual caring skills and competencies. These considerations can also be challenges in working with experts or patients outside of the virtual classroom.

Facilitators to Teaching About Virtual Care in Online Environments

Educators identified several facilitators for online teaching and learning related to virtual caring skills. These facilitators included well-defined learning objectives, supportive technology software and assistance, effective teaching support, active stakeholder engagement, and a commitment to flexibility.

Clearly Defined Learning Objectives

Educators brought up their awareness of key graduate expectations, competencies, and learning objectives in both the open-ended survey questions and interview responses. Some educators were challenged in aligning new virtual contexts with previously defined learning competencies:

> *I've had to reconsider how my own caring is conveyed and recognized in different circumstances. I've also begun to theorize about how caring is connected to key graduate learning expectations and competencies.* [P66, survey, education educator]

Other participants, like this one from medicine, asserted that the learning objectives should remain consistent despite the shift to online learning:

> *I don't think we've changed the learning objectives. I think that they remain relatively constant, it's how you achieve them. And with the remote learning, the remote learning has allowed the interaction, but it's the interaction I think that's more important than the virtual way of doing things.* [P5, interview, medicine educator]

Other educators spoke about how the processes of learning caring competencies might not change in virtual contexts, but students may struggle to see the value of acquiring virtual caring skills:

> *If they [students] don't care about something, it doesn't become part of a learning repertoire. Then what you have to then wonder if you're just covering material for the sake of covering...it's not enough that I care about the ideas, I need to get them to care about the ideas as well.* [P4, interview, education educator]

Despite the various viewpoints on how learning objectives were achieved, there was consistent support across the participants for the development and use of clear learning objectives related to virtual care. Particularly for participants who had relied previously on in-person assessments of learning objectives, there was an intentionality to focus and be explicit on what the learning objective was and how virtual care considerations were necessary.

Technology Software and Support

Participants identified that possessing knowledge and intentionally using technology and virtual caring software could enhance the development of virtual caring skills. Others identified the benefits of providing orientation and skill development sessions to familiarize individuals with the use of technology:

> *Some of the [online] programs demanded a lot of interaction...so it started off with teaching people how to do things [in the online programs]*. [P5, interview, medicine educator]

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Furthermore, survey participants asserted that ongoing technical assistance was important to successfully integrate new technologies into the virtual caring curriculum. One survey participant commented on the positive advancement of technology and its influence on education. They wrote, "The technology has come so far that teaching online is often equivalent to in person" (P51, survey, social work). Some of the examples of technology use included telehealth, podcasting, video creation, Zoom, and virtual simulations.

In one example with clinical practice, learners were actively engaged with a particular client population online. Students were tasked with using technology and software to interact with the client. Experimenting with the various features of the technology provided an additional way for students to learn new ways to establish connections with clients:

> *They hear the [diagnosis], and they're like, oh, they can't do anything. But they were having fun with the little apps that turn your hair green, or give you bunny ears, and stuff like that. So, they're going through and playing with all that kind of stuff. I don't even know where half that stuff is or how they find it. But it's hilarious and it's fun to watch. So, it becomes a medium and a tool kind of thing.* [P7, interview, nursing educator]

It is important for students to gain a clear understanding of how to use virtual caring technologies efficiently and effectively to make meaningful caring connections with clients. The perspective from both survey and interview participants reinforced that having access to the tools was important, with support and familiarity requiring time and resources for tool use competency.

Teaching Support

Educators identified that various teaching supports were necessary for fostering initial self-awareness and skill development when teaching in virtual settings. Ongoing development and the exchange of best practices helped build and sustain confidence and competence in using virtual caring technology. Many educators turned to others for teaching support, including teaching and learning departments and teams, or external networks to help support their personal learning needs. Others found teaching support from within their own faculty and professional organizations:

> *My colleagues and my own field professional organization was better in terms of teaching strategies or things to do within a lesson.* [P6, interview, education educator]

Overall, educators were motivated to seek out ways to enhance their teaching practice of virtual caring skills.

Stakeholder Engagement

Study participants identified stakeholder support and engagement as important to virtual caring skill development. One survey respondent contributed that "online teaching is forcing me to get creative...I learned to rely more on facilitating students' own motivation and initiative to seek community involvement" (P40, survey, medicine educator). Educators sought to encourage students to engage with clients in the community to help inform their virtual caring practices. Another survey participant indicated the importance of consulting various stakeholders, including students and educators, regarding their experiences with virtual caring technology by suggesting faculties should do the following:

> *[Engage in] consultation with students to understand their experiences as the end user/recipient of any technologies used for developing caring skills; [develop] a long-term vision/strategy for implementing, evaluating, and updating technology; [and link] technology use to program intent/pedagogy so that it makes sense to teachers/learners and is not just used for the sake of it.* [P5, survey, nursing educator]

Others highlighted the value of engaging with a range of stakeholders, including caregivers, clients, students, and instructors, in the virtual care setting:

> *We would invite the clients and the caregivers, or whoever was in the home to set up the screen and make sure that all of the controls were kind of off so that we could control it. And so as long as they could log in, we could get them into a breakout room. We would put the student in there with them. We would put a mentor from the [organization] in there with them. And then as instructors, we would go into each breakout room and just listen, make sure everything was okay, answer any questions, and then go to the next one and kind of wander through that way. And it worked really well.* [P7, interview, nursing educator]

Participants indicated that various stakeholders bring valuable and diverse perspectives to virtual caring experiences and harnessing these viewpoints can help facilitate more effective teaching and learning about virtual care.

Flexibility

Educators identified various ways that they chose to adjust, alter, change, or remain open to alternative ways of engaging in their practices for teaching, learning, and providing virtual care. The theme of flexibility emerged prominently in the survey responses, with a focus on being flexible with students. One survey participant emphasized the importance of "just being open and available and allowing students to set the stage for how they want to show up and learn and to be open if they are finding the online approach to learning challenging" (P79, survey, social work educator). Another perspective on flexibility was that it "allowed for more flexible scheduling and allow(ed) me to reach international students easier" (P15, survey, medicine educator). The connection to students in conducting, developing, or framing the learning space was recognized as a key element in building the flexibility to permit learning that incorporated virtual learning skills. This flexibility contributed to a more dynamic and inclusive learning environment.

Principles of Virtual Care

In our analysis, we identified principles of virtual care that reflect what educators reported as important considerations to how they approached teaching and learning virtual caring skills.

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These principles include emphasis on connection and interaction; compassion, empathy, and care; and vulnerability.

Connection and Interaction

Educators identified how important connections and interactions were for teaching about and providing virtual care. This perspective was particularly present for a nursing educator who described how technical nursing skills were not as important as making personal connections with the clients, which is vital when providing virtual care:

> *[Students] felt that they were missing out on some of those skills, like IV starts because obviously we didn't do that [in a virtual environment]. But no, those are not the most important skills in nursing. It's the interaction. It's the education...nursing is not all about skills.* [P1, interview, nursing educator]

Some educators were thoughtful in their approach to providing students with purposeful opportunities to develop connections with clients:

> *I would want to be in a different room, with my camera off, observing the whole encounter...be the fly on the wall...and then be able to deliver feedback after the appointment.* [P8, interview, medicine educator]

All educators identified through the interviews that personal connections and prioritizing interactions were desired, and even necessary, before skill development in virtual environments.

Compassion, Empathy, and Care

Educators shared how emotional labor and intentional considerations are required to design learning experiences around compassion, empathy, and care, particularly in virtual contexts. One survey respondent suggested that "students of any caring profession know they need emotional bravery and an ability to handle very difficult situations with empathy and calmness even when they do not feel that way" (P34, survey, social work educator). Participants also indicated they needed this emotional bravery to successfully implement online teaching and learning technologies to support students in developing virtual caring skills. Educators acknowledged the impact and challenges associated with emotional labor and considered their role as educators in addressing issues like compassion fatigue:

> *Emotional labor and compassion fatigue...because those aspects impact the degree to which somebody wants to try something new or continue a practice that used to work, that doesn't seem to be working now.* [P3, interview, education educator]

One interview participant considered the impact of learning activities with a focus on social and emotional learning for individual well-being:

> *I also am a very active and dynamic facilitator, even online, so I use teaching strategies that I would use in the classroom and I get my students to actually get up and do things if I'm talking about a social emotional learning activity, something that's for wellbeing, because taking care of yourself is as important as you know what you're teaching, and you will impact the wellbeing of your own students or patients by the way you are as well. So, if I'm talking about just a simple social-emotional piece where it is maybe a five, four, three, two mindfulness activity, I do it with them.* [P6, interview, education educator]

Compassion, empathy, and care were viewed as important considerations in teaching, learning, and providing virtual care. These qualities could manifest authentically in a variety of ways, depending on the context of the teacher, learner, or client.

Vulnerability

The theme of care extended to include a focus on educator vulnerability and the willingness to embrace new approaches, recognizing that things might not always go as planned. However, this willingness by the educator required creating safer learning and caring spaces:

> *In caring skills and competencies, there's a level of vulnerability there that you must have. And so, when you're starting out with online courses, you need to build that caring atmosphere within your virtual online environment in a way that students feel safe.*
>
> *If you have a course, you have the time, and you utilize facilitation methods that are similar to what you are expecting them to be able to do as well, then that's helpful, right? I guess it comes back to that theory practice piece.* [P6, interview, education educator]

Another participant spoke about the need to break down barriers by creating relationships that push virtual caring efforts to meet clients' needs:

> *They [clients] put up their own barriers, to be perfectly honest. Because if you want it, you'll find a way to do it. But…If you have the goal in mind that, then all you need to do is figure out how to get there. It's a lot easier…I mean, create relationships. Ask people if they want to try something. And don't think you can't do it just because nobody's done it before...See if it works. Not everything works the first time. Well, I know that's why this is important too, right? It's like you evaluate and you figure out what works, what doesn't work.* [P7, interview, nursing educator]

There was a shared sense among participants that without the educator's sense of vulnerability and willingness to try something new and create intentional efforts toward connection through compassion and care, educational practice for virtual care would not be able to move forward.

Discussion

Principal Findings

In this sequential explanatory mixed methods study [24] we explored the experiences and perceptions of educators in caring professions as they navigated online teaching to facilitate the development of virtual caring skills and competencies among students. Educators identified both barriers and facilitators to

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engaging in this mode of teaching and learning as well as identified key principles underlying virtual caring.

Quantitative and qualitative data were integrated following individual analysis. The most common online instructional methods used to teach virtual caring skills were reflection, online modules, and online discussion boards. Only 26% (21/80) of the participants indicated that they provided experiential learning via consultation with clients on the quantitative survey. In qualitative interviews, participants discussed barriers to this educational modality, such as lack of time, indicating that providing virtual caring experiences could be less efficient than providing in-person clinical learning. Furthermore, 21% (17/80) of the educators indicated that they had not used online technology to teach virtual caring skills. This was reflected in the qualitative data when participants discussed the challenges of fitting more content into an already crowded curriculum. As virtual environments increase in the caring professions, it is important that virtual caring curriculum becomes a more permanent fixture within program curricula [35], rather than treated as a specialty consideration that can be included if time permits. This highlights the attention for program-level considerations for technological literacy and use development. It is not enough for educators to be able to use the technology effectively and use tools in one course; instead, there is a need to identify opportunities across a program to support the learning and development of digital literacy and technology-use competencies.

Educators had varying levels of satisfaction with their online teaching and learning strategies to enhance virtual caring skills. Less than half of the participants (34/80, 43%) indicated that they were satisfied with their online teaching and learning strategies, with other educators indicating that they were either somewhat satisfied or not satisfied. Through the qualitative survey and interview data, educators expressed frustration regarding the lack of engagement or connection with their students, which created difficult teaching environments. Educators also expressed concern regarding students' access to technology devices and reliable internet. Bolster et al [35] expanded this idea when discussing that clinical patients that might have limited access to virtual caring technologies or may lack digital literacy. In this study, the challenges discussed by educators may have influenced their overall satisfaction with their ability to execute effective teaching and learning strategies. In the survey qualitative responses, those that were "satisfied" (34/80, 43%) often cited reasons such as the smooth functioning of technology and active student engagement. Educator and student interactions with technology appear to be influential to educators' satisfaction with the teaching experience. Leaders from across the United States emphasized the importance of optimizing the logistics of technology when they met for a symposium titled Crossing the Virtual Chasm: Rethinking Curriculum, Competency, and Culture in the Virtual Care Era [35]. They reported that the need to optimize logistics, including providing equitable technology access and user software training, was one of the levers that can improve virtual care education [35].

Although educators' likelihood to use online teaching and learning technology was mixed in quantitative surveys, there was notable support to develop learning objectives to enhance virtual caring skills. Educators discussed facilitators that could enhance the teaching and learning of virtual caring skills in interviews. Survey respondents who identified as very likely to use online teaching and learning technologies (37/70, 53%) indicated via qualitative responses that teaching support through professional development, ongoing technology assistance, and student engagement was essential to support students in developing virtual caring skills. Addressing challenges that arise while teaching and learning virtual caring skills in an online environment can be beneficial to student outcomes and educators' satisfaction and increase their likelihood to use such technologies. Although higher education institutions are working to keep up with evolving technologies, specialized attention will be required in the virtual caring education context [35].

Surveys and interviews were undertaken with educators across caring professions, including education, medicine, nursing, and social work, within a research-intensive educational institution in western Canada. Quantitative analysis revealed interesting insights into educators' satisfaction with online teaching and learning strategies and their likelihood to use online teaching and learning technologies. Overall, educators were somewhat satisfied with the online teaching and learning strategies they were using in their classrooms. Furthermore, they felt that they were somewhat likely to use online teaching and learning technology to support student learning of virtual caring skills. Through inferential analysis, we found that educators with experience designing and teaching ≥8 classes (considered expert level) had statistically greater satisfaction with the teaching and learning techniques they used in online learning environments. This finding indicates that educators could benefit from more experience in online teaching. This is congruent with the findings reported by Rhode et al [7], indicating that educators with more experience teaching in online environments had more positive attitudes toward online teaching and learning.

In addition, we found that educators from the faculty of education reported significantly higher satisfaction levels in teaching virtual care in an online modality compared to their counterparts in medicine or nursing. This may be largely due to the longer history that education faculties may have had in providing instruction in an online environment. This finding highlights the importance of offering additional support and professional development to educators in traditionally in-person programs, enabling them to effectively meet the needs of an increasingly online student population. In an integrative review, Cutri and Mena [36] discuss the cultural and structural challenges of traditionally in-person educators transitioning to online teaching and learning, including the workload required and readiness to transition to the online environment. Considering these challenges, academic institutions should consider implementing robust professional development programs to better support faculty engaging in online teaching and learning, ensuring optimal support for students learning virtual caring skills.

Educators identified several barriers to online teaching and learning related to the development of virtual caring skills, including time constraints, underdeveloped virtual caring curricular content, lack of engagement, and limited access to

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virtual caring equipment and technology. Time constraints may pose a significant challenge for educators as they strive to cover comprehensive content within limited time frames. Furthermore, educators may struggle to find room for virtual caring skills within their current curriculum, recognizing that to include additional content, other content will have to be reduced or eliminated. The underdeveloped nature of virtual caring curricular content may result in teaching and learning practices that lack the depth and breadth required to adequately prepare students for the nuances of virtual care. A notable barrier to teaching virtual caring skills in online environments, seen in this study and the literature, is the struggle to maintain student engagement, as online settings often hinder active participation and interaction. Students are more likely to be engaged when they have active learning opportunities, a positive learning climate, and meaningful interaction with faculty and peers [37]. Furthermore, limited access to virtual caring equipment and technology has exacerbated the challenge of teaching online [38] and hindered caring professionals' practical application of virtual care concepts [39]. Addressing these barriers is crucial to ensuring a robust and effective virtual care education within online learning environments.

Educators in this study identified several facilitators of online teaching and learning related to virtual caring skills, such as clearly defined learning objectives, technology software and support, teaching support, stakeholder engagement, and flexibility. Clear and well-defined learning objectives play a pivotal role in ensuring quality education, providing a road map for both educators and students to navigate curriculum with clarity and purpose. Adequate technology software and support are essential facilitators, enabling seamless integration of virtual caring skills into the online environment. Teaching support, including resources, training, and guidance, enhances educators' ability to effectively convey virtual caring concepts. In a grounded theory study, Shepherd et al [40] explored medical faculty and learner experiences regarding the learning of virtual caring skills during the COVID-19 pandemic. Despite medical faculty recognizing how virtual care can benefit patients, they were reluctant to continue to teach in virtual clinics, due to barriers at the individual, institutional, and systemic levels, citing challenging technology platforms and a lack of professional development as 2 of the limitations [40]. Stakeholder engagement, involving collaboration with health care professionals, institutions, and communities, may foster a more holistic approach to virtual care education. In addition, flexibility in instructional methods and assessment allows for adaptive learning experiences, catering to diverse student needs and optimizing the acquisition of virtual caring skills in an online setting.

Educators identified connection and interaction; compassion, empathy, and care; and vulnerability as key considerations when developing online teaching and learning experiences to support students in developing virtual caring skills. Fostering meaningful connections and interactions within the virtual learning space is essential for educators to create engaging and supportive learning environments. Encouraging compassionate and empathetic attitudes is fundamental, as these qualities are at the core of effective virtual care. Our findings mirrored the assertion by Bolster et al [35] that connection in virtual care is an essential component of "webside manner," indicating the importance of rapport building through technology. Integrating opportunities for students to understand and express vulnerability is equally important, as it promotes authenticity and a deeper understanding of the human aspect of health care. By prioritizing these elements, online educational experiences can transcend physical barriers, providing a rich and holistic foundation for students to develop the interpersonal skills necessary for effective virtual caring [16,41-44].

This study is part of a larger multistudy research project intended to provide a framework for virtual caring skill development in higher education. This study explores the educator's perspectives, while another study explores the student's perspectives. The final integrated findings will inform a framework to guide educators from varied professions as they develop virtual caring curricula. By gaining educator and student perspectives, we aim to provide a comprehensive view of core principles, competencies, teaching methods, facilitators, and barriers to teaching and learning virtual caring skills.

Strengths and Limitations

Our sequential explanatory mixed methods study provided a thorough examination of caring profession educators' perceptions of virtual caring skill development within a specific educational institution. The inclusion of participants from various caring professions offered diverse perspectives, enhancing the study's comprehensiveness. By incorporating surveys and interviews, the research amalgamated quantitative and qualitative data, enabling a more profound insight into educators' experiences and perspectives in online teaching related to virtual care. However, it is essential to acknowledge the study's limitations, warranting caution in interpreting the findings. The focus on a singular institution may limit the generalizability of these findings to broader contexts. Furthermore, the participant pool from a single institution may lack diversity, potentially affecting the external validity and transferability of findings to a more varied population. Despite these constraints, this study lays the groundwork for exploring virtual caring skill development, inspiring further research, and offering potential insights for enhancing the delivery of virtual care in educational settings.

Conclusions

Educators in caring professions require specialized knowledge and skills to effectively teach and support students in developing virtual caring skills and competencies. Our study highlights the barriers, facilitators, and principles of teaching virtual caring skills online. As we contribute to the growing body of educational research on virtual caring skills, we share insights from caring profession educators. Future research should continue to explore how educators in more traditionally in-person teaching and learning can be supported to meet modern-day needs. In addition, more evidence is needed to explore effective teaching and learning strategies to teach virtual caring skills in a variety of contexts. Our findings offer practical strategies to enhance teaching and learning within educational programs for caring professions.

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Conflicts of Interest

None declared.

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Edited by E Borycki; submitted 19.07.24; peer-reviewed by D Patel, S Otero; comments to author 23.09.24; revised version received 11.11.24; accepted 28.11.24; published 15.01.25.

Please cite as:
Nowell L, Johnston S, Dolan S, Jacobsen M, Lorenzetti DL, Oddone Paolucci E
Exploring Educators' Perceptions and Experiences of Online Teaching to Foster Caring Profession Students' Development of Virtual Caring Skills: Sequential Explanatory Mixed Methods Study
JMIR Nursing 2025;8:e64548
URL: https://nursing.jmir.org/2025/1/e64548
doi:10.2196/64548
PMID:39608377

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Evaluating Nurses' Perceptions of Documentation in the Electronic Health Record: Multimethod Analysis

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Abstract

Background: Nurses are one of the largest user groups of the electronic health record (EHR) system, relying on its tools to support patient care and nursing workflows. Recent studies suggested that the redesign of nursing documentation may reduce the time spent in the EHR system and improve nurse satisfaction.

Objective: We aimed to assess nurses' perceptions of the redesigned EHR, evaluate the impact of documentation interventions, and identify future improvement needs.

Methods: Guided by the American Nursing Informatics Association's Six Domains of Burden conceptual framework, this multimethod project combined both qualitative and quantitative approaches. Registered nurses across the academic health system were recruited via email invitations to participate in focus group discussions. The focus groups were conducted via a web conference and ranged from 60 to 90 minutes in duration. The focus group discussions were transcribed and analyzed through thematic analysis. The EHR vendor's time data were used to analyze nurses' time spent in documentation.

Results: In total, 20 registered nurses participated in the focus group discussions, and 17 nurses completed the demographic survey; 88% (15/17) of participants had ≥3 years of EHR experience at the academic health system, and 53% (9/17) self-reported being competent in the EHR system. The following six themes emerged: positive feedback, usability and workflow opportunities, nuisance, training and education, communication, and time spent in the system. EHR vendor time data revealed that the time spent in flowsheets averaged 31.11% per 12-hour shift.

Conclusions: Overall, participants reported a positive experience and that the EHR supported patient care. There are opportunities to further reduce redundancies in documentation and implement programs that support continuous learning about EHR and health technology tools. Specific suggestions include optimizing the oral health assessment tool. Analyzing frontline nursing perspectives in the redesign of EHR workflows is imperative for identifying interventions that support nurses' satisfaction with the EHR.

(JMIR Nursing 2025;8:e69651) doi:10.2196/69651

KEYWORDS

electronic health record; nurse; documentation burden; focus group; usability; documentation

Introduction

Background

Nursing documentation is critical for high-quality patient care and effective communication among health care professionals. Before the implementation of electronic health records (EHRs), clinician documentation was primarily recorded by using paper-based methods [1]. The Health Information Technology for Economic and Clinical Health (HITECH) Act, which passed in 2009 in the United States, aimed to improve health care quality and safety and encourage the efficient use of health ITs, such as the EHR [2]. Hospitals were incentivized to implement EHR systems, resulting in 98.3% of hospitals adopting electronic-based systems in recent decades [3]. The increased sophistication of EHR systems has introduced documentation requirements and clinician decision support tools, potentially increasing clinicians' documentation burden [4]. The American

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Medical Informatics Association (AMIA) describes *documentation burden* as the stress resulting from excessive work that is required to document in the EHR [5].

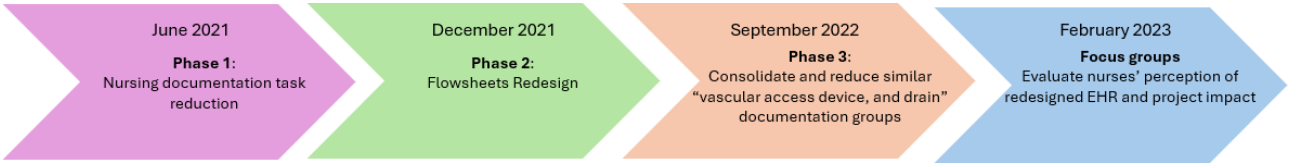
Nurses are one of the largest user groups of the EHR system and are primary users of flowsheet tools for documentation [6]. Flowsheets are structured tools in the EHR system; they are used to record discrete data over time and are designed in a tabular format. Resembling a spreadsheet, each column represents a date and time, while each row is designed to capture selectable options or free-text values. Nurses capture assessments and observations in flowsheets and, on average, document 631 to 875 flowsheet data entries within a 12-hour shift, equating to approximately 1 data entry per minute [6,7].

There is increased awareness among national government entities and professional health care organizations across the United States regarding the need to implement initiatives that address EHR documentation burden. For instance, the 21st Century Cures Act identified the following three goals for reducing clinician burden: (1) reduce the time and effort needed to document health information, (2) reduce the time and effort needed to meet regulatory requirements, and (3) improve usability [8]. Similarly, in 2021, the AMIA Task Force aimed to reduce clinician documentation burden by 25% within 5 years [5,9]. Additionally, the American Nursing Association's Principles for Nursing Documentation recommend that nursing data entries should be meaningful and nonredundant [10]. Further, a prior study found that flowsheet redesign saved an average of 10 minutes per shift in flowsheets [11]. Other interventions, such as EHR optimizations and training, could improve clinician satisfaction, and nurses show increasing utilization of documentation efficiency tools once such tools are available [12,13].

The American Nursing Informatics Association (ANIA) developed the Six Domains of Documentation Burden conceptual framework, defining the factors that contribute to documentation burden as follows: reimbursement, regulatory, quality, usability, interoperability/standards, and self-imposed [14]. Nursing flowsheet documentation represents a significant amount of the overall documentation time for nurses, making it a prime area for burden evaluation through ANIA's framework.

During the COVID-19 pandemic, our academic health system (AHS) reduced nursing flowsheet documentation by requiring only the documentation of critical assessments. Along with national calls to action for reducing documentation burden, this streamlined documentation approach served as a catalyst for the chief nursing officer, IT analysts, and nursing informatics team to optimize the nursing digital experience across the enterprise. We adopted a phased implementation approach to address challenges. In 2021, nursing informatics and IT analysts led nursing documentation enhancement workgroups with direct care nurses across the AHS. Nurses highlighted areas of the EHR system that were burdensome and suggested improvements. The nursing informatics team analyzed data from the EHR to identify flowsheet rows with minimal to low usage rates and brought these up as discussion points during workgroup meetings. Additionally, nursing informatics and IT analysts conducted an analysis of the various "vascular access device and drain" documentation groups. Cross-referencing these documentation groups revealed opportunities to consolidate similar documentation groups. During the workgroup sessions, direct care nurses expressed a preference to group and reduce the amount of "vascular access device and drain" documentation groups. Nursing informatics and IT analysts presented proposed changes to the steering council (comprised of the chief nursing officer and cross-campus nursing senior directors) for approval. Projects for implementation were prioritized into the following three phases (Figure 1): phase 1 focused on reducing nonmeaningful nursing documentation tasks, phase 2 involved redesigning flowsheets, and phase 3 involved consolidating and reducing similar "vascular access device and drain" documentation groups. Throughout each phase of the implementation, the nurse workgroup participants contributed recommendations and served as liaisons, gathering feedback from respective units and specialties. After the implementation of the three phases, our AHS sought to evaluate the project's impact and determine if further improvements were needed.

Figure 1. Improvement of nursing documentation experience: phased implementation and focus groups. EHR: electronic health record.



Objective

We aimed to assess nurses' perceptions of the redesigned EHR, evaluate the impact of documentation interventions, and identify future improvement needs.

Methods

Setting

Our assessment, which used qualitative and quantitative methods, was conducted at an AHS with 4 teaching hospitals in the northeastern region of the United States; each teaching hospital was designated as an American Nurses Credentialing Center Magnet site. The AHS employs almost 10,000 nurses, and it implemented the current EHR system in 2012.

Design

In our multimethod assessment, qualitative data were collected during 5 focus group sessions. A focus group method was chosen to evaluate the phased interventions and participants' lived experiences with documenting in the EHR [15]. Focus groups were selected for their ability to facilitate active

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interaction among participants and generate opinions, suggestions, and feedback through group dynamics [16]. Our quantitative data consisted of monthly data supplied by the EHR vendor, which summarized the time nurses spent in the EHR system. The system logged the time each user spent within the EHR by tracking the time spent performing clicks, scrolls, keystrokes, and mouse movements [17]. These quantitative data could be divided based on EHR-related activities, such as nursing flowsheet documentation, medication administration, and task management.

Sample

The quality improvement project team recruited inpatient registered nurses across the AHS through an electronic flyer. Recruitment was performed during a pre-existing focus group process known as "Ideas for Innovation in Nursing." This process provided an opportunity for nurses to share their ideas about a given topic (ie, use of 3D printing in nursing practice). The full-page electronic flyer was embedded in the AHS's monthly nursing science newsletter, which has a distribution list of approximately 8000 nurses and provides information about upcoming focus groups. The registered nurses who were interested in participating in the focus groups were required to complete the electronic registration form, which involved selecting a preferred session date and time.

Data Collection and Analysis

The quality improvement team members (DJ, JW, DD, BD, KEZ, and KO) met to develop open-ended questions for guiding focus group discussions. Prior to conducting the focus groups, DJ, JW, and DD were trained by BD and KEZ, who were experienced in qualitative methods and focus group facilitation. Additionally, BD and KEZ participated as comoderators in each focus group discussion. The moderator (DJ) led the focus group sessions, introduced the purpose and formatting of the focus group, and facilitated the questions. The observers (JW, DD, BD, and KEZ) used a template to document notes on and observations of participants' sentiments, behaviors, and nonverbal reactions. Sessions were conducted via a web conferencing platform. The focus group sessions ranged from 60 to 90 minutes in duration.

At the end of each focus group, participants received a link to an anonymous survey. The survey, which was administered via an administration platform, gathered demographic information, self-assessments of EHR competency, and feedback specifically about the focus group sessions. Participants' perceived level of EHR competency was defined by using Benner's [18] novice to expert theory. Benner's [18] model was initially used to understand how nurses develop clinical competence, but it has expanded to evaluate EHR skills [19]. The project team members (DJ, JW, DD, BD, KEZ, and KO) debriefed at the end of each session to review notes, identify themes, and compare findings from prior focus group discussions. Sessions were recorded and transcribed by using a web videoconferencing platform. The transcriptions were validated by the project team. The project team members (DJ, JW, DD, BD, KEZ, and KO) met to confirm that saturation was reached. Transcriptions were entered into ATLAS.ti Web (version v9.4.3; ATLAS.ti Scientific Software Development GmbH)—a qualitative data analysis software for coding. Thematic analysis with an inductive coding process was used to discover themes. The primary coder (DJ) completed initial coding and developed the codebook. The secondary coder (LG) independently reviewed and validated the codes. The coders met to identify patterns and themes within the data, leveraging The Six Domains of Burden conceptual framework to organize the codes and examine the multifaceted burden experienced by nurses [10]. All quotes were reviewed by DJ and LG to reach consensus on discrepancies and further refine codes.

EHR activity data regarding the time spent in flowsheets were calculated for February 2023—the same month as when the focus group discussions were conducted. These activity data were time-stamped, allowing for the calculation of the time spent specifically within that month. The average time spent in a documentation activity was calculated as a percentage for all nurses in the AHS system. This quantitative approach was designed to provide context to the qualitative data. This quality improvement project was reported in accordance with the SQUIRE (Standards for Quality Improvement Reporting Excellence) 2.0 guidelines [20].

Ethical Considerations

This project was undertaken as part of a quality improvement project for evaluating nursing documentation experiences with the EHR. The project team completed an NYU Langone Health Institutional Review Board–approved quality improvement self-certification. Participants voluntarily registered to take part in the focus group discussions and were not provided with any form of compensation. At the beginning of each focus group, participants provided verbal agreement for sessions to be recorded and transcribed while maintaining their anonymity.

This project was determined to not meet the criteria for human subjects research, as guided by the NYU Grossman School of Medicine's Institutional Review Board policy.

Results

Participants

A total of 50 nurses responded via the electronic flyer's registration link. Of those, 20 participated in the focus groups, with an 85% (n=17) response rate for the demographic survey; 3 participants declined to complete the survey. Each focus group composition was made up of nurses from different hospitals and units. The focus group participants' demographic characteristics are listed in Table 1. Of the 17 respondents, most (n=12, 71%) were full-time employees, and the participants' primary area of practice was inpatient units (n=10, 59%). Further, 35% (n=6) of participants had been working at the AHS for 3 to 5 years, 47% (n=8) had 3 to 5 years of EHR system experience, and 53% (n=9) self-reported being competent in the EHR system.

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Table . Focus group participants' demographics (n=17).

Demographics	Participants, n (%)
Employment status	
Full-time	12 (71)
Part-time	4 (24)
Per diem	1 (6)
Area of practice	
Inpatient (acute, intensive care unit, maternal/child)	10 (59)
Emergency medicine	1 (6)
Perioperative	4 (24)
Other	2 (12)
Years at academic health system	
1 - 2	2 (12)
3 - 5	6 (35)
6 - 10	4 (24)
11 - 15	2 (12)
16 - 20	1 (6)
>20	2 (12)
EHR[a] system experience (years)	
1 - 2	2 (12)
3 - 5	8 (47)
6 - 10	5 (29)
>10	2 (12)
EHR system proficiency	
Advanced beginner	1 (6)
Competent	9 (53)
Proficient	5 (29)
Expert	2 (12)

[a]EHR: electronic health record.

Focus Group Findings

Overview

Herein, our findings are presented over the following six major themes: positive feedback, usability and workflow opportunities, nuisance, training and education, communication, and time spent in the system. Quantitative analysis results for EHR activity data regarding the time spent in flowsheets are reported for the "time spent in the system" theme, which included participants' subjective descriptions of how their shift time is spent; details of the analysis are presented in the *Time Spent in the EHR System* section.

Positive Feedback

Overview of Positive Feedback

Seventeen nurses in 5 focus groups provided positive feedback on the benefits of improved EHR workflows, including nursing documentation task management, flowsheet documentation, communication, and device and vendor integration. Positive feedback included the following subthemes: safe patient care, efficiency, and ease of use. Nurses reported positive sentiments on the nursing documentation programs that were implemented to improve documentation, such as the following:

> *The central lines....The date change row, all that I appreciate, because we did not have that for a while, and a lot will get lost in translation....There is a lot of improvements especially with skin,...Central lines catheters and drains. I appreciate all the changes that have been done, it's easier to just go back and backtrack to see when the last dressing was done or how it looked before the wound images.* [Participant 15]

Safe Patient Care

Five nurses in 3 focus groups reported that the EHR system supported safe patient care delivery. Two nurses commented

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on the ease of viewing patients' surgical history along the continuum of care. One participant said:

> *I think it's a great system. You know, coming from the paper charting to this...when you think about it. How crazy that time was - I cannot imagine not having the electronic chart....Really, it's great. It's great for follow up. It's great for care. I think it improves health.* [Participant #1]

Efficiency

Nurses commented that efficiency tools, such as the vital signs integration and copy and paste, aid in reducing manual documentation, resulting in less time spent in the EHR system. For instance, a participant stated:

> *I find it helpful when you hook them up to the monitor and the vitals automatically get transferred....Very helpful for us because we see so many patients a day....It saves us the time of having to sit there manually inputting them.* [Participant #18]

Focus group participant #1 also reported that "the more we can integrate the better."

Ease of Use

Four nurses appreciated the EHR task management feature and noted that the enhancements made the workflow easier. Six nurses expressed that the flowsheets were intuitive for documentation and were streamlined. One said:

> *It's super-duper easy. I usually take 5 minutes to finish my baseline charting.* [Participant #13]

Interdisciplinary Communication

An EHR functionality allowing secure, direct messaging between clinicians was cited by 4 nurses in 3 different focus groups as something that improved their clinician experience through convenience and features such as the ability to send an image of an electrocardiogram directly to a covering radiology cardiology resident. The direct messaging feature was appreciated, while workflows involving calls to unit-based landline phones were highlighted as being particularly disruptive. The nurses carried work-issued mobile devices, which can be called directly. Further, a participant stated:

> *I mean, I love this system. Because whatever I do, we connect with each other.* [Participant #13]

Usability and Workflow Opportunities

Fourteen nurses in 5 focus groups reported usability and workflow opportunities in the EHR. Nurses commented on the desire for the standardization and consistency of documentation template design. For example:

> *There are some things that go in alphabetical order. And then something else will go in order of head to toe. And then something else will go in order of like, abnormal, abnormal, abnormal, and then normal. And so, it feels like it changes...if it were just consistent, I think it would be easier.* [Participant #9]

Three nurses commented on the need for specialty-specific documentation templates to support clinical workflows. One reported:

> *I think the flowsheets are more catered to inpatient nurses...for telehealth nursing we use the flowsheets that were already in [redacted] but I think most of the questions in there are not telehealth specific, and also the nursing assessment is completely different over the phone because we obviously can't visualize the patient. I think there's definitely a lot of improvement that we can go forward with documentation in terms of telehealth.* [Participant #3]

Nuisance

Redundant Documentation

Four nurses in 2 different focus groups described redundant documentation during the admission process. The EHR frequently prompted them for information that was elsewhere in a patient's chart:

> *It asks me to put in if the patient received their COVID vaccination....I have to click on it but it's already on the storyboard. So, I think that's just added documentation that is unnecessary on our end.* [Participant #6]

Eight nurses reported that in some cases, documentation was repetitive, as they had to document the same finding in several different places within the EHR. Examples included multiple places for documenting paper tape, skin assessments, patient activity, and patient positioning. Nurses described how the repetition was time-consuming and that they desired documentation to be streamlined.

Nonmeaningful Documentation

Four nurses in 2 focus groups described nuisances related to nonmeaningful documentation. They cited oral assessment items that needed to be documented for all patients, irrespective of patients' needs; verbalized emotional states; subjective findings; and national standards, which necessitate documenting every 15 minutes. Although nurses understood the nature of hospital protocols, they felt that some documentation was more for "covering" oneself rather than serving an actual clinical purpose.

Training and Education

Ten nurses in 4 focus groups discussed training and education related to the EHR. Four nurses described the learning curve for new nurses to acclimate to the EHR system. One participant said:

> *I also like the tip sheets because if you don't do something for quite a long time, you forget how to do it. The tip sheets are very helpful - tell you how to document.* [Participant #4]

Two nurses reported their dissatisfaction with the EHR optimizations and communication method. For example:

> *I think it's very easy to miss those general broadcast emails. I think just like, batching changes would probably be most helpful. This group of changes is*

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happening rather than 1 change here or 1 change here and there's 10 different emails about it. [Participant #8]

Communication

Six nurses discussed how the EHR system supports communication. Three nurses commented on the clinical mobile device and its strengths and weaknesses particularly around meeting patients' needs regarding their preferred language. The clinical mobile device, which paired with a mobile app for interpreter support, excelled at simplifying the process of connecting to a remote interpreter:

The steps saved from when you used to call, and they ask you what department you were calling from and what language you needed. That saves you a few minutes and that is priceless on its own. [Participant #10]

Time Spent in the EHR System

Participants self-reported that 10% to 50% of their shift is spent documenting in the EHR system, and many perceived this time to be appropriate. The EHR vendor time data were analyzed during the focus group period. The EHR vendor time data for February 2023 revealed that the average EHR time spent in flowsheets was 31.11% per 12-hour shift. In relation to the time spent in flowsheets, one participant stated:

I would definitely say the shift assessment takes up your biggest amount of time. You want to be thorough; you don't want to miss things. So, that really is the largest amount of time. [Participant #1]

Discussion

Principal Findings

The project's aims were to explore nursing documentation experiences related to the EHR and evaluate how the documentation reduction interventions impacted perceptions. Themes included positive feedback, usability and workflow opportunities, nuisance, training and education, communication, and time spent in the system. Nurses perceived that the EHR supported the delivery of safe patient care and care team communication. Participants complimented the EHR system's easier flow and remarked on the general improvements. The project revealed that while the nurses overall had a positive experience with using the EHR system, there are further opportunities to optimize the EHR design. The implementation of voice recognition tools for nursing documentation supports the capture of patient assessments in real time by reducing the average time spent documenting by more than 2.6 minutes per assessment [21].

The focus group participants did not describe burden from using the EHR; rather, they noted redundant and nonmeaningful documentation as a nuisance. Focus group participants suggested solutions for reducing nonmeaningful documentation, such as optimizing the oral health assessment tool and only requiring oral health assessment documentation for ventilated and tracheostomy patients, which aligns with the AHS's policies and standards. Due to this project, this enhancement request was implemented at the AHS, with positive sentiments from nurses. Many documentation burden reduction interventions have shown improved satisfaction with the EHR among clinicians [22].

The Six Domains of Documentation Burden conceptual framework on EHR documentation burden indicates that most health care system cultures adhere to the ideology of "if it's not documented, it's not done" [10]. As a result, some nurses may document due to perceived legal implications. Focus group participants discussed documentation volume and the sense that they document too much. Health care system accreditation organizations have recognized the need to reduce documentation burden. In 2023, The Joint Commission aimed to eliminate 14% of standards and updated 13 standards [23]. Individual hospitals can make impacts to address EHR documentation barriers and reduce documentation through shared governance workgroups that include frontline nurses [24].

The project's findings reveal opportunities for continuous EHR education. Per the focus group participant survey results, 47% (8/17) of participants had 3 to 5 years of EHR experience, and 53% (9/17) of participants self-reported being competent in the system. Some focus group participants discussed not being familiar with efficiency tools, such as the EHR search toolbar for quickly finding information within a patient's chart. Training sessions can enhance perceptions of efficiency [25]. Future studies should explore the use of the Digital Literacy, Usability, and Acceptability of Technology Instrument for Healthcare—a validated instrument for evaluating frontline nurse competency and usability with respect to the implementation of continuous health IT learning programs [26].

The findings from the focus group discussions prompted the project team to implement strategies that aimed to augment the nursing documentation experience in the EHR system. To support continuous EHR learning, the nursing informatics and IT training teams provided nursing staff with interactive enrichment classes that focused on nursing efficiency and common EHR workflows. The training content was developed based on frontline staff recommendations. The nursing informatics and IT training teams conducted nursing wellness fairs as drop-in opportunities during shifts to showcase EHR efficiency and tips. Remote sessions were offered for nurses to learn about upcoming documentation enhancements that would improve workflow and to provide feedback. As a result of the focus groups, the oral health assessment was optimized such that it only displayed in the EHR for ventilated and tracheostomy patients, rather than being required for all patients, as part of a shift documentation assessment; this change aligned with the AHS's policies and standards. Additionally, efforts were made, in collaboration with direct care nurses, to streamline and reduce wound and skin documentation.

We acknowledge limitations related to our qualitative and quantitative approaches. Our sample did not include nurses from pediatric, behavioral health, or rehabilitation units. The recruitment flyer was distributed within an email newsletter and may not have been seen by all nurses. Further, due to this being a quality improvement project, we could not look at individuals' utilization patterns, and quantitative metrics were summarized

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for all inpatient nurses at the hospital. Additionally, perceived documentation time spent in the EHR system was self-reported by focus group participants, and the EHR vendor time data analysis was not limited to focus group participants. Moreover, the focus group discussions were not limited to nurses who were employed prior to the documentation reduction interventions. However, this group made up a small fraction of the interviewees. Lastly, self-reported time spent documenting in the EHR might be influenced by group conformity bias. Participants in focus groups may be hesitant to express views that dissent from those of the group. Future work should explore a validated method for measuring burden [27].

Conclusion

Our focus group discussion findings suggest that the implemented nursing documentation improvement interventions had an overall positive impact on the nurses' EHR experience. As health care technology and documentation requirements continue to advance, the EHR experience requires ongoing evaluation. Analyzing frontline nursing perspectives in the restructuring of EHR workflows is imperative for identifying interventions that support nurses' satisfaction with the EHR. Future work is needed in supporting nurses after the EHR system onboarding training period.

Conflicts of Interest

None declared.

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Abbreviations

AHS: academic health system
AMIA: American Medical Informatics Association
ANIA: American Nursing Informatics Association
EHR: electronic health record
HITECH: Health Information Technology for Economic and Clinical Health
SQUIRE: Standards for Quality Improvement Reporting Excellence

Edited by E Borycki; submitted 04.12.24; peer-reviewed by M Lindsay, N Dobroff; revised version received 21.03.25; accepted 22.03.25; published 28.04.25.

Please cite as:
Jacques D, Will J, Dauterman D, Zavotsky KE, Delmore B, Doty GR, O'Brien K, Groom L
Evaluating Nurses' Perceptions of Documentation in the Electronic Health Record: Multimethod Analysis
JMIR Nursing 2025;8:e69651
URL: https://nursing.jmir.org/2025/1/e69651
doi:10.2196/69651

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Stress and Well-Being Intervention and mHealth Delivery Adaptation for Latinx Millennial Caregivers: Qualitative User-Centered Design Approach

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Abstract

Background: This study aimed to adapt a stress and well-being intervention delivered via a mobile health (mHealth) app for Latinx millennial caregivers. This demographic, born between 1981 and 1996, represents a significant portion of caregivers in the United States, with unique challenges due to higher mental distress and poorer physical health than noncaregivers. Latinx millennial caregivers face additional barriers, including higher rates of being uninsured and increased caregiving burdens.

Objective: We used a community-informed and user-centered design approach to tailor an existing mHealth app to better meet the stress and well-being needs of Latinx millennial caregivers.

Methods: We used a 2-step, multifeedback approach. In step 1, Latinx millennial caregivers participated in focus groups to evaluate wireframes for the proposed mHealth app. In step 2, participants engaged in usability testing for 1 week, concluding with short interviews for feedback. Participants were recruited through various channels, including social media and community clinics. Data were analyzed inductively using a rapid qualitative content analysis approach.

Results: A total of 29 caregivers (n=20, 69% women) participated in the study. Participants had a mean age of 31 (SD 4.10) years, with most (n=28, 97%) caring for an adult and 3% (1/29) caring for children with chronic conditions. All participants completed the step 1 focus groups, with a subset of 10% (3/29) of the caregivers completing the usability testing in step 2. The most liked features included (1) the stress rating scale because it helped them understand stress and mental health; (2) the mindfulness options, which allowed for flexible timing of activities; (3) the journaling prompts for addressing daily challenges and positive experiences; and (4) the resource list for its employment and financial content. One concern was that the journaling prompts may take too much time to complete after a long and hard day. Some suggestions for improvement included a better tracking system, gamification, caregiving education, a checklist of emotions to use with the journal, tailored resources, and ways to connect with other caregivers. During step 2, participants noted that the app was user-friendly but had some glitches and unclear privacy policies. Participants liked the meditation options, resource variety, and daily stress log but wanted more journaling space, longer meditations, and additional relaxation activities.

Conclusions: Future iterations should consider integrating more personalized and community-specific resources, leveraging platforms such as podcasts for broader engagement, and the use of information-based videos to support caregiver skill acquisition. Caregivers expressed needs beyond the scope of the app, such as resource access, demonstrating the need for upstream and downstream interventions. This study reinforces that user-informed design is an ongoing and iterative process that requires balancing the needs of stakeholders and the feasibility of the recommended adaptations.

(JMIR Nursing 2025;8:e73621) doi:10.2196/73621

KEYWORDS

Latinx; family caregiver; millennial; mobile health; mHealth; user-centered design

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Introduction

Background

Millennial caregivers are individuals born between 1981 and 1996 who are care providers to family members and loved ones with serious health conditions. They comprise an estimated 25% of caregivers in the United States [1,2]. The number of millennial caregivers will continue to grow as people are living longer with multiple chronic health issues [1-3]. Caring for a loved one with a chronic condition can lead to adverse physical, psychological, and social outcomes [2,4]. Millennial caregivers experience higher levels of mental distress and worsened physical health than their noncaregiver peers [3].

Millennial caregivers in the United States are a more diverse group than previous generational cohorts, with 27% identifying as Hispanic or Latinx [1]. Historically, members of the Latinx community have experienced negative determinants of health related to a lack of access to health care and health insurance [5]. These factors contribute to Latinx Americans being at higher risk of Alzheimer disease, diabetes, obesity, hypertension, and kidney disease than the general US population [4], likely increasing burdens of caregiving among the Latinx population.

Latinx millennial caregivers are at higher risk of negative health outcomes than their non-Latinx peers. The rate of uninsured Latinx citizens is more than double the rate of uninsured non-Latinx White citizens [5]. Coupled with the low rates of insurance coverage reported by millennial caregivers, Latinx millennial caregivers are at increased risk of poor health outcomes and higher rates of disease [2,5]. Latinx millennial caregivers are 34% more likely to provide a higher number of hours of caregiving than those of other races or ethnicities in the millennial caregiving population while simultaneously working more hours per week [1].

There is a dearth of research exploring interventions to enhance stress management and well-being among Latinx caregivers. The few interventions studied are highly varied and lack methods of adaptation to address the specific needs of individual caregivers [6]. Language is a significant potential barrier for this population. In the United States, 51.3% of Latinx individuals report needing translation services in health care settings, yet many trainings and public health campaigns for caregivers are only provided in English [4]. While research detailing the experiences and needs of millennial caregivers highlights the necessity for support, there is a gap regarding interventions available and tailored to this population [7,8].

Due to balancing work, family, and caregiving responsibilities, Latinx millennial caregivers may have less time to engage in coping and well-being strategies [2,7]. With the population's needs in mind, a mobile health (mHealth) app was designed with meditation and journaling self-care exercises for the general millennial population [9,10]. The concept of an integrated mindfulness and journaling intervention delivered through an app was inspired by the dynamic fit model, which focuses on in-the-moment and long-term strategies to manage stress. Mindfulness was identified as an in-the-moment response to stress, whereas journaling would address the long-term sustained stress of caregiving [11]. A user-centered design approach modeled after the work by Still [12] was implemented to adapt the mHealth app. Feedback from the general millennial population identified the need for a resource list for caregivers and a daily stress measure in addition to mindfulness and journaling exercises. Thus, a caregiver resource list was added addressing chronic disease, work, general caregiving information, and financial information. A 1-item stress rating measure using a 10-point Likert scale was added [10]. While a resource list expanded upon the original intervention, it still remained true to the intent of supporting stress and emotional regulation. The provision of resources and information to support caregiving is a form of informational support, an important dimension of social support [13]. Social support has been found to decrease stress and burden in family caregivers [14,15].

Objectives

The purpose of this research study was to use both community-informed and user-centered design approaches to adapt a stress and well-being app intervention for Latinx millennial caregivers during formative intervention design. The following research questions guided this study: What are Latinx millennial caregiver perspectives regarding the scope and content of the stress and well-being app intervention? What additional components or content are needed to address Latinx millennial caregiver needs? What app usability issues impact caregivers' ability to engage with the intervention? For this adaptation, we continued to apply the approach by Still [12] coupled with a community-engaged lens [16]. Still [12] describes the importance of engaging users early and often, designing for use in context, giving users control, keeping things simple, designing for emotion, ensuring user triangulation, and discovery before designing and delivering. Wallerstein [16] describes their approach to community-based participatory research, including the contexts of research participants; partnering processes between research participants and researchers; the use of shared decision-making for research design; and outcomes that center social justice, health, and equity. This study focused on engagement rather than a full community-based participatory research approach, but we did address contexts, partnering processes, and shared decision-making throughout data collection and analysis.

Methods

Study Design and Participants

This was the second phase of a 3-phase multimethod study to examine the needs and experiences of Latinx millennial caregivers and adapt and refine an mHealth intervention for this population. The first phase, which focused on Latinx millennial caregivers' needs and experiences, is reported elsewhere [7]. This second phase was focused on the adaptation and refinement of an mHealth intervention using a stepped approach. The initial qualitative descriptive analysis of focus group interviews with Latinx millennial family caregivers was followed by user testing and short interviews.

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Ethical Considerations

The focus group interviews, usability testing, and short interviews were approved by the University of Texas at Austin Institutional Review Board (STUDY00002382). Participants provided written informed consent. Confidentiality was maintained by deidentifying and storing all study data, such as notes, focus group transcripts, and data analyses, within a collaborative secure cloud storage accessible solely by research team members. Participants were provided with a US $70 gift card for taking part in the focus groups or interviews.

Step 1

Participants were recruited using purposive sampling through multiple formats. Paid social media advertising and informal advertising within online family caregiver support group platforms was used, flyers were posted in community clinics serving low-income and uninsured individuals in Texas and Utah, and flyers were emailed to professional contacts and national caregiving groups. Finally, participants from a list from previous studies who had given permission to be recontacted were sent the study information. The eligibility survey was completed through the REDCap (Research Electronic Data Capture; Vanderbilt University) tool hosted by the University of Texas at Austin [17,18]. This survey required participants to meet the following inclusion criteria: being born between 1981 and 1996, identifying as Latinx, and providing care to a family member or friend for at least 10 hours per week. Participants were excluded if they did not have the technological capability to engage in Zoom (Zoom Video Communications) focus groups through a computer or smartphone, allowing for greater participation. According to the Pew Research Center, 93% of Latinx adults have a smartphone (similar to 91% of their White counterparts), and 75% have home broadband, with 20% of Latinx adults being dependent on a smartphone for going online. An estimated 97% of millennial adults own a smartphone, which is the age demographic for this study [19,20]. Potential participants chose the date and time of the focus group interview that would work for them, allowing for flexibility for other forms of internet access, such as through local libraries, community centers, and Wi-Fi hot spots [21].

Step 2

A subgroup of participants was emailed about usability testing and short interviews, with an emphasis on inclusion of both Apple and Android users, gender-diverse participants, and bilingual participants to test English- and Spanish-language functionality. Initial app functionality was tested by 3 study team members before usability testing. During this portion of the study, both Latinx (n=3) and non-Latinx (n=3) millennial caregivers completed usability testing—the non-Latinx population was used as a cross-check with the Latinx population, but their data are not reported in this paper. While there is no one-size-fits-all number for usability testing, between 3 and 20 users are enough for valid results. Five to 10 users are recommended as an initial baseline for problem discovery with usability testing. The task complexity and product risk were low, so we included 3 Latinx and 3 non-Latinx users for testing [22]. For this part of the study, individuals were excluded if they did not have access to a smartphone. Participants were given instructions on how to download the app from either the Apple App Store or Google Play Store and an access code that would allow them app use for 1 week. Participants were provided with the following instructions:

- Access the phone app and use it at least 4 times per week in English and Spanish
- Access and use the meditation videos; the Stop, Take a Breath, Observe, Proceed (STOP) audio recording; and the instruction steps for loving kindness, mountain meditation, STOP, mindful breathing meditation, and journal exercises on the app at least once during the 1-week period
- Access each of the resources on the resource list on the app at least once during the 1-week period
- Complete the app reliability questionnaire at the 1-week time point
- Complete the stress measure one time during the week

It was expected that they would need to spend 1 hour over the entire week on the Uplode app to test the intervention components and app functionality.

App use data were collected on the back end to be sure that app engagement took place. Within the app, there was a link to access support from the app developer. Participants were contacted following usability testing for a short Zoom interview.

Approach

Focusing on adaptation and refinement for the Latinx millennial caregiver population, both user-centered design and community-engaged methods were used to ensure that the functionality and content were tailored to the specific needs of this population [12,16]. Two stages of interviews with Latinx millennial caregivers were used to address stakeholder feedback, evaluate the clarity of the Spanish translation, and ensure both the usability and content tailoring of the app. In the original iteration of the mHealth intervention for millennial caregivers, cognitive interviews were used to adapt the stress and well-being mHealth intervention from a gratitude, exercise, and mindfulness intervention developed for nurses, but due to an emphasis on community engagement, we opted to use a focus group approach to support the synergy that occurs within a group dynamic [23,24].

Data Collection

Step 1

Participants first indicated whether they would take part in an online focus group in the eligibility survey. Willing and eligible participants were contacted by a graduate research assistant via email, who provided participants with a link to a Zoom meeting. The principal investigator, trained in qualitative research and group facilitation, conducted 5 Zoom focus groups of 60 to 90 minutes with between 3 and 10 individuals (Textbox 1). At the end of the focus groups, participants reviewed 4 wireframes (layout of an app page that demonstrates interface components) of an mHealth app with 4 intervention components: a stress rating tool, a mindfulness activity, journaling prompts, and caregiving resources [25]. Structured questions were asked about each wireframe, and participants were encouraged to share their opinions and perspectives (Textbox 1). Before the focus

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groups, the principal investigator provided an introduction regarding the purpose of the focus group and ground rules for participation, including turn taking, confidentiality, and respectful communication. To avoid dominant voices within the group, individuals were cued to provide feedback for each question during the focus group interviews. Participants could build on each other's comments and engage in group dialogue. In the case of discussion drift or a dominant voice, the principal investigator would redirect participants back to the purpose of the focus group and invite additional participation. The principal investigator used methods of deep listening, silence, probes, clarifying questions, and summarization [26]. A trained research assistant independently recorded observations in a separate document during the focus group meetings. The focus groups were recorded and transcribed verbatim. The focus groups were sequentially held until thematic saturation was achieved [27]. While the focus group interviews were offered in both English and Spanish, no participants requested Spanish interpretation during the interviews. Multiple participants identified themselves as fluent in both English and Spanish. Upon completing the focus group, participants were sent a demographic questionnaire administered through REDCap, including questions about caregiving experiences.

Textbox 1. Interview questions.

Wireframe questions

- Based on feedback from other Millennial caregivers, we have developed an app and intervention that focuses on stress, emotional regulation, and providing resources for support. We would like some feedback from each of you about what we have so far. We are sharing wireframes on the screen.
- We will start with wire frame 1, which is a stress rating scale. What do you think about this scale? Would this be helpful for you? When would it be helpful?
- We will go to wireframe 2, which is a mindfulness activity. What do you think about mindfulness? Would this be helpful for you? When would it be helpful?
- We will go to wireframe 3, which is a daily journal. It asks about what was most challenging/distressing and about what you felt most positive about for each day. What do you think about this? Would this be helpful for you? When would it be helpful?
- Now we will go to wireframe 4, which is a resource list. Looking at the headings, can you see any type of resource that would be helpful for you? Is there a type of resource that is missing?
- If you had your wish for anything to make caregiving better or easier, what would that be?
- Thank you so much for your time and participation in this study. Once again, we appreciate your contributions and the work you do as a family caregiver.

Usability questions

- What worked well for you with the app?
- What did not work well or was confusing?
- What did you like?
- What did you not like or what was missing?

Step 2

Back-end app data were collected and verified for participant use of the app. In addition, participants were asked to answer an app reliability questionnaire to identify usability issues with each app component, including mindfulness, journaling, resources, stress rating scale, and surveys. Participants engaged in a brief 15-minute Zoom interview on their experiences using the app following 1 week of use (Textbox 1). Notes were taken during these short interviews, but the interviews were not recorded or transcribed. These participants also received a gift card for their participation.

Analysis

Step 1

Demographic data were analyzed for frequencies and descriptive statistics. Data from the focus group interviews were analyzed inductively using a rapid qualitative content analysis approach by the research team for coder triangulation [28,29]. An initial read-through with open coding of the interviews was conducted with 2 members of the research team to identify the main categories for matrix creation. The matrix was then tested in a coding meeting and applied to 1 focus group interview. Matrix revision was conducted, and the matrix was then applied to the rest of the focus group interviews to identify subcategories and additional main categories. Final organization of main and subcategories was conducted, including collapsing categories where appropriate. On the basis of the main and subcategories, a summary of the recommendations for changes was then reviewed with the entire team, including the app developer. A final list of revisions was created based on user and team feedback (Textbox 2). Coders and team members addressed their positionality throughout the app revision process: 2 team members identify as family caregivers, 4 identify as millennials, and 3 identify as Latinx. Discussion of identity and how this impacts data analysis and interpretation took place to ensure that team members remained close to the data and reflected what participants communicated [28]. Notes were taken during

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data analysis and each team meeting to serve as an audit trail [28].

Textbox 2. App and intervention changes.

Changes after focus group findings

- Spanish translation
- Caregiver support plan
- Flexibility with journaling content and amount (including emotion checklist)
- Varied mindfulness options
- Resource section: caregiving, culture, and faith; physical care tips; caregiver support groups; and state-by-state resources

Changes after usability testing

- App functionality issues, including Spanish-language functionality, addressed and checked by team members
- Privacy policy reviewed and addressed as a team to ensure clarity

Future changes

- Skill-based videos
- Podcast-like caregiver interviews
- Self-care videos
- App tailoring with activities connected to stress rating scale
- Education on cloud sharing for medication information, calendar management, and the use of a shared calendar

Step 2

Back-end use data were confirmed for participant use, and reliability questionnaire data were summarized and compared to those of non-Latinx millennial caregivers for similarities and differences. Open-ended response questions were analyzed along with the brief interviews using the rapid qualitative content analysis approach described for step 1. Functionality issues reported by users were relayed to the app developer.

Results

Overview

Results are presented sequentially by step, and participants' quotes are shared with designation for the participant (P) and focus group (G). Changes made after each step are presented in Textbox 2. Categories and participant suggestions are outlined in Table 1.

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Table . Qualitative findings.

Category and subcategory	Participant suggestions
Wireframe focus group findings	
Features that participants liked	• Stress rating scale was helpful to understand mental health • Multiple mindfulness options (recording and step-by-step guide) and flexibility to use them throughout the day • Journaling prompts for challenges and good things may help with therapy • Journal and mindfulness pages were simple and not overwhelming • They liked that the integrated resources included employment-focused information
Features that participants disliked	• Writing a long journal entry on difficult days or having the journal be mandatory
Recommended additions	• Better tracking system over time for stress and journaling • Rewards and personalized notifications within the app • Tracking of stages and needs of the person they cared for, including medications and health care appointments, and having more educational information on caregiving skills • Being able to select how they felt under the journaling option with a click as an alternative to writing (both positive and negative emotions) • More flexibility with timing of activities • Include a sleep meditation • Include resources that are state specific, include more information about financial needs, and address diverse employment experiences • More social options within the app to connect with other caregivers and receive answers to questions about unique needs • Other stress-relieving activities such as gaming, music, in-app chatting, recipe sharing, coping with COVID-19, videos on managing stress, or other caregiver-preferred activities • Connect stress rating to app activities, such as what to do with high stress levels • Recommend multiple lengths of time for mindfulness (short, medium, or long)
Usability interviews	
Features that worked well	• User-friendly or not overwhelming • Spanish translation • App was helpful when stressed
Features that did not work well or were confusing	• Switching to Spanish on the app • Some days, the stress log and journal did not work • The meditation would stop playing when the phone went into sleep mode • Unclear privacy policy • Speech-to-text function did not work well
Features that participants liked	• Meditation—different meditations were useful; they liked the short length • Resources • Daily stress log • Journaling was a nice way to look back at the day
Features that participants disliked or felt were missing	• Not enough space for journaling • Ability to go back to the journal entries and edit them • Longer meditation options • More activities to help with relaxation

Step 1

Overview

For step 1 of the app and intervention revision, 29 participants took part. Of these 29 participants, 20 (69%) identified as women. Participants had a mean age of 31 (SD 4.10) years, with most (n=28, 97%) caring for an adult (sibling, parent, or grandparent) and 3% (1/29) caring for children with chronic conditions.

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Features That Participants Liked

Participants described liking the app features generally, including the stress rating scale, having multiple mindfulness options, the journaling prompts, and the resource list. Regarding the stress rating scale, they described it as being helpful in understanding stress and mental health. One participant stated that it would be "a way to keep track of what was really going on with my stress level" (P1G1). The flexibility of the mindfulness activities was noted, with P4G4 noting the importance of having options for "timing for both long and short time." Regarding a journaling question focused on the challenges of the day and a good thing that happened that day, caregivers appreciated addressing both:

> *...you can kind of look back and be like okay well least this was one good thing, and this was the thing that was bad that happened, but you always have that good in the mix of it.* [P2G4]

Regarding the integrated resources, caregivers expressed interest in the employment and financial resources:

> *I just want to compliment you all on the financial aspect down there because you know that was something that would have been really helpful for us in the beginning.* [P1G2]

Features That Participants Disliked

One concern described by caregivers was having to write a long journal entry at the end of a difficult day or having the journaling questions be mandatory:

> *...maybe sometimes you're too stressed and depending how my day went to be able to sit down and type a long journal may be a little bit hard for me.* [P1G1]

Recommended Additions

Caregivers provided multiple suggestions to improve the app both for their needs and for usability.

The need for a tracking system for stress and journaling was highlighted, including a responsive system for high stress ratings that would include app activities:

> *I love being able to, you know, track everything and then at the end of the month, or the end of the weekend, you can go back.* [P4G2]

Gamification, rewards, flexibility with the timing of activities, and personalized notifications were recommended to increase engagement:

> *...there could be a little reward encouraging to do that caregiving job.…Also if the app could have a reminder.* [P2G1]

Regarding the resource list, caregivers wanted more education about caregiving skills and space to document medication lists and health care appointments:

> *I think, for me, maybe like tips.…We were kind of really inexperienced with, you know, how to shower my grandfather.* [P1G2]

Caregivers suggested having a checklist of emotions rather than completing a full journal entry on the days when they were too tired or busy:

> *…maybe on two days I can just maybe click on how I'm feeling.* [P1G1]

Other stress-relieving activities were recommended, such as gaming, music, recipe sharing, videos for managing stress, and information on coping with COVID-19:

> *Space to add some music...I do love classical music.* [P2G1]

They also described the need for multiple lengths of time for mindfulness ("timing for both long and short" [P4G4]) and a sleep meditation ("like a night meditation" [P1G4]).

Regarding the resource list, caregivers described wanting tailored resources specific to their state, work situation, or caregiving needs:

> *...having it more where you can actually look for your particular state, because each state kind of offers different benefits.* [P2G4]

Caregivers wanted more connection with other caregivers for "a community to share problems" (P2G2) and to receive advice:

> *...it would be nice, knowing that there are other people like me, too, and we could share useful info and advice.* [P3G5]

Step 2

Overview

After app revisions were made (outlined in Table 1), a subsample (3/29, 10%) completed usability testing and included 67% (2/3) women and 33% (1/3) men. General millennial caregivers (n=3) who were fluent in English and Spanish completed usability testing concurrently, although only findings from Latinx caregivers are reported in this paper. App use, reliability questionnaire, and qualitative findings are outlined for each step in the following sections and in Table 1.

App Use and Reliability

All 3 participants completed the requested activities in English, and 67% (2/3) of the participants completed them in Spanish unless there were reported functionality issues associated with an activity reported through the app reliability questionnaire. One participant could not complete the activities in Spanish, although during the interview, this issue was clarified, with the participant not understanding how to switch from English to Spanish. The main functionality issues reported through the questionnaire were with loading the mindfulness and journaling activities. Similar issues arose for both Latinx and non-Latinx millennial caregivers. One user reported timing out of the mindfulness recordings and videos and one activity not loading at all (3 events). One participant noted the stress rating scale not recording on one day and the journaling activity not loading one day. No other functionality issues were reported.

Features That Worked Well

One participant described the app as user-friendly, "easy to implement," and not overwhelming. In total, 67% (2/3) of the

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participants felt that the Spanish translation worked well. One participant described the app as being helpful when they were stressed.

Features That Did Not Work Well or Were Confusing

For one participant, switching to Spanish did not work. During the interview, the issue was clarified, and the participant was able to then switch to Spanish. Participants noted a few glitches, such as the stress log or journal not working on some days, the meditation not working while in sleep mode, and the speech-to-text function for journaling not working well within the app. One participant described the privacy policy for the app as unclear.

Features That Participants Liked

Participants again described liking most dimensions of the app, including the meditation length and variety, the resource variety, the daily stress log, and the use of the journal for reflection on the day.

Features That Participants Disliked or Felt Were Missing

Participants recommended having more space for journaling, the ability to edit journal entries, longer meditation options, and more activities to help with relaxation.

Discussion

Principal Findings

In this study, we sought to integrate community- and user-informed design into our adaptation of an mHealth stress and well-being intervention for Latinx millennial family caregivers. The original intervention was developed for the general millennial caregiver population. Significant differences we noted in the needs and preferences between groups (general millennial caregiver population and the Latinx millennial family caregiver population) were the inclusion of other stress-relieving activities beyond mindfulness and journaling, having an option not to journal and just indicate their emotions, and having tailored employment and financial resources for their specific situations and locations that extended the resources already embedded in the app [7,8,10]. Similar to general millennial users, the Latinx users identified the need for social engagement and community [7,10].

This 2-step process of adapting and refining an mHealth app–delivered intervention for Latinx millennial family caregivers revealed the need to expand resources, such as state- and community-focused resources that address financial and employment needs. Religious and cultural information, state resources, and support groups were added to the resource list to address the need for more resources and social connection. A caregiver support plan informed by safety plans for individuals at risk of suicide [30] was created. The mHealth app and intervention were also translated into Spanish to address language access [31]. This expansion of social support resources remains aligned with the original intent of the intervention to support stress and well-being [13-15]. The addition of the emotion checklist provides more of the in-the-moment response to stress that is found with mindfulness, emphasizing awareness of the present moment and acknowledgment of one's emotions [32]. There may be a limitation for some users who only use in-the-moment responses with mindfulness and an emotion checklist versus those who have a sustained response to stress through journaling [11]. For Latinx millennial caregivers, there is an important balance in adapting interventions to align with their busy schedules while also providing a therapeutic and research- and theory-informed approach to intervention delivery [1,8,33]. With future research, we can assess whether differences in use among the emotion checklist, journaling, or both impact caregivers' stress and well-being outcomes.

We recognize that gaps remain regarding the desire for community and having resources that are tailored to the individual. This might call for a layered intervention approach that leverages mHealth and individual or group-based caregiver coaching (either in-person or remote coaching) to address these additional needs [34]. This might also require artificial intelligence solutions to pull in comprehensive, tailored, and location-based resources, such as the PaidLeave.AI platform developed by Moms First [35]. Indeed, most mHealth apps and interventions focused on family caregivers have limited functionality; thus, there is a need for multifunctional and adaptable mHealth interventions for this population [36].

While mHealth interventions have the benefit of being accessible and time-limited [37], which works well for the millennial caregiver population [38], they often do not solve larger system issues such as resource access, social isolation, navigation, and advocacy that can help this group of Latinx caregivers who are already navigating system-level barriers and power structures [39,40]. This calls for upstream interventions, which were largely outside the scope of this study but could be considered for future intervention iterations as findings and resources expand. This tightrope of addressing user feedback while not overstretching resources is a well-acknowledged challenge in product development and technology-based interventions [41]. A strength of this specific study was ensuring that stakeholder needs were addressed and shared decision-making took place [16].

Considerations for changes in the future include leveraging podcast delivery methods to share caregiver stories and skill-based and self-care content. The podcast platform is widely used by millennials and has been found to support health outcomes such as behavior change and social interaction [42,43]. For Latinx individuals specifically, the podcast platform is a growing medium [44]. Caregivers have anecdotally and in formal reports expressed the desire for a one-stop shop platform that addresses financial or employment, educational, navigation, shared care, and self-care needs [45]. Further iterations could explore the feasibility of these options [36]. One danger is the platform becoming unwieldy, difficult to use, and less reflective of stakeholder-reported needs, thereby violating the principles of simplicity and shared decision-making. Therefore, continued stakeholder feedback will be required [12,16].

Despite noted gaps in our app-based intervention currently, we believe that there are important future opportunities to address Latinx millennial family caregiver well-being. The population interviewed in this study was in early and middle adulthood, a critical life phase for adult development; they experience health

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disparities related to system-level issues regarding insurance, health care access, and economic opportunities, and they are navigating caregiving while also balancing work, family, and other social responsibilities [1,2,4,5]. Thus, their risks of long-term health consequences related to family caregiving are high, and there continues to be a gap in interventions tailored to this specific group [6]. It is important to intervene early with this population to address these health consequences that may influence their life trajectories. With our app-based intervention, we hope to meet caregivers where they are in an accessible format to support their well-being. Future research will not only continue to address cultural, contextual, and usability issues regarding this mHealth intervention but also address its feasibility, acceptability, and efficacy.

Limitations

Our study had important limitations that should be considered when interpreting our findings. First, we had an overrepresentation of female Latinx millennial family caregivers. In the Latinx millennial population, the gender split is almost even [1,2]. Due to our emphasis on a user-informed process, this overrepresentation of women could have affected our findings and subsequent intervention and app adaptations. Interestingly, this gender split is reflective of a broader trend in the literature, with women engaging more with mHealth interventions than men [46]. Future research steps should implement recruitment measures that address these gender inequalities in mHealth research. In addition, our usability testing sample of Latinx millennial caregivers was small but within the recommended parameters for usability testing. This size is adequate for problem testing but may not have been adequate for additional usability issues involving a broader and more diverse sample. We also used a disease-agnostic approach, which means that our intervention and app were not tailored to the specific disease process that these caregivers were supporting. Further iterations could address more tailored applications for disease-related issues. Finally, our sample only included participants with access to a computer or smartphone for focus group participation and a smartphone for usability testing. While the percentage of Latinx individuals in the United States with a smartphone is high (93%), there remains a proportion of the population that would have been excluded from the study [20]. This population would be more likely to be of a low income. This affects the generalizability of our findings. In future work, provision of smartphones with data plans would overcome this gap.

Conclusions

With our user-informed process, we adapted a stress and well-being intervention for Latinx millennial family caregivers. During this process, we noted the difficulty of aligning the study purposes and resources with stakeholder feedback. We acknowledge that user-informed design is an ongoing and iterative process that requires balancing the needs of stakeholders and the feasibility of the recommended adaptations. We anticipate ongoing intervention and mHealth app adaptations that address more stakeholder-identified needs, more thoroughly address the need for social connection, and are individually tailored.

Acknowledgments

This study was funded through St. David's Center for Health Promotion and Disease Prevention Research in Underserved Populations at the University of Texas at Austin and through the Myrtie Fulton Endowed Mentoring Award at Brigham Young University. The authors would like to thank Senda LLC for the technology support and Catie Cleary and Anna Welling for their contributions to the project.

Conflicts of Interest

None declared.

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Abbreviations

mHealth: mobile health
REDCap: Research Electronic Data Capture
STOP: Stop, Take a Breath, Observe, Proceed

Edited by D Dordunoo; submitted 14.03.25; peer-reviewed by C Or, T Adebambo; revised version received 04.08.25; accepted 26.08.25; published 06.10.25.

Please cite as:
Thomas Hebdon M, Dupree GD, Hernandez J, Cuevas H, Thomas M, Burt S, Peterson N, Horner SD
Stress and Well-Being Intervention and mHealth Delivery Adaptation for Latinx Millennial Caregivers: Qualitative User-Centered Design Approach
JMIR Nursing 2025;8:e73621
URL: https://nursing.jmir.org/2025/1/e73621
doi:10.2196/73621

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Interpretation of Health-Smart Home Data and Implications for Clinical Decision-Making: Inductive Content Analysis

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Abstract

Background: Health-smart home technologies offer real-time sensor-based monitoring of older adult activities of daily living, allowing for early detection of changes in health. The way clinicians interpret and use this data, particularly in visualized formats, such as bar, line, and pie graphs, remains underexplored.

Objective: A qualitative descriptive study design with a quantitative component was used to explore how nurses interpret sensor-derived health data from health-smart homes in 3 cases.

Methods: Using an inductive content analysis approach, we analyzed nurses' qualitative interpretations of existing sensor-derived health data from health-smart homes from 3 older adults living with ambient whole-home sensing. Nurses provided structured written feedback on visualized trends in sensor-derived health data, including activity, sleep, and mobility patterns.

Results: The findings highlight both opportunities and challenges of using sensor-derived health data in older adults' care. Nurses identified key patterns in sleep, mobility, and home engagement, but interpretation difficulties, such as unclear sleep metrics and lack of clinical context, hindered decision-making. Nurses preferred bar and line graphs over pie charts for interpreting these data. Survey results show a statistically significant difference in how nurses rated different graph types (χ^2_2=17.1, P<.001), with pie charts rated significantly lower than both bar and line graphs (P<.001 and P=.008, respectively). These findings underscore the need for improved data visualization and integration to enhance the clinical utility of sensor-derived health data from health-smart homes.

Conclusions: Findings indicate that nurses were able to provide accurate interpretations of the sensor-derived health data from health-smart homes. However, there is a need for improved visualization techniques and clinician training to optimize health-smart home data for early intervention. Standardized approaches to data representation could enhance nurses' ability to detect and act on subtle yet important information about older adults' health changes occurring in home settings.

(JMIR Nursing 2025;8:e75234) doi:10.2196/75234

KEYWORDS

health-smart home; digital health; data visualization; content analysis; nursing; aging-in-place

Introduction

Overview

With the global population aging and an increasing number of older adults living with chronic conditions, there is growing interest in health-smart home (HSH) technologies to support aging in place [1-3]. Traditionally, nursing homes have been the primary setting for older adult care, but concerns over the quality of care in institutional settings and a strong preference in older adults to remain living at home have led to the exploration of alternative solutions. Activities of daily living (ADLs) are routine self-care tasks, such as bathing, dressing, eating, and mobility. In the context of HSH technologies, ADLs are captured as indicators of functional health and independence. Health-smart home technologies can provide real-time, unobtrusive sensor-based monitoring of ADLs, offering opportunities for early detection of health changes [4,5]. This can help address exacerbations in chronic disease early, potentially reducing hospitalizations and unnecessary emergency department visits, and may additionally reduce costs associated with long-term residential care [6-8].

HSH technologies are particularly valuable for tracking ADLs, such as movement around the home, interest in food, toileting and hygiene, gait speed, overall activity levels, and sleep patterns [9,10]. Deviations from typical behaviors associated with these activity patterns may indicate emerging health

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concerns [11]. Aging in place, facilitated by HSH technologies, may not only support greater independence and social connectivity but also has the potential to reduce health care costs associated with long-term residential care. However, while HSH technologies generate large volumes of sensor-derived health data, their clinical utility depends on how well health care professionals, particularly nurses, can interpret and act on this information [11].

Despite the increasing adoption of data-driven decision-making in health care, little is known about how nurses interact with visualized HSH sensor data generated by older adults living with HSH technology, including bar, line, and pie graphs to assess trends and patterns in ADLs. Previous research has focused predominately on the technical aspects of HSH sensors, but there remains a critical gap in understanding how nurses interpret and use the HSH sensor data for decision-making [12]. The effectiveness of these technologies depends not only on the accuracy of HSH sensor data but also on how well meaningful clinical insights can be extracted from visual representations of that data [13].

This study uses a subsample dataset that includes clinicians' interpretations of HSH sensor data that were collected for the purpose of creating a clinician-in-the-loop visual interface for nurses observing HSH sensor data derived from continuous unobtrusive sensor-based monitoring of older adults at home. Quantified findings from the larger study are published elsewhere (Ghods et al.2018).

Distinctive to this work is our in-depth inductive qualitative analysis of narrative descriptions written by a subsample of nurses who provided clinical validation for the larger study's clinician-in-the-loop visual analytics. In this substudy, we seek to understand how nurses think about HSH sensor data in the context of symptom presentation and illuminate challenges encountered with providing meaningful and accurate clinical interpretations. While Ghods et al [14] addressed interpretation challenges as usability barriers within a developing clinician-in-the-loop analytics system, the current substudy isolates visualization types as a key factor influencing nurses' ability to interpret HSH sensor data. Rather than refining a single system, this substudy compares different visual formats to determine which best supports clinical reasoning, providing unique insights into how nurses cognitively process HSH sensor data.

Purpose of the Study

The purpose of this study was to explore (1) how nurses interpret HSH sensor data derived from ambient sensors presented in bar, line, and pie graph formats and (2) to identify the challenges nurses encounter when analyzing ADL data. By applying an inductive content analysis approach [15], this study aimed to uncover key themes in nurses' interpretations in 3 cases, assess barriers to effective data use, and provide recommendations for improving HSH sensor data visualization techniques and clinician training. The findings from this study will contribute to the development of standardized, clinically relevant HSH sensor data visualizations to enhance nurses' ability to identify and respond to early changes in health in clients living with HSH technology.

Background

A global trend is emerging around providing health services to older adults in their homes. It is now common for older adults to receive home care, and the sophistication of that care is advancing. In Australia, about 17% of the population is older than 65 years, and 20% receive formal in-home care or support [16]. In the European Union (EU), data from 2019 indicates that nearly 30% of people aged 65 years and older with difficulties in personal care or household activities used home care services [17]. In the United States, approximately 12 million people receive home health care services annually, with the majority being older than 65 years [18]. The United States Census Bureau estimates that by 2050 the number of persons aged 65 years and older will reach 83.9 million. Demand for home care services continues to grow. The United States Census Bureau survey (2020) found that between 2013 and 2020, usage of US home health care services increased 50.5% [19].

As older adults increasingly seek to remain living at home with the support of home health services, many face the challenge of managing chronic conditions that require ongoing monitoring and timely intervention. Conditions, such as cardiovascular disease, diabetes, respiratory disorders, and neurodegenerative diseases often contribute to functional decline, unplanned health care usage, and institutionalization in nursing homes. Despite the increasing use of home care services among older adults, many experience reduced access to primary care. For instance, a study found that older adults in the United States generally receive good quality primary care, but challenges persist in establishing and maintaining access, as well as involving patients in disease management [20].

Traditionally, older adults with higher acuity and more advanced health monitoring needs were transitioned into nursing homes where their health status could be more closely monitored. However, because costs are increasing while access is decreasing, this option is inaccessible or impractical for many [21-24]. In addition, a scoping review of barriers to accessing aged care services for culturally and linguistically diverse older adults in Australia identified issues, such as cultural insensitivity, language barriers, and affordability concerns, which further limit access to necessary services [25]. Similar barriers exist in the United States with older adults and informal caregivers affected [26]. The emergence of HSHs offers an alternative, allowing for continuous, unobtrusive monitoring of key health indicators while enabling older adults to remain safe in their own homes [2,11].

The increasing adoption of digital health tools in aging-in-place models presents new opportunities for remote patient monitoring [1,27,28]. Data visualization converts raw HSH sensor data into visually structured and easily interpretable graphics, improving comprehension, enabling trend identification, and simplifying the communication of complex information to diverse audiences.

However, while these HSH technologies generate large volumes of quantitative data, the way nurses interpret visualized HSH sensor data trends to inform decision-making remains understudied [12,18,29].

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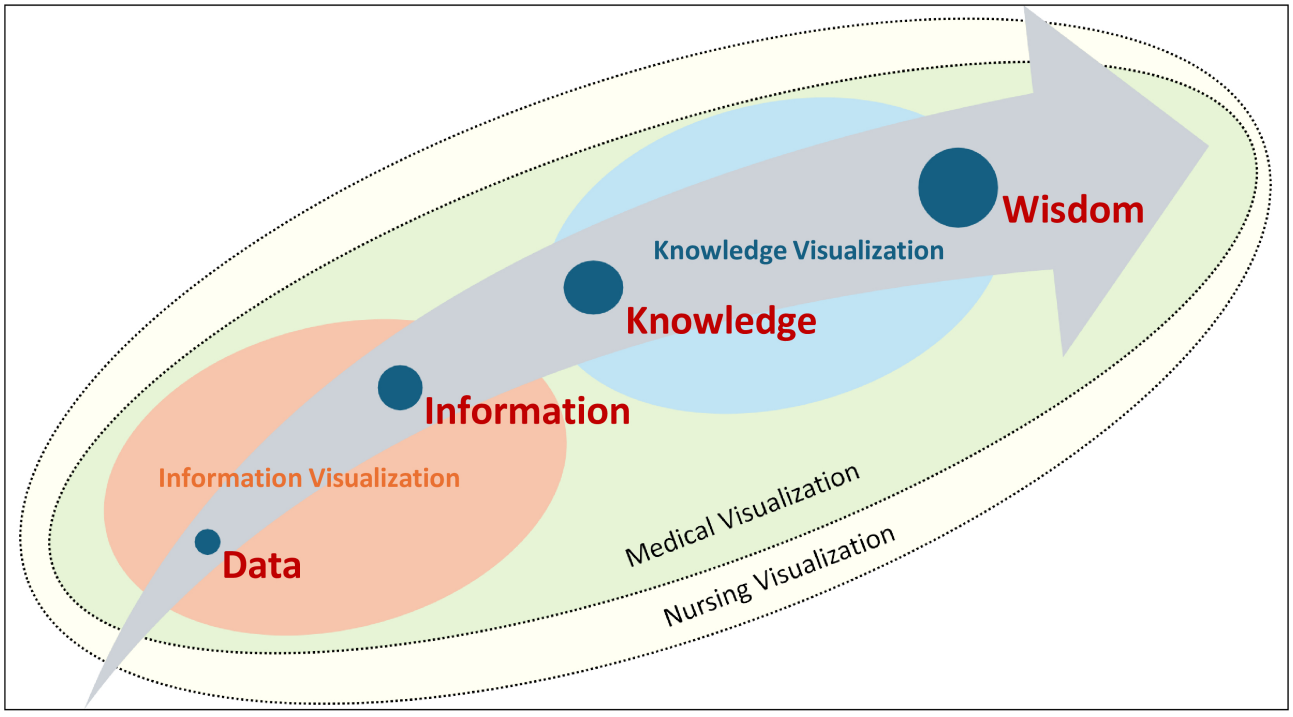
Conceptual Perspectives

In the context of HSH technologies, poorly designed visualization interfaces—whether overly complex, visually cluttered, or misaligned with clinical needs—can obscure critical insights, delaying or even compromising patient care. Optimizing data visualization for nurses requires a balance of information density, intuitive design, and real-time interpretability to ensure digital health tools enhance, rather than hinder, decision-making and workflow efficiencies [12,30]. However, little attention has been given to the visualization of HSH sensor data. Consequently, there remains an overreliance on medical visualizations that may not align with the specific needs of nursing practice.

The medical visualization field aims to advance communication of complex medical data in a way that is understandable and actionable for health care professionals (eg, graphs and interactive visuals). This includes significant advances in human-computer interaction [29,30]. Recent advances influencing medical visualization include artificial intelligence and machine learning, the growth of wearable and ambient sensor technology, demand for telehealth and remote health monitoring, integration of augmented and virtual reality, computational power and cloud infrastructure, and personalized medicine. Examples of frequently used medical visualizations include statistical data (bar, line, and pie graphs), such as those used in patient-reported outcome measures (PROMS) and quality indicator data [31], as well as time series graphs, such as electrocardiograms (ECGs) [32], and spatial imaging (computed tomography and magnetic resonance imaging) [33]. Heatmaps and color maps are used for quickly identifying patterns in biological data collected from chemical analysis [34].

Just as statistical visualizations can mislead, suggesting false patterns or concealing key trends [35], similar risks exist in HSH sensor data. Traditional medical visualizations, such as fever charts, ECG waveforms, and blood pressure trends, focus on single physiological measures, making them intuitive for clinical interpretation. In contrast, HSH sensor data integrate multiple variables (eg, sleep, mobility, and room occupancy), requiring a more complex and contextual interpretation process. Unlike a fever chart that clearly shows temperature fluctuations, HSH sensor data visualizations must convey multiple dimensions without overwhelming users or obscuring key insights. If poorly designed, they risk misinterpretation, either overemphasizing anomalies or concealing meaningful trends. Nurses must connect disparate data points, recognize patterns, and determine clinical relevance, making the choice of visualization format critical. In addition to engaging nurses with HSH sensor data visualizations, it is important to understand how their cognitive process interprets the data. Clinical reasoning in this context requires pattern recognition, contextual knowledge, and judgment about what is clinically significant, as seen in the HSH sensor data visualizations. Effective visualizations must support, not hinder, this process, ensuring that critical health insights are easily identified and acted upon. When designing visualizations, it is important to consider the data-to-wisdom continuum and how information visualization (transforming data into useful information) and knowledge visualization (transfer of knowledge between humans) play key roles in assisting with wise clinical decision-making [12,36-39]. The data-to-wisdom model illustrates the progression of raw data to valuable, actionable insights [40]. For nurses working with HSH sensor data, the transformation from data to wisdom goes beyond medical information to include patients' in-home situational context (ie, social and economic health determinants; Figure 1).

Figure 1. Data to wisdom continuum in the context of health-smart home data visualizations, which includes medical visualizations and much-needed nursing visualizations.



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Data Visualization in Nursing Decision-Making

Previous research has explored the relationship of data visualization dashboards and quality of care and clinicians' satisfaction. Findings suggest that well-designed data visualizations improve efficiency by reducing cognitive load, enhancing pattern recognition, and supporting predictive analytics for patient care [12]. Medical visualizations are typically suited for discrete, physiologic measures (eg, temperature, ECG waveforms, and blood pressure), designed for rapid detection of deviations from a norm. By contrast, nursing visualizations often need to integrate multidimensional and contextual information (eg, ADLs, mobility, sleep, and room use), reflecting functional health and daily living patterns over time rather than isolated biomedical parameters [29,38]. While data visualization tools are well-established in acute care settings, such as adult intensive care units [12,39], their application in community-based settings such as home care remains underexplored. As health care increasingly shifts toward aging in place and remote monitoring, a growing opportunity exists to leverage HSH technologies to enhance care coordination [41]. HSHs equipped with passive sensor-based monitoring systems can provide real-time data on ADLs, mobility patterns, and other key health indicators [42]. By integrating remotely collected HSH sensor data streams into meaningful visual representations, clinicians, particularly nurses, could effectively interpret trends, identify early signs of health deterioration, intervene proactively, and work more efficiently [43]. We emphasize nurses because they are the largest group of health care professionals globally and play a central role in monitoring ADLs and functional health, particularly in community and aged care contexts where HSH technologies are most relevant. While this study refers to nurses generally, future work could examine whether visualization needs differ across contexts, such as geriatric care or assisted living. This transition from institutional to HSH sensor data visualization introduces new challenges and opportunities in designing user-friendly, clinically relevant interfaces that support remote decision-making and optimize patient outcomes [43].

Nurses' Interpretation of HSH Data

For decades, nurses have provided health care services to people in their homes. They collect physiological, psychosocial, and functional data that informs health care decisions [44]. Integrating remotely collected HSH sensor data of community-dwelling clients into nursing practice could enhance patient monitoring, speed up the recognition of changes in health, and promote early and proactive interventions. Studies have demonstrated that continuous HSH sensor-based monitoring in home settings enables automated detection of health events, allowing nurses to initiate preventive strategies and provide timely interventions [11]. In addition, research indicates that HSH sensor technology can detect early signs of health changes, sometimes even before patients become aware, facilitating early detection and management of health deterioration [27]. These findings support the potential of HSH technologies to augment traditional nursing assessments, leading to improved patient outcomes and supporting aging in place [11,28].

Equally critical is the design of HSH sensor data that is transformed into visualizations, which must strike a balance between simplicity and utility [38]. For nurses to leverage these tools effectively under the time pressures and cognitive demands of clinical practice, these visualizations must be intuitive and accessible, requiring minimal training to interpret, while retaining the depth and precision necessary to support meaningful interpretation and decision-making [29]. Poorly designed interfaces—whether overly complex, visually cluttered, or functionally clunky—may result in nurses not having actionable insights, posing a risk of undermining the very efficiencies and improvements that digital health tools aim to deliver [30]. Thus, understanding nurses' interaction with HSH sensor data visualizations and optimizing design are twin imperatives for advancing care delivery in HSH technology-enabled settings.

Research Questions

This study aimed to explore:

1. How nurses interpret HSH sensor data visualizations and the clinical implications of their interpretations.
2. How nurses interpret bar, line, and pie graphs displaying HSH sensor data?
3. What patterns and challenges emerge in their analysis of patient activity, sleep, and mobility?

Methods

Study Design

This study used a qualitative descriptive design with inductive content analysis, an approach well-suited for exploring participants' experiences, perceptions, and insights [15,45]. Qualitative descriptive research focuses on exploring participants' experiences and perspectives, staying close to their words and meanings without extensive interpretation or theoretical abstraction [46], making it particularly valuable in health care research where understanding practical applications and real-world experiences is essential.

Sample and Recruitment

This study used a combination of purposive and convenience sampling to recruit participants with relevant expertise in nursing practice, health informatics, and education. Purposive sampling was used to ensure the inclusion of Registered Nurses (RNs) with at least 5 years or more experience working in clinical practice, clinical decision-making, and exposure to health informatics.

Convenience sampling was applied due to the accessibility of participants within academic and professional networks. Recruitment was conducted via course announcements, professional networks, and targeted email invitations. Study participants (N=14) were experienced RNs who were either (1) enrolled in a Doctor of Nursing Practice Family Nurse Practitioner program at a university in the Pacific Northwest region of the United States and were completing a graduate course in health informatics or (2) nursing faculty from various schools of nursing (associate, bachelor's, or graduate nursing degree programs) in the Pacific Northwest region of the United

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States. All participants held a bachelor's or higher nursing degree from accredited nursing schools in the United States, and all were female. Age was not obtained. The sample for this substudy is a subset of a total RN sample of (N=60) described elsewhere (Ghods et al [14]). The nursing text-based data analyzed here were provided by the nurses (N=14) who provided clinical validation for the larger study.

Research Team and Reflexivity

All researchers (RLF, DJC, and GD) held academic positions in research-intensive universities. DJC held an academic position in engineering; RLF and GD taught in various nursing programs All reserachers are females with PhDs. RLF and GD are RNs with extensive clinical nursing experience spanning several decades. All have have expertise in deploying health-smart homes and conducting qualitative and mixed research. In addition, they have personal experience caring for frail older family members, including those with dementia, which informs their vested interest in advancing the integration of health-smart homes into new models of care. RLF introduced the study and full study purpose to the potential participants. Participants were not interviewed; instead, they provided written responses.

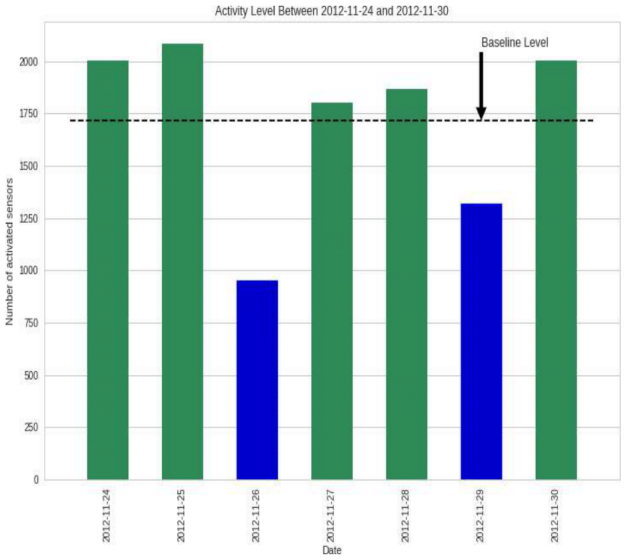
Data Collection Approach

Nurses who consented to the study were sent an asynchronous email with a Microsoft PowerPoint document (without audio-video) with a 5-slide, written explanation of the health-smart home as well as a short instruction manual on how to use the interactive data visualization tool prepared using Grafana, which was accessible using a web link. All study activities were completed in the private time of the participants. The Microsoft PowerPoint presentation introduced 3 participant cases, each with background information, including biological sex, age, primary diagnosis, and a specified 7-day period for analysis. The cases were purposively selected to represent variation in age and diagnosis among older adults living alone, which was consistent with the study aim of exploring how nurses interpret HSH sensor data relevant to community-dwelling older adults: (1) Case 1 was an 87-year-old female with lung cancer undergoing daily radiation treatments, (2) Case 2 was a 92-year-old female with nonspecific insomnia, and (3) Case 3 was an 89-year-old female with no medical history provided. Nurses were provided with a home floor plan with sensor placements and multiple Grafana-generated HSH sensor data visualizations, including bar graphs for activity levels and sleep duration (weekly and monthly), line graphs for sleep interruptions and walking speed (weekly and monthly), and pie charts representing time spent in different home locations (weekly and monthly). While 31-day visualizations were provided for context, the health event of interest occurred within a specified 7-day window, which was the primary focus of analysis and purposefully selected by the researchers. Nurses could draw on either the 7-day or 31-day visualizations when making their interpretations, but the health event of interest was located within the defined 7-day window. The HSH sensor data used in the visualizations for this study were from the HSH sensors placed in the homes of community-dwelling older adult participants from multiple health-smart home studies conducted at Washington State University's Center for Advanced Studies in Adaptive Systems [47]. An example of the visualizations provided to participants is shown in Figure 2. Nurses accessed the Grafana Dashboard to review these HSH sensor data visualizations and respond to structured questions based on the specific data window required.

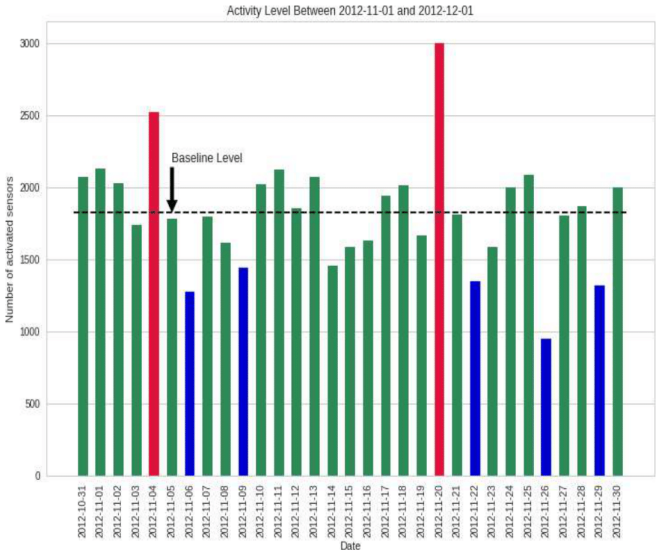
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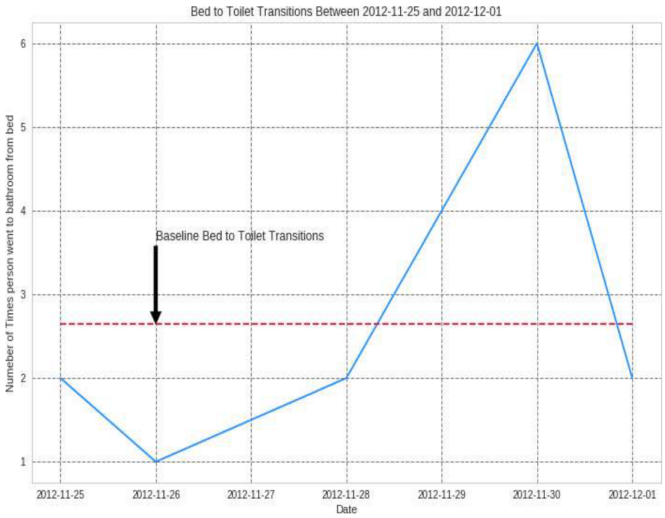
Figure 2. Exemplar health-smart home sensor data visualizations that Registered Nurse participants were asked to interpret.

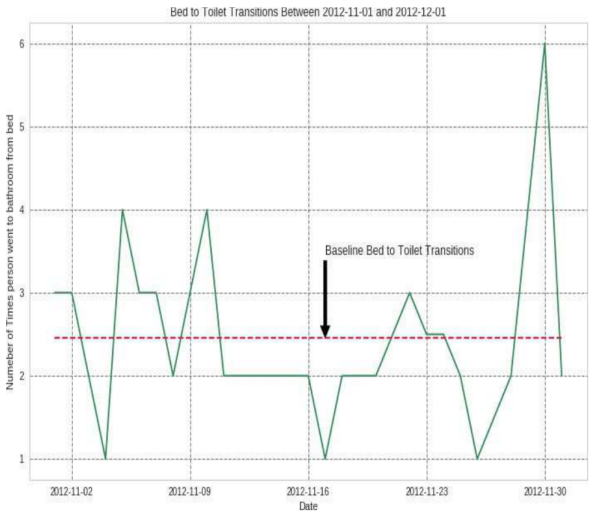
Week

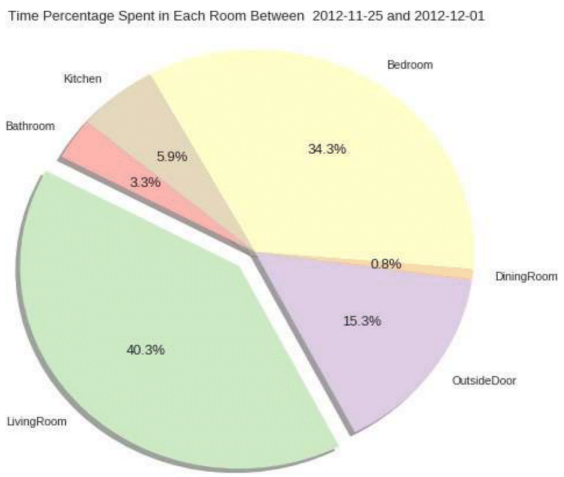


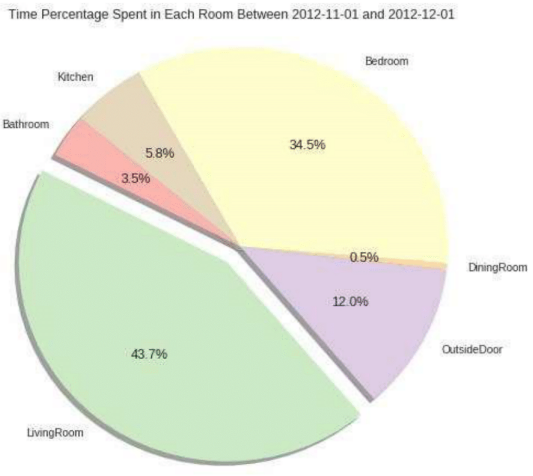
Month











HSH sensor data included passive infrared motion, temperature, humidity, light, and door use (magnetic) contact sensors placed on the ceilings and walls of older adults' residences. To facilitate data exploration and pattern identification, Grafana was used

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to generate a dashboard with interactive visualizations of the HSH sensor data. The details on how the visualizations were developed are described elsewhere [14]. Grafana is an open-source data visualization and monitoring platform that integrates with various data sources, including Prometheus (a monitoring system for collecting and querying time-series data), InfluxDB (a high-performance database designed for time-stamped HSH sensor data), and MySQL (a widely used relational database for structured data storage). These integrations enable Grafana to aggregate and display real-time and historical health-related data, making it a valuable tool for nursing research, digital health applications, and HSH monitoring.

Participants responded to a combination of 9 structured questions (1 open-ended) and a 7-point Likert scale survey, adapted specifically for this study [48], which was not pilot tested. The structured questions (Textbox 1) aimed to assess nurses' interpretations of the visualized data and their perceptions of its usability. Participants were asked to identify any changes in health status or events, describe their clinical interpretations based on the graphs, and specify which charts they used in their decision-making. Additional questions explored graph interpretability, including which visual formats were easiest to use, how the graphs could be improved, and whether alternative graph types would better represent specific data points (eg, activity level, sleep duration, and walking speed). Participants also provided general feedback on the overall usefulness of the visualizations, indicated whether any relevant information was missing or unnecessary, and offered suggestions for redesigning the graphs (eg, modifications to colors, axis scales, or graph types). Finally, participants recorded the approximate time spent on the tasks, providing insight into the cognitive workload associated with interpreting the data.

Textbox 1. Structured questions

- What change in health status or health event (if any) do you identify for this patient?
- What clinical interpretations would you make about this patient based on these graphs?
- Which charts did you use to make your interpretations?
- Which types of graphs were easiest to interpret? How could these graphs be improved to make them easier and more efficient to interpret?
- Would it be more useful to see any of the characteristics (ie, activity level, sleep duration, sleep interruptions, walking speed, and percentage of time spent in locations) represented by a different type of graph?
- Please comment on the overall usefulness of the graphs.
- Is there any information you would like to see on the visualization that is not present? Is there any existing information on the visualization that was not useful to you?
- Please provide any comments or suggestions you have about how you would redesign this visualization (eg, colors, type of graph or chart, scales of x and y axes).
- Please record the approximate amount of time you spent working on these tasks.

Survey

The Post-Study System Usability Questionnaire (PSSUQ), developed by Lewis [48], is an 18-item instrument designed to evaluate user satisfaction with system usability, structured around 3 factors, namely System Usefulness, Information Quality, and Interface Quality. The scale uses a 7-point Likert format (1=strongly agree and 7=strongly disagree), with high internal reliability (Cronbach α=0.97).

For this study, an adapted version of the PSSUQ was used, comprising 11 selected items tailored to assess nurses' perceptions of smart home data visualizations. The modifications ensured relevance to clinical usability, ease of interpretation, and decision-making support while maintaining the original scale's structure and reliability. The survey was used to gain preliminary insights into the participants' views on the usability and clinical relevance of the different visualization types, including bar, line, and pie graphs (Table 1). The selected 11 items align with established principles of usability assessment, particularly in the context of health informatics and clinical decision support tools. These questions assessed key domains of visualization effectiveness, ensuring that the presented data support accurate interpretation and informed clinical decision-making. Participants were instructed to rate each statement for each visualization graph type (bar, line, and pie) on a 7-point Likert scale, with response options of 1 (strongly agree), 2 (agree), 3 (somewhat agree), 4 (neutral), 5 (somewhat disagree), 6 (disagree), and 7 (strongly disagree). A numbered scale from 1=strongly agree to 7=strongly disagree was displayed at the top of the questionnaire to ensure clarity in response options. In selecting a 7-point Likert scale over a 5-point scale, the goal was to enhance response sensitivity and capture more nuanced participant perceptions. However, the primary goal of this study was not to generalize statistical findings, but rather to provide contextual and quantifiable information to gain additional insights into the qualitative exploration of nurses' interpretations of the HSH sensor data visualizations. The idea was that the Likert-scale responses would offer structured insights into the qualitative perceptions of usability and data clarity while maintaining the exploratory nature of this research.

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Table . Health-smart home survey.

Interpretation	Meaning
Comprehensibility and ease of use	
• "Overall, I am satisfied with how easy it is to understand the visualization of the data." [P1] • "The information provided by the visualization was easy to understand." [P6] • "The organization of the visual data was clear." [P7]	These items assess cognitive load and how intuitively nurses can interpret the data without additional explanation, an essential factor in clinical decision support.
Interpretation and clinical meaning	
• "I was able to efficiently interpret the visual data." [P2] • "The visual data is presented in a clinically meaningful way." [P9] • "I am confident that visualizing data in this format would allow me to identify clinically meaningful change in health status." [P10]	These items measure the effectiveness of the visualization format in enabling clinicians to recognize trends, patterns, and health changes in a way that informs practice.
Usability and workflow integration	
• "I felt comfortable interpreting this visualization." [P3] • "I believe I could become productive quickly using this visualization." [P4] • "It was easy to find the information I needed in this visualization." [P5]	These statements reflect usability heuristics, such as learnability, efficiency, and confidence in decision-making, which are critical for technology adoption in nursing.
Data completeness and satisfaction	
• "The visualization contains all of the information I would expect it to have." [P8] • "Overall, I am satisfied with this visualization." [P11]	These items assess perceived completeness and user satisfaction, which influence engagement and continued use of visualization tools in clinical settings.

Data Analysis Approach

Text-Based Evaluation Data

This study used general inductive content analysis [15] to analyze nurses' written feedback on structured questions related to HSH sensor data visualizations, including graphs depicting sleep, activity, and mobility trends of 3 smart home participant cases. Content analysis is a systematic and objective research method used to describe and quantify phenomena, often applied to document analysis. It enables researchers to organize data into meaningful categories, assuming that words and phrases classified together share a common meaning [15,49]. This approach helps test theoretical concepts, derive insights, and generate practical knowledge [50]. By applying an inductive content analysis approach, this study aimed to uncover key themes in nurses' interpretations, assess barriers to effective data use, and provide recommendations for improving data visualization techniques and clinician training. The goal of the researchers was to capture the breadth and depth of participant feedback to ensure a comprehensive understanding of the data. Accordingly, for this study, data saturation was not the intended criterion for determining adequacy of data; rather, the approach focused on ensuring exploration of participant perspectives and identifying patterns and variations in responses. Therefore, the analysis aimed to reflect the full range of participant experiences rather than achieving theoretical saturation. Data were analyzed by GD and RLF following a 3-phase inductive process described by Thomas [15]. In Phase 1 (open coding), 2 researchers (GD and RLF) independently reviewed participants' responses, identifying key statements and applying initial descriptive codes. In Phase 2 (categorization), similar codes were grouped by GD and RLF into broader categories to reflect patterns in how nurses engaged with the visualizations. In Phase 3 (theme development), categories were synthesized (GD and RLF) into higher-order themes, representing overarching interpretations of how the visual data were perceived and used. Throughout the process, the researchers engaged in reflexive discussions to ensure that the themes emerged from the data rather than being imposed. To enhance trustworthiness and rigor, both researchers independently coded the data and then met to compare interpretations, resolving discrepancies through discussion. Manual coding was used by GD and RLF to maintain close engagement with the data, rather than relying on qualitative analysis software. Representative participant quotations were selected to illustrate each theme, ensuring transparency in how interpretations were derived from the raw data. Participants were not asked to provide feedback on the findings.

Survey

Descriptive statistics were computed using SPSS (version 30; IBM Corp) to summarize participants' perceptions of the 3 visualization types (bar, line, and pie). Mean and SD values were calculated for each of the 11 survey items across the 3 visualization types. Given the Likert scale structure (1=strongly agree and 7=strongly disagree), lower mean scores indicate stronger agreement with a statement, while higher mean scores indicate greater disagreement. These summary statistics provided an initial assessment of perceived usability, interpretability, and clinical relevance across the 3 visualization types. Since participants responded to the same set of 11 survey items for all 3 visualization types, the dataset was treated as repeated measures, allowing for within-subject comparisons. A Friedman test was conducted to determine whether there were significant

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differences in ratings across the 3 visualization types. The Friedman test is a nonparametric alternative to repeated-measures ANOVA, appropriate for ordinal Likert-scale data and small sample sizes (N=14). To ensure that within-subject variability was preserved, each individual response across all 11 survey items was included in the analysis rather than averaging responses at the participant level.

If a significant difference was detected, post hoc pairwise comparisons were conducted using the Wilcoxon signed-rank test, a nonparametric test for paired samples, to identify specific differences between graph types (bar vs line, bar vs pie, and line vs pie). An alpha level of .05 was used to determine statistical significance for all analyses [51].

Ethical Considerations

This study was determined to be exempt research by the Washington State University Office of Research Assurances (Institutional Review Board number 16457). Participation was voluntary, with informed consent, and participants could withdraw at any time before submitting their responses, which were treated privately and confidentially, ensuring autonomy and adherence to ethical research principles. For those enrolled in courses, participation had no bearing on grades or academic standing, ensuring that responses were given freely and without obligation. After participants submitted their responses, all written responses were deidentified, and the associated email was deleted, making it impossible to retract or exclude a response after submission. Compensation was not offered.

Results

Text-Based Evaluation Data

All RNs (N=14) responded to the structured questions for each of the 3 smart home participants and completed the 11-question Likert scale survey. No participants withdrew. All participants answered all structured qualitative questions in writing across the 3 smart home participant cases and completed the 11 survey questions for bar, line, and pie visualizations. The average time reported by participants spent working on reviewing the health-smart home data visualization across all 3 smart home participant cases and providing written responses was 71 minutes.

Inductive Content Analysis of Nurses' Evaluations

Case 1

The qualitative analysis of nurses' evaluations of HSH sensor data visualizations for smart home participants Case 1, an 87-year-old female living on her own with a diagnosis of lung cancer undergoing radiation treatments 5 days per week, revealed four overarching themes: (1) sleep disruptions and nocturnal activity, (2) mobility declines and fatigue-related activity fluctuations, (3) home environment usage and social engagement, and (4) challenges in interpreting smart home data. These themes reflect how nurses interpreted the patient's sleep, mobility, and activity patterns, as well as the challenges they encountered in using HSH sensor data visualizations for clinical decision-making.

Sleep Disruptions and Nocturnal Activity

Nurses identified significant sleep disturbances in smart home participant Case 1, particularly in relation to the patient's radiation treatment cycle. HSH sensor data visualizations showed erratic sleep patterns, with poor sleep the night before treatment and longer rest posttreatment, which nurses linked to fatigue and recovery. In addition, frequent nocturnal awakenings and bed-to-toilet transitions were observed, leading nurses to speculate on possible urinary issues, discomfort, or pain-related sleep disruption. One nurse noted, "Sleep is being interrupted," (P12) while another highlighted the increasing bed-to-toilet transitions, stating:

> *She had less transitions from bed-to-toilet after her radiation and then slowly increased in frequency over the week.* [P4]

One participant noted that more information is needed to make clinically relevant inferences, noting:

> *Only looking at night-time use of bathroom does not give me a good enough clinical picture. Was there something that occurred during the before the nighttime of increased bathroom use that would explain it? (increased consumption of liquids, change in meds?) To many unknowns to draw meaning here.* [P14]

In addition, a recurring challenge was distinguishing true sleep from inactivity, as nurses noted uncertainty in interpreting whether long sleep durations indicated restful sleep or prolonged immobility due to illness or fatigue. One participant expressed this challenge, stating:

> *It is hard to tell if she is getting up or just rolling around.* [P2]

Some nurses suggested anxiety before treatment may have contributed to pretreatment sleep loss, as one remarked:

> *The patient slept very little and poorly the night before radiation treatments.* [P5]

Clinical Implications

Nurses linked sleep disturbances in smart home participant Case 1 to health status and treatment effects, emphasizing the need for improved sleep monitoring methods.

They suggested potential interventions to address nocturia and anxiety-related sleep loss, highlighting the importance of assessing sleep in conjunction with other clinical indicators. However, one participant noted that more information was needed to make clinical inferences:

> *Patient with more sleep interruptions last ½ of month. This could be clinically relevant, depending on the diagnosis and medications/doses (or changes in meds/doses). Need more context. As is, cannot infer anything.* [P14]

Mobility Decline and Fatigue-Related Activity Fluctuations

HSH sensor data visualizations for smart home participant Case 1 indicated progressive mobility decline, which nurses

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interpreted as radiation-related fatigue. A noticeable reduction in walking speed was observed throughout the treatment cycle, with the slowest movement occurring on the fourth and fifth treatment days. One nurse noted:

> *Thursday and Friday (4 - 5 treatments of Radiation), the patient's walking speed slows due to fatigue, pain, and/or discomfort and the patient takes a significantly longer time getting to the bathroom at day 4 or 5 of radiation.* [P5]

Another participant observed:

> *The participant's walking speed declined progressively throughout the treatment week, with the slowest movement observed on the fourth and fifth treatment days.* [P3]

Nurses also noted increased sedentary behavior, as smart home participant Case 1 spent more time with "less activity on the third and sixth days of this week" (P10), or sitting post treatment, which they attributed to fatigue, pain, and overall physical decline. One participant described this as:

> *The patient spends a lot of time watching TV and being sedentary in the living room.* [P5]

In addition, delayed and more difficult bathroom transitions were observed, leading some nurses to express concern about increased fall risk, particularly toward the end of the treatment week. One nurse warned:

> *This patient could experience an increased risk for falls due to the number of bed transfers.* [P4]

Clinical Implications

Nurses emphasized the need for closer monitoring of mobility patterns in smart home participant Case 1, particularly in relation to fall risk and functional decline. They suggested that gait assessments and tracking bathroom transitions over time could provide early warning signs of worsening fatigue and mobility impairments.

Home Environment Usage and Social Engagement

HSH sensor data visualizations for smart home participant Case 1 provided insights into daily routines and home environment use. Nurses observed consistent room usage, with most time spent in the bedroom and living room, while minimal time was spent in the kitchen and dining areas. One participant noted:

> *Minimal time in the bathroom and kitchen. Equal time in living room and bedroom. Time is spent outside.* [P1]

This led to speculation about possible reduced meal preparation and food intake, suggesting potential nutritional concerns. Limited outdoor activity was also noted, with smart home participant Case 1 leaving home primarily for medical appointments. Some nurses speculated that frequent door openings could indicate smoking habits or social visits, though this remained unclear. One participant questioned:

> *There were periods of time where the door would open and close and then open and close again minutes later throughout the day, I wondered if possibly the patient was going outside to smoke but that could just be my bias.* [P11]

Clinical Implications

Nurses highlighted fatigue-related lifestyle changes that may require nutritional support and strategies to promote social engagement for smart home participant Case 1. Understanding patterns of home and community interaction may provide useful indicators of overall well-being and functional status.

Challenges in Interpreting Smart Home Data

Despite the valuable insights provided by the HSH sensor data visualizations, nurses faced multiple challenges in interpretation for smart home participant, Case 1. Walking speed metrics were particularly difficult to assess, as nurses questioned whether changes reflected fatigue, pain, or another condition. One participant expressed confusion, stating:

> *I do not know how to interpret walking speed. What is the unit of measure? Does walking slower mean the patient was in pain? More sleepy? Less alert?* [P6]

Sleep data interpretation was another challenge, with nurses struggling to differentiate between sleep and prolonged inactivity and lacking more context, making it harder to determine true sleep quality.

> *Is the baseline specific to the patient? Or is it a standardized baseline? I wonder why the slow increase in sleep hours in the week?* [P13]

Another participant noted:

> *On the previous graph, 11/30 showed that the patient slept more hours than usual. I think perhaps what the graph was showing was how many hours they were in bed and not how many hours they were sleeping as this graph shows the patient was up 6 times to go to the bathroom.* [P6]

One participant remarked:

> *Patient with more sleep interruptions last ½ of month. This could be clinically relevant, depending on the diagnosis and medications/doses (or changes in meds/doses). Need more context. As is, cannot infer anything.* [P14]

Regarding data visualization, nurses found that line graphs and trend analyses were more useful, whereas pie charts were seen as less informative. One participant stated:

> *I used the graph charts and the links to the sensor data. The pie chart didn't provide much information.* [P1]

In addition, nurses noted that raw sensor data alone lacked sufficient clinical context, reinforcing the need for integrating HSH sensor data with clinical benchmarks to enhance usability.

> *Not sure what was happening on 11/26, was the patient not home? I could look at the raw sensor data, but not sure if that would answer the question.* [P13]

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Clinical Implications

Nurses emphasized the need for enhanced data visualization techniques, including clearer reference values for mobility metrics and improved methods for interpreting sleep data for smart home participant Case 1. They also highlighted the importance of pairing HSH sensor data with clinical evaluations to ensure that findings are clinically meaningful and actionable. In summary, nurses effectively used HSH sensor data to identify key patterns related to sleep, mobility, and home activity in smart home participant Case 1, linking these trends to radiation therapy effects, fatigue, and potential health risks. However, challenges in data interpretation highlighted the need for improved contextualization, enhanced data visualization, and clearer clinical benchmarks to optimize the integration of smart home technology into patient care.

Case 2

The qualitative analysis of nurses' evaluations of HSH sensor data visualizations for smart home participants Case 2, a 92-year-old female living alone with a diagnosis of nonspecific insomnia, revealed four overarching themes: (1) chronic sleep disruptions and nighttime activity, (2) nighttime bathroom usage and health implications, (3) activity patterns: stability with periodic declines, and (4) low engagement and reduced activity levels. These themes illustrate nurses' interpretations of the patient's sleep, mobility, and home environment usage while highlighting the challenges they encountered in making clinical assessments using HSH sensor data visualizations.

Chronic Sleep Disruptions and Nighttime Activity

Nurses identified severe sleep disturbances in smart home participant Case 2, with erratic sleep patterns making it difficult to establish a consistent sleep schedule. HSH sensor data visualizations revealed alternating periods of no sleep and oversleeping, suggesting disordered sleep cycles.

Frequent nocturnal awakenings were also common, with the participant waking between 2 and 8 times per night. One nurse noted:

> *On average there were 5 hours of sleep and a few times there were 9 hours or below 2 hours.* [P1]

Another participant highlighted the frequency of awakenings, stating*:*

> *Frequently disturbed sleep, with some periods of being considerably disrupted.* [P2]

Poor sleep hygiene was also a concern, with some nurses speculating that bedroom use patterns indicated nonsleep activities, such as watching television. In addition, nurses noted inconsistencies in HSH sensor data visualizations, with one nurse commenting:

> *She does not appear to have a decrease in sensor activity that would allow me to interpret her amount of sleep.* [P4]

This raised concerns about whether HSH sensor data visualizations could reliably differentiate true sleep from stillness or inactivity. The potential relationship between different patterns, such as insomnia and slower walking, was noted:

> *Most of the month she is moving slower than her norm. Not sure this has anything to do with insomnia, or maybe insomnia is only one of the factors affecting walking speed.* [P14]

Clinical Implications

Nurses recommended improved sleep monitoring techniques to better distinguish sleep from prolonged stillness. In addition, they suggested potential sleep hygiene interventions to optimize conditions for sleep and reduce nighttime awakenings. Given the frequent disruptions, some nurses also proposed further evaluation for nocturia or an overactive bladder as a possible contributor to fragmented sleep.

Nighttime Bathroom Usage and Health Implications

A consistent finding in smart home participant Case 2 was the impact of frequent nighttime bathroom trips on sleep quality. The participant exhibited high rates of nighttime bed-to-toilet transitions, with increased bathroom visits before and after sleepless nights. One nurse observed:

> *Her bed-to-toilet transitions are above her baseline over 50% of the time.* [P4]

Another nurse noted:

> *Patient's sleep interruptions varied from being below her baseline half of the month and spikes in the middle and end of the month showing she was interrupted more frequently to go to the bathroom (6 - 8 times) 'Why is the baseline different for the week and the month?'* [P8]

Some nurses speculated that the participant may have undiagnosed urinary issues, such as nocturia or an overactive bladder, which exacerbated insomnia. One nurse suggested:

> *She has an overactive bladder and needs evaluation to rule out other possibilities related to her urinary health or dietary plan (too much caffeine).* [P12]

Fluctuations in bathroom visit frequency were also noted, with spikes occurring at certain times of the month, raising questions about whether this pattern correlated with medications, sleeplessness, hydration habits, or other health factors.

> *More trips to the bathroom occur when the patient is not sleeping well, or does the patient not sleep well because always getting up to the bathroom?* [P13]

Clinical Implications

Nurses recommended further clinical evaluation for nocturia or overactive bladder, given its potential role in disrupted sleep patterns. They also suggested tracking fluid intake, medication use, and other behavioral factors to assess whether they contributed to nighttime awakenings. However, additional clinical correlation was deemed necessary to determine whether nocturia was a primary cause of sleep disturbances or a secondary effect of another condition.

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Activity Patterns: Stability with Periodic Declines

The overall activity levels for Patient Case 2 remained relatively stable, but nurses observed fatigue-related fluctuations that affected mobility. The patient's baseline activity level was generally consistent, but some days exhibited extreme drops. One nurse noted:

> *The patient was close to her baseline activity most of the month with 4 days of increased activity. She had 7 days of the month where she was below her activity baseline.* [P7]

Fatigue-related declines in mobility were particularly evident after nights of poor sleep, leading nurses to speculate that sleep deprivation contributed to daytime inactivity. One participant stated:

> *Walking speed decreased for about one week out of the month.* [P2]

However, occasional spikes in activity were also noted, leading some nurses to question whether these fluctuations were linked to medication effects, visitors, or anxiety-related restlessness. One nurse commented:

> *This patient had a huge increase in their relative walking speed the week in focus compared to the entire month.* [P4]

Clinical Implications

Nurses emphasized the need for regular mobility assessments to monitor gait stability and assess fall risk. Some nurses suggested that walking speed data required clearer reference points to determine whether changes were clinically significant or within normal variability. Others proposed that increased mobility episodes could be linked to anxiety or restlessness, warranting further evaluation.

Low Engagement and Reduced Activity Levels

HSH sensor data visualizations revealed patterns of low engagement and limited activity within the home environment. Nurses observed that Patient Case 2 spent most of the time in the bedroom and living room, with minimal time in the kitchen or other areas. One nurse noted:

> *Majority of time is in bedroom, rarely outside. Not using work area (not sure what this is). Little time in kitchen but could be prepping food and eating in another room.* [P1]

Another participant speculated that this pattern reflected social withdrawal or reduced motivation for daily activities

> *Patient spends the majority of her time in her bedroom and living room. She spends very little time in the other rooms. She is in the bathroom more than she is in the kitchen and dining room. She doesn't go outside or lets in visitors much.* [P7]

While activity levels remained mostly low and stable, occasional short bursts of movement were observed. Some nurses speculated that these brief periods of increased movement might be linked to anxiety, discomfort, or external factors.

Clinical Implications

Nurses recommended further assessment of the patient's social and emotional well-being to determine whether isolation, depression, or other mental health factors contributed to low engagement. In addition, some suggested that light physical activity or a structured daily routine might help reduce prolonged sedentary behavior. Given the minimal kitchen use, nurses also recommended tracking mealtime routines to assess for dietary concerns.

In summary, nurses interpreted HSH sensor data visualizations from smart home participant Case 2 to identify chronic sleep disruptions, frequent nighttime awakenings, fluctuations in mobility, and patterns of low engagement. While the HSH sensor data visualizations provided valuable insights into daily routines and health behaviors, nurses faced challenges in data interpretation, particularly in distinguishing true sleep from stillness, assessing the clinical significance of mobility changes, and linking nocturnal bathroom usage to underlying conditions. These findings highlight the need for improved contextualization, enhanced data visualization techniques, and clearer clinical reference points to optimize the integration of smart home technology into patient care.

Case 3

The qualitative analysis of nurses' evaluations of HSH sensor data visualizations for smart home participants Case 3, an 89-year-old female living alone without a medical history provided, revealed five overarching themes: (1) fluctuating sleep and activity patterns, (2) increased nighttime bathroom trips and their impact on sleep, (3) walking speed decline and mobility variability, (4) home usage patterns and sedentary lifestyle, and (5) challenges in data interpretation and clinical context. These findings reflect nurses' interpretations of the patient's sleep, mobility, and home environment usage, as well as the limitations they faced in drawing clinical insights due to missing medical history.

Fluctuating Sleep and Activity Patterns

Nurses observed erratic sleep behaviors and inconsistent activity levels, making it difficult to establish a stable daily routine for Case 3. The HSH sensor data visualizations indicated persistent low sleep levels, with frequent awakenings affecting rest. Sleep duration ranged from as little as 3 hours to over 7 hours, with no discernible pattern. One nurse noted, "Average 5 - 7 hours' sleep. Few greater and one 3 hours" (P1). In addition, nighttime restlessness was evident, as HSH sensor activity remained high even during supposed sleep periods. One nurse noted, "great variety in sleep with more fluctuation towards the end of the month" (P6). Another nurse noted an interesting pattern of insomnia and then sleep recovery, stating:

> *Patient is having some nights where she doesn't sleep much but tends to follow this with a good sleep day (recovery).* [P14]

There were concerns about whether HSH sensor-detected inactivity truly reflected sleep.

> *Over the month, sleep interruptions hovered close to baseline. There was one spike mid-month where her*

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> *sleep interruptions increased dramatically to 20 times.* [P7]

Furthermore, activity levels varied significantly, with some days showing increased movement followed by sharp declines, making overall behavioral patterns difficult to interpret.

> *I am unable to make any interpretations based off of this information.* [P4]

Clinical Implications

Nurses suggested that erratic sleep cycles could contribute to fatigue, cognitive impairments, and reduced mobility. They recommended further assessment of sleep hygiene and potential interventions for insomnia or anxiety. In addition, tracking factors such as caffeine intake, medication effects, or psychological stressors could help clarify the underlying causes of sleep disturbances.

Increased Nighttime Bathroom Trips and Their Impact on Sleep

A key finding in nurses' interpretations was the high frequency of nighttime bed-to-toilet transitions, which appeared to correlate with poor sleep quality. Smart home participant Case 3 woke up multiple times per night, with some nights exceeding 20 trips to the bathroom. One nurse stated:

> *The patient barely slept on 3 of 7 days and 4 other days patient slept 7 to 9 hours.* [P3]

Another participant noted:

> *The patients transfers [to toilet] increased over 50% of their baseline during the week in observation. With days 10/03/17 & 10/07/17 showing less than baseline activity.* [P4]

Nurses speculated that the frequent nocturnal awakenings could indicate undiagnosed urinary health issues, such as nocturia, an overactive bladder, or a possible urinary tract infection. One nurse commented:

> *Possible UTI or increased diuresis? Patient awakens in spikes to use the bathroom at night.* [P6]

In addition, nurses noted a clear correlation between bathroom use and sleep disruptions, where nights with fewer bathroom trips were associated with longer and more restful sleep.

Clinical Implications

Nurses recommended further assessment of urinary function, hydration patterns, and medication side effects to determine if nocturia was a primary cause of sleep disturbances. They also suggested dietary adjustments (eg, limiting caffeine intake) and nighttime toileting strategies to help mitigate sleep disruptions.

Walking Speed Decline and Mobility Variability

Nurses examined walking speed data to assess mobility and potential health risks, identifying notable trends for smart home participant Case 3. The participant exhibited significant fluctuations in walking speed, with some days showing markedly slow movement followed by brief spikes in speed. One nurse noted, "Walking speed fluctuated greatly throughout the week" (P6). There was a clear correlation between bathroom trips and walking speed, with nurses observing that on nights with fewer bathroom trips, walking speed was faster, whereas frequent nighttime awakenings led to slower movement. One nurse stated:

> *The patient walks more quickly on nights that she gets more sleep. This could be due to urgency.* [P11]

Another participant added:

> *The patient walks quickly on the nights that she goes to the bathroom less.* [P5]

In addition, a gradual decline in mobility over time was noted, with nurses raising concerns about fatigue, potential muscle weakness, or an undiagnosed condition. One nurse commented, "Significant decreased walking speed overall" (P1).

Clinical Implications

Nurses highlighted that variability in walking speed could indicate episodic changes in energy levels, urgency, or discomfort. They recommended tracking patterns between sleep, fatigue, and mobility changes to provide insights into the patient's overall health status. Further assessment for fall risk or muscle weakness was suggested to identify early mobility decline.

Home Usage Patterns and Sedentary Lifestyle

HSH sensor data visualizations provided insights into smart home participant Case 3's daily movement within her home, revealing low engagement and limited room usage. The participant spent most of her time in the bedroom and living room, with minimal movement to the kitchen, dining room, or office. One nurse noted:

Another participant added, "Majority of time is in bedroom, rarely outside" (P3). Nurses speculated that limited home engagement could be a sign of social withdrawal, cognitive decline, or fatigue-related lifestyle changes. One participant remarked:

> *he patient spent less time in the office and more time in the bathroom during the week where she had two nights of poor sleep. She also spent much less time in the kitchen and less time outside.* [P5]

In addition, some nurses observed that periods of poor sleep or increased bathroom trips correlated with reduced movement throughout the home during the day, further reinforcing the connection between nighttime disruptions and daytime fatigue.

Clinical Implications

Nurses suggested encouraging structured movement, social interaction, or small daily tasks to help increase activity levels. In addition, tracking longitudinal changes in home usage could provide insights into potential cognitive, emotional, or functional declines.

Challenges in Data Interpretation and Clinical Context

While HSH sensor data visualizations provided valuable insights, nurses faced several challenges in interpretation, particularly due to missing medical history and unclear reference points. Unclear sleep patterns made it difficult to determine whether periods of inactivity represented true sleep or simple rest without movement. One nurse noted, "Decreased sensors when asleep, with no clinical data hard to draw on inferences."

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Assessing walking speed was another difficulty, as standardized clinical benchmarks were lacking. One participant questioned, "Uncertain of the difference in pace as defined by the seconds?" In addition, some nurses struggled to interpret erratic activity trends, as short bursts of movement occurred without an obvious explanation. One nurse stated, "The graphs do not show any patterns that would identify any health status change in the patient." Finally, the lack of medical history made it challenging to draw conclusions about sleep, mobility, and bathroom usage patterns.

Clinical Implications

Nurses highlighted the need for better integration of HSH sensor data with medical records and clinical notes to improve interpretation accuracy. In addition, they suggested that more intuitive visualizations and standardized reference values for sleep, activity, and mobility metrics could enhance clinical decision-making.

In summary, nurses used HSH sensor data visualizations to evaluate Case 3's sleep, mobility, and home engagement patterns, identifying frequent nighttime awakenings, walking speed variability, and reduced engagement in daily activities. However, challenges in data interpretation—including unclear sleep metrics, lack of medical history, and difficulties with mobility data interpretation—limited the ability to make definitive clinical judgments. These findings underscore the importance of improved contextualization, enhanced data visualization, and the integration of HSH sensor data visualizations in conducting assessments with clinical evaluations to support the use of smart home technology in patient care. Across all cases, data interpretation challenges limited clinical decision-making. Nurses encountered ambiguities in sleep data, questioning whether HSH sensor inactivity truly reflected sleep. Similarly, walking speed fluctuations were difficult to assess due to the lack of standardized clinical reference values. The absence of medical history in some cases further hindered interpretation, as HSH sensor data alone lacked sufficient context to support definitive clinical conclusions. These findings highlight the need for better integration of HSH sensor data with medical records, improved data visualization techniques, and clear clinical benchmarks to enhance usability for health care professionals.

Survey Results

A total of 14 nurse-participants were included in this study, each of whom evaluated all 3 graph types (bar, line, and pie). The 11-item (Table 1), 7-point Likert scale questionnaire provided preliminary insights into participants' perceptions of HSH sensor data visualizations. Given that each participant responded to all 11 items for each of the 3 graph types, this resulted in 154 total responses per graph type (14 participants×11 items), yielding a dataset of 462 responses across all graph types. There was no missing data, and each response was complete, ensuring data integrity. Descriptive analysis revealed differences in perceived usability and clinical relevance across the 3 visualization types (Table 2). Bar graphs and line graphs were rated the most favorably, with participants generally agreeing that they were easy to understand and clinically useful (bar: mean 3.64 - 4.57, SD 1.49 - 2.22; line: mean 3.93 - 4.86, SD 1.55 - 2.28). In contrast, pie charts were generally rated less favorably, with more neutral to somewhat disagree responses (mean 4.14 - 5.29, SD 2.10 - 2.44), particularly for ease of finding information and overall clarity. The lowest-rated item for pie charts was "The organization of the visual data was clear" (mean 5.29, SD 2.23), indicating potential difficulties in interpreting structured information. These findings suggest that bar and line graphs are more effective for clinical decision-making, whereas pie charts may require design improvements to enhance interpretability and usability.

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Table . Results of survey questions (N=14).

Nurses Feedback	Bar, mean (SD)	Line, mean (SD)	Pie, mean (SD)
"Overall, I am satisfied with how easy it is to understand the visualization of the data"	4.07 (2.02)	4.36 (1.74)	4.86 (2.38)
"I was able to efficiently interpret the visual data"	4.07 (1.94)	4.43 (1.55)	4.57 (2.44)
"I felt comfortable interpreting this visualization"	3.79 (2.22)	4.14 (2.28)	4.93 (2.2)
"I believe I could become productive quickly using this visualization"	4.07 (2.16)	4.21 (2.08)	4.71 (2.3)
"It was easy to find the information I needed in this visualization"	4.14 (1.96)	4.43 (1.65)	5.14 (2.21)
"The information provided by the visualization was easy to understand"	4 (2.18)	4.21 (1.72)	5 (2.15)
"The organization of the visual data was clear"	4.57 (2.03)	4.86 (1.83)	5.29 (2.23)
"The visualization contains all of the information I would expect it to have"	3.71 (1.49)	3.93 (2.02)	4.14 (2.32)
"The visual data is presented in a clinically meaningfully way"	4 (1.88)	4.36 (1.91)	4.64 (2.21)
"I am confident that visualizing data in this format would allow me to identify clinically meaningful change in health status"	3.64 (1.82)	4 (2.11)	4.14 (2.25)
"Overall, I am satisfied with this visualization"	3.86 (1.83	4.07 (1.82)	4.43 (2.1)

The Friedman test was conducted to determine whether there were significant differences in participants' ratings of the 3 visualization types. Each participant's individual ratings across all 11 questions for the 3 visualization types (bar, line, and pie) were included in the test to account for within-subject variability. The results indicated a statistically significant difference across the 3 visualization types (χ^2_2=17.1; P<.001), confirming that participants rated bar, line, and pie charts differently in terms of usability and clinical relevance. Post-hoc Wilcoxon signed-rank tests were conducted to determine which visualization types differed significantly in participant ratings. The results indicated that there was no significant difference between bar and line graphs (W=2857; P=.10), suggesting that both were perceived similarly in terms of usability and clinical relevance. However, pie charts were rated significantly lower than both bar graphs (W=1437; P<.001) and line graphs (W=2678.5; P=.008), confirming that participants found pie charts less useful for clinical decision-making. These findings support the qualitative feedback that bar and line graphs were more effective in conveying HSH sensor data, whereas pie charts presented challenges in clarity and interpretation.

Integration of Content Analysis and Survey Findings

The findings from the 3 cases illustrate both the potential value and challenges of using HSH sensor data visualizations to assess sleep, mobility, and home engagement in older adults. Across all cases, nurses were able to identify key patterns, such as frequent nighttime awakenings, fluctuations in mobility, and variable home engagement, demonstrating how smart home technology can provide real-time insights into health status and functional changes. However, common challenges in data interpretation—including unclear sleep metrics, difficulties distinguishing true rest from inactivity, lack of clinical context, and limitations in mobility assessments—highlight the need for improved contextualization and integration of HSH sensor data with clinical evaluations.

The survey results broadly confirm the qualitative findings from the inductive content analysis, particularly in relation to the challenges nurses faced when interpreting HSH sensor data visualizations and their preferences for certain visual formats. However, the extent of this alignment varies across specific themes. The survey results confirm several key findings from the qualitative analysis, particularly in relation to challenges in interpreting smart home data. The Friedman test indicated a statistically significant difference in how nurses rated different graph types (χ^2_2=17.1, P<.001), with pie charts rated significantly lower than both bar and line graphs (P<.001 and P=.008 respectively). This supports nurses' qualitative feedback that pie charts were less useful and harder to interpret for clinical decision-making. Nurses explicitly stated that line graphs and trend analyses were more useful, whereas pie charts lacked sufficient information, as highlighted in statements such as: "The pie chart didn't provide much information."

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Further, the survey results confirmed difficulties in interpreting sleep and mobility data, with "The organization of the visual data was clear" receiving the lowest rating for pie charts (mean 5.29, SD 2.23). This aligns with qualitative concerns that HSH sensor data, such as sleep and mobility data, were difficult to interpret without additional clinical context. Nurses struggled to differentiate true sleep from inactivity and had difficulty interpreting walking speed metrics, questioning whether variability was due to fatigue, pain, or another factor. Statements, such as: "I do not know how to interpret walking speed. What is the unit of measure?" directly reflects the survey results, where participants rated clarity and interpretability lowest for pie charts. In addition, the survey results confirmed that both bar and line graphs were rated similarly in terms of usability and clinical relevance, with no significant difference between the two. This supports the qualitative finding that both formats were generally effective for clinical interpretation. Nurses preferred visualizations that allowed them to track trends over time, reinforcing the survey finding that bar and line graphs provided more clinically meaningful insights than pie charts. This was further validated by qualitative statements such as: "I used the graph charts and the links to the sensor data. The pie chart didn't provide much information." These findings collectively suggest that bar and line graphs are more effective for clinical decision-making, while pie charts may not provide sufficient clarity or actionable insights in this context.

Discussion

Principal Findings

The integration of smart home technologies in health care presents significant opportunities for enhancing the remote monitoring and management of older adults with chronic diseases. However, the effectiveness of these technologies is closely tied to the design of data visualizations and the proficiency of nurses in interpreting and acting upon this data.

Co-Designing Health-Smart Home Data Visualizations With Nurses

Involving nurses in the co-design of health-smart home data visualizations is crucial. Nurses play a pivotal role in patient care and are increasingly engaged in remote health monitoring. Their insights can ensure that data visualizations are intuitive, relevant, and actionable [52]. By collaborating with nurses in the design process, visualizations can be tailored to meet clinical needs, thereby enhancing the quality of remote monitoring and patient outcomes [53]. This collaboration enhances the usability of tools and reduces cognitive load through features like color-coded alerts. It ensures that data are presented in ways that not only provide information but also support holistic knowledge of the older adult and their life contexts. Such knowledge is needed for rapid clinical decision-making in an era of precision medicine, where emphasis is placed on patients' autonomy and right to self-determination.

Furthermore, as patient advocates, nurses can shape visualizations to facilitate communication with older adults and their families, translating complex HSH sensor data into meaningful, actionable insights for themselves. Addressing challenges like data overload or technical skepticism through co-design can also foster trust in these systems, ultimately enhancing adoption and positive end-user experiences.

Enhancing Nurses' Proficiency in Remote Monitoring

The efficacy of smart home systems in detecting health changes is significantly influenced by nurses' proficiency in using data dashboards, alongside access to clinical history and in-person collected data. A study examining nurses' practices in remote monitoring of patients with chronic diseases found that nurses use data in the form of graphs, alerts, questionnaires, and messages to personalize care [54]. This underscores the necessity for comprehensive training programs that equip nurses with the skills to interpret complex HSH sensor data and integrate it with traditional clinical assessments and medical history. In addition to the design of visualization tools, nurses' own competencies in data literacy and numerical literacy are critical factors influencing interpretation. Studies highlight that variability in nurses' confidence with quantitative data can affect how effectively they identify patterns or assess clinical significance [29,38]. Integrating targeted education on data and numerical literacy into training programs may therefore enhance the safe and effective use of HSH sensor data. Furthermore, the development and implementation of nurse-based remote patient monitoring programs have demonstrated that dashboards available through software platforms allow RNs to monitor patients effectively, viewing and responding to real-time alerts when data falls outside predefined limits. This integration of technology into nursing practice not only enhances patient care but also supports nurses in making informed decisions based on a combination of real-time data and clinical expertise [55].

New Types of Evidence for Evidence-Based Practice

Introducing nurses to data derived from unobtrusive, continuous ambient sensing is important to growing their knowledge about how to use this new type of data as evidence for evidence-based decision-making. Nurses and other health care team members are currently not trained to use this type of data. This will result in the need for training to increase comfort with relying on the data and associated visuals (graphs and charts). We posit that obtaining knowledge and comfort with information provided by smart homes will require similar changes to thinking about data as the introduction of smart infusion pumps, automated medication dispensing machines, and other information derived from remote patient monitoring equipment. Embracing a growth mindset as new forms of data emerge, including information outputs from devices featuring artificial intelligence, will position nurses for the future of health care.

Nurses as Future Data Brokers

Given that artificial intelligence capabilities will continue to rapidly change how and when we receive information about the health of patients, and given nurses are currently the information hub for most complex cases (eg, case managers), they are well-positioned to be future health care information data brokers. Nurses already use scientific principles, mathematical concepts, and cutting-edge technology featuring artificial intelligence to assess, diagnose, and plan patient care [56]. As nurses become experts in new and more sophisticated technologies, they will

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likely lead their health care teams in translating HSH sensor data into knowledge that reliably informs care decisions and interventions.

Limitations

The small sample size and characteristics restrict generalizability of the findings, and participants' perspectives may not reflect the experiences of nurses in different clinical settings. In addition, the study relied on self-reported interpretations, which introduces the potential for bias. No participants had prior experience working with smart home data; however, all were experienced nurses with at least 5 years of clinical practice. In addition, the scenarios chosen for this study were vetted by a nurse scientist (RF) having experience working with HSH sensor data and creating visualizations. Scenarios were purposively chosen containing data about health events that subjectively represented easy, medium, and hard-to-interpret data. No scenarios were presented that were deemed impossible to interpret. Future research should examine how nurses with varying levels of data literacy and technology exposure engage with HSH sensor data visualizations, incorporate objective usability assessments and comparative studies to strengthen the reliability of findings, and should explore how training in HSH data literacy and digital health tools impacts nurses' ability to use HSH sensor data effectively.

Conclusion

This study provides new insights into nurses' interpretation of health-smart home-generated data, revealing key challenges in sleep, mobility, and activity trend analysis. Findings highlight the need for improved visualization techniques, clinician training, and standardized benchmarks to optimize clinical decision-making in home care settings using HSH sensor data visualizations.

Acknowledgments

We thank Alireza Ghods, Kathleen Caffrey, Beiyu Lin, and Kylie Fraga for their iterative design efforts during data collection; we thank the Center for Advanced Studies in Adaptive Systems (CASAS) Lab staff, and the Washington State College of Nursing for supporting recruiting for this project in a graduate-level informatics course. During the preparation of this work, the author(s) used Grammarly to enhance sentence structure. Its contributions were limited to enhancing efficiency and clarity while ensuring that the researchers of this study have critical oversight and academic integrity throughout the research process. The authors take full responsibility for all interpretations, analyses, and conclusions presented in this paper.

Funding

This study was funded in part by the National Institute of Nursing Research (R01NR016732).

Data Availability

Data are available for scientific purposes upon request.

Authors' Contributions

Dermody and Fritz led the conceptualization of this paper and contributed to data interpretation and manuscript development. Fritz and Dermody jointly conducted the content analysis and contributed to the interpretation of findings. Fritz designed the iterative visual analytics framework and led data collection. Fritz and Dermody collaborated on the development and refinement of the visual analytics framework. Cook, as Director of the CASAS Lab, provided the technical infrastructure, data access, and methodological expertise required for data acquisition and system configuration. All authors contributed to critical manuscript revisions, approved the final version, and agree to be accountable for all aspects of the work.

Conflicts of Interest

None declared.

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Abbreviations

ADL: Activities of daily living
ECG: Electrocardiogram
EU: European Union
HSH: Health-smart home
IRB: Institutional Review Board
PROMS: Patient-reported outcome measures
PSSUQ: Post-Study System Usability Questionnaire
RN: Registered Nurse

Edited by E Borycki; submitted 30.03.25; peer-reviewed by N Mukkapati, J Chung, M Rantz; revised version received 01.10.25; accepted 02.10.25; published 21.11.25.

Please cite as:
Dermody G, Cook DJ, Fritz RL
Interpretation of Health-Smart Home Data and Implications for Clinical Decision-Making: Inductive Content Analysis
JMIR Nursing 2025;8:e75234
URL: https://nursing.jmir.org/2025/1/e75234
doi:10.2196/75234

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Development of a Knowledge Base for an Integrated Older Adult Care Model (SMART System) Based on an Intervention Mapping Framework: Mixed Methods Study

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Abstract

Background: Although mobile health apps integrated with Internet of Things–enabled devices are increasingly used to satisfy the growing needs for home-based older adult care resulting from rapid population aging, their effectiveness is constrained by 3 key challenges: a focus on specific functions rather than on holistic and integrated support, absence of a solid theoretical framework for development, and a lack of personalized, real-time feedback to address diverse care needs. To overcome these limitations, we developed a knowledge-based clinical decision support system using mobile health technology—an intelligent and integrated older adults care model (SMART system).

Objective: This study aims to systematically outline the development process and outcomes of a knowledge base and trigger rules for the SMART system.

Methods: Our study adopted a user-centered approach guided by the nursing process and intervention mapping (IM) framework. We first identified older adult care needs through semistructured, in-depth interviews. Guided by the nursing process and informed by guidance from the World Health Organization's Integrated Care for Older People and World Health Organization International Classification of Functioning, Disability, and Health, along with the North American Nursing Diagnosis Association-I nursing diagnosis, we then determined care problems along with their underlying causes and risk factors and diagnostic criteria. Building on these findings, we applied the first 3 steps of the intervention mapping framework to formulate corresponding long-term and short-term care objectives, select appropriate evidence-based interventions, and match practical implementation approaches, which were grounded in rigorous evidence derived from systematic literature reviews, clinical guidelines, and expert insights. We also developed a set of trigger rules to link abnormalities in older adults with corresponding care problems and interventions in the SMART knowledge base.

Results: The semistructured in-depth interviews identified 5 types of care needs—daily life care, health care, external support, social participation, and self-development—which formed the foundation of the SMART knowledge base. Based on this, we identified 138 care problems, each with associated causes and risk factors and diagnostic criteria. The objective matrix comprised 138 long-term and 195 short-term care objectives. Guided by 15 expert-defined selection criteria, we then selected 450 evidence-based interventions, each paired with at least 1 feasible and practical implementation approach. Additionally, we developed diagnostic rules to match the assessment data with relevant care problems and their causes and risk factors and intervention trigger rules to formulate personalized interventions based on individual characteristics, ensuring tailored care aligned with specific care objectives.

Conclusions: This study outlines the development process and outcomes of the SMART knowledge base and trigger rules. The study methodology offers theoretical support for developing knowledge bases and trigger rules of similar clinical decision support systems for home-based older adult care.

(JMIR Nursing 2025;8:e59276) doi:10.2196/59276

KEYWORDS

older adults; home-based care; clinical decision support system; knowledge base; intervention mapping; mHealth

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Introduction

As populations age rapidly worldwide, a growing number of older adults are experiencing physiological decline and various health issues [1]. This demographic shift necessitates increased daily assistance and medical care to ensure optimal quality of life, thereby exerting substantial pressure on global health and social care systems [2]. In China, home to the largest older adult population globally, the burden of older adult care is particularly pronounced [3]. The country has adopted the "9073" model, in which 90% of older adults are cared for in their own homes, 7% rely on community services, and 3% receive institutional care [4]. However, this model faces substantial challenges, as the one-child policy and the rising labor mobility from urbanization have eroded traditional family-based care structures [5]. At the same time, older adult care services are often fragmented and inconsistent, involving multiple providers across different institutions. These issues, combined with a shortage of professional care providers, have resulted in a suboptimal home-based older adult care model that struggles to meet the complex needs of older adults [6,7]. As a result, informal caregivers are burdened with heightened stress, emotional strain, and financial pressure as they need to coordinate care, manage complex health needs, and navigate various health care systems [8]. At a societal level, these systemic inefficiencies can lead to redundant treatments, delayed interventions, and resource inefficiency, ultimately elevating health care costs and threatening economic sustainability [9,10].

A proactive older adult care model emphasizes continuous monitoring of older adults' health and living conditions, allowing early detection of health changes and timely identification of care needs. This approach supports prompt and targeted interventions to prevent health deterioration. However, traditional monitoring methods, such as routine home visits, periodic paper-based assessments, and manual health checks, are often impractical due to the dispersed living situations of older adults and the severe shortage of older adult care resources [11]. The emergence of mobile health (mHealth) technology, in conjunction with the Internet of Things, offers a promising alternative to traditional monitoring methods. mHealth apps, often supported by Internet of Things–enabled devices such as wearable sensors and remote monitors, are increasingly used in older adult care for communication, real-time tracking, education, and chronic disease management, providing cost-effective and scalable solutions unrestricted by time or location [12,13].

While these technologies hold great potential to transform older adult care, their current apps remain limited by several challenges. One major challenge is the lack of a comprehensive understanding of older adults' diverse and evolving care needs. As a result, many apps tend to focus narrowly on specific functions such as daily care or medication reminders, rather than delivering integrated and holistic support [14,15]. Another challenge is that many apps were developed without a structured and theory-driven framework, resulting in poorly supported evidence for their effectiveness [16,17]. Furthermore, given the diversity and complexity of older adults' health status and characteristics, such as variations in chronic conditions, functional abilities, and care preferences, personalized interventions are essential to ensure that care strategies are tailored to each individual's unique needs. Real-time feedback is also critical for promptly detecting health fluctuations, enabling timely adjustments to care plans, and preventing minor issues from developing into serious complications. Unfortunately, most existing apps lack these features, making them less effective compared to interactive apps that support personalized care and timely decision-making [18].

To address the limitation of current mHealth apps being confined to specific functions, a user-centered design approach offers a promising solution. Unlike traditional software-centric design, user-centered design emphasizes the perspectives and experiences of older adults, thus enabling a deeper understanding of their multifaceted care needs [19]. Additionally, the Continuity Assessment Record and Evaluation (CARE) tool (Multimedia Appendix 1), developed by the Centers for Medicare & Medicaid Services, can serve as a tool to ensure continuous, consistent, and comprehensive assessments of older adults by measuring their medical, functional, cognitive, and social support factors. Its multidimensional structure enables a holistic understanding of individual care needs, supporting integrated older adults care plans. The Chinese version of the CARE tool has demonstrated good reliability and validity, particularly in stroke patients, reinforcing its applicability in home-based older adult care [20].

A promising solution to the lack of a structured and theory-driven framework in many mHealth apps lies in the use of the intervention mapping (IM) framework. This systematic approach guides the development of behavior change interventions through six sequential steps: (1) conducting a needs assessment and building a logic model, (2) specifying change objectives, (3) selecting theory-informed methods and practical strategies, (4) designing the intervention program, (5) planning for adoption and implementation, and (6) developing an evaluation strategy [21,22]. Grounded in social and behavioral science theories, IM has been proven effective in various public health contexts, especially in chronic disease self-management [23]. Its structured nature and theoretical grounding make it well-suited for determining interventions that respond to the complex care needs of older adults living at home.

Regarding the limitation of lacking personalization and real-time feedback, clinical decision support systems (CDSSs) present a more reliable option by linking individual health data with medical knowledge [24]. CDSSs are technology-driven systems to enhance health care delivery by facilitating medical decisions through the use of targeted clinical knowledge and patient data. Based on decision-making mechanisms, CDSSs are categorized into data-based and knowledge-based systems [25]. While some data-based CDSSs benefit from advances in explainable artificial intelligence (AI), they are still often considered "black-box" models, where the reasoning processes are difficult to trace. This opacity can result in inaccurate or conflicting recommendations that may deviate from the established guidelines and even jeopardize the health of older adults [26]. In contrast, knowledge-based CDSSs provide more transparent decision-making support by correlating individual data with

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relevant information in a knowledge base through a reasoning module known as an inference engine [27]. The inference engine uses a set of predefined rules and algorithms to analyze the collected data, drawing on the preset knowledge items in the corresponding knowledge base to generate transparent and evidence-based recommendations that assist clinicians in making informed decisions.

Therefore, leveraging mHealth technology, we have developed a knowledge-based CDSS for proactive home-based older adults care—an Intelligent and Integrated Older Adults Care Model. Similar to how the neural reflex functions in biological systems, the model functions as the "neural reflex" for older adults care, which includes Sensors and Scales (serves as the receptor), a mobile phone autonomous response system for the app (serves as the nervous system in the spinal cord), a remote cloud and management center (serves as the central nervous system in the brain), and total care system (serves as the effector, where various care providers are incorporated for specific types of care services for older adults), collectively referred to as the SMART system. The Sensors and Scales component collected integrated data from older adults via periodic CARE self-assessments and wearable devices. These data were automatically uploaded to the Remote Cloud and Management Center via Wi-Fi or 5G networks for comprehensive analysis to detect abnormalities and diagnose current or potential care problems using preconfigured knowledge items and trigger rules. Based on the diagnostic results, and considering each individual's characteristics and preferences, the Remote Cloud and Management Center can formulate tailored interventions, which are then appropriately distributed to daily caregivers (eg, family members and nannies) or professional care providers (eg, doctors, nurses, and domestic workers) within the Total Care System. The Mobile Phone Autonomous Response System was a set of simple algorithms to deal with simple but urgent care problems, similar to the coordinated reflex actions within the spinal cord, such as the withdrawal reflex from a painful stimulus. The entire process targets 12 key domains for older adults: decreased or lost self-care ability, falls, impaired skin integrity, delirium, dysphagia, urinary retention, constipation, common diseases, incontinence, cognitive decline, depression, and psychosocial issues.

This paper aims to outline the development of the SMART system's knowledge base and trigger rules guided by a qualitative, user-centered approach to determine older adults' care needs. The development process followed the nursing process and the IM framework. Additionally, the paper presents the results of this innovative knowledge base.

Methods

Overview

The nursing process and IM framework jointly guided the development and maintenance of our SMART knowledge base and trigger rules. Guided by the nursing process, we first determined care problems along with their underlying causes and risk factors and diagnostic criteria. Building on these findings, we applied the first 3 steps of the IM framework to formulate corresponding long-term and short-term care objectives, select appropriate evidence-based interventions, and match practical implementation approaches. Steps 4 - 6 of the IM framework, which pertain to program production, implementation, and evaluation, were used to guide the design, development, and evaluation of the SMART system and have been reported elsewhere [28].

A multidisciplinary team with extensive experience in gerontological care, cognitive and socio-psychological care, cardiovascular care, delirium care, and emergency care collaborated to develop the SMART knowledge base and trigger rules. The core development of the SMART knowledge base and trigger rules was conducted between December 2015 and December 2016. Due to significant changes in economic conditions, technological advancements, and shifts in the health care landscape, some aspects of home-based older adult care have evolved, rendering previous practices less relevant and introducing new interventions. To ensure the knowledge base remains up-to-date and aligned with current older adult care priorities, our research team conducted maintenance and updates of the SMART knowledge base and trigger rules between October 2024 and March 2025 to ensure its scientific rigor, relevance, and logical consistency.

We reported the development process in accordance with the Template for Intervention Description and Replication (TIDieR) checklist [29].

Ethical Considerations

The study was approved by the Institutional Review Committee of the Capital Medical University (approval numbers 2015SY49U and 2020SY047). Before participating in the study, we provided all potential participants with a comprehensive explanation of the study's objectives, methods, procedures, and the data to be collected. Written informed consent was obtained from each participant before their enrollment in the study. Participants were assured of their right to withdraw from the study at any time without any penalties or adverse consequences. To safeguard participants' privacy and confidentiality, all personal identifiers were securely stored in password-protected files. The analysis and reporting of study findings used only deidentified or anonymized data, ensuring that participants' identities remained confidential.

Step 1: Needs Assessment of Older Adults and Their Caregivers

We conducted needs assessments using semi-structured in-depth interviews to explore home-based care needs and preferences regarding system functionality (eg, reminders) and the user interface of the SMART system for older adults and their caregivers. We also assessed their preferences for system workflow, information presentation formats, and intervention delivery methods (eg, text, voice, or video).

After obtaining ethical approval, trained interviewers conducted 2 rounds of face-to-face, semistructured, in-depth interviews. The first round took place in Guangnei Street, Xicheng District, Beijing, between December 2015 and March 2016 (approval no. 2015SY49), and the second round was carried out in Youzhu Community, Fengtai District, Beijing, between October 2024 and November 2024 (approval no. 2020SY047). In both rounds,

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purposive sampling was used to recruit adults aged 60 years and older who had lived in the respective districts for at least 6 months if they had either been diagnosed with at least 1 noncommunicable disease or experienced physical or cognitive disabilities of different severity. Older adults were excluded if they (1) were unable to speak or understand Mandarin, (2) had severe bilateral hearing impairment, or (3) refused to participate.

After explaining the study purpose and interview process to each participant or their surrogate, interviewers conducted the interviews following a predefined guide (File 1 in Multimedia Appendix 2) in participants' homes, a relatively quiet and familiar setting, until theoretical saturation was reached. Theoretical saturation was defined as the interviewers agreed no new information was generated from new participants. The interview guide consisted of several open-ended questions initially drafted by the interviewers and subsequently refined by the broader research team. All interviews were recorded in both written and audio formats, with informed consent obtained from the participants or their surrogates.

Step 2: Determining Care Problems, Causes and Risk Factors, and Diagnostic Criteria

In the initial core development of the SMART knowledge base, we followed the guidance of the World Health Organization's (WHO's) Integrated Care for Older People (ICOPE) and the WHO International Classification of Functioning, Disability, and Health (ICF), along with the North American Nursing Diagnosis Association (NANDA)-I (2015 - 2017) nursing diagnosis framework to identify care problems and their causes and risk factors. During the maintenance phase of the SMART knowledge base, in light of the recent updates to the NANDA-I framework, we compared the NANDA-I (2015 - 2017) and NANDA-I (2024 - 2026) editions to identify discrepancies. Based on this analysis, we revised the identified care problems, introduced new care problems, and accordingly updated the associated causes and risk factors and diagnostic criteria.

The ICOPE guideline provides a proactive model for older adult care, emphasizing both functional ability and individual needs [30]. The ICF framework helps evaluate levels of functioning and disability among older adults by considering the interaction between health conditions, environmental factors, and personal attributes [31]. Meanwhile, the NANDA-I framework offers standardized terminology and supports the determination of diagnostic criteria for care problems [32]. Diagnostic criteria for the care problems were determined based on the NANDA-I.

Since the main goal of this study was to develop a knowledge base and trigger rules that could support the SMART system, we only included a limited set of common diseases, including hypertension, coronary heart disease, diabetes mellitus, and pneumonia, to reduce workload and ensure feasibility in the development of the SMART knowledge base [33].

Step 3: Development of Evidence-Based Interventions, Implementation Approaches, and Trigger Rules

Generation of Care Objectives Corresponding to the Care Problems

During both the initial development and subsequent maintenance of the SMART knowledge base, we formulated long-term and short-term care objectives instead of performance objectives and change objectives suggested by the IM framework. This is because the IM is primarily used to guide the development, implementation, and evaluation of behavioral change, while our interventions were aimed at solving older adults' care problems. The long-term care objectives represent the expected outcomes after providing care services, while the short-term care objectives are periodic objectives that will collectively achieve the long-term care objectives.

Determination of Criteria for the Selection of Evidence-Based Interventions

A set of criteria for selecting potentially effective evidence-based interventions for older adults is of vital importance [34]. Based on the IM framework, we determined 2 types of criteria for both the initial development and maintenance phases of the SMART knowledge base: general criteria, the most basic and necessary criteria to identify the existing effective interventions that are appropriate for older adults, and desirable criteria, all other criteria to ensure interventions are practical, safe, and helpful for older adults cared for at home [35].

Review of the Existing Evidence-Based Interventions

During the initial development and subsequent maintenance of the SMART knowledge base, we conducted 2 systematic literature reviews to identify relevant studies and guidelines on evidence-based interventions for the identified care problems by searching the PubMed database thoroughly. The first review focused on publications before December 2016, when we began developing the SMART knowledge base. The second supplementary review was conducted between December 2024 and February 2025, primarily targeting new literature and guidelines from December 2024 to March 2025. Both reviews followed the same search strategy, with the detailed methods summarized in File 2 of Multimedia Appendix 2. We did not restrict the search by publication type or language. Reports on randomized controlled trials (RCTs), non-RCTs, and relevant guidelines were all included. To assess the quality and effectiveness of the interventions, we used the 5-point Jadad scale [36] for RCTs and the UK Cochrane Center Evidence Level (2001) for non-RCTs.

Selection of the Evidence-Based Interventions

During the initial development of the SMART knowledge base, the research team selected potentially effective evidence-based interventions after multiple discussions according to the predefined general and desirable criteria. In total, 5 researchers independently screened for interventions from the identified guidelines and literature according to the general criteria, excluding those that did not meet the requirements. Subsequently, each researcher independently ranked the

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remaining interventions against the desirable criteria. Final decisions were made through team discussions until consensus was reached. Similarly, during the maintenance phase of the SMART knowledge base, 4 researchers followed the same process to screen and rank new evidence-based interventions based on newly identified guidelines and literature.

The identified care problems, associated causes and risk factors, corresponding diagnostic criteria, and the drafted evidence-based interventions were confirmed through consultations with a multidisciplinary expert panel (MEP). Specifically, 2 rounds of expert consultation (rounds 1 and 2) were conducted during the initial development phase, while an additional round (round 4) was carried out during the maintenance phase on March 6, 2025. The composition of the MEP remained consistent throughout the process, comprising 2 gerontological care experts, 1 geriatric physician, and 1 geriatric nurse. These consultations also provided valuable recommendations on other potentially effective interventions and critical considerations for developing the SMART system.

Development of Intervention Categories

Most older adults have multiple care problems, and interventions targeting different care problems might have the same methods (eg, diet and nutrition). However, the specific requirements of interventions might be different or even conflicting (eg, a high-protein diet for severe anemia and a high-quality, low-protein diet for chronic renal failure). To address this, we created intervention categories (eg, health education, diet, and nutrition) that allow us to assign each intervention into 1 category only. After the SMART system automatically develops an integrated care plan, this approach allows us to combine similar interventions and examine whether there are different or even conflicting interventions for the same intervention category (eg, diet, exercise), and to select the most appropriate interventions for older adults according to their holistic conditions. The intervention categories were applied throughout the initial development and subsequent maintenance of the SMART knowledge base.

Translation From Evidence-Based Interventions Into Implementation Approaches

To improve the accuracy and efficiency of intervention delivery, we combined the characteristics, preferences, and ambient conditions of the care providers to translate evidence-based interventions into practical implementation approaches by clearly presenting what (content to deliver or methods to deliver the intervention), when (time to deliver), how many (dose), how often (frequency), who (the person who will implement the interventions), and by what types of presentation format for information sent to the care providers [37]. To make the implementation approaches clearer and easier to understand, the presentation format varies among care providers and situations. For example, interventions targeting older adults, family members, and informal care providers will be delivered in the form of pictures, comics, voice, and video. In contrast, interventions targeting professional nursing staff will mainly be provided by text and pictures. This process applies to both the initial development and subsequent maintenance phases of the SMART knowledge base.

Formulation of Trigger Rules

Considered as one of the most widely used reasoning methods in knowledge-based CDSSs, IF-THEN rules were used within the SMART system's inference engine to enable reasoning and trigger relevant implementation approaches. These rules are categorized into diagnostic rules and intervention trigger rules. The diagnostic rules match the assessment data (eg, the older adults' abnormal conditions) with the determined care problems and their causes and risk factors, while the intervention trigger rules ensure that older adults receive personalized interventions tailored to their characteristics (eg, demographic features, medical conditions, functional status, cognitive status, and preferences) to achieve the care objectives developed based on the identified care problems and their causes and risk factors. The inference engine processes these rules by continuously evaluating the collected data, dynamically diagnosing accurate care problems, and appropriately matching the most appropriate interventions, ensuring timely delivery and feedback based on real-time patient conditions.

During the initial development of the SMART knowledge base, the accuracy and feasibility of the implementation approaches and trigger rules were assessed through a third round of consultation with the MEP (round 3). In the maintenance phase, a fifth round of expert consultation (round 5) was conducted on March 25, 2025, to evaluate the accuracy and feasibility of the newly revised implementation approaches and trigger rules.

Results

Needs of Older Adults

A total of 26 older adults were interviewed, with 21 in the first round and an additional 5 participants in the second round. The average age was 79.15 (SD 7.78) years old, with 46.15% (n=12) being male. The detailed baseline characteristics of the interviewees are summarized in File 3 of Multimedia Appendix 2. Since this paper aims to report the development process and results of the SMART knowledge base and trigger rules, only the care needs related to the intervention contents for older adults are presented. The identified care needs include 5 types: daily life care, health care, external support, social participation, and self-development. The first 4 types were identified in the first round of interviews, while the self-development needs, identified in the second round, specifically emphasize the need for digital inclusion and technology use training. Full details of the interview results are presented in File 4 of Multimedia Appendix 2.

Care Problems, Causes and Risk Factors, and Diagnostic Criteria

During the initial development process of the SMART knowledge base, we identified 11 core domains of care problems in alignment with the ICOPE guidelines, ICF, and NANDA-I (2015 - 2017), while incorporating insights from needs assessments and considering the distinctive characteristics, preferences, and environmental conditions of older adults. These domains include decreased or lost self-care ability, falls, delirium, dysphagia, incontinence, constipation, urinary retention, cognitive decline, depression, impaired skin integrity,

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and common diseases. We further divided each domain into 2 subdomains: risk for care problems and presence of care problems. Through collaborative discussions, we identified a total of 137 care problems, along with their causes and risk factors, from these 11 domains. Following the first 2 rounds of consultations with the MEP, an additional care problem was identified: risk for delayed detection of delirium causes. Consequently, the initial knowledge base comprises a total of 138 care problems.

In the subsequent maintenance phase of the SMART knowledge base, we identified a new core domain of care problems: psychosocial issues. Within this domain, we recognized 3 additional care problems: loneliness, social isolation, and digital divide. Additionally, we refined the descriptions of the previously identified 138 care problems. The final compilation encompasses 141 care problems systematically categorized under the 12 core domains and subdomains, with detailed information available in File 5 of Multimedia Appendix 2. Table 1 presents examples of nursing issues, including their classification and associated causes and risk factors.

Table . Matrices of care problems and their subdomains, associated causes and risk factors, and diagnostic criteria related to the impaired skin integrity domain: examples.

Care problems	Subdomains of care problems	Causes and risk factors	Diagnostic criteria
Risk for pressure ulcers, related to prolonged periods of unrelieved pressure	Risk for impaired skin integrity	Prolonged periods of unrelieved pressure due to extended bed rest	Older adults are recorded not rolling left and right for more than 4 hours AND score 1[a]/2[b]/3[c] on CARE[d] item VI-C3[e]
Risk for diabetic foot ulcers	Risk for impaired skin integrity	DM[f] with loss or decrease of sensation in the lower extremities	Older adults experience difficulties from DM (CARE item III-B) AND have weakened sensation in their lower extremities
Impaired skin integrity: Stage 3 pressure ulcers	Presence of impaired skin integrity	—[g]	Older adults score 1[h] on CARE item III-G2[i] AND score 1/2/3/4/5/6/7/8[j] on CARE item III-G2b[k]

[a]1 score for VI-C3: dependent.

[b]2 scores for VI-C3: Substantial or maximal assistance.

[c]3 scores for VI-C3: Partial or moderate assistance.

[d]CARE: Continuity Assessment Record and Evaluation.

[e]VI-C3: the ability to roll from lying on back to left and right side and roll back to back.

[f]DM: diabetes mellitus.

[g]Not applicable.

[h]1 score for III-G2: this patient has one or more unhealed pressure ulcer(s) at stage 2 or higher or unstageable.

[i]III-G2: does this patient have one or more unhealed pressure ulcer(s) at stage 2 or higher or unstageable?

[j]1/2/3/4/5/6/7/8 for III-G2b: the number of stage 3 pressure ulcers is 1/2/3/4/5/6/7/8.

[k]III-G2b: please specify the number of pressure ulcers at stage 3.

Evidence-Based Interventions, Implementation Approaches, and Trigger Rules

Care Objectives Corresponding to the Care Problems

During the initial development phase of the SMART knowledge base, we conducted a thorough analysis of the identified 138 care problems and their causes and risk factors, establishing 138 long-term and 195 short-term care objectives. Additionally, in response to 3 care problems identified in the maintenance phase, we formulated 3 long-term and 6 short-term care objectives. As a result, the final SMART knowledge base comprises 141 long-term and 201 short-term care objectives. These objectives align closely with the primary goal of our SMART system: to reduce physical or cognitive disabilities, preserve physical and cognitive capacities to the fullest extent, and promote rehabilitation to mitigate functional decline in older adults. To facilitate implementation, we categorized the care objectives into 2 groups: those targeting prevention and early detection and those directed toward prompt intervention and early rehabilitation. Table 2 illustrates the care objectives matched to the identified care problems and their corresponding causes and risk factors.

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Table . Matrices of care objectives matched to the identified care problems and their corresponding causes and risk factors related to the impaired skin integrity domain: examples.

Care problems	Causes and risk factors	Categories of care objectives	Long-term care objectives	Short-term care objectives
Risk for pressure ulcers, related to prolonged periods of unrelieved pressure	Prolonged periods of unrelieved pressure due to extended bed rest	Prevention and early detection of impaired skin integrity	Maintain skin integrity	Reduce pressure time at the bony prominence
Risk for diabetic foot ulcers	DM[a] with loss or decrease of sensation in lower extremities	Prevention and early detection of impaired skin integrity	Avoid diabetic foot	Avoid damage to foot skin
Impaired skin integrity: stage 3 pressure ulcers	—[b]	Prompt intervention and early rehabilitation of impaired skin integrity	Facilitate the healing of pressure ulcers through dedicated care	Prevent the advancement of pressure ulcers to stage 4

[a]DM: diabetes mellitus.

[b]Not applicable.

Criteria for the Selection of Evidence-Based Interventions

As detailed in Textbox 1, during the initial development phase of the SMART knowledge base, we formulated 2 general criteria and 13 desirable criteria to guide the selection of potentially effective evidence-based interventions for older adult care. These criteria were also used in the subsequent maintenance phase of the SMART knowledge base. The general criteria focus on interventions that directly address the identified care problems and care objectives, tailored to the specific causes and risk factors of these care problems. The desirable criteria encompass factors such as availability, safety, effectiveness, integration, personalization, simplicity, and affordability.

Textbox 1. Criteria for selecting evidence-based interventions for older adult care.

General criteria:

- Related to the care problems and short-term care objectives
- Designed for the causes and/or risk factors corresponding to the care problems

Desirable criteria:

- Effectiveness indicated by a high odds ratio from the existing literature
- Recommended in existing guidelines
- Recognized by health professionals in the field of aging
- Easy to deliver in a home context
- Safe for the target older adults
- Culturally appropriate
- Able to integrate into older adults' daily life and habits
- Simple and straightforward to understand
- Easy to implement
- Personalized
- With appropriate frequency and dose
- With positive feedback from older adults shown in existing literature
- Time-saving, labor-saving, and money-saving

Evidence-Based Interventions and Intervention Categories

After systematically searching the PubMed database using established strategies, our research team identified relevant literature and guidelines and accessed their full texts from appropriate databases. A subsequent quality assessment revealed that the majority of the retrieved literature was of low quality. As a result, we primarily incorporated relevant guidelines to derive evidence-based interventions. Specifically, during the initial development phase of the SMART knowledge base, the research team drafted a total of 446 evidence-based interventions that satisfied our selection criteria after 9 rounds of discussion. In total, 2 rounds of consultation with the MEP (File 6 of Multimedia Appendix 2) led to the inclusion of 4 more evidence-based interventions, bringing the total to 450.

During the maintenance phase, the research team added 7 new evidence-based interventions, which were subsequently

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confirmed through a round of consultation with the MEP. As a result, the final SMART knowledge base comprises a total of 457 evidence-based interventions. Table 3 provides information about these 7 new interventions in detail.

Table . The 7 new evidence-based interventions identified in the maintenance phase.

Domains of care problems	Evidence-based interventions
Falls	• Home environment modifications: Install grab bars, non-slip flooring, and remove tripping hazards after a safety audit
Cognitive decline	• Use digital cognitive training platforms for daily mental exercise
Common diseases	• Use smart pill dispensers to improve medication adherence
Psychosocial issues	• Introduce AI-powered[a] social robots to provide companionship, reminders, and friendly dialogue • Facilitate participation in web-based or face-to-face interest groups • Provide structured, age-friendly training on using smartphones, tablets, and health apps • Organize intergenerational programs linking youth and older adults both online and in person

[a]AI: artificial intelligence.

Based on the finalized 457 evidence-based interventions, we created 13 intervention categories: health education, diet and nutrition, rest and exercise, monitoring of physiological function and health status, addressing basic living and safety needs, skin cleaning and hygiene, functional exercise, rehabilitation, implementation of nursing and treatment procedures, medication management, social support, psychological support, and lifestyle monitoring. We then classified the determined interventions into these 13 categories according to their characteristics, target population, mode of delivery, and purpose.

Implementation Approaches and Trigger Rules of the Evidence-Based Interventions

For each determined evidence-based intervention, we developed at least 1 feasible and practical implementation approach suitable for specific contexts. We further validated the feasibility of these approaches during the third consultation with the MEP in the development phase and the fifth consultation with the MEP during the maintenance phase of the SMART knowledge base. Table 4 presents examples of care problems, evidence-based interventions, intervention categories, and implementation approaches related to the impaired skin integrity domain.

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Table . Matrices of care problems, evidence-based interventions, intervention categories, and implementation approaches related to the impaired skin integrity domain: examples.

Care problems	Interventions	Intervention categories	Intervention trigger rules (IF)	THEN: implementation approaches					
				What	Who	How many	How often	When	By what types of presentation format
Risk for pressure ulcers, related to prolonged periods of unrelieved pressure	Frequent repositioning	Rest and exercise	Older adults score 1[a]/2[b]/3[c] on CARE[d] item VI-C3[e] AND remain the same position for ≥4 hours	Mr. Li has been in the same position for over 4 hours, increasing his risk of pressure ulcers. Regular turning can prevent sustained pressure and the onset of ulcers. Please assist Mr. Li in changing positions now, and fill out the turning record form in the SMART system.	Family members or primary caregivers	__[f]	Once every 2 hours	Every 2 hours after the initial trigger	Text and tutorial video
Risk for diabetic foot ulcers	Knowledge tips for foot skin protection	Health education	Older adults score 13 - 15[g] on CARE items IV-B3a, IV-B3b, and IV-B3c[h] AND score 3 on CARE item V-C1c[i]	Mr. Li, please check between your toes for ulcers or discoloration. Also, please take a photo and upload it to the SMART system so that we can detect any abnormality of your foot skin in time.	Older adults	—	Once a day	7 PM daily	Text
Impaired skin integrity: Stage 3 pressure ulcers	Wound care: cleansing	Skin cleaning and hygiene	Older adults are rated as E3d[j] or E4d[k] on CARE item II-E1d	Mr. Li has developed stage 3 pressure ulcers and is prone to infection. Please take Mr. Li to a professional hospital department and consult an experienced nurse for treatment.	Family members or primary caregivers	—	—	Once evaluated	Text

[a]1 score for VI-C3: dependent.

[b]2 scores for VI-C3: Substantial or maximal assistance.

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[c]3 scores for VI-C3: Partial or moderate assistance.

[d]CARE, Continuity Assessment Record, and Evaluation.

[e]VI-C3: the ability to roll from lying on back to left and right side and roll back to back.

[f]Not applicable.

[g]13 - 15 on IV-B3a, IV-B3b, and IV-B3c: normal cognitive function.

[h]IV-B3a, IV-B3b, and IV-B3c: brief interview for mental status.

[i]3 scores for V-C1c: ability to see in adequate light is adequate (see fine detail, including regular print in newspapers or books).

[j]E3d on II-E1d: Caregivers will need training and other supportive services in medical procedures/treatments.

[k]E4d on II-E1d: Caregivers not likely to be able in medical procedures or treatments.

Each implementation approach operates on a set of IF-THEN rules, targeting either older adults, their primary caregivers, or medical staff, depending on who will implement the intervention. Consider the case of an older adult, Mr. Li. *IF* Mr. Li is identified with the care problem "risk for pressure ulcers, related to prolonged periods of unrelieved pressure" due to prolonged bed rest, *THEN* the personalized intervention involves prompting frequent repositioning, which falls under the intervention category of rest and exercise. For instance, *IF* Mr. Li cannot independently reposition and the SMART system has not received a repositioning record for over 4 hours, *THEN* the SMART system automatically sends a message (what) to his primary caregiver (who) every 2 hours (how often), using a standardized text format (by what types of presentation format). The message reads: "Mr. Li has been in the same position for over four hours, increasing his risk of pressure ulcers. Regular turning can prevent sustained pressure and the onset of ulcers. Please assist Mr. Li in changing positions now, and fill out the turning record form in the SMART system."

Discussion

Principal Findings

This paper outlines the systematic development and outcomes of the knowledge base and trigger rules for our SMART system, a comprehensive and integrated care model designed to proactively deliver home-based care for older adults. The knowledge base, developed in accordance with the nursing process and IM framework, incorporates interventions tailored to older adults' specific care needs. These interventions are grounded in the latest literature, guidelines, and expert opinions. To the best of our knowledge, this study represents the first exploration of a knowledge-based CDSS in the realm of integrated home-based care for older adults. Our meticulous methodology provides a theoretical foundation for the future development of knowledge bases in CDSSs aimed at supporting the delivery of home-based care for this population.

Contemporary knowledge-based CDSSs predominantly focus on disease diagnosis in clinical settings [38], necessitating extensive knowledge from diverse fields and intricate operating rules to function effectively [39]. However, the vastness, complexity, and rapid evolution of medical knowledge pose significant challenges in developing and maintaining these knowledge bases as well as the corresponding rules [40,41]. Our SMART system, however, stands out for practical feasibility, as it concentrates on delivering home-based care for older adults. This focus entails a more limited scope of professional knowledge, thereby significantly reducing the costs associated with both development and upkeep.

The SMART knowledge base was initially developed between December 2015 and December 2016, before the widespread adoption of many transformative digital health technologies. At that time, tools such as AI-powered CDSSs, Food and Drug Administration–approved consumer-grade wearable devices, integrated telehealth platforms with social engagement features, and large language models were either in their early stages or unavailable. Since then, both the care needs of older adults living at home and the field of home-based older adult care have evolved significantly. Previously effective interventions may no longer be suitable, while new evidence-based strategies have emerged to address evolving priorities in older adult care.

To ensure the SMART knowledge base remains aligned with current priorities, a comprehensive maintenance was conducted between October 2024 and March 2025. Following renewed ethical approval in 2020, we expanded semistructured in-depth interviews with older adults and their primary caregivers to explore emerging care needs from October to November 2024. In updating care problems, associated causes and risk factors, and diagnostic criteria, we adopted the NANDA-I (2024 - 2026) guidelines instead of the 2015 - 2017 edition. A supplementary review of the latest guidelines and studies (December 2024-February 2025) identified emerging evidence-based interventions and flagged outdated ones, which were thoroughly discussed during an expert consultation on March 6, 2025. A final consultation on March 25, 2025, ensured the updated implementation approaches and trigger rules reflected current best practices.

Notably, our extended interviews revealed a self-development need among older adults, particularly related to digital inclusion and technology use training. This finding underscores a growing trend of accelerated technology adoption and affirms the potential of our system to support older adults in engaging with digital tools to some extent. In addition, several entries in the SMART knowledge base were updated to reflect advancements in information technology and large language models, including digital cognitive training platforms for mental exercise, smart pill dispensers to improve medication adherence, and AI-powered social robots for companionship and reminders.

A key strength of this study is the adoption of the user-centered design. In contrast to many apps for older adults that rely on software-centric design and often overlook users' actual care needs [42,43], the user-centered interview approach enables a comprehensive understanding of the multifaceted care needs of older adults. This approach enhances the precision and relevance

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of the recommended interventions, promotes comprehensive care management, and improves overall health outcomes, while also fostering greater trust in the SMART model among older adult individuals [44,45].

The systematic development of evidence-based interventions in our SMART knowledge base represents another notable strength. Although the range of interventions targeting older adults is expanding, many lack a structured and systematic framework for development and are often supported by limited or insufficient evidence [46]. To enhance the potential effectiveness of these interventions, we amalgamated comprehensive insights from user-centered interviews and an exhaustive literature review to identify relevant care problems, guided by ICOPE, ICF, and NANDA-I guidelines. Following the IM framework, we thoroughly reviewed the latest literature and guidelines to formulate evidence-based interventions [47]. Furthermore, our iterative refinement process, including 4 rounds of expert consultations, allowed us to adjust the interventions from a professional perspective, thereby enhancing both the effectiveness and the practical applicability of our SMART knowledge base [48].

However, this study has several limitations. First, excluding professional medical staff from the interviews may have resulted in overlooking certain care needs [49]. Although this gap was partially addressed through consultations with the MEP, the potential for oversight remains. Second, we primarily included individuals who were cognitively intact and willing to participate, which may have introduced survivorship bias. Older adults with cognitive limitations often have more complex and diverse care needs, and their perspectives may be underrepresented in our findings. To address this, we interviewed family members or primary caregivers of older adults who could not communicate and also reviewed relevant literature and guidelines to ensure a comprehensive understanding of care needs. Third, our literature review was confined to the PubMed database, which, despite being a comprehensive biomedical literature resource, might have led to omissions of valuable information [50]. Fourth, in the common disease category, our focus was restricted to major health-impacting conditions, such as hypertension, diabetes mellitus, coronary heart disease, and pneumonia. While this focus aligns with the aim of supporting home-based older adult care, it inevitably narrows the scope of disease management. Fifth, although the knowledge base was updated between October 2024 and March 2025, new evidence may still emerge that has not yet been incorporated. We will continue maintaining the knowledge base and explore the integration of large language models with knowledge graphs to accelerate the updating process. Lastly, although grounded in robust literature evidence and expert insights following a theoretical framework, the real-world usefulness of the SMART knowledge base remains unverified, as the acceptability, feasibility, and effectiveness of its interventions have not been empirically validated. An RCT is planned to evaluate these aspects, and the results will be disseminated in future publications.

Conclusions

This article presents the development and outcomes of the knowledge base and trigger rules of the SMART system. The study methodology provides theoretical support for further development of knowledge bases in CDSSs aimed at delivering home-based older adults care.

Acknowledgments

We thank all participants who were included in the semistructured interviews. We also extend our sincere appreciation to all experts for their professional guidance and valuable insights.

This research was supported by a grant (CX23YZ02) from the Chinese Institutes for Medical Research, Beijing, and the Key Program of the National Natural Science Foundation of China (72034005). The funding source had no role in the study design, data collection, data analysis, data explanation, or manuscript writing.

Data Availability

The datasets generated or analyzed during this study are not publicly available due to ethical and legal restrictions but are available from the corresponding author upon reasonable request.

Authors' Contributions

RG contributed to the methodology, investigation, data curation, and writing of original draft. SX, FY, and HF contributed equally to the methodology, investigation, and data curation. YX and XY contributed to the methodology and data curation. YW contributed to the conceptualization, methodology, funding acquisition, manuscript review and editing, and supervision.

Conflicts of Interest

None declared.

Multimedia Appendix 1
CARE tool.
[DOCX File, 1993 KB - nursing_v8i1e59276_app1.docx]

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Multimedia Appendix 2
Detailed methods and results of interviews and expert consultations.
[DOCX File, 82 KB - nursing_v8i1e59276_app2.docx]

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Abbreviations

AI: artificial intelligence
CARE: Continuity Assessment Record and Evaluation
CDSS: clinical decision support system
ICF: International Classification of Functioning, Disability, and Health
ICOPE: Integrated Care for Older People
IM: intervention mapping
MEP: multidisciplinary expert panel
mHealth: mobile health
NANDA: North American Nursing Diagnosis Association
RCT: randomized controlled trial
TIDieR: Template for Intervention Description and Replication
WHO: World Health Organization

Edited by E Borycki; submitted 02.01.25; peer-reviewed by H Sjöland, J Walsh; revised version received 26.04.25; accepted 19.05.25; published 14.08.25.

Please cite as:
Guo R, Xiao S, Yang F, Fan H, Xiao Y, Yang X, Wu Y
Development of a Knowledge Base for an Integrated Older Adult Care Model (SMART System) Based on an Intervention Mapping Framework: Mixed Methods Study
JMIR Nursing 2025;8:e59276
URL: https://nursing.jmir.org/2025/1/e59276
doi:10.2196/59276

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Evaluating Social Assistive Robots in Clinical Nursing Care: Mixed Method Pilot Study on Health Care Workers' Perceptions and Adoption

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Abstract

Background: The growing demand for older adults care due to aging populations and health care workforce shortages requires innovative solutions. Socially assistive robots (SARs) are increasingly explored for their potential to reduce workload by handling routine tasks. Yet, adoption can be hindered by various health care workers' concerns.

Objective: This study examined the perceptions of health care workers toward SARs before and after a pilot use in a clinical nursing care setting. The study focused on SAR usability, emotional appropriateness, and readiness for adoption.

Methods: A mixed methods pilot study was conducted at the East Tallinn Central Hospital's Nursing Care Clinic in collaboration with Tallinn University of Technology. The TEMI v3 (Robotemi) robot was used for 2 weeks for visitor guidance, goods delivery, and patrolling tasks. Health care workers filled in pre- and postintervention questionnaires with Likert-scale items and a broad open-ended question. Quantitative data were analyzed for changes in perceived safety, trust, and usability. Qualitative data underwent thematic analysis to understand participants' opinions.

Results: Out of 45 involved health care workers, 20 completed the pretest questionnaire, and 5 completed the posttest questionnaire (a 75% attrition). Pretest results show that 17 of 20 (85%) participants had limited previous exposure to SARs and mixed perceptions of their role, with 9 (45%) viewing SARs as machines and 6 (30%) as somewhat human-like. Although 60% believed SARs could become mainstream within 5 - 10 years, there were concerns about the robot's emotional adequacy and job displacement. Posttest findings showed increased confidence in SARs, with all respondents perceiving them as safe tools. Qualitative results indicate improved trust and readiness to integrate SARs into daily routines, with 4 out of 5 (80%) being willing to advocate for SAR use. Still, participants noted limited impact on facilitating their jobs.

Conclusions: The study indicates that short-term collaboration with SARs can enhance health care workers' confidence and their readiness for adoption. However, actual use would need proper emotional adequacy from the robot and aligning its functionalities with specific care needs. The future studies need to examine long-term impacts on care quality and job satisfaction, and also strategies to address generational differences and technophobia among health care staff. Transparent communication and proper training are required to ensure acceptance.

(JMIR Nursing 2025;8:e70305) doi:10.2196/70305

KEYWORDS

aging population; nursing; socially assistive robots; technology acceptance in healthcare; human-robot interaction

Introduction

Background

The growing integration of socially assistive robots (SARs) into older adults' care settings offers transformative potential to address workforce resource limitations and improve care delivery [1]. Throughout Europe, including Estonia, the aging population has placed a significant burden on health care systems, the demand for older adults' care is growing while the shortages of qualified labor are increasing, and existing staff experience burnout due to high workloads and emotional demands [2,3]. In this context, robot assistants such as the TEMI v3 (Robotemi) robot are emerging as viable solutions to assist health care workers in performing routine and physically demanding tasks, allowing workers to focus on more complex and interpersonal care responsibilities. SARs, with their wide range of designs (humanoid, animal-like, telepresence, etc), can

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provide assistance and improve patient engagement in care settings [4].

A typical SAR can navigate autonomously or semiautonomously, it can recognize voice and process natural language, and it can also be used for enhanced video conferencing with improved social presence, potentially improving thus communication and interaction in hospitals and homes [5,6]. For instance, the TEMI robot can autonomously navigate predefined areas, use telepresence to relay interaction between patients and medical personnel or their relatives, and perform simple service tasks [7]. SARs are designed to assist users through social interaction, focusing on cognitive and social assistance. These robots interact with humans using natural language, body language, and social behaviors, enhancing psychological and emotional well-being and complementing traditional caregiving services [1]. In health care, SARs provide services that directly benefit patients, health care professionals, and caregivers. They are particularly useful in supporting older adults and patients with chronic illnesses, who require continuous monitoring and social interaction. SAR functions include remote patient monitoring, facilitating swift responses to incidents like falls or medical emergencies, measuring vital signs (eg, pulse, blood pressure, and oxygen saturation), and assisting in remote consultations between patients and health care providers [8,9]. These robots are also used to combat social isolation, significantly enhancing patients' sense of companionship and social presence in long-term care facilities or for individuals confined at home [10].

Leaning on the context of using SARs in health care to empower health care workers' professional capabilities, the aim of this study was to examine the effects of using the TEMI v3 robot assistants for 2 weeks in a nursing clinic's daily practices to examine the feasibility and usability of SARs as perceived by health care workers. The study is arranged as follows: (1) first, we open the Theoretical Background by examining studies about the real-world use of SARs in health care, discussing appropriate technology acceptance models and relevant concepts, and exploring the challenges in adopting novel technologies in health care. Then, in (2) the Methods, we discuss the study design, sample, and procedure, describe the methods for collecting and analyzing data, and present ethical considerations. Followed in (3) the Results, we give a detailed overview of our quantitative and qualitative results, together with a comparison of pre- and posttest findings. And we conclude with (4) the Discussion that includes a description of the study's limitations and suggestions for future research and practice.

Real-World Use of SARs in Health Care

Although SARs with their modern functionalities are relatively new technologies, there are already a few studies that have investigated their efficacy in health care. The results of these studies give knowledge of how SARs can enhance patient well-being, support health care professionals, and improve the overall quality of care.

The CARESSES (Culture-Aware Robots and Environmental Sensor Systems for Elderly Support) randomized controlled trial was a good example of such studies [11]. This trial explored the impact of culturally competent SARs (in this case, the Pepper robots) on older adults in care homes. The study involved 33 residents across facilities in England and Japan, who interacted with SARs that were programmed with varying levels of cultural competence. The findings indicated that participants who engaged with culturally competent robots exhibited significant improvements in emotional well-being, as measured by the SF-36 emotional well-being subscale, compared with those receiving standard care. While changes in loneliness scores were observed, they did not reach statistical significance. These results suggest that customizing robot interactions to consider the users' cultural backgrounds can enhance the psychological benefits of SARs in older adult care settings [11].

In pediatric health care, SARs have been used to alleviate distress and anxiety related to medical procedures. A systematic review by Trost et al [12] examined the effectiveness of SAR interventions in reducing pain and emotional discomfort among children. The review concluded that while SARs show promise in reducing distress and anxiety, evidence regarding their impact on pain reduction remains inconclusive. The authors emphasized the need for further research to establish standardized protocols and assess the long-term benefits of SARs in pediatric settings.

For individuals with dementia, SARs have been used to evoke positive emotional responses and reduce apathy. A pilot study by Otaka et al [13] investigated the immediate emotional reactions of nursing home residents with dementia to multisensory stimuli presented by SARs. Using facial expression analysis, the study found that participants exhibited increased expressions of happiness, particularly when engaging with animal-like or doll-type robots that provided combined visual, auditory, and tactile stimuli. These findings highlight the potential of SARs to enhance emotional engagement in dementia care, especially when designed to offer multimodal interactions.

In the realm of rehabilitation, SARs have been integrated into poststroke therapy to provide personalized coaching and monitoring. Lee et al [14] developed an interactive SAR system that combines neural network and rule-based models to assess patients' rehabilitation exercises in real time. The system was evaluated with 15 poststroke survivors, demonstrating its ability to adapt to individual patient needs and provide corrective feedback. Participants reported increased motivation and satisfaction with the robot-assisted therapy, suggesting that SARs can play a valuable role in enhancing rehabilitation outcomes.

These studies indicate that SARs can be versatile when addressing health care challenges. The robots can improve the quality of care and support in medical settings when their interactions are programmed to consider specific patient needs and cultural contexts. From the technical point of view, however, the introduction and acceptance of SARs in health care settings face several challenges. These include the necessity for robust and reliable internet connectivity, technical support for robot operation, and modifications in physical spaces to accommodate robot navigation. There are also limitations related to sensory input, such as restricted visual and auditory capabilities, potentially leading to communication challenges and reduced social presence compared with face-to-face interactions [1,15]. In addition, the introduction of SARs raises significant emotional

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and professional concerns for both health care professionals and patients. Next, we examine these issues while addressing specific fears associated with SARs such as job relocation, loss of human contact, emotional unsuitability to care settings, and a general inability to adapt to new technologies. These concepts frame the complexities of SAR integration, demonstrating both the opportunities and challenges of SARs in the health care sector.

Technology Acceptance in Health Care

The adoption of SARs in health care can be studied through widely established technology acceptance models, mainly the Technology Acceptance Model (TAM) [16] and the Unified Theory of Technology Acceptance and Use (UTAUT) [17]. These models emphasize the importance of perceived usefulness and ease of use, suggesting that when users find new technologies useful and easy to understand, their willingness to adopt these technologies increases. Research also emphasizes that technology readiness, that is, user readiness and willingness to adopt and engage with new technology, is a critical factor in health care settings [18,19]. In health care, the application of technology such as SARs brings additional considerations beyond functionality and ease of use, particularly the socio-emotional implications of care [19,20]. Social exchange theories also provide a basis for understanding how the relational aspects of care affect technology acceptance, emphasizing that perceived coldness or impersonality of robots can hinder their acceptance in contexts that require empathy and warmth [21]. Health care workers often need special training and time to adapt to SAR technology, which is central to reducing fear and increasing confidence in robotic assistance. In addition, participatory training can significantly improve technology adoption and smooth transitions to new work processes [11]. Our pilot study, based on the use of the TEMI v3 robot, emphasized these readiness principles by adding predeployment training and scenario-based familiarization that allowed personnel to engage in SARs in a controlled environment before full deployment.

Challenges in Adopting New Technologies

One of the main concerns regarding the implementation of SARs in health care is the fear of job displacement. Many health care workers perceive the introduction of robots not only as a complement to their roles, but as a potential threat to workplace safety. Such fears are supported by research showing that job displacement problems are common among workers in automated industries [22]. In the health care context, where relationships and personalized communication are critical, these concerns are even more acute [23]. Although SARs are designed to support tasks that do not require human contact, employees may feel uncertain about the boundaries of their roles as the capabilities of SARs expand. Thus, clear communication of SAR's supportive, not substitute, role may help alleviate this fear.

Another barrier to integrating SARs into health care is the reluctance or inability of individual staff members to adapt to new technologies, especially those with limited digital skills or existing technophobia. Technophobia, or the fear of engaging with new technologies, can manifest in many ways, from general anxiety about using technology to concerns about one's ability to learn and adapt to robotic systems [24]. This fear is especially pronounced among older health care workers or those who are limited by digital tools. Research shows that this lack of technological readiness can hinder the successful deployment of SARs, highlighting the need for robust training programs that build familiarity and confidence among staff [20,25].

Health care providers and patients express serious concerns about the perceived emotional inadequacy of SARs in sensitive treatment contexts. The "human touch" is a key aspect of geriatric care, as many older adult patients depend on interpersonal interactions for emotional support and social bonding. Research has shown that SARs are often perceived to lack the warmth and empathy essential to their caregiving roles, leading to resistance from both patients and caregivers [23]. Although SARs can perform tasks efficiently, their inability to mimic human empathy or intuition limits their suitability for roles involving complex emotional needs, such as comforting an anxious patient or providing personalized encouragement during rehabilitation exercises.

Methods

Study Design

This study used a quasi-experimental mixed methods design to assess health care workers' perceptions and experiences with SARs, using the TEMI v3 robot as an example, within a real-world health care setting. Applying mixed methods in pilot feasibility studies is justified when integrating quantitative and qualitative data could provide a comprehensive understanding of implementation feasibility, acceptability, and practical implications of new interventions [26]. A quasi-experimental design was specifically chosen due to the study's exploratory nature, the limited duration of 2 weeks, practical constraints in the clinical setting, and the intention to gather initial insights into changes in staff perceptions and experiences following robot deployment. The pilot study was part of a broader registered social scientific feasibility research (the ethics committee registration details are provided under "Ethical Considerations"), conducted at the East Tallinn Central Hospital's Nursing Care Clinic in Estonia, in collaboration with Tallinn University of Technology. The design involved pre- and postintervention questionnaires, including both closed and open-ended questions, allowing for quantitative comparisons and qualitative insights into health care workers' attitudes and readiness concerning SARs before and after exposure. In addition, scenario-based role assignments were used, simulating practical usage situations to capture nuanced staff reactions, emotional responses, and potential concerns in a controlled yet realistic environment. Over a period of 2 weeks in the summer of 2024, 3 distinct SAR usage scenarios (visitor guidance, delivery assistance, and facility patrolling) were trialed. These scenarios (see "Procedure" for more details) were carefully selected based on the robot's technical abilities and preliminary discussions with health care staff and administrators, reflecting ancillary tasks that would support rather than replace the primary caregiving roles of human staff.

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Our study addressed the challenges described in the "Challenges in Adopting New Technologies" section in the following manner. First, we strategically deployed SARs in ancillary rather than primary health care roles; for example, the robots were used for visitor guidance, delivery, and patrolling functions. These tasks complement people's care by reducing workload without compromising the interpersonal aspects that are central to caring for older adults. During our pilot, health care administrators played an essential role in clearly communicating to staff members the specific purpose and scope of the SARs deployment. Administrators were involved because their responsibility in decision-making processes and in organizational change management put them in the position where they could address the personnel's concerns about job security and explain how SARs are used strictly as supportive tools instead of being replacements for human staff members. To avoid any perceived power imbalance, administrators took part in structured meetings, where dialogue and feedback regarding the roles assigned to SARs were encouraged. These discussions were helpful for keeping transparency and supporting collaboration where employees felt safe to present their suggestions and concerns. Next, the robot's tasks were structured to assist rather than replace human interaction. For example, a robot's role as a tour guide or logistical assistant fulfills functional needs without infringing on the emotionally charged tasks performed by health care providers. This design choice reflects a "complementarity model" where SARs are positioned to enhance caregivers' capabilities without diminishing the importance of human connection [27]. Finally, we implemented short training sessions, allowing staff to interact with the robot in a supportive, low-stakes environment before integrating SARs into daily operations, in order to increase user confidence, reduce technophobia, and promote an inclusive environment that accommodates different levels of digital competence. In addition, involving employees directly in defining the roles and tasks for SARs has been shown to be effective in reducing resistance, as it empowers them to shape how the technology fits into their existing workflows, rather than feeling like it is being imposed by administrative decision-making alone [11].

Participants

The sample consisted of 45 employees of East Tallinn Central Hospital's long-term Nursing Care Clinic, all of whom were invited to participate in the study voluntarily. A total of 20 of them completed the pretest and 5 completed the posttest questionnaire. The participants represented a variety of roles in the clinic, including nurses, care workers, and other health care professionals, and administrative staff who interact with patients and the hospital environment on a daily basis. To ensure inclusiveness, all employees who could encounter the TEMI v3 robot in their daily activities were given the opportunity to participate. Anonymity was maintained throughout the study to encourage honest feedback. To this end, throughout the study, anonymity of responses to the questionnaires was emphasized, and for this purpose, gender information was excluded as the employees at this clinic were predominantly female. Demographic information, including age range but excluding gender, was collected to understand differences in employee technology adaptation.

Procedure

Preintervention Training and Questionnaire

Before SAR implementation, participants underwent short training to familiarize themselves with the functions, controls, and user interface of the TEMI v3 robot. The training covered robot navigation, object transport, patrol functionality, and interaction options. After the training, participants completed a preintervention questionnaire to capture initial attitudes, perceived ease of use, usefulness, and potential fears (eg, job relocation and loss of human contact in caregiving). This questionnaire included both quantitative items on a modified Likert scale and an open-ended question for qualitative feedback.

Application of the Robot in 3 Scenarios

During a 2-week period, TEMI v3 was used in the clinic to perform 3 specific functions, each tailored to complement routine tasks without replacing human care:

- Visitor guidance (Scenario 1): TEMI v3 was programmed to navigate visitors to specific locations in the clinic (eg, patient rooms and nurse stations) on request. Visitors could select destinations on the robot's interface screen, after which TEMI guided them to the desired location. This task required minimal interpersonal interaction on the part of the staff while allowing feedback on SAR effectiveness and usability to be monitored.
- Goods delivery (scenario 2): TEMI v3 was equipped with a tray for the delivery of light items such as personal items or documents between rooms or departments. Workers placed items on TEMI's tray, selected a delivery location through the robot's interface, and TEMI delivered the items autonomously. This scenario simulated the use of SARs for logistical support in day-to-day maintenance.
- Patrol functionality (scenario 3): TEMI v3 performed patrol duties in the corridors of the clinic during the evening and night shifts, moving between predetermined points. The patrol function allowed staff to monitor corridors via TEMI's real-time video feed without compromising patient privacy as no data were recorded. This feature provided additional security and oversight without directly replacing employee roles.

Postintervention Questionnaire and Feedback Collection

At the end of the 2-week period, a follow-up seminar was held to allow participants to discuss their experiences with TEMI v3 in a group. This provided additional insight into employee concerns, perceived benefits, and the emotional and practical impact of SARs on their work environment. During the seminar, the participants also completed a postintervention questionnaire that had the same questions as the preintervention questionnaire (including the open-ended question for qualitative data), recording changes in participants' perceptions of SAR use, perceived usefulness, ease of use, and emotional impact. As participation in the study was voluntary, the postintervention questionnaires were made available to the participants who were present at the seminar, and to those who wanted to add their

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reflections, although they were not able to be present. The pre- and postintervention qualitative data were used together to extract as many potential themes to describe the perceived roles of SARs or their influence on involved people (we did not measure changes in these perceptions).

Measures and Data Analysis

Pre- and Postintervention Questionnaires, Quantitative Data

The pre- and posttest questionnaires that were filled in by the participants according to the procedure described in the previous subsection used Likert-scale items (n=19) to measure participants' perceptions toward SAR adoption, perceived usefulness, perceived ease of use, and perceived threats (eg, fear of job transfer, emotional inadequacy, and inability to adapt). The prequestionnaire established the basis for these perceptions, while the postquestionnaire aimed to assess changes in perception after the 2-week intervention. The questionnaires included both quantitative items for analysis and an open-ended question for qualitative exploration of nuanced responses and issues. The questionnaires were based on established frameworks and approaches to understand user perceptions and readiness to adopt SAR in health care. The TAM and the UTAUT were the underlying models. TAM emphasizes the importance of perceived usefulness and ease of use in technology acceptance [16], while UTAUT extends this to include social influence and facilitating conditions as key determinants of user intentions and behavior [17]. In addition, elements from human-robot interaction (HRI) and social presence theory were added to assess participants' perceptions of the SAR's "personality" and the social dynamics of their interactions with it. This is critical in health care, where the perceived warmth and empathy of technology can influence acceptance, particularly in aged care settings [21]. Questions assessing trust, security, and reliability were based on the principles of trust in automation, which consider predictability and reliability important for developing user trust in automated systems [28,29]. Finally, the concept of technology readiness was integrated to measure health professionals' confidence and propensity to engage in SARs in line with the Technology Readiness Index (TRI), which measures a person's readiness to adopt new technologies [30] (Textbox 1).

Textbox 1. Metrics captured by the questionnaire.

Specifically, the questionnaires included:

- Demographic information (3 items): length of employment in health care (categories from less than 1 year to more than 5 years); age group (up to 30 years, 31-50 years, and 51 years and older); frequency of previous interactions with robots in education or work contexts; and frequency of previous interactions with robots in education or work contexts.
- Perceptions of future use of robots (2 items): expectations of robot usage in health care within 5-10 years; Perceptions of robots' roles as colleagues, competitors, or tools.
- Interaction experience with robot during trial (3 items): frequency of interactions with the robot during the trial period; perception of the robot as a machine or human-like during interactions; and general evaluation of robot usage frequency.
- Robot interaction quality and usability (7 items): ease of cooperation with the robot; clarity and comprehensibility of communication with the robot; suitability of robot's physical position and height; perceived safety while interacting with the robot; trustworthiness of the robot; pleasantness of interaction; and confidence while interacting with the robot.
- Readiness and acceptance of robot integration (4 items): willingness to use robots regularly in daily work; perceived potential of robots to simplify work tasks; willingness to actively support the introduction of robots into the workplace; and expectation of robots' long-term impact on work.

The collected paper-based questionnaire responses were first digitized and manually entered into a Microsoft Excel spreadsheet for analysis. The Likert-scale responses were summarized by grouping related response categories to simplify interpretation and amplify clarity of outcomes (ie, for each Likert-scale item, responses were categorized into 3 groups: positive [eg, "Trustworthy" and "Very Trustworthy"], negative [eg, "Untrustworthy" and "Very Untrustworthy"], and neutral or uncertain midscale responses]). After categorizing responses into these groups, the frequency and proportion of participants falling into each category (positive, negative, neutral, or uncertain) were calculated. Demographic information was analyzed by summarizing frequencies and proportions in each demographic category. The summarized data were presented using descriptive statistics, such as percentages or frequencies, to clearly illustrate the distribution of responses and identify meaningful patterns or changes attributable to the intervention.

Qualitative Data

A broad, open-ended questionnaire question ("Do you have any thoughts?") was included to gather richer, detailed insights beyond what the quantitative Likert-scale responses could capture. These written responses were digitized from paper questionnaire sheets and entered into a Microsoft Excel database for analysis. A thematic textual analysis was conducted following a structured inductive approach, which involved systematically coding the qualitative data to identify recurring patterns and significant themes. The initial codes were generated by highlighting salient words, phrases, or sentences representing key ideas and experiences expressed by participants. These initial codes were then grouped and categorized into broader themes, such as perceived advantages of robot usage, concerns and apprehensions, suggestions for improvements, emotional reactions, and reflections on robot-human interactions.

Ethical Considerations

The study was reviewed and approved by the Research Ethics Committee of the National Institute for Health Development in Estonia (#8.3/13 - 24 from May 29, 2024). All participant interactions with TEMI v3 were anonymous, and no patient or visitor data were recorded. Participants were informed about the purpose of the study, their voluntary participation, and the

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nonrecording of identifiable data. Participants received no compensation for their participation. Informed consent was obtained from all participants and clear instructions were given regarding robot interactions, particularly in the patrol scenario, to ensure privacy and security protocols were followed.

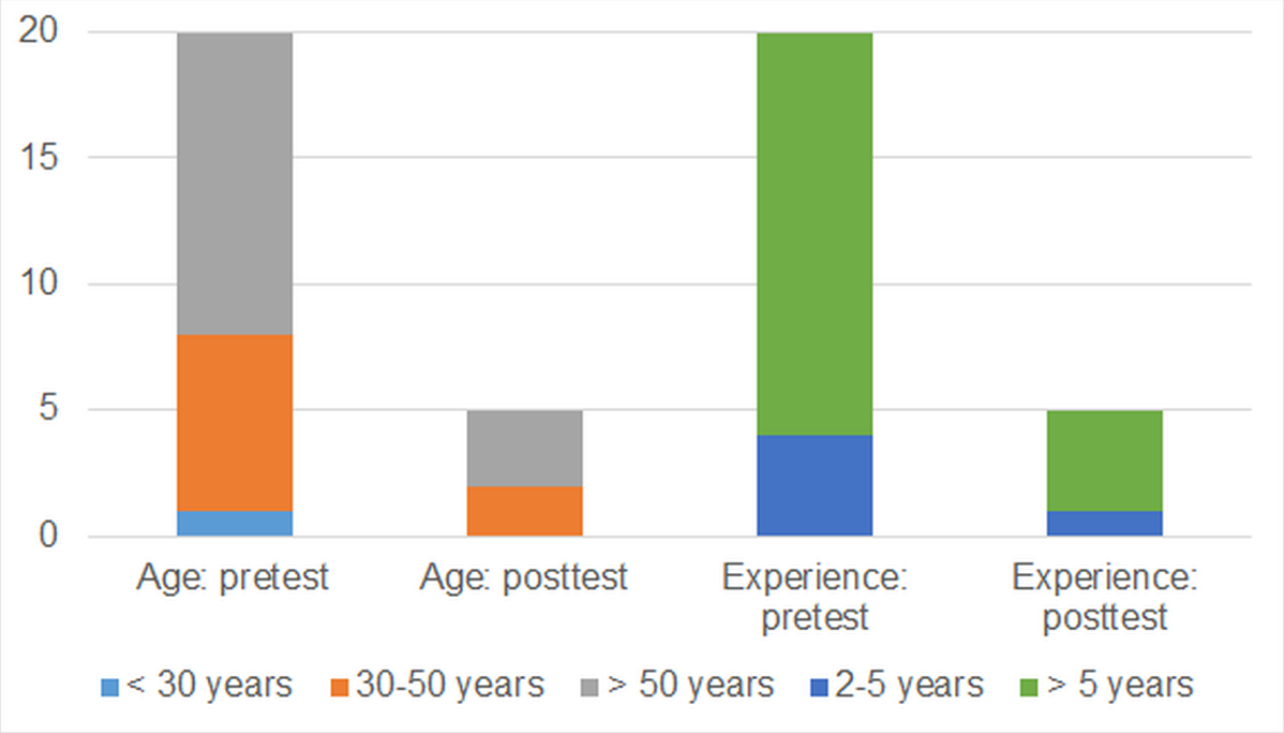
Results

Response Overview

20 responses were received to the initial pretest questionnaire, which provided a broad overview of the attitudes and demographic information of participating health care workers. As the unit was relatively small, with administrative personnel having previous long-term experience as ordinary older adult health care employees, we did not collect separate information about the employees' current positions. The posttest questionnaire was completed only by 5 participants, representing a significant attrition rate of 75% (n=15). The possible reasons are discussed under the "Limitations" section. The professional experience duration of participants, together with their age, is shown in Figure 1.

As demonstrated in Figure 1, the majority of participants had more than 5 years of experience in the health care sector and were older than 50 years. In the posttest group, similar tendencies were seen.

Figure 1. The age and work experience of the participants who filled in the pre- and posttest questionnaires.



Quantitative Results

Pretest Results

Of the pretest respondents, 85% (n=17) reported no significant prior experience with robots in their work, 10% (n=2) had some experience, and 5% (n=1) used robots frequently. When asked if they saw robots as colleagues or competitors, 5% (n=1) saw them as colleagues, 95% (n=19) saw them as tools, and none saw robots as competitors (Figure 2, right). Almost half of the participants (45%, n=9) considered robots to be machines, 30% (n=6) perceived them similar to humans, while one quarter of participants (n=5) were unsure (Figure 2, left).

Participants also shared their previous experience with SARs; 85% (n=17) had low experience with them, 10% (n=2) had insignificant experience, and 5% (n=1) had considerable experience with SARs (Figure 3, left). Regarding the potential for robots to become mainstream in their field in the next 5 - 10 years, 60% (n=12) thought it was realistic, while 40% (n=8) were unsure (Figure 3, right).

Participants then rated specific aspects of working with robots (see Figure 4). When it comes to collaboration simplicity, 75% (n=15) found it easy, 20% (n=4) were unsure, and 5% (n=1) found it a challenge. Communication clarity with the robot was rated good by 55% (n=11), while 30% (n=6) were not sure and 15% (n=3) rated it bad. The height of the robot was considered suitable by 80% (n=16) of respondents, 20% (n=4) were undecided.

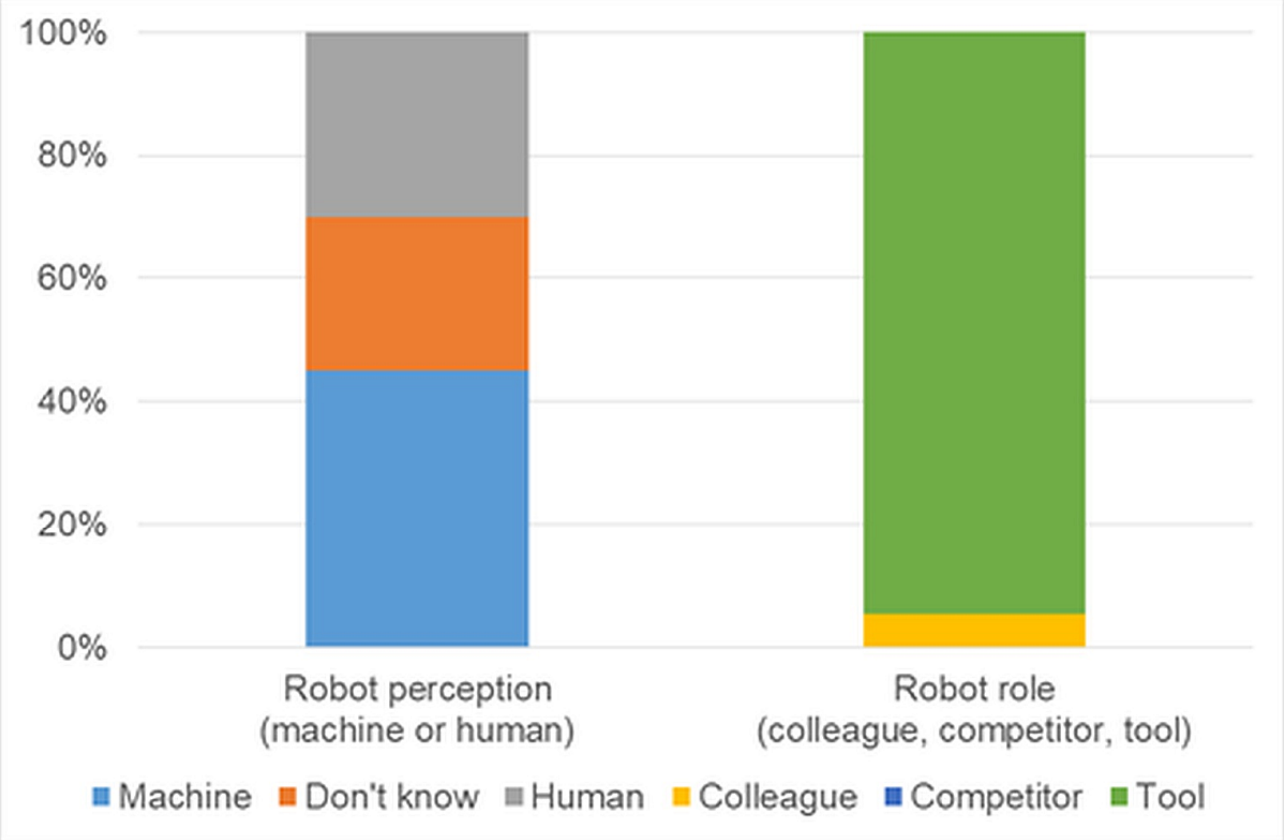
In terms of safety, 65% (n=13) of respondents believed that robots are safe, 20% (n=4) were not sure, and 15% (n=3) felt that robots were not safe. 55% (n=11) of participants considered robots trustworthy, while 35% (n=7) were unsure and 10% (n=2) considered them untrustworthy. A significant 80% (n=16) of respondents found robots to be *pleasant*, although 20% (n=4) were undecided. Regarding *c*onfidence in working with robots, 80% (n=16) felt confident, 5% (n=1) were unsure, and 15% (n=3) were uncertain.

When considering the integration of robots into daily work, 70% (n=14) were ready, 15% (n=3) were not, and 15% (n=3) were unsure. Regarding the potential of robots to make their

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jobs easier, 60% (n=12) agreed, 20% (n=4) disagreed, and 20% (n=4) were unsure. In addition, 80% (n=16) were ready to promote the use of robots in their workplace, while 20% (n=4) were unsure. Finally, when asked about the impact of robots on the future of their work, 30% (n=6) thought robots would have an impact, while 35% (n=7) thought that robots would not have any impact and another 35% (n=7) were unsure.

Figure 2. Percentage distribution of responses for robot perception and role in the workplace.



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Figure 3. Percentage distribution of responses for previous experience with robots and likelihood of robots in the next 5 - 10 years.

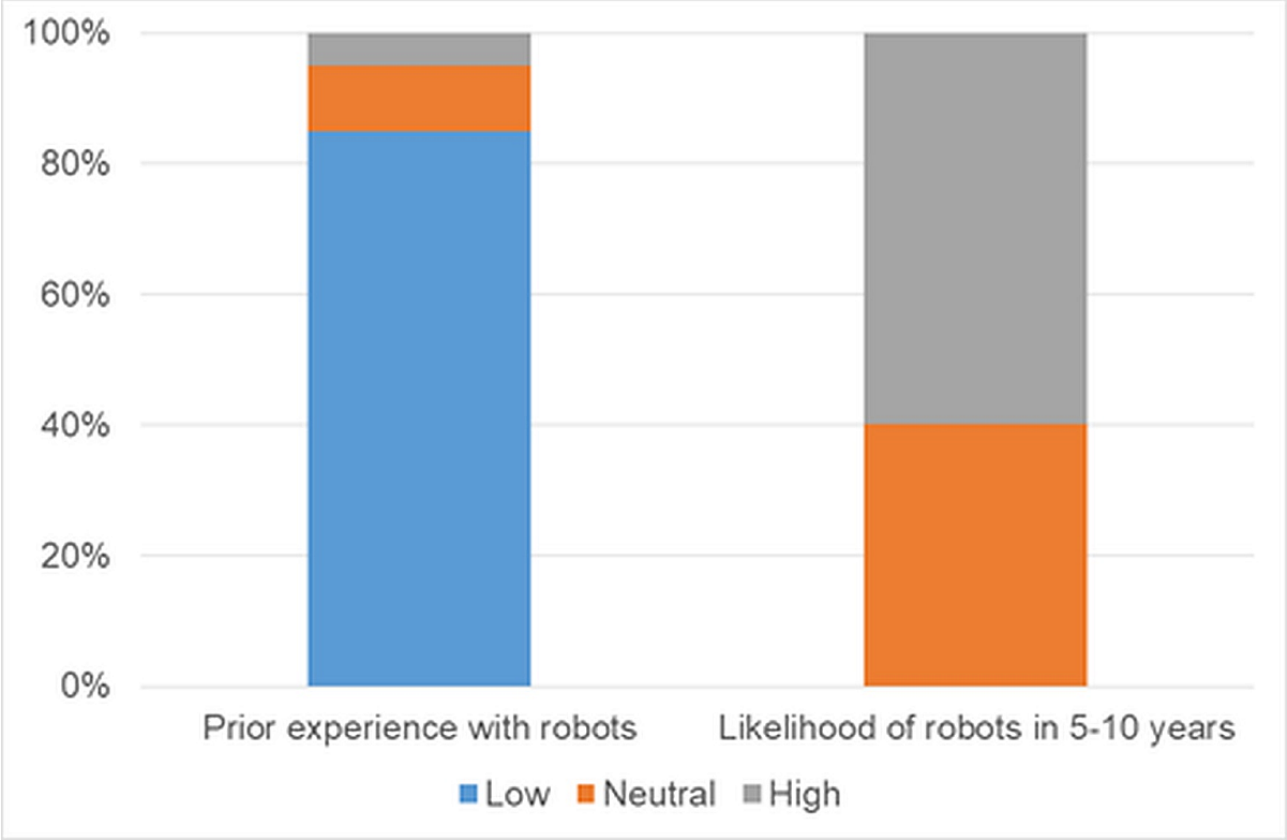
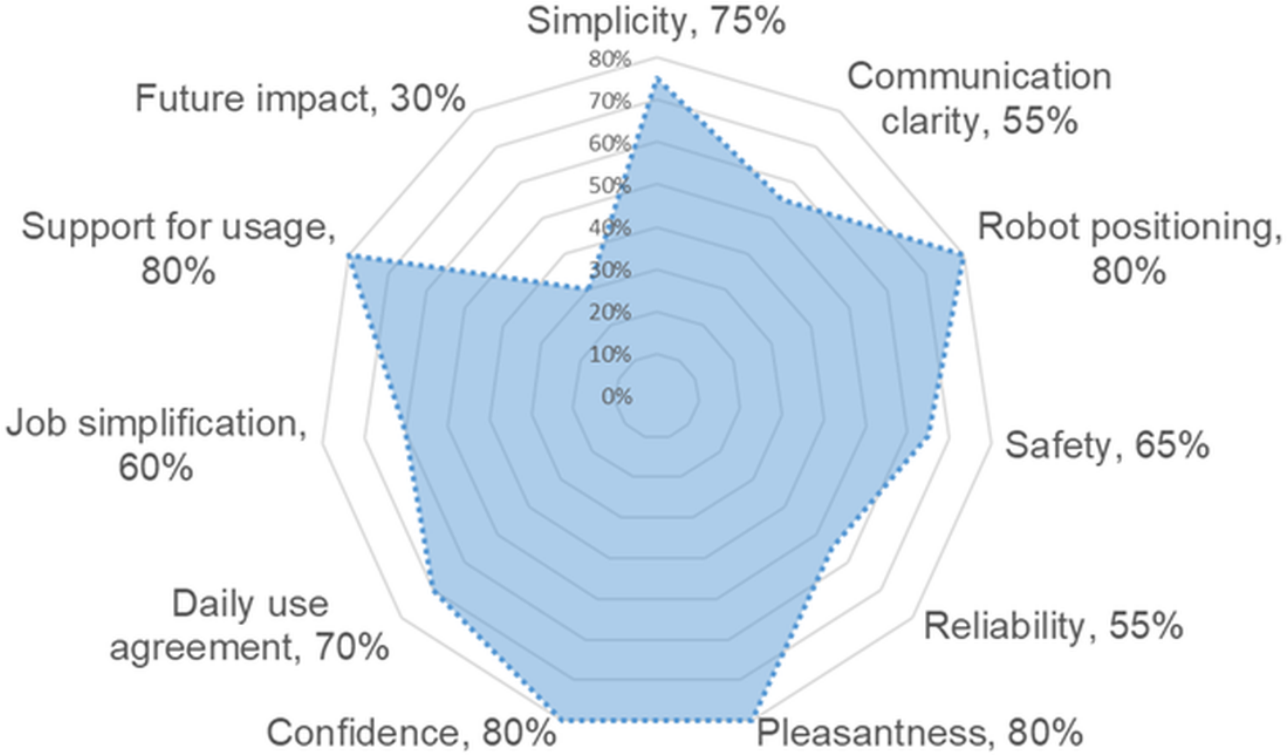


Figure 4. Percentage distribution of high ratings (5-7) across robot collaboration attributes, pretest.



Posttest Results

Among the posttest respondents, 100% (n=5) reported some experience with robots. Regarding the potential for robots to become mainstream in their field within the next 5 - 10 years, 60% (n=3) found it realistic, with the remainder undecided. In terms of perception, all participants identified the TEMI V3 robot as a machine, with no participants considering it human-like. When asked whether robots would be viewed as

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colleagues, tools, or competitors, 100% (n=5) considered them as tools.

For specific aspects of working with robots, 80% (n=4) of participants felt that collaboration with robots was straightforward, while 20% (n=1) were uncertain. Communication clarity was rated positively by 80% (n=4) of respondents, with 20% (n=1) uncertain. The robot's height was deemed appropriate by 80% (n=4), with 20% (n=1) undecided.

Regarding safety, 100% (n=5) of respondents felt that robots were safe. Robots were deemed trustworthy by 60% (n=3), while 40% (n=2) were uncertain. Furthermore, all respondents found robots pleasant. For self-confidence in working with robots, 80% (n=4) felt assured, and 20% (n=1) were uncertain.

On the integration of robots into daily tasks, 80% (n=4) were willing to incorporate them into their work, and 20% (n=1) were uncertain. Regarding robots' potential to facilitate work, 60% (n=3) disagreed, with 20% (n=1) uncertain and 20% (n=1) agreed. In addition, 80% (n=4) were prepared to advocate for robot use in the workplace, while 20% (n=1) were unsure. Finally, regarding the impact of robots on future work, 40% (n=2) believed robots would have an impact, 40% (n=2) did not think so, and 20% (n=1) were undecided.

Comparison of Pre- and Posttest Results

In both the pretest and posttest groups, participants expected robots to become mainstream in the clinical care of older adults within the next 5 - 10 years. However, some changes in robot perception and comfort were observed between the results of the 2 tests, suggesting that there was an increase in positive perceptions and confidence in collaborating with robots, particularly regarding safety, reliability, and the potential role of robots in the workplace.

In the pretest, 45% (n=9) of respondents perceived TEMI V3 as a machine, 30% (n=6) found it somewhat human, and 25% (n=5) were not sure. In the posttest, all participants (n=5) consistently identified the TEMI v3 robot as a machine, indicating a shift towards viewing robots as nonhuman tools. Comfort and confidence in working with robots also increased in the posttest. Perceptions of safety improved significantly, with 100% (n=5) of posttest respondents considering the robots to be safe, compared to 65% (n=13) in the pretest. Reliability ratings similarly increased, with all posttest respondents (n=5) finding robots enjoyable to work with, while 20% (n=4) in the pretest were undecided.

However, it seems that after having an actual experience with SARs, the participants' belief in the robots' ability to simplify their work decreased. Despite this, posttest respondents showed a stronger willingness to integrate robots into their daily work (80%, n=4 ready compared with 70%, n=14 pretest) and a greater willingness to promote the use of robots in the workplace. This openness extended to confidence about the impact of robots on future work, with a slight increase in the number of people expecting a positive impact.

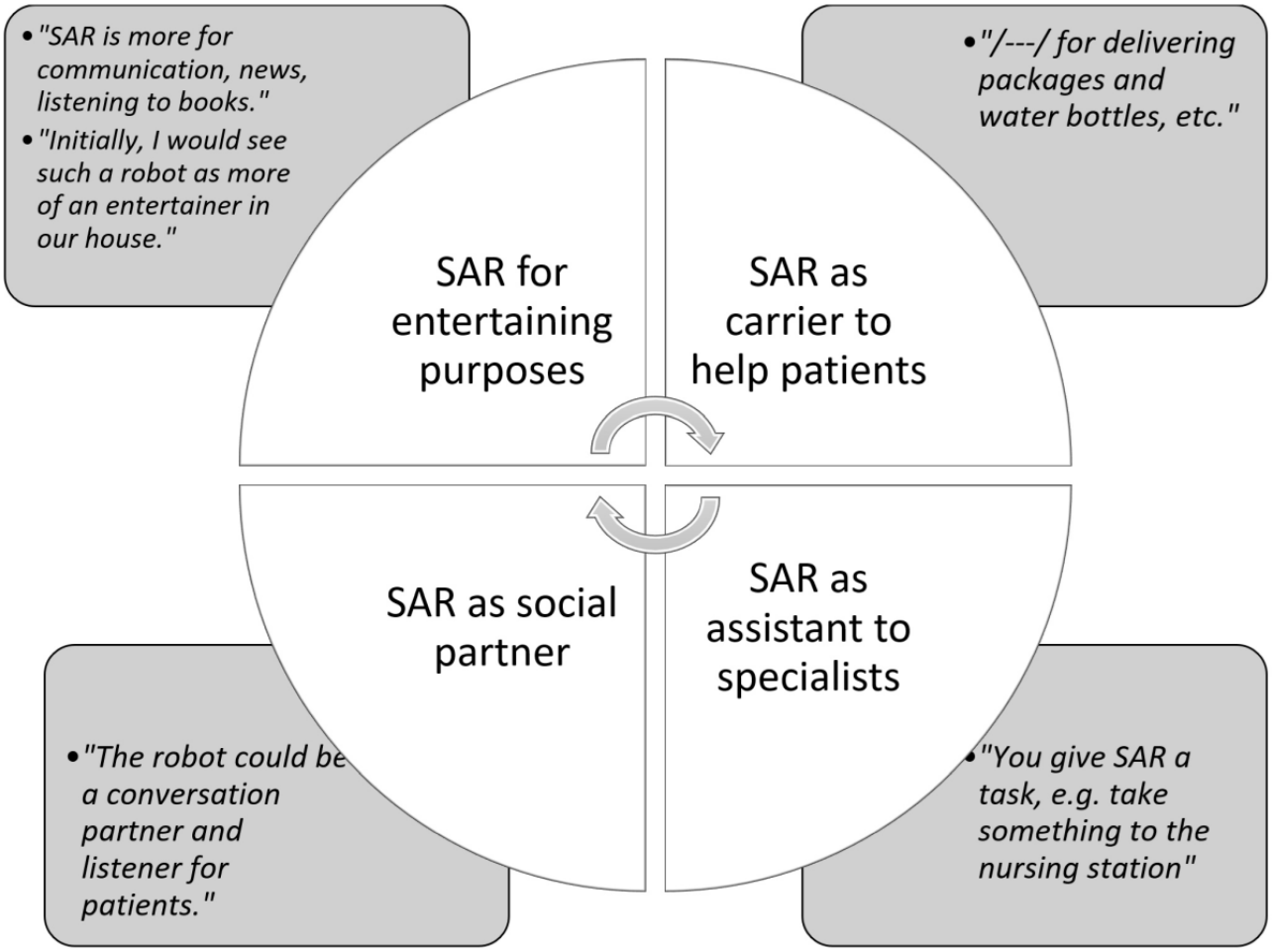
Qualitative Results

An open-ended questionnaire question ("Do you have any thoughts?") provided detailed insights in addition to the quantified data from the Likert-scale responses. Digitized responses underwent thematic textual analysis, key phrases were highlighted as initial codes and grouped into broader themes to identify recurring patterns. The main themes of qualitative analysis are seen in Figure 5.

As seen from Figure 5, participants proposed several functional and emotional roles for the TEMI robot in a health care facility. Many envisioned TEMI as a mobile assistant that could be summoned via a Wi-Fi-connected station, useful for tasks such as delivering items to the nurse's station, reducing the need for staff to carry them manually. TEMI was also seen as a tool to improve the patient experience, provide entertainment, deliver items, and be a conversational partner. Respondents felt that TEMI could lift patients' moods by providing social interaction, news, and audiobook playback.

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Figure 5. Potential roles for socially assistive robots (presented with illustrative quotes). SAR: socially assistive robots.



Discussion

Principal Findings

This study explored the potential benefits and challenges of integrating SARs, such as TEMI v3, into nursing care facilities. SARs provide value in supporting health care workers by performing noncore tasks such as guidance, delivery, and patrolling, thereby allowing staff to focus on complex interpersonal care tasks. However, the implementation of SARs in health care also presents a variety of emotional, professional, and technical challenges that need to be addressed through thoughtful strategies.

One of the most important findings is the importance of balancing technological efficiency with the emotional needs of older adult patients. The “human touch” is crucial in aged care, where personal interaction promotes emotional support and social inclusion [27]. Consistent with previous research, our results suggest that health care professionals were concerned about SARs replacing human roles that require empathy and warmth and perceived that SARs lacked the human-like intuitive and comforting qualities that patients value [21]. Similar findings were observed by Turja et al [23,31], who reported that SARs may have problems achieving the warmth needed in their caregiving roles, which may lead to resistance from patients and caregivers. By positioning SARs in complementary roles, such as logistical support rather than personal care, we sought to preserve the human aspects of care while benefiting from the robot’s hands-on capabilities. This “complementarity model” aligns with the view of Sharkey and Sharkey [27], who advocate SARs as an aid rather than a substitute in situations that require emotional connection. In addition, transparent communication and role clarification, emphasizing that SARs are designed to support, not replace, staff, are essential to addressing these issues.

Possible generational differences in SAR acceptance must be considered. Czaja and Lee [32] found that younger people are generally more adaptable to new technologies. These findings suggest that younger health care workers could be more susceptible to SARs, implying that deployment strategies need to include tailored training and engagement. These findings highlight the importance of addressing job security fears as part of a holistic approach to SAR integration. Research also shows that older adults often experience technophobia, which is defined as fear or anxiety of technology [24]. Consistent with our findings, Barnard et al [25] and Yusif et al [33] suggest that older health workers may have concerns about adapting their routines to SARs. To mitigate this barrier, structured, scenario-based training sessions should be designed to introduce staff to SARs in a supportive, low-stakes environment, building trust and reducing resistance. Papadopoulos et al [11], emphasize that participatory training significantly improves technology adoption by empowering users to adopt new tools. Our study’s training approach is consistent with these findings, as it provided

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staff with hands-on interactions that increased their comfort and understanding, ultimately promoting a more inclusive environment for SAR adoption.

The issue of effective training of SARs needs to be approached systematically, because even when fears about new technology are addressed and workers have had time to familiarize themselves with SARs, integrating these robots into the clinic's everyday life remains a challenge. Interestingly, the number of people who thought SAR did not make their work easier, already high at the start of the study, increased after 2 weeks of exposure, while the number of people who were ready to integrate robots to their daily routines also stayed high. This increase suggests that 2 key factors may be necessary for the successful implementation of SARs in aged care settings. First, a high level of customization is required to ensure that SARs meet the specific demands of aged care. For example, in our experiment, the software design lacked an iterative development approach that would have allowed user feedback to shape and refine the robot's features and behavior. Second, it seems important to equip health care professionals with established methods and routines tailored to meaningfully incorporate SARs into their workflows. This dual approach—favoring iterative, user-driven customization with the provision of well-defined routines—may play an important role in increasing the perceived utility and acceptance of SARs in daily health care practices.

Although participants found SARs relatively easy to use, this does not mean that these robots inherently facilitate human tasks unless their implementation is carefully planned. For SARs to be truly effective, health care professionals need to be confident that robots can be trusted to provide real support, and it is up to senior stakeholders, such as management, to clearly demonstrate how SARs can positively impact staff's daily routines. Furthermore, it is possible that SARs may not significantly reduce the workload of health care professionals, but rather provide greater value by improving the quality of life and meaningful experiences for patients. It is important to understand whether SARs can fulfill this role effectively, and future research should explore this potential by assessing the long-term impact of SARs on both patient well-being and health care provider job satisfaction.

Limitations

Some limitations of the study must be acknowledged. First, SARs were tested in one nursing clinic in a relatively short period of time, so the findings cannot be generalized to all Estonian health care workers. Second, the study site was located in the capital of Estonia, and the study does not provide an overview of possible differences in perceptions in rural or peripheral areas, which could be important in terms of general trust in the use and ability to use technology in older adults care settings. Third, due to piloting in a single care clinic, we also had a limited sample of 45 participants with a participation rate of <50% in the pretest phase and even lower in the posttest period. This decline is likely due to a combination of the following factors: (1) loss of interest in the technology—some participants may have lost interest in SARs after initial engagement, perceiving limited personal benefits or finding the technology less impactful than expected; and (2) focus on primary responsibilities—it is likely that, for reasons discussed in the introduction, participants found it difficult to allocate extra time to nonessential tasks such as the SAR study. In addition, the implementation scenarios for Temi v3 robot in this study were specifically designed to act on an auxiliary basis, without impact on the day-to-day care processes (ie, the robot did not participate independently directly in treatment nor tendance, making it more difficult for the employees to grasp the beneficial impact of using the robot on their tasks). The study did not include nursing clinic patients and focused on the perspective of health care professionals, so it is not clear whether and how professionals' perceptions would change if patients liked or disliked SARs, eg, whether acceptance would be higher or fears and emotions lower if patients perceived SAR as useful and acceptable. Despite all these limitations, we believe that this study provides valuable information on the potential of implementing SARs in nursing clinical care, outlining areas that need to be considered in future research and implemented in daily practice.

Implications for Future Research and Practice

The results of the study confirm the need for a step-by-step and inclusive approach to the integration of SARs that considers the emotional dimensions of older adults' care, concerns about job displacement, and varying levels of technological readiness. Future research should explore strategies to maintain engagement among all age groups, particularly among older health professionals who may find SARs distracting or irrelevant. Longitudinal studies can provide deeper insight into how SARs affect patient and staff experiences over time, allowing researchers to track changes in perceptions as SARs become more common in health care settings. In addition, continued exploration of SARs in different roles, such as logistics and routine support, is vital to identify where SARs add the most value without compromising the essential "human touch" of aged care.

Data Availability

Data will be promptly made available by the corresponding author upon request.

Conflicts of Interest

None declared.

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Abbreviations

CARESSES: Culture-Aware Robots and Environmental Sensor Systems for Elderly Support
HRI : human-robot interaction
SAR : Socially Assistive Robot
TAM: Technology Acceptance Model
TRI: Technology Readiness Index
UTAUT: Unified Theory of Technology Acceptance and Use

Edited by E Borycki; submitted 19.12.24; peer-reviewed by M Kleib; revised version received 23.04.25; accepted 03.06.25; published 01.08.25.

Please cite as:
Leoste J, Lubi K, Marmor K, Kangur K
Evaluating Social Assistive Robots in Clinical Nursing Care: Mixed Method Pilot Study on Health Care Workers' Perceptions and Adoption
JMIR Nursing 2025;8:e70305
URL: https://nursing.jmir.org/2025/1/e70305
doi:10.2196/70305

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Effectiveness of Patients' Education and Telenursing Follow-Ups on Self-Care Practices of Patients With Diabetes Mellitus: Cross-Sectional and Quasi-Experimental Study

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Abstract

Background: Information and communications technology can be used in telenursing to facilitate remote service delivery, thereby helping mitigate the general global nursing shortage as well as particular applications (eg, in geographically remote communities). Telenursing can thus bring services closer to end users, offering patient convenience and reduced hospitalization and health system costs, enabling more effective resource allocation.

Objective: This study aims to examine the impact of patients' education and telenursing follow-ups on self-care indicators among patients with type I and type II diabetes mellitus (DM).

Methods: In phase I, a cross-sectional descriptive analysis was conducted to evaluate the self-care practices of 400 patients with DM at Kafr El Sheikh University Hospital in Egypt. In phase II, a pretest-posttest experiment was applied with a selected group of 100 patients purposively recruited from phase I due to their low self-care practice knowledge to ascertain the impacts of a 4-week intervention delivered via telenursing. They were reminded via telephone follow-up communication of the importance of adhering to recommendations on physical activity, nutritional intake, and the management of blood sugar (ie, insulin). Data collection was undertaken using a structured quantitative questionnaire, encompassing sociodemographic characteristics, medical symptoms and history, and knowledge of DM. Paired *t* test analysis was applied to study pre- and postintervention self-care behaviors.

Results: Participants had a mean age of 49.7 (SD 11.5) years. More than one-third received their DM diagnosis over a decade previously (135/400, 33.8%) and were obese (147/400, 36.8%). Almost half (176/400, 44%) received insulin, and the majority had cardiac disease (231/400, 57.7%) and the DM symptom of elevated blood sugar levels while fasting (365/400, 91.3%). A relatively high score of DM knowledge was reported (255/400, 63.7%). Males exhibited significantly lower knowledge levels (102/200, 51%) compared to females (153/200, 76.5%; $P<.001$). The intervention was effective in improving knowledge of DM ($t_{99}=30.7$, two-tailed; $P<.001$), self-care practices ($t_{99}=53.7$, two-tailed; $P<.001$), and self-care skills ($t_{99}= 47$, two-tailed; $P<.001$) among patients with DM.

Conclusions: The emergent evidence suggests that patients' education and telenursing follow-ups have the potential to improve self-care behavior in patients with DM. The delivery of frequent nursing reinforcement via telenursing enables improved self-management while contemporaneously reducing the need for patients to visit clinical settings (ie, improving patient condition and reducing net health system costs). The outcomes of this research underscore the need to integrate telenursing within conventional care for DM, and more research is needed to longitudinally assay its efficacy and sustainability over the long term and in different clinical and geographical contexts.

(JMIR Nursing 2025;8:e67339) doi:10.2196/67339

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KEYWORDS

diabetes mellitus; education; knowledge; self-care; telenursing

Introduction

Diabetes mellitus (DM) is a chronic metabolic disorder characterized by elevated blood glucose levels resulting from defects in insulin secretion, insulin action, or both. Insulin is a hormone produced by the pancreas that regulates blood sugar levels and facilitates the uptake of glucose into cells for energy. There are 3 main types of DM (type I DM, type II DM, and gestational DM), each with etiological and pathological characteristics. Type I DM is a condition of the autoimmune system, arising from the lack of functioning beta cells generating insulin. Type II DM is more common and is generally attributable to lifestyle attributes and nutritional factors (eg, sedentary behavior and high sugar consumption), albeit genetic predispositions are also instrumental. Gestational DM occurs during pregnancy and typically resolves after delivery, although it increases the mother's risk of developing type II diabetes later in life.

DM poses a significant threat to the safety of hundreds of millions of people worldwide, with disconcertingly escalating prevalence. It is estimated that 643 million people will be diagnosed by 2030, rising to 783 million by 2045, up from 537 in 2021 [1]. This estimated increase can be associated with global population growth and the rising prevalence of diabetes due to unhealthy lifestyle-related factors and aging populations. The prevalence is significantly higher in certain regions, including the Middle East, where more than 70 million people are currently affected by DM. According to the International Diabetes Federation, Egypt ranks ninth globally for DM prevalence. In early 2020, there were approximately 8.85 million people with DM in the country, representing a prevalence rate of 15.2% [2].

DM entails direct costs in itself, and it also entails secondary costs related to interlinked conditions (which may themselves be causative or reciprocally exacerbated by DM). DM is often associated with complications such as vision impairment and blindness, cardiovascular diseases, and kidney failure and may require foot amputation [3]. In order to mitigate the more serious impacts of the condition and enable patients to have a better quality of life, DM must be managed with a strong autonomous role of patients themselves, including consistent adherence to practices recommended for self-care, such as frequent monitoring of their blood glucose levels, appropriate nutritional intake, recommended levels of physical activity, and medication compliance [3].

While patients tend to be aware of the imperatives associated with such positive behaviors, they commonly struggle to implement them in their daily lives, especially as metabolic disorders and DM itself commonly arise from a knowing lack of compliance with positive behaviors (ie, the general public typically knows that eating large amounts of processed sugar and having a sedentary lifestyle will predispose them to DM, yet they continue to indulge in such behaviors, leading to or exacerbating diabetes) [3]. In low-income countries, research has consistently shown that a large proportion of patients with DM typically adhere to negative self-care, essentially manifesting poor control of their glycemic index and a commensurately elevated propensity toward serious resultant issues [4,5].

The accelerating development and adoption of many useful technological solutions in health care services over the last 2 decades have led to greatly expanded opportunities for the more effective management of chronic illness, including DM. Telenursing, which is defined as the use of technological channels (eg, telephone or video calls) to provide nursing services to individuals in remote locations, has offered ways in which to reduce the distance between health care services and patients, as well as reducing the need for some patients to attend traditional care venues (thereby reducing pressure on limited resources) [6]. Its obvious advantages include increasing health providers' interaction with service users, including for symptoms monitoring and educating service users without expensive and burdensome face-to-face clinical appointments.

Telenursing fundamentally increases the ability of health care professionals to deliver services remotely, which has obvious implications for more frequent monitoring of patient symptoms and escalating interventions where appropriate, with personalized assistance for service users in the comfort of their homes and everyday lives [7]. As DM management is particularly sensitive to general lifestyle factors, the telenursing paradigm can be particularly useful to extend the reach of health care providers to give patients with DM additional support and encouragement in their daily lives, especially with engagement for reminders and follow-up on particular issues [7].

It should be noted that telenursing benefits encompass important clinical outcomes in addition to practice expedience in communication; the more frequent and direct communication engendered by telenursing formats enables increased patient adherence to medication, self-care, and other outcomes, which intrinsically comprises improved quality of care and contributes to optimized patient prognosis [8]. A systematic review found that telenursed patients displayed statistically significant enhancement in their glycemic control, with 0.5% reduced HbA_{1c} (glycated hemoglobin A_{1c}) levels over half a year, alongside decreased BMI in some studies that effectively leveraged "combined" interventions [9].

Additionally, telenursing mitigates the burden placed on health services by obviating in-person (face-to-face) attendance at traditional care delivery venues, which is especially valuable in resource-constrained contexts, such as low-income countries or remote geographical regions [10]. In areas suffering from a dearth of conventional health care resources, telenursing offers essential care delivery channels for patients with DM, preventing the escalation of patients' conditions and reducing net health care costs (eg, timely telenursing interventions can reduce the need for hospital admission) [11].

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Among the particular services that can be enhanced by telenursing, limited research has explored its potential to play a role in improving DM patients' capacity to undertake self-care practices. It appears to offer notable advantages, but differing results have been found in practice, with some studies reporting tangible positive outcomes, and others identifying substantive barriers in terms of technological issues and the stakeholder engagement, which can hamper the long-term sustainability of telenursing services [8]. A recent narrative review of 18 randomized controlled trials (RCTs) and 5 quasi-experimental studies worldwide concerning telenursing for DM care reported that a telenursing intervention of weekly telenursing contact over 3 months achieved no significant influence on BMI or weight loss, while a 6-month telenursing program attained no significant differences in either BMI or HbA_{1c} [8]. A systematic review of adherence to medication regimens among patients with DM found that there was no study that had reported consistent improvement due to telenursing [12]. Such negative findings are contrary to expectations, given the potential promise of telenursing; thus, further studies are needed to ascertain telenursing impacts on self-care practices among patients with DM in numerous different and varied health care settings.

This study seeks to fill this research gap by ascertaining the impacts of patients' education and telenursing follow-ups on self-care practices among patients with DM at an Egyptian tertiary hospital. Using a single-group pretest-posttest design and cross-sectional analytical approaches, this research sought to evidence telenursing's scope to enhance self-care practices, thereby improving the quality of care and outcomes for patients with DM. The outcomes can guide practice in clinical contexts and advance emerging studies on digital health solutions for the management of chronic diseases, especially DM. The insights gained from this research are particularly important in considering the intervention impacts to improve self-care practices among patients with DM, especially for contexts where conventional care is limited or hard to access.

Methods

Study Design

This 2-phase study encompassed a cross-sectional assessment of self-care (phase I) and a single-group quasi-experimental pretest-posttest design to assess the impacts of telenursing education on patients' knowledge, skills, and self-care (phase II).

Study Setting

The research setting was the outpatient clinic for diabetes care at Kafr El Sheikh University Hospital. This is the main diabetes care hub for the whole governorate. The sessions for patient education were delivered in specially allocated locations within the clinic, and the phase II follow-up interventions were delivered remotely using WhatsApp or SMS text messages.

Sampling

Inclusion Criteria

To be eligible for the study, participants had to (1) be adult patients with a diagnosis of DM for at least 1 year, (2) be aged between 18 and 65 years, (3) have access to and the ability to use a smartphone, (4) have HbA_{1c} level greater than 7, and (5) express interest in and willingness to participate in the study's interventions. Patients were excluded if they had psychological illnesses, speech or hearing impairments, or failed to respond to mobile phone contact for 2 weeks.

Sample Size and Sampling Technique

For phase I, clinical records for outpatients during 2020 were analyzed. The outpatient clinic records for the year 2020 were reviewed to determine the patient population. Using the Roasoft calculation program with a 50% response rate, a 95% CI, and a 5% margin of error, the required sample size was calculated to be 384. In order to attain more robust data, we purposively selected 400 eligible patients who met the inclusion criteria (above), comprising 200 males and 200 females.

The preliminary analysis of the data collected in phase I showed that 255 (63.7%) of 400 patients were categorized as having poor knowledge and poor self-care practice. Based on the inclusion criteria, a purposive sample of 100 patients was selected for phase II, focusing specifically on those with the lowest scores in both knowledge and self-care practices, as they were identified as the patients most in need of educational intervention.

Data Collection Tools

Sociodemographic and Medical Data Questionnaire

This tool gathered data on sociodemographic features such as age, educational level, and marriage status, and clinical attributes such as time since diabetes diagnosis, presence and type of comorbidities, fasting blood glucose levels, and BMI.

Knowledge Assessment Questionnaire

Participants' knowledge about DM (hereinafter "knowledge") was gathered using 23 open-ended questions divided into 8 categories: basic knowledge about diabetes and its complications (10 questions), treatment regimens (3 questions), physical exercise (2 questions), the importance of follow-up visits (2 questions), dietary patterns (2 questions), foot care (2 questions), bad habits that worsen the disease (1 question), and sources of knowledge (1 question). Responses were scored using a system where correct and complete answers received 5 marks, correct but incomplete answers received 4 marks, incomplete answers received 3 marks, incorrect answers received 2 marks, and answers of "don't know" received 1 mark. Each subsection score was averaged, with total knowledge scores ranging from 23 to 115 marks. Scores were then classified into poor knowledge (less than 60%, ≤69 marks) and fair knowledge (60% or more, ≥70 marks).

Self-Care Practices Questionnaire

This questionnaire focused on self-care practices among patients with DM and covered 43 different practices, which were categorized into 6 areas: nutritional practices and adherence to the DM dietary regimen (12 practices), practices related to medication regimen (5 practices), practices related to glucose monitoring (6 practices), practices related to physical activity (8 practices), practices to avoid complications (6 practices), and

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practices related to foot care (6 practices). The self-care practices were assessed using a 3-point Likert scale, where responses were rated as “always” (2 marks), “sometimes” (1 mark), and “rarely” (0 marks). Scores for each subsection were summed, and the total scores were classified into 3 categories: poor practices (less than 60%), fair practices (60% to <75%), and good practices (75% or more).

Self-Care Skills Checklist

The researchers used the self-care skills checklist in phase II to evaluate participants’ practical self-care skills through direct observation. This assessment focused on 3 key tasks: preparing and injecting insulin (comprising 9 and 7 steps, respectively) and testing glucose levels in urine (9 steps). Conducting direct observations and assessments postintervention enhanced objectivity, providing a more reliable evaluation compared to patients’ subjective self-ratings. The checklist used a 3-point scoring system for each step: 3 points for correctly performed steps, 2 points for incorrectly performed steps, and 1 point for steps not performed. Subtotal scores for each skill were calculated, and participants’ performance was categorized as either satisfactory (≥60%) or unsatisfactory (<60%) based on the total score for each individual skill and the overall score.

Language of Data Collection Tools

Questionnaires in this study were used to accommodate the linguistic and practical needs of the participants and researchers. All questionnaires, except the self-care skills checklist, were in Arabic to ensure clear and effective communication with the study participants, who are native Arabic speakers. Delivering the questionnaire in their native language facilitated accurate comprehension of the questions and reliable responses, minimizing the risk of misinterpretation. The self-care skills checklist was in English, as it was designed for and completed by the researchers, all of whom possess a high level of proficiency in English. Using English for the researcher-administered questionnaire allowed for precision in recording and interpreting data while maintaining consistency with standard scientific and academic conventions. This dual-language approach ensured that both participants and researchers could engage effectively with the study materials, optimizing the validity and reliability of the data collected.

Piloting and Validation

The developed tools were validated by a panel of experts from the Faculty of Nursing at Kafr El-Shiekh University. The panel consisted of 5 experts: 2 professors of medical-surgical nursing, 1 professor of medicine from the Faculty of Medicine, 1 assistant professor, and 1 lecturer of medical-surgical nursing from the Faculty of Nursing. The tool underwent both face and content validity assessments. The content validity focused on evaluating the clarity, appropriateness, applicability, wording, and comprehensiveness of the tool. To assess the internal consistency of the tool, the Cronbach α test was used. The results showed a Cronbach α of 0.78 for the knowledge assessment questionnaire, 0.8 for the reported self-care practice scale, and 0.88 for the diabetic self-care practice checklist. The same group of experts also validated the scientific content of the educational program.

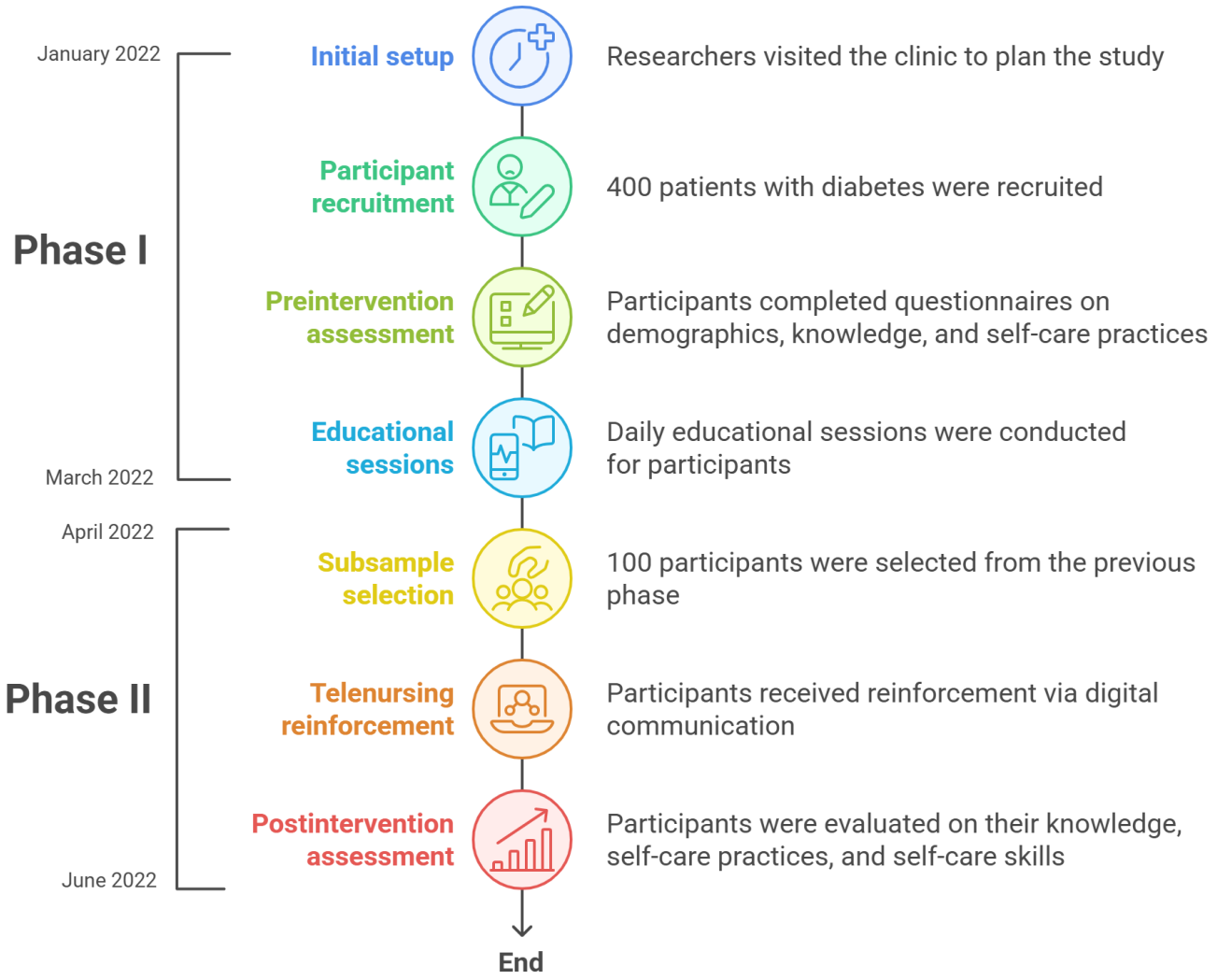
After incorporating the experts’ recommendations, the questionnaire was pilot tested. The pilot study was conducted over 3 weeks and included 10% (40/400) of the sample size (40 patients with DM in phase I and 10 patients in phase II). The purpose of the pilot study was to evaluate the clarity, applicability, and comprehensiveness of the tools and to assess the feasibility of the study process. Based on the findings from the pilot study, necessary modifications were made, such as the omission or addition of certain questions, to enhance the content, improve simplicity and clarity, and ensure the tools were concise and focused. The patients who participated in the pilot study were excluded from the main study sample.

Data Collection Process

Data collection spanned approximately 6 months, from January 2022 to the end of June 2022, and consisted of 2 phases as shown in Figure 1.

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Figure 1. Data collection process.



Phase I

The researchers first visited the diabetic clinic to discuss the research objectives and methods with nursing leaders. During this visit, they coordinated meetings with potential participants and identified private spaces for conducting interviews and delivering the initial intervention sessions. A sample of 400 patients with DM, meeting the previously described inclusion criteria, was selected to explore their knowledge of DM and self-care practices. Potential participants were informed about the study's purpose and invited to participate if they were interested in receiving the intervention. Data collection took place for those who agreed to participate, with each interview lasting between 15 and 30 minutes (approximately 10 - 14 participants were interviewed per day, one-on-one).

Participants were grouped according to their outpatient appointments, and the educational intervention sessions were conducted in groups ranging from 10 to 15 members. Sessions were held daily, excluding Fridays, with each session lasting 30 - 40 minutes. Each session began with a welcome and icebreaker, followed by an explanation of the session's objectives and topics, and concluded with a recap and time for participants to ask questions. The sessions ended with an open discussion, allowing participants to address any clarifications, and handouts related to the content were distributed for participants to read at their convenience.

Phase II

As mentioned earlier, a purposive sample of a hundred patients from phase I was selected to undergo phase II. Participants underwent telenursing reinforcement of the educational intervention content from phase I via calls, SMS text messages, WhatsApp messages, videos, and voice notes. This was undertaken over 4 weeks (details of this intervention are provided in the following section). One month after the telenursing reinforcement, a posttest assessment was carried out at the outpatient clinic in Kafr Elshiekh Hospital. During this assessment, patients were interviewed to evaluate their knowledge, reported self-care practices, and self-care skills.

Intervention

Intervention Design

The intervention in this study was developed by the researchers, all of whom were diabetes nursing specialists, to enable patients with DM to enhance their self-care practices in response to the needs of patients. The intervention included educational sessions and telenursing follow-ups as described below.

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Educational Sessions

The researchers delivered 6 educational sessions to the 400 participants in phase I at Kafr El Sheikh University Hospital's outpatient diabetes clinic. The educational sessions were held daily, excluding Fridays, with each session lasting 30 - 40 minutes. The educational sessions involved 3 theoretical and 3 practical sessions on diabetes. Specifically, the theoretical sessions covered essential topics such as basic knowledge of DM and its management (including medical treatment, physical exercise, dietary management, foot care, follow-up, and lifestyle habits that exacerbate the disease). The practical sessions focused on promoting healthy lifestyles (eg, dietary practices and physical exercises) and self-care practices (eg, insulin preparation and injection, glucose testing in urine, blood glucose monitoring, medication schedules, prevention of complications, and foot care practices).

To reinforce the learning experience, the educational content was compiled into a booklet distributed to participants after the sessions, serving as a reference for the information provided. A variety of pedagogical methods were used during the sessions, including practical demonstrations, abstract lectures, group discussions, and role-playing activities. These diverse teaching styles were designed to accommodate different learning preferences and build participants' confidence and adherence to the intervention. Additionally, visual aids such as images, physical models, and PowerPoint presentations were used to enhance understanding and engagement throughout the sessions.

Telenursing Follow-Up

During phase II, 100 participants were purposively selected for a 4-week telenursing follow-up. This intervention aimed to reinforce the educational content provided in phase I and support patients in adopting effective self-care practices. The follow-up schedule included daily 10 - 15-minute calls in the first week, twice-weekly calls in the second week, and weekly calls in the final 2 weeks. These personalized interactions focused on revisiting the educational material and addressing any questions or challenges faced by the participants.

During the follow-up period, participants received daily health education through various channels, including SMS text messages, WhatsApp messages, voice notes, and videos, all of which reiterated the information provided in the educational booklet. To further encourage adherence to self-care practices, daily reminders and audio recordings were sent to prompt actions such as blood glucose self-assessment, medication compliance, foot care, physical activity, and following the recommended diet plan. The content of the telenursing follow-up was meticulously developed by the researchers, drawing on insights from phase I, evidence-based diabetes self-care guidelines, and input from diabetes nursing specialists and clinical researchers. This ensured the content was accurate, culturally relevant, and aligned with the specific needs of the participants.

Statistical Analysis

Data collection, coding, and analysis were undertaken using SPSS (version 20, IBM Inc). Mean and SD values were used to report continuous data (with independent sample *t* testing to compare group differences) and frequency and percentage values for categorical data (with chi-square and Fisher exact probability tests to determine intervariable relationships). Pretest-posttest differences were determined using paired sample *t* tests and the McNemar test, indicating binary categorical variables' changes following the intervention. The robustness of the contingency table analyses was assured using Monte Carlo simulations. The application of these methods of statistical analysis affirmed cross-comparison results' reliability and mitigated risks of erroneously rejecting null hypotheses, as presented in the following section. After adjustments, a P value of ≤.05 was assumed to indicate statistical significance.

Ethical Considerations

Kafr El Sheikh University granted ethical approval for this study (KFIRB200-9). Studied patients gave verbal consent to taking part after full disclosure of the nature and scope of the research and their rights, including their ability to decline to take part or to subsequently withdraw without any consequences for their health care services or statutory rights. They were assured of their right to confidentiality, and that all data are reported anonymously in this study, with coding. All participants were informed that the data related to their participation would only be used for the current research purpose as per ethical guidelines for participant protection.

Results

Overall Findings

As described in the following subsections, significant shortcomings were discovered in participants' knowledge and skills at baseline, especially for female patients. The results after the intervention revealed significant enhancements in self-care practice and knowledge scores (P<.001). All of the patients were able to ascend from "unsatisfactory" to "satisfactory" scores in relation to skills for DM self-care, underscoring the efficacy of the intervention in enabling patients to achieve improved self-management of DM.

Sociodemographic Characteristics

The total studied sample comprised 400 people with DM, who had a mean age of 49.7 (SD 11.5) years. As shown in Table 1, the largest cohort (143/400, 35.7%) was aged 55 - 65 years, while over a fifth (86/400, 21.5%) each were aged 35 - 44 and 45 - 54 years. The vast majority of patients resided in family residences (399/400, 99.7%) and were married (325/400, 81.3%). A large minority (149/400, 37.2%) reported being illiterate, while almost a third (130/400, 32.5%) cited secondary school as their highest educational level and a negligible proportion (12/400, 3%) reported being university-educated. Females were significantly more likely to be illiterate (108/200, 54%) than males (41/200, 20.5%; P<.001). Furthermore, a negligible proportion (1/200, 0.5%) of male participants were unemployed, while none of the female participants were employed.

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Table . Participants' sociodemographic characteristics.

Variables	Male (n=200)	Female (n=200)	Total (N=400)	χ^2 [a]	*P* value
Age (years), n (%)				4.6	<.001
29 - 34	42 (21)	16 (8)	58 (14.5)		
35 - 44	41 (20.5)	45 (22.5)	86 (21.5)		
45 - 54	40 (20)	46 (23)	86 (21.5)		
55 - 64	69 (34.5)	74 (37)	143 (35.7)		
65 - 72	8 (4)	19 (9.5)	27 (6.8)		
Mean (SD)	47.1 (11.4)	52.3 (11.1)	49.7 (11.5)		
Marital status, n (%)				9.2	.1
Single	8 (4)	3 (1.5)	11 (2.7)		
Married	170 (85)	155 (77.5)	325 (81.3)		
Widowed	22 (11)	42 (21)	64 (16)		
Living alone?, n (%)				-	.317[b]
Yes	0 (0)	1 (0.5)	1 (0.3)		
No	200 (100)	199 (99.5)	399 (99.7)		
Education, n (%)				59.2	<.001
Illiterate	41 (20.5)	108 (54)	149 (37.2)		
Literate	41 (20.5)	39 (19.5)	80 (20)		
Preparatory	21 (10.5)	8 (4)	29 (7.3)		
Secondary	87 (43.5)	43 (21.5)	130 (32.5)		
University	10 (5)	2 (1)	12 (3)		
Work status, n (%)				-	<.001[c]
Working	199 (99.5)	0 (0)	199 (49.7)		
Not working	1 (0.5)	200 (100)	201 (50.3)		

[a]Two-tailed.

[b]*P* value for Living alone? is based on Fisher exact test.

[c]*P* value for Work status is based on Monte Carlo exact test.

Clinical Characteristics

As Table 2 shows, one-third (135/400, 33.8%) of patients in this study received their DM diagnosis over 10 years previously, and the majority (231/400, 57.7%) had the comorbidity of cardiac disease. Concerning the latter condition, males (82/200, 41%) were significantly less likely to have it than females (149/200, 74.5%; *P*<.001). Almost half (176/400, 44%) of patients just received insulin treatment, while almost a quarter (93/400, 23.3%) additionally received oral hypoglycemic medications. The vast majority of patients exhibited elevated blood glucose (365/400, 91.3%), and most were overweight (146/400, 36.5%) or obese (147/400, 36.8%); females were disproportionately more prone to obesity (135/200, 67.5%) than their male counterparts (12/200, 6%).

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Table . Participants' medical symptoms.

Medical data	Male (n=200), n (%)	Female (n=200), n (%)	Total (N=400), n (%)	χ^2 [a]	*P* value
Disease onset (years)				22.8	<.001
<1	28 (14)	42 (21)	70 (17.5)		
1 - 5	34 (17)	49 (24.5)	83 (20.7)		
5 - 10	48 (24)	64 (32)	112 (28)		
10+	90 (45)	45 (22.5)	135 (33.8)		
Other chronic diseases					
None	117 (58.5)	51 (25.5)	168 (42)	5.9	<.001
Cardiac disease	82 (41)	149 (74.5)	231 (57.7)	4.2	<.001
Hypertension	19 (9.5)	6 (3)	25 (6.2)	1.7	.541
Renal disease	0 (0)	2 (1)	2 (0.5)	0.51	.814
Rheumatic disease	2 (1)	1 (0.5)	3 (0.7)	0.5	.885
Liver disease	5 (2.5)	4 (2)	9 (2.2)	0.1	.924
Type of diabetes treatment regimen				28.2	<.001
Oral hypoglycemic drugs	65 (32.5)	66 (33)	131 (32.7)		
Insulin	107 (53.5)	69 (35.5)	176 (44)		
Both	28 (14)	65 (32.5)	93 (23.3)		
Commitment to follow-up schedule					
Always	200 (100)	200 (100)	400 (100)	N/A[b]	N/A
Fasting blood glucose				0.83	.662
Below normal	1 (0.5)	1 (0.5)	2 (0.5)		
Normal	14 (7)	19 (9.5)	33 (8.2)		
Above normal	185 (92.5)	180 (90)	365 (91.3)		
BMI				94.2	<.001
Normal	79 (39.5)	28 (14)	107 (26.7)		
Overweight	109 (54.5)	37 (18.5)	146 (36.5)		
Obese	12 (6)	135 (67.5)	147 (36.8)		

[a]Two-tailed.

[b]N/A: not applicable.

Baseline Knowledge Scores

In terms of knowledge, the majority (255/400, 63.7%) exhibited poor knowledge at baseline, albeit this was significantly less pronounced among males (102/200, 51%) than females (153/200, 76.5%; *P*<.001), as shown in Table 3. About half (98/200, 49%) of male participants had "fair" knowledge, while less than a quarter (47/200, 23.5%) of females did. Consequently, the outcomes underscore major differences in baseline knowledge among males and females, especially concerning comprehension of appropriate DM management practices, as affirmed by results on actual practices (discussed below), indicating the necessity of specific educational interventions targeted to females.

Table . Baseline diabetes mellitus knowledge.

	Male (n=200), n (%)	Female (n=200), n (%)	Total (N=400), n (%)	χ^2	*P* value
Knowledge level				28.1	<.001
Poor (<60%)	102 (51)	153 (76.5)	255 (63.7)		
Fair (≥60%)	98 (49)	47 (23.5)	145 (36.3)		

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Baseline Self-Care Practices

At the beginning of the intervention, most patients (248/400, 62%) exhibited inadequate baseline self-care practices, albeit this was significantly lower among males (96/200, 48%; *P*<.001) than females (152/200, 76%), as shown in Table 4. "Good" practices for self-care were only reported among 24% (48/200) of males and 8% (16/200) of females. The lowest adherence was noted for blood glucose monitoring (316/400, 79%), physical exercise (296/400, 74%), and the prevention and management of acute complications (268/400, 67%). Critical shortfalls in self-care behaviors were thus observed, especially with regard to females, which indicates that more targeted interventions are needed to enhance essential self-care among female service users (in addition to the general need for improved self-care among DM patients in general).

Table . Pretest self-care practice scores.

	Male (n=200), n (%)	Female (n=200), n (%)	Total (N=400), n (%)	χ^2	*P* value
Total practice score				35.2	<.001
Good (≥75%)	48 (24)	16 (8)	64 (16)		
Fair (60 - 74%)	56 (28)	32 (16)	88 (22)		
Poor (<60%)	96 (48)	152 (76)	248 (62)		

Intervention Impacts on DM Knowledge

Table 5 demonstrates that the intervention achieved significant enhancements of patients' DM management knowledge for all studied domains (*P*<.001). The biggest improvements were seen concerning physical exercise knowledge, which saw a mean increase of 6.6 points, and tangible improvements were seen in knowledge of dietary choices and regimens of treatment.

Table . Mean of diabetes mellitus knowledge scores before and after the intervention (n=100).

Knowledge domains	Score, mean (SD)		Mean change[a]	*t* test[b]	*P* value
	Preintervention	Postintervention			
Basic knowledge about DM[c]	12.1 (3.7)	40.3 (7.4)	28.2	31.8	<.001
Treatment regimen	6.2 (1.9)	10.5 (1.5)	4.3	9.5	<.001
Physical exercise	1.2 (0.5)	8.2 (1.9)	7	37.4	<.001
Importance of follow-up visits	5 (0)	5.8 (0.4)	0.8	21.9	<.001
Dietary knowledge	3 (1.3)	6.5 (1.2)	3.5	22.9	<.001
Foot care knowledge	1.4 (0.6)	3.8 (0.6)	2.4	25.6	<.001
Knowledge of bad habits increasing DM severity	2.1 (0.5)	3.8 (0.5)	1.7	23.5	<.001
Total knowledge score	29.6 (3.9)	71.8 (13)	42.2	30.7	<.001

[a]Mean change = Posttest score – Pretest score.

[b]Two-tailed paired sample *t* test.

[c]DM: diabetes mellitus.

Intervention Impacts on Self-Care Practices

As shown in Table 6, the applied intervention achieved statistically significant enhancements of practices for self-care for all studied domains (*P*<.001). Mean increases of 8.15 points each were attained for the practices of "foot care" and "blood glucose monitoring," with a more modest increase in exercise practices of 3.45 points. These outcomes indicate that the intervention successfully improved participants' self-care behaviors for improved DM management.

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Table . Mean of self-care practice scores before and after the intervention (n=100).

Practice domains	Score, mean (SD)		Mean change[a]	*t* test[b]	*P* value
	Preintervention	Postintervention			
Nutritional practices	8.4 (2.2)	21.2 (2.3)	12.8	40.4	<.001
Treatment regimen adherence	2.3 (0.6)	7 (0)	4.7	55.4	<.001
Monitoring of blood glucose level	1.6 (0.9)	10.3 (2.5)	8.7	36.9	<.001
Physical activities	3.8 (1.7)	14.2 (1.1)	10.4	55.1	<.001
Practices to avoid complications	5.2 (2)	10.2 (1.2)	5	21.9	<.001
Foot care practices	1.6 (0.9)	10.3 (2.5)	8.7	36.9	<.001
Total practice score	20.8 (4.5)	59.9 (7)	39.1	53.7	<.001

[a]Mean change = (Posttest score – Pretest score)/Pretest score.

[b]Two-tailed paired sample *t* test.

Intervention Impacts on Self-Care Skills

Significant improvements were seen following the intervention in patients' self-care skills, as shown in Table 7. Every participant went to "satisfactory" postintervention from "unsatisfactory" at baseline (400/400, 100%; $P<.001$), as reflected in the baseline scores for insulin preparation (mean 12.3, SD 2.1), self-injection (mean 11.8, SD 2.5), and glucose testing (mean 10.5, SD 1.9) increasing to 25.4 (SD 3), 24.8 (SD 2.8), and 23.5 (SD 2.4), respectively. These results underscore the effectiveness of the intervention to empower patients with prerequisite DM management skills, demonstrating the efficacy of practical instruction and reminders and reinforcement via telenursing, with the possibility of scalability for different and varied populations.

Table . Level of self-care skills before and after the intervention.

Self-care skills	Preintervention	Postintervention	χ^2 [a]	*P* value
Insulin preparation (n=58), n (%)			47	<.001
Unsatisfactory	58 (100)	0 (0)		
Satisfactory	0 (0)	58 (100)		
Insulin injection (n=58), n (%)			47	<.001
Unsatisfactory	58 (100)	0 (0)		
Satisfactory	0 (0)	58 (100)		
Urine glucose testing (n=100), n (%)			51.9	<.001
Unsatisfactory	100 (100)	0 (0)		
Satisfactory	0 (0)	100 (100)		

[a]McNemar test for related groups.

Discussion

Main Outcomes

Summary of Key Findings

This study on patient education and telenursing impacts concerning self-care practices among DM patients produced statistically significant outcomes, encompassing quantifiable improvements in skills, knowledge, and practices. Consequently, the intervention was effective in improving DM self-management and mitigating risks, as described below.

Improved DM Knowledge

The intervention resulted in patients with DM attaining significantly improved DM knowledge, especially concerning physical exercise, nutrition, and compliance with treatment. A more in-depth understanding of physical exercise was reflected in the postintervention increase in mean knowledge about physical exercise (and its impact on blood glucose) by 6.6 points [13]. This was striking, as education for patients with DM often lacks sufficient attention to physical exercise, despite its fundamental place in managing blood glucose and avoiding DM complications [13]. Improved knowledge scores concerning

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regimens and nutrition were also significant, and these outcomes are essential for the strategy of managing diabetes.

The intervention analyzed in this research effectively addressed existent educational needs among DM patients, offering them accurate and clear information they could apply, via easy-to-use formats (eg, SMS text messages, telephone calls, and WhatsApp). The ease of access enabled patients to effectively manage their conditions, which was particularly useful for the subset recruited for phase II, due to their particularly poor knowledge and self-care determined in the preliminary assessment. Although individual needs of specific patients were not targeted by the studied intervention, it was directed to commonly identified barriers and needs among patients requiring such services, offering scope for genuine enhancements in patients' outcomes and self-care behaviors.

Improved Self-Care Practices

Self-care practices significantly increased participants' scores for practices following the intervention, including monitoring blood glucose, undertaking appropriate foot care, and physical exercise. For monitoring blood glucose and foot care, participants achieved a mean improvement of 8.15 points each, highlighting the efficacy of the intervention in terms of encouraging positive practices to avoid long-term complications and deteriorating health conditions, including serious ones commonly affecting patients with DM due to a dearth of appropriate self-care (eg, neuropathy and foot ulcers) [14]. Physical exercise-related self-care practices also yielded an improvement of 3.45 points, showing more likelihood of undertaking exercise after the intervention. This addresses a core aspect of the management of diabetes, enhancing sensitivity to insulin and lowering the risk of cardiovascular damage [15].

Improved Self-Care Skills

The effects of the intervention on participants' self-care skills were substantial; all 100% (400/400) had "unsatisfactory" skills preintervention, and 100% (400/400) had "satisfactory" skills after it, in terms of preparing and injecting insulin and testing glucose in urine. This demonstrates the potentially remarkable effectiveness of patient education and telenursing follow-ups to enable patients with DM or other serious conditions to more proactively improve and maintain positive skills and behaviors, thereby improving their health outcomes (and substantially reducing costs for health systems).

Relation to Existing Literature

The outcomes of this study affirm those of the broader literature on positive telenursing impacts on the management of chronic diseases, such as DM [6,16]. Previous studies have extensively demonstrated particular impacts of telenursing in terms of enhanced engagement and medication adherence among patients, which ultimately contribute to improved prognosis [17,18]. This research contributes to the literature by presenting how a holistic telenursing intervention combining educational with skills-based content delivered via modern telecommunications (eg, WhatsApp messages) can facilitate major breakthroughs for patients in terms of increased self-care practices and DM management knowledge. This notably goes beyond most DM-related research, which tends to prioritize fundamental biomedical indicators of telenursing effectiveness (eg, HbA_{1c} and BMI), without commensurate attention to the holistic dimensions of DM care and self-management for patients (eg, exercise) [8,19].

Implications for Practice and Research

The intervention used in this research achieved notable benefits for patients, offering broader potential impacts for health practice and studies. For practitioners, the outcomes of this study affirm the effectiveness of patient education and telenursing follow-ups to improve diabetes care services, and personalized support and education delivered remotely via modern technologies, which are increasingly ubiquitous, can enlarge patient access to education and improve medication and healthy behavior adherence. Such impacts reduce demand for conventional clinical resources and avoid the escalation of negative DM-related conditions, thereby improving quality of care (ie, patient health and satisfaction) while achieving maximum resource deployment efficiency for health systems, which is essential for contexts with limited resources (eg, in low-income countries or remote geographical areas).

This research suggests that the effectiveness of patient education and telenursing follow-ups can be enhanced by adopting a patient-centered approach that addresses specific gaps in skills and knowledge among particular patient groups or individual patients. A personal paradigm considering each patient's particular requirements, as applied in this study, can enable patient education and telenursing follow-ups to offer its full benefits, reducing net costs on conventional health care resources, especially for chronic and serious conditions requiring improved self-management by patients, such as DM. In terms of implications for research, this study leaves open the requirement to investigate longitudinal effects of patient education and telenursing follow-ups to see if the advantages for self-care practices and DM knowledge recorded after a few weeks in this research can be sustained over time, and the extent to which they affect health indicators over the longer term (eg, reduced rates of DM complications and improved glycemic control). Furthermore, the cost efficiency of patient education and telenursing follow-ups in various potential applications can be compared to enable policy development to optimally deploy such initiatives for the maximum benefits. Finally, future studies should consider conducting 2-arm RCTs to compare patient education and telenursing follow-ups with standard care. Research involving diverse populations would also help determine the broader applicability of this approach. Additionally, integrating mobile health applications with automated reminders could enhance communication and patient adherence, potentially improving self-care related outcomes.

Limitations

The foremost limitation of this study pertains to its reliance on patients' own self-perceived and rated performance for some of the tools used, which is obviously subject to various forms of bias (including social desirability bias concerning self-care practices when reporting data in health care contexts). Furthermore, it was not possible to objectively measure patient indicators outside of clinical settings, including their exercise habits, nutrition, and blood glucose levels; such data would

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have offered improved, robust proof concerning the positive impacts of the intervention.

The used design, with a single group and pretest-posttest format, precludes the use of a control group, which consequently reduces the confidence with which observed changes can be solely attributed to the intervention. It should also be remembered that many patients in real clinical contexts lack access to the internet, smartphones, etc, due to socioeconomic and geographical barriers and digital literacy, which can affect the applicability of this and other interventions, undermining the equity of telenursing care. The single setting from which participants were recruited is also an issue that reduces generalizability. It is advised that researchers use objective methods of measuring patients' clinically relevant data in studies of their self-care behaviors, use control groups, and recruit participants from multiple contexts in order to generate more generalizable feedback about patient needs and the efficacy of interventions. Researchers should also always consider accessibility issues, including with regard to the use of digital technologies to deliver care.

Conclusions

The results affirm that an appropriately designed educational telenursing intervention can achieve significantly improved patient knowledge, self-care practices, and skills among patients with DM. Delivered via numerous modern methods of telecommunication, the intervention was successful in targeting essential issues in DM management to prevent complications, including monitoring blood glucose, physical exercise, and appropriate care for the foot. These results buttress calls for telenursing inclusion in conventional care for patients with DM, especially in contexts where conventional resources are not optimally accessible for all patients. This study's outcomes highlight the potential of patient education and telenursing follow-ups as an effective and scalable intervention to enable improved self-care practices, skills, and knowledge for patients with DM. The statistically significant enhancements demonstrated by this research support the use of patient education and telenursing follow-ups to help address the expanding costs of diabetes care, especially in contexts with limited resources. Nevertheless, more studies are required to ascertain whether the outcomes of this study are similar across different service user populations and to assay the long-term clinical and economic sustainability of education and telenursing solutions for such care.

Acknowledgments

The publication of this article was funded by the Weill Cornell Medicine – Qatar Health Sciences Library.

Conflicts of Interest

None declared.

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Abbreviations

DM: diabetes mellitus
HbA_{1c}: glycated hemoglobin A_{1c}
RCT: randomized controlled trial

Edited by E Borycki; submitted 10.10.24; peer-reviewed by C Li, H Monkman; revised version received 08.12.24; accepted 08.12.24; published 21.03.25.

Please cite as:
Alsahli M, Abd-alrazaq A, Fathy DM, Abdelmohsen SA, Gushgari OA, Ghazy HK, Abdelwahed AY
Effectiveness of Patients' Education and Telenursing Follow-Ups on Self-Care Practices of Patients With Diabetes Mellitus: Cross-Sectional and Quasi-Experimental Study
JMIR Nursing 2025;8:e67339
URL: https://nursing.jmir.org/2025/1/e67339
doi:10.2196/67339

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Self-Health Monitoring by Smart Devices and Ontology Technology for Older Adults With Uncontrolled Hypertension: Quasi-Experimental Study

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Abstract

Background: Hypertension is a prevalent concern among older adults, often leading to complex cardiovascular complications when uncontrolled. Telenursing technology facilitates self-management, and the integration of domain-specific ontology allows real-time interpretation of behavioral and biometric data to provide personalized recommendations, enhancing patient engagement and self-care.

Objective: This study aimed to examine the within-group and between-group effects of self-health monitoring using smart devices combined with ontology technology on hypertension-controlling behavior and mean arterial pressure among older adults with uncontrolled hypertension.

Methods: The quasi-experimental design was conducted with 91 older adults in Bangkok, Thailand (46 experimental and 45 comparison participants). Participants in the experimental group used the "HT GeriCare@STOU" app on smartphones, linked to smartwatches for blood pressure monitoring, step count, and sleep pattern, with telenursing support via video calls. Data on hypertension-controlling behavior were collected using a validated questionnaire (Cronbach α=0.83; content validity index=0.98). Descriptive statistics and *t* tests were used to analyze within-group and between-group differences.

Results: Within-group analysis revealed that experimental participants showed improved hypertension-controlling behavior and reduced mean arterial pressure after the program. Between-group comparisons indicated that mean arterial pressure in the experimental group was significantly lower than in the comparison group (P<.05), although hypertension-controlling behavior did not differ significantly between groups. Older adult participants and nurses reported high satisfaction, noting that real-time feedback increased awareness of blood pressure and motivated independent health behavior adjustments.

Conclusions: Self-health monitoring using smart devices integrated with ontology technology effectively improved physiological outcomes and supported self-management in older adults with uncontrolled hypertension. The ontology framework enabled personalized, real-time decision support, highlighting its novelty, and potential to enhance nursing practice. Future studies with larger samples and longer follow-up are recommended to further evaluate the intervention's effectiveness and scalability.

Trial Registration: Thai Clinical Trials Registry TCTR20250110003; https://www.thaiclinicaltrials.org/show/TCTR20250110003

(JMIR Nursing 2025;8:e73386) doi:10.2196/73386

KEYWORDS

Thailand; self-health monitoring; smart devices; ontology technology; older adults; uncontrolled hypertension

Introduction

Background

Hypertension is a major public health challenge worldwide, with its prevalence continuing to rise, particularly among older adults. In Thailand, the age-standardized prevalence of hypertension among older adults was estimated at 60% in 2019 - 2020. Alarmingly, 77.3% of hypertensive patients nationwide had uncontrolled blood pressure (>140/90 mm Hg), reflecting a critical gap in disease management [1].

Bangkok, which officially became an aging society between 2020 and 2022, saw its older adult population increase from 20.40% to 21.6%. In 2021 alone, 1.23 million older adults were living in the city, 20.60% of whom had hypertension [2]. During the same period, the proportion of patients with uncontrolled hypertension rose from 40.62% in 2020 to 60.55% in 2022,

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surpassing the city's target of keeping this figure below 50% [3]. In 2022, 102,471 hypertensive patients received care at 69 public health centers [3], and more than half were estimated to have inadequately controlled blood pressure. These trends underscore the urgent need for targeted blood pressure management strategies for older adults, aiming for systolic blood pressure (SBP) <140 mm Hg or diastolic blood pressure (DBP) <90 mm Hg to prevent complications.

The Ministry of Public Health has implemented measures to improve health behaviors in at-risk groups and patients with chronic diseases, such as reducing sugar, fat, and salt intake, promoting smoke- and alcohol-free habits, and encouraging home blood pressure monitoring. Hypertension management in Bangkok communities follows these guidelines [4]: (1) annual follow-ups for registered patients, (2) education and behavioral modification on at least 3 topics per year, (3) a referral system to public health centers or hospitals for patients with complications, and (4) monitoring blood pressure, with monthly home visits for patients with uncontrolled issues. Empowering hypertensive patients, especially older adults, to manage their health ensures sustainable control and may reduce health care costs. However, changing health behaviors in older adults is challenging and requires significant time, resources, and consistent effort.

A study found that older adults with hypertension often felt frustrated with management, as their blood pressure fluctuated despite their self-care efforts, leading to decreased motivation [5]. Key barriers to self-care include motivation and age. The 2022 evaluation of noncommunicable disease services showed that efforts to modify health behaviors in diabetes and hypertension patients were unclear, inconsistent, and not personalized to individual lifestyles [6]. This lack of clarity and consistency contributed to the low motivation among at-risk individuals and patients to adopt healthier behaviors.

To prevent complications in patients with chronic diseases, the Ministry of Public Health has proposed guidelines to enhance health literacy and self-awareness (Know Your Number) among normal, at-risk, suspected, and patient groups. This included communicating risks to encourage awareness and behavior modification in both diabetes and hypertension patients. Given the challenges faced by older adults and the health care system, it was clear that empowering adults and older adult patients with hypertension to independently seek knowledge, make informed decisions, and manage their behaviors was crucial for addressing daily life challenges related to hypertension.

A systematic review of self-management found that, over 12 months, it could reduce SBP by 3.2 mm Hg [7,8]. Another review of hypertension intervention activities from 2008 to 2018 [9] showed that combining health education, counseling, and management effectively reduced blood pressure, lowering systolic by −5.34 mm Hg and diastolic by −3.23 mm Hg. Tucker et al [8] found that self-monitoring alone was not sufficient to reduce blood pressure; it should be combined with cointerventions and supported by close monitoring, including systematic medication adjustments in collaboration with doctors, pharmacists, and patients, along with health education or counseling for lifestyle changes.

Previous studies have shown that hypertension management was typically carried out by doctors, nurses, or community health volunteers, which could lead to patients becoming overly dependent on the health care system. However, with about 90% of urban Thai people using electronic media, studies indicated that older adults had a high level of technology acceptance. Moolsart and Kritpolviman [10] found that 76.73% of older adult patients with uncontrolled hypertension receiving care at public health centers in Bangkok owned smartphones, with LINE (LY Corporation) being the most commonly used app. Furthermore, older adults showed a moderate interest in using information technology for managing their health conditions.

The prevention and treatment of high blood pressure could be greatly aided by mobile health (mHealth) technologies [11]. However, technology had not been widely used for treating hypertension in older adults, and there was still limited research in this area. Therefore, developing electronic media for self-monitoring health conditions in older adults with hypertension was an effective way to provide knowledge tailored to urban lifestyles. Allowing older adults to continuously assess their health and manage behaviors related to diet, exercise, stress, and medication adherence could help control their condition, reducing the need for medical treatment and hospital visits. Chaipattanamethi [12] developed a multimedia food system on dietary approaches to stop hypertension (DASH) for older adults, which was a lesson installed on portable personal computers (notebooks). When tested with older adults, user satisfaction was found to be high overall.

Research Rationale and Aim

This study aimed to assess the effectiveness of technology-based interventions for monitoring the health conditions of older adults. Specifically, it focused on the impact of self-health monitoring using smart devices combined with ontology technology on hypertension-controlling behavior and mean arterial pressure (MAP) among older adults with uncontrolled hypertension.

Ontology refers to a formal representation of knowledge comprising a set of concepts and their interrelationships, designed to be shared and reused across systems. In health informatics, ontology enables the structured organization of domain-specific knowledge, supporting semantic understanding, automated reasoning, and intelligent information retrieval [13-15]. In this study, ontology technology was used to construct a health knowledge base tailored to older adults with hypertension. This ontology-based system served as the foundation for semantic web technologies, enhancing the accuracy and efficiency of health information access through interconnected and user-centered data services.

To operationalize this approach, the intervention integrated the HT GeriCare@STOU mobile app [10], smartwatch-based blood pressure monitoring, training in health knowledge and digital literacy, telenursing via LINE for home-based care, and professional-led online knowledge sharing. These components were designed to promote self-regulation: self-observation through real-time monitoring of blood pressure and physical activity via smartwatch; self-judgment through personalized feedback and goal tracking in the mobile app; and self-reaction

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through behavioral prompts, telenursing support, and health education. It was hypothesized that older adults who previously struggled to control their hypertension would improve their self-management skills, thereby reducing complications and enhancing their quality of life.

Methods

Study Design

A 2-group pretest-posttest design was used in this quasi-experimental investigation. The study, which lasted 12 weeks, examined the effects of ontology technology and smart device-based self-health monitoring on hypertension-controlling behavior and MAP in older adults with uncontrolled hypertension.

Sample and Setting

The sample group consisted of older adults aged 60 - 75 years who had been diagnosed with essential hypertension and exhibited uncontrolled blood pressure. All participants resided in Bangkok.

To organize the sampling framework, Bangkok's 69 public health facilities were grouped into 6 administrative zones. Two of these zones were selected by matched community clusters to form experimental and comparison groups. Authorization to conduct the study was obtained from 13 public health facilities within these zones. Among these, 8 facilities were assigned to either the experimental or comparison group based on their geographic location to minimize cross-contamination. The remaining 4 facilities had a small number of eligible participants; one of these was selected for piloting the research instruments. Although randomization was not applied, this quasi-experimental design used geographical allocation and comparable facility profiles to reduce potential selection bias.

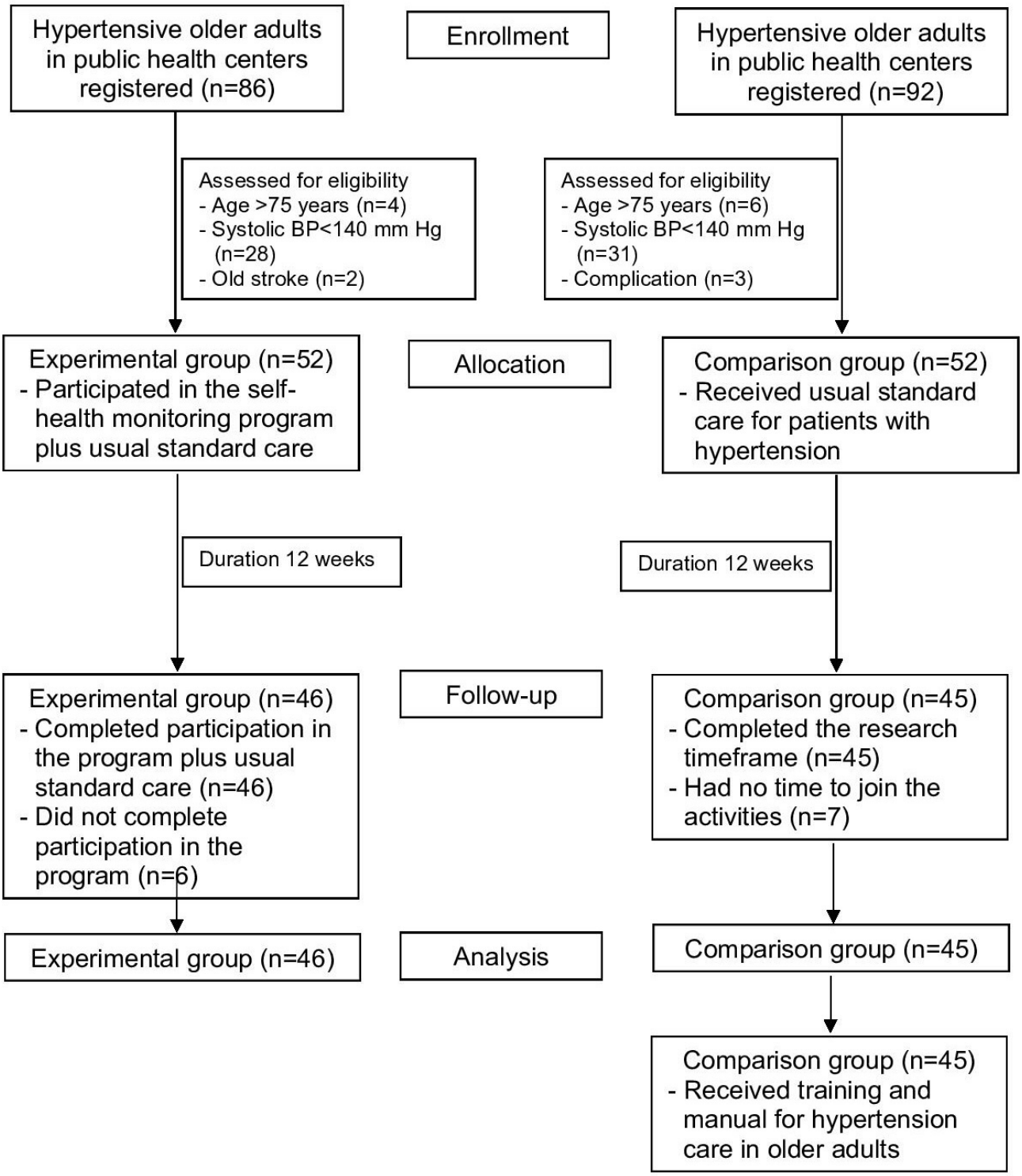
The sample size was calculated using the G*power program (Heine University of Düsseldorf) applying the statistical test means: the variation of 2 independent means (2 groups). The effect size was examined and computed as 0.7, representing a medium effect size (as no research contrasts with this study, this is an approximation). Using an alpha value at .05 and a power of .95, the sample size calculation program determined 45 people per group. However, in this study, to prevent sample loss, an additional 15% was added to the sample size. Therefore, the sample size in both the experimental and control groups was increased to 52 people each, totaling 104 people.

Due to ethical constraints, random sampling from lists of patients with uncontrolled hypertension was not feasible, as patient identities could not be disclosed by the participating health facilities. Therefore, a voluntary enrollment approach was used. Older adults who met the inclusion criteria were invited to participate through health facility announcements and outreach by local health personnel. Participants were then screened and selected based on eligibility criteria.

The inclusion criteria were older adults aged 60 - 75 years who were hypertensive with SBP levels exceeding 140 - 180 mm Hg or DBP levels exceeding 90 - 109 mm Hg. They did not have any comorbidities or complications related to hypertension, such as diabetes, cardiovascular diseases, kidney diseases, and eye diseases. They could read and write, had normal cognitive function, and were not depressed, which would be screened using the Thai version of the Mini-Cog screening tool [16] and the 2-question (2Q) depression assessment. Older adults or their caregivers using smartphones were recruited. Exclusion criteria included withdrawal from the program, problems, or a major sickness that prevented participation, as well as participation in the program for fewer than 12 weeks in a row. A total of 86 and 92 older adults initially volunteered for the experimental and comparison groups, respectively. Following eligibility screening based on the inclusion criteria, 52 participants were included in each group (Figure 1). Both groups of participants joined the program and engaged in the following activities: (1) the experimental group received the self-health monitoring program and usual standard care for 12 weeks; (2) the comparison group received care services according to the standards of the public health service centers, and at the end of the 12-week trial, they underwent teaching and a hypertension manual to develop their self-health management skills. After 12 weeks, 46 participants (88.46%) in the experimental group and 45 participants (86.54%) in the comparison group completed the study, as shown in Figure 1.

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Figure 1. A Consolidated Standards of Reporting Trials (CONSORT) flow diagram of selecting the participants in this study. BP: blood pressure.



To minimize potential confounding factors, the study applied strict inclusion criteria. All participants were diagnosed with essential hypertension and had been receiving similar classes of antihypertensive medications with stable regimens for at least four weeks before enrollment. Participants with significant comorbidities such as diabetes, cardiovascular diseases, renal insufficiency, or cognitive impairment were not recruited to reduce variability. Moreover, the study required that all participants had a designated caregiver who could assist with self-monitoring activities and attend training sessions. This ensured consistency in caregiver engagement across both intervention and comparison groups, reducing its potential confounding effect.

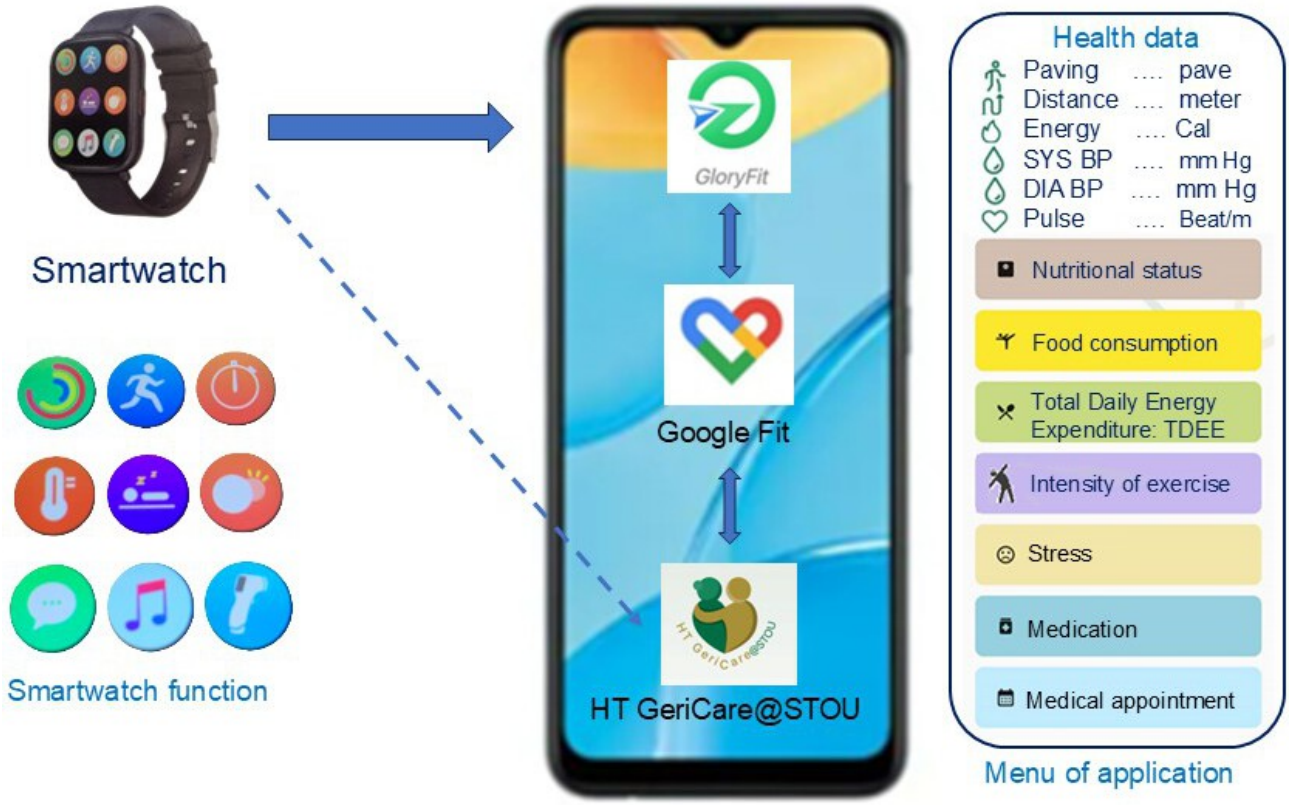
Instruments

The research implementation tool was a self-health monitoring program designed by researchers for older adults who had difficulty managing their hypertension. The program was grounded in Bandura's [17] self-regulation theory and lasted for 12 weeks. The intervention included a smartwatch capable of measuring key life indicators such as blood pressure, heart rate, body temperature, blood oxygen levels, daily steps, and

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sleep patterns. The smartwatch data were automatically transmitted to a mobile app called "HT GeriCare@STOU" developed by the research team [10] as shown in Figure 2.

Figure 2. The linkage between the smartwatch and the HT GeriCare@STOU app on the smartphone and the menus.



The app was developed based on prior formative work, including needs assessment and usability testing, to ensure it met user needs and facilitated engagement. Built as an ontological technology, the mobile app was developed based on a domain-specific ontology for hypertension management. This ontology-based system allowed the integration and semantic interpretation of user data, including dietary intake, physical activity (total daily energy expenditure), stress levels, and biometric information. The ontology enabled the app to perform basic rule-based reasoning—categorizing blood pressure readings as high, normal, or low— and generating personalized feedback or alerts accordingly. It also provided suggestions for stress reduction, dietary modification, and exercise intensity based on predefined knowledge rules and health guidelines. These data were made accessible to nurses through a linked dashboard to support individualized planning before home-based care by LINE, thereby enhancing both patient self-regulation and professional support. For example, when a participant's blood pressure was ≥140/90 mm Hg, the system inferred high blood pressure and generated the message: "*Please recheck your medication adherence, reduce risk factors, sleep 6 - 8 hours, practice meditation, among other recommendations.*"

Cognitive function (Mini-Cog) screening tool owned by the Institute of Geriatric Medicine was permitted to be used. Mini-Cog is a brief cognitive screening tool used to detect dementia or cognitive impairment in older adults. It consists of a 3-item recall test and a clock-drawing test. Scoring ranges from 0 to 5, with recall of each word scoring 1 point and the clock drawing scored 0 or 2 points. A total score below 3 indicates possible cognitive impairment. Mini-Cog is widely used due to its simplicity, speed (approximately 3 minutes), and good sensitivity and specificity for early detection of cognitive decline. Depression was assessed by asking two questions: (1) During the past 2 weeks, have you often felt down, depressed, or hopeless? And (2) During the past 2 weeks, have you often had little interest or pleasure in doing things? The 2Q depression screening tool is a freely accessible instrument that has been recommended for routine use by the Department of Mental Health, Ministry of Public Health, Thailand. As a public domain tool, it does not require prior permission for application in research or clinical practice. A positive response to either question indicated the need for further evaluation. If any cognitive impairment and depression were detected using the Mini-Cog and 2Q, the participant would be referred to the nurse at the local health service center for further evaluation and care. Such individuals would not be recruited from the study sample.

The data collection tools developed by researchers included a hypertension-controlling behavior questionnaire. The questionnaire consisted of two sections: (1) general demographic and health information (24 items), and (2) 39 items on hypertension-controlling behaviors, organized into 4 domains: food consumption, exercise, stress management, and medication adherence. Each item was rated on a 5-point Likert scale [18], ranging from 1 (never practiced) to 5 (regularly practiced). Behavioral scores were interpreted as follows: least practiced (1.00 - 1.50), somewhat practiced (1.51 - 2.50), moderately

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practiced (2.51 - 3.50), very practiced (3.51 - 4.50), and most practiced (4.51 - 5.00).

The questionnaire items were developed based on a review of relevant literature, expert consultation, and alignment with national hypertension management guidelines. Sample items included: "*I reduce salt in my meals*" (food consumption domain), "*I exercise at least 30 minutes per day*" (exercise domain), and "*I take prescribed antihypertensive medication without missing doses*" (medication adherence domain).

Content validity was established through evaluation by 5 experts in community nursing, geriatric care, and behavioral science, yielding a content validity index of 0.98. A pilot test was conducted with 30 older adults who met the inclusion criteria but were not participants in the main study. The questionnaire demonstrated good internal consistency, with a Cronbach α coefficient of 0.83. Although factor analysis was not performed due to sample size limitations, the items were developed using a conceptually grounded framework and were validated through both expert review and pilot testing.

Blood pressure was measured using 3 digital automatic blood pressure monitors. All devices were calibrated and validated to ensure consistency across the three units and accuracy against the standard device used at the primary health care center.

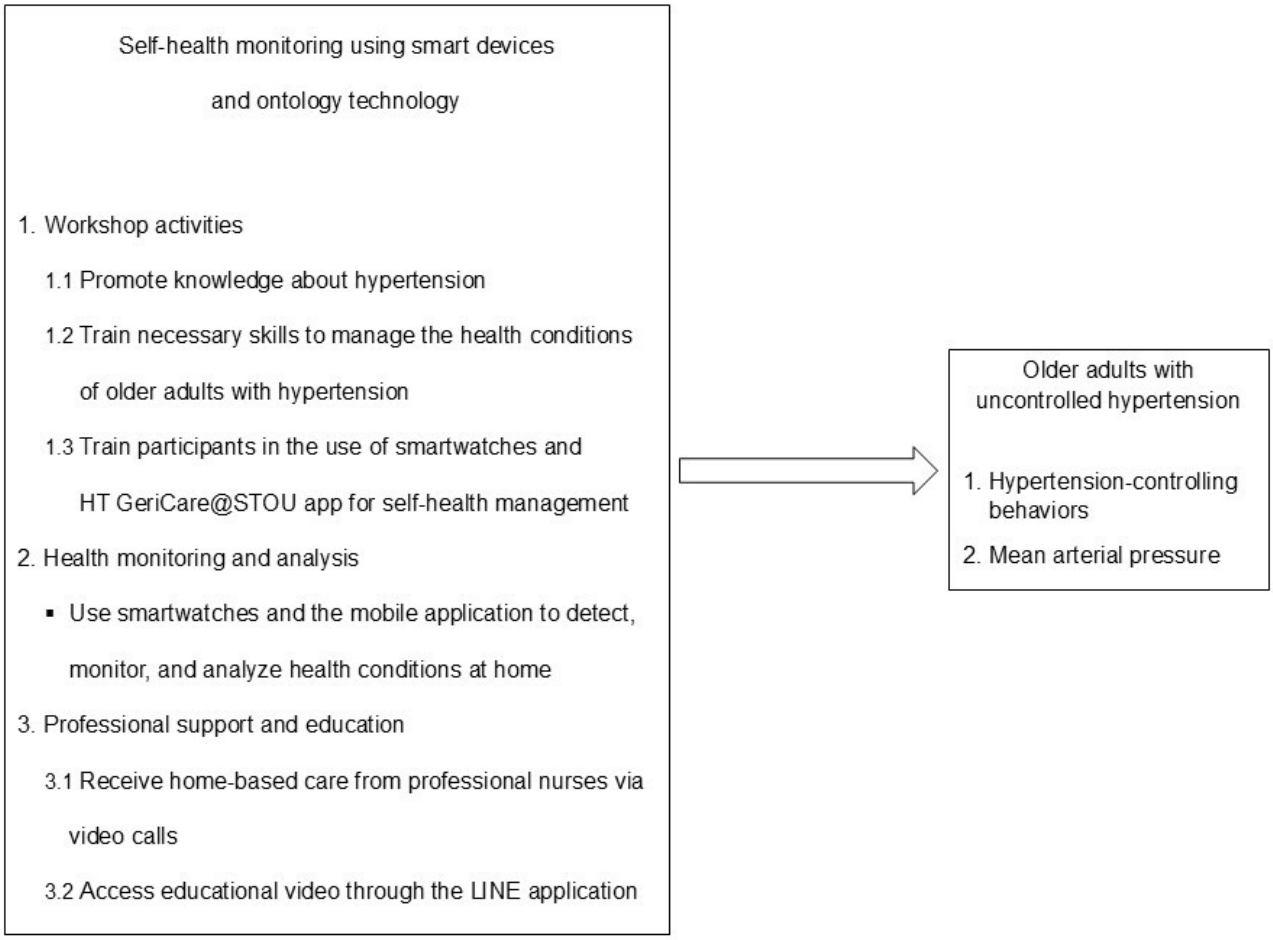
Interventions

Bandura's self-regulation theory [17] believes that individuals can do something to control their thoughts, feelings, and actions based on intention and desire through practice and self-development. Self-regulation consists of three processes. (1) Self-observation is a process where individuals evaluate themselves, set goals, and monitor their performance outcomes to create motivation for changing behaviors to achieve desired goals. (2) The judgment process is comparing self-evaluation results with personal goals or standards, considering the desired outcomes and one's own limitations. Learning and correcting lead to decisions in setting new directions that are suitable for oneself and close to the standards. (3) Self-reaction is the response to the evaluation of one's behavior from the judgment process. If a person successfully performs a behavior according to the set goals, they will show a positive reaction toward themselves or reward themselves. But if the person performs the behavior below the target, they will show a negative reaction toward themselves, punish themselves, or not react toward themselves.

Participants in the experimental group were able to perform self-evaluations using smartwatches to measure blood pressure, daily step count, sleep pattern, and heart rate during exercise. These data would be sent to an app "HT GeriCare@STOU" on their mobile phone. By planning previous care through online home-based care, nurses were able to identify this data. The duration of the program was 12 weeks. The first week of the program began with technological training and an invitation for nurses and the older adult to download the app to their phones. A handbook on how to use the smartwatch and its apps, as well as information on how to manage hypertension, was then given to the older adults, who also spent an hour learning and sharing their knowledge. Participants were instructed to wear the smartwatch throughout the day and night, except during bathing for the duration of the 12-week program to monitor their blood pressure, pulse, walking steps, and sleeping hours, and setting goals for hypertension control in terms of energy requirements, exercise, weight, and body mass index, as shown in Figure 3. Each morning, they measured their blood pressure, recorded body weight weekly, and logged dietary intake on 3 designated days per week. Nurses reviewed participants' data weekly to guide personalized home-based care through LINE phone conversations and shared their knowledge and videos online throughout the third, sixth, and tenth weeks of telenursing. The research team also conducted biweekly LINE follow-ups during the first month and monthly follow-ups during months 2 and 3 to identify usage barriers and provide technical support. If participants missed recordings or encountered technical difficulties with the devices or app, the research team followed up by phone or in person to provide support and ensure protocol adherence. In the final week, the nurses and older individuals were asked to provide feedback on the program and to summarize their experiences.

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Figure 3. The activities and outcomes of a self-health monitoring program using smart devices combined with ontology technology.



Data Collection

The data gathering and program execution occurred from June 15 to September 7, 2024. On each data collection, study assistants measured participants' blood pressure and administered structured questionnaires regarding hypertension-controlling behaviors. The assistants confirmed that all older adults had completed the questionnaires themselves.

Participants in the experimental group received a 12-week self-monitoring program in addition to standard care. Older adult participants and their caregivers received a set of refreshments and lunch per person, as well as a fixed travel allowance. In addition, participants were provided with a smartwatch on loan for a 12-week period, accompanied by a user manual to support its use throughout the study. Adherence to the smartwatch and app usage was monitored via both automated backend data and manually recorded entries. Weekly data, including body weight, dietary intake, blood pressure, and perceived stress, were to be input regularly by participants using the app, following a standardized handout. In cases of difficulty, participants, caregivers, or community nurses could contact the research team through a dedicated LINE messaging group. Participants generally adhered to the intervention protocol, completing scheduled measurements and logs as instructed. This active monitoring and support contributed to high intervention fidelity, supporting the validity of the observed physiological and behavioral outcomes.

The comparison group received standard care only. The research assistant scheduled follow-up appointments with participants in this group for reassessment 12 weeks later, which included completing the same hypertension-controlling behavior questionnaires and measuring blood pressure. After completing the final data collection, participants in the comparison group were provided with basic education training on key topics related to healthy eating, physical activity, stress management, and medication adherence. This training was delivered after all outcome assessments were completed and was not part of the intervention program.

Data Analysis

The computer app was used to analyze the data. In order to assess general information, descriptive statistics such as frequency, percentage, mean, and SD were used. Using the Kolmogorov-Smirnov test, the pre-experimental data were examined for normality under the *t* test (1-tailed) statistical assumptions.

Given the study's quasi-experimental design with 2 groups (intervention and comparison) and 2 time points (pre- and postintervention), paired *t* tests were used to compare within-group changes, and independent *t* tests were used to compare between-group differences.

Although repeated measures ANOVA or mixed-effects models are often applied in studies with longitudinal data, these methods were not used due to the limited sample size, unequal group

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sizes, and the fact that only 2 time points were assessed. The statistical assumptions for using *t* tests, including normality and homogeneity of variance, were tested and found to be acceptable. Therefore, the *t* test was considered the most appropriate and interpretable method for this study. All statistical analyses were performed using SPSS (version 27; IBM Corporation). A *P* value of <.05 was considered statistically significant.

Ethical Considerations

The research was approved by the School of Nursing Ethical Committee, Sukhothai Thammathirat Open University (NS 1/2566; Jan 12, 2023) and the Bangkok Research Ethics Committee (E007he/67; June 4, 2024). The trial was registered with the Thai Clinical Trials Registry (TCTR20250110003). All participants were informed about the study objectives, procedures, confidentiality, potential risks, and benefits and provided written informed consent prior to participation. Participation was voluntary, and participants could withdraw at any time without any impact on their health care. Data were kept confidential and used exclusively for research purposes.

Results

Participant Characteristics

The demographic characteristics of participants in both the experimental and comparison groups were similar, with no statistically significant differences observed (all *P*>.05), as shown in Table 1.

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Table . Demographic and health characteristics of the experimental and comparison groups.

Demographic and health characteristics	Experimental group (n=46)	Comparison group (n=45)	Statistical testing	
			Chi-square or *t* test (*df*)	*P* value
Sex, n (%)			0.4 (1)[a]	.55
Male	7 (15)	9 (20)		
Female	39 (85)	36 (80)		
Age (year)			1.504 (89)[b]	.14
Mean (SD; range)	68.57 (4.79; 60-78)	67.04 (4.85; 60-79)		
Age group, n (%)				
60 - 65	12 (26)	19 (42)		
66 - 70	15 (33)	15 (33)		
71 - 75	19 (41)	11 (24)		
Religion, n (%)			3.2 (1)[a]	.07
Buddhism	42 (91)	35 (78)		
Islam	4 (9)	10 (22)		
Marital status, n (%)			0.009 (1)[a]	.93
Single, widowed, separated	26 (57)	25 (56)		
Couple	20 (43)	20 (44)		
Education, n (%)			1.9 (2)[a]	.38
Uneducated	2 (4)	5 (11)		
Primary or secondary	30 (65)	30 (67)		
Undergrade and graduate	14 (30)	10 (22)		
Occupation, n (%)			0.2 (2)[a]	.91
Unemployed	26 (56)	24 (53)		
Agriculture or merchant	11 (24)	11 (24)		
Retired	9 (20)	10 (22)		
Duration of hypertension			1.179 (89)[b]	.24
Mean (SD; range)	4.70 (0.80; 3-7)	4.51 (0.67; 4-7)		
Duration (years), n (%)				
Less than 5	30 (65)	34 (76)		
6 - 10	16 (35)	11 (24)		

[a]Chi-square test.

[b]*t* test.

Most participants in both groups were female (n=39, 85% in the experimental group and n=36, 80% in the comparison group). The mean age was 68.57 (SD 4.79) years in the experimental group and 67.04 (SD 4.85) years in the comparison group. The majority of participants in both groups practiced Buddhism, followed by Islam. Regarding marital status, most participants were single, widowed, or separated (n=26, 57% in the experimental group and n=25, 56% in the comparison group). In terms of education, most had completed primary or secondary education (n=30, 65% in the experimental group and n=30, 67% in the comparison group). Regarding occupation, the majority in both groups were unemployed (n=26, 56% in the experimental group and n=24, 53% in the comparison group), with the remainder primarily engaged in agriculture or small trade.

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Effect of Health Monitoring Program on the Hypertension-Controlling Behavior

Before the intervention, there were no statistically significant differences between the experimental and comparison groups in overall or domain-specific hypertension-controlling behaviors, as shown in Table 2.

Table . Comparison of hypertension-controlling behaviors and mean arterial pressure of older adults with uncontrolled behavior between the experimental group and the comparison group.

Hypertension-controlling behaviors	Experimental group (n=46)		Comparison group (n=45)		*t* test (*df*)	*P* value
	Mean (SD)	Level	Mean (SD)	Level		
Food consumption						
Preprogram	3.27 (0.72)	Moderate	3.25 (0.69)	Moderate	0.101 (89)	.92
Postprogram	3.43 (0.66)	Moderate	3.41 (0.56)	Moderate	0.139 (89)	.89
Exercise						
Preprogram	3.38 (1.16)	Moderate	2.91 (1.21)	Moderate	1.891 (89)	.06
Postprogram	3.78 (0.90)	Very practiced	3.63 (1.13)	Very practiced	0.645 (89)	.52
Stress management						
Preprogram	3.76 (0.64)	Very practiced	3.62 (0.67)	Very practiced	0.992 (89)	.32
Postprogram	4.05 (0.56)	Very practiced	4.21 (0.62)	Very practiced	−1.196 (89)	.24
Medication adherence						
Preprogram	4.36 (0.66)	Very practiced	4.22 (0.68)	Very practiced	0.995 (89)	.32
Postprogram	4.49 (0.47)	Very practiced	4.46 (0.53)	Very practiced	0.281 (89)	.78
Hypertension-controlling behavior in total						
Preprogram	3.69 (0.49)	Very practiced	3.50 (0.50)	Moderate	1.832 (89)	.07
Postprogram	3.94 (0.42)	Very practiced	3.93 (0.50)	Very practiced	0.069 (89)	.94
Mean arterial pressure (mm Hg)						
Preprogram	107.14 (7.74)	High	106.86 (8.56)	High	0.163 (89)	.87
Postprogram	96.82 (8.85)	Normal	104.16 (10.52)	High	−3.604 (89)	<.001

After the 12-week program, the experimental group demonstrated significant within-group improvements, particularly in exercise and stress management domains ($P<.05$). Within-group analysis showed that the experimental group experienced a moderate improvement in hypertension-controlling behavior (Cohen $d=0.55$, 95% CI 0.24 - 0.86), while the comparison group exhibited a large effect size (Cohen $d=0.86$, 95% CI 0.52 - 1.20). However, despite the within-group improvements, no statistically significant difference was observed between groups in postprogram behavior scores, with a negligible effect size (Cohen $d=0.02$, 95% CI –0.39 to 0.43). This suggests that while the program may have supported individual improvement within the experimental group, its differential effect compared to usual care was limited (Table 3).

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Table . Comparison of hypertension-controlling behaviors and mean arterial pressure of older adults with uncontrolled behavior between the pre- and postprogram enrolling.

Hypertension-controlling behaviors	Preprogram enrolling		Postprogram enrolling		*t* test	*P* value
	Mean (SD)	Level	Mean (SD)	Level		
Food consumption						
Experimental group	3.27 (0.72)	Moderate	3.43 (0.66)	Moderate	−1.242 (45)	.22
Comparison group	3.25 (0.69)	Moderate	3.41 (0.56)	Moderate	−1.720 (44)	.09
Exercise						
Experimental group	3.38 (1.16)	Moderate	3.78 (0.90)	Very practiced	−2.457 (45)	.02
Comparison group	2.91 (1.21)	Moderate	3.63 (1.13)	Very practiced	−4.584 (44)	<.001
Stress management						
Experimental group	3.76 (0.64)	Very practiced	4.05 (0.56)	Very practiced	−2.652 (45)	.01
Comparison group	3.62 (0.67)	Very practiced	4.21 (0.62)	Very practiced	−5.025 (44)	<.001
Medication adherence						
Experimental group	4.36 (0.66)	Very practiced	4.49 (0.47)	Very practiced	−1.420 (45)	.16
Comparison group	4.22 (0.68)	Very practiced	4.46 (0.53)	Very practiced	−2.586 (44)	.01
Hypertension-controlling behavior in total						
Experimental group	3.69 (0.49)	Very practiced	3.94 (0.42)	Very practiced	−3.202 (45)	.003
Comparison group	3.50 (0.50)	Moderate	3.93 (0.50)	Very practiced	−5.690 (44)	<.001
Mean arterial pressure (mm Hg)						
Experimental group	107.14 (7.74)	High	96.82 (8.85)	Normal	6.109 (45)	<.001
Comparison group	106.86 (8.56)	High	104.16 (10.52)	High	1723 (44)	.09

Effect of Health Monitoring Program on the Mean Arterial Pressure

In the experimental group, SBP significantly decreased from 150.60 (SD 9.67) to 135.93 (SD 12.04) mm Hg, and DBP decreased from 85.41 (SD 9.30) to 77.26 (SD 8.59) mm Hg. The within-group effect size for SBP was a Cohen *d* of 1.34 (95% CI 0.94-1.74), and for DBP was a Cohen *d* of 0.91 (95% CI 0.57-1.25), indicating large effects [19,20]. MAP also showed a statistically significant reduction from 107.14 (SD 7.58) to 96.82 (SD 9.09) mm Hg, with a large effect size (Cohen *d*=1.22, 95% CI 0.83-1.60).

In contrast, the comparison group showed a nonsignificant reduction in SBP from 151.70 (SD 10.78) to 145.37 (SD 15.68) mm Hg, and a slight decrease in DBP from 84.44 (SD 9.83) to 83.56 (SD 10.08) mm Hg. The within-group effect size for SBP was a Cohen *d* of 0.47 (95% CI 0.16-0.78; moderate), and for DBP was a Cohen *d* of 0.09 (95% CI –0.20 to 0.38; negligible effect). MAP in the comparison group showed a minor, nonsignificant decrease from 106.86 (SD 8.69) to 104.16 (SD 10.62) mm Hg, with a small effect size (Cohen *d*=0.30, 95% CI –0.02 to 0.63).

Discussion

Principal Findings

Effect of Health Monitoring Program on the Hypertension-Controlling Behavior

The improved overall, exercise, and stress management behaviors in older adults with uncontrolled hypertension in the experimental group could be attributed to the program's activities, which applied Bandura's self-regulation concept through a 3-step process [17]. Self-observation involved older adults with uncontrolled hypertension using smartwatches to monitor key parameters like blood pressure, pulse, step count, and energy expenditure. A manual encouraged goal-setting to adjust these parameters, allowing them to track behaviors and performance outcomes to motivate behavior change and achieve their goals. The judgment *process* helped older adults compare their self-assessment results with personal goals using the "HT GeriCare@STOU" app and manual. It covered areas like diet, exercise, stress management, and medication adherence. Daily reflections allowed them to make adjustments and set new, personalized guidelines aligned with their goals. In self-reaction, older adults responded to their behavior evaluation from the judgment process. If they met their goals, they rewarded

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themselves positively; if not, they worked to improve and achieve better results.

While hypertension-controlling behaviors were high, they did not reach the highest level. Statistically significant improvements at the .05 level were observed in exercise and stress management. This improvement may be attributed to older adults in the experimental group, who tracked their daily activities using a smartwatch to count steps and assess pulse, ensuring exercise intensity aligned with their goals (55% - 80% of maximum pulse). In addition, videos sent via the LINE app in Weeks 2, 6, and 10 provided guidance on walking exercises and stress management techniques, such as relaxation breathing and positive thinking. While these interventions led to improved exercise and stress management behaviors, age-related limitations and some older adults' independent lifestyles may have prevented them from achieving the highest level of performance.

Although food consumption and medication intake showed increased average values, they were not statistically significant at the .05 level. This may be due to limited ability to immediately change dietary habits, as meal preparation often depends on family caregivers. In addition, living in a large city like Bangkok, where ready-to-eat meals are widely available, older adults and their families often opted to buy food rather than cook, which made it harder to avoid high-fat foods, as reflected in the average scores on related questions.

The average scores for fruit and vegetable consumption among older adults in the experimental group were low, with about 2 handfuls consumed. This could be due to the availability of inexpensive, hard fruits like guavas and mangoes, which were difficult for older adults to chew. As for medication intake, older adults already displayed good adherence, so no significant changes were observed, especially in monitoring abnormal symptoms. Since they took their medication regularly, they tended to forget to observe these symptoms. However, older adults significantly demonstrated good dietary behaviors in reducing or avoiding sweet fruits and adding fewer seasonings to their meals. This knowledge was shared through videos in the LINE app during Weeks 2, 6, and 10, alongside food tracking in the "HT GeriCare@STOU" app. The food menu provided details on carbohydrates, proteins, fats, sugars, and sodium, helping older adults recognize the importance of various food types and assess their eating habits periodically, leading to positive behavioral changes in sweet and salty foods.

However, this study underscores the critical role of nurses as facilitators of technology-driven interventions. Nurses not only interpreted real-time health data but also provided individualized feedback, guided behavioral modifications, and supported adherence to hypertension management through telenursing home-based care. Their active involvement was pivotal in helping older adult participants understand their health status, translate data into actionable steps, and sustain hypertension-controlling behaviors. These findings highlight nurses' unique capacity to bridge technology with patient-centered care, demonstrating their essential contribution to the successful implementation of mHealth interventions and reinforcing the broader implications for integrating such technologies into nursing practice and health systems.

Effect of Health Monitoring Program on the Mean Arterial Pressure

The improvement in MAP may be attributed to positive lifestyle behaviors promoted through the program, such as reduced intake of sweet fruits and excessive seasonings high in sugar and salt which could decrease blood vessel elasticity and narrow the arteries [21].

According to the Thai Hypertension Association (2019), reducing sodium to no more than 2300 milligrams per day could lower SBP by 2 - 8 mm Hg [22], and further restriction to 1800 milligrams per day could lead to more substantial reduction by −5.0 mm Hg and DBP by −2.7 mm Hg in hypertensive patients [23].

Furthermore, participants in the experimental group showed significant improvements in stress management behaviors. Stress was a well-established contributor to hypertension through increased sympathetic activity and vascular resistance [24]. The program emphasized deep breathing exercises, which had been shown to increase vagal tone and reduce sympathetic dominance [25], thereby reducing blood pressure and stress [26,27]. In this study, systolic and diastolic pressures were significantly reduced by −14.67 mm Hg and −8.15 mm Hg, respectively, with large effect size (SBP: Cohen d=1.34, 95% CI 0.94 - 1.74; DBP: Cohen d=0.91, 95% CI 0.57 - 1.25) [19]. The impact of this program reduction exceeded that of home blood pressure monitoring alone [28], aligning with previous studies on self-monitoring combined with app-based feedback or mHealth interventions [29-32]. These results supported the assertion that the ontology framework used in this study functioned not merely as a classification system, but as an integrated decision-support tool. By linking symptom patterns and behavioral data to generate tailored feedback, it enabled personalized recommendations based on individual risk profiles and user behavior, ultimately enhancing participant engagement and improving self-care adherence.

The primary outcome of this study was the reduction in MAP, which showed significant improvement in the intervention group. Although overall behavioral scores did not differ significantly between groups, several specific lifestyle behaviors changed meaningfully. Participants in the intervention group reported reduced use of seasoning, decreased intake of sweetened foods, and increased daily step counts.

These targeted behavioral modifications, even if modest, likely contributed to the observed improvements in blood pressure. Consistent small changes in key behaviors can accumulate to produce meaningful physiological effects, even when overall behavioral scores appear unchanged. The combination of self-monitoring through wearable devices, real-time feedback, and personalized guidance from nurses likely reinforced these behaviors, enhancing adherence and translating into measurable MAP reductions.

This suggests that interventions focusing on key actionable behaviors, even without broad changes across all measured domains, can produce significant clinical benefits. Future studies

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could further explore how specific behavioral pathways mediate physiological outcomes and consider integrating objective behavioral metrics alongside self-reported measures to capture subtle but clinically relevant changes.

Feedback from older adult participants in the final evaluation indicated a high level of satisfaction (mean 4.16, SD 0.44). Similarly, nurse participants reported high satisfaction (mean 4.31, SD 0.41), noting that using the device allowed patients to observe daily results, increasing their awareness of blood pressure levels in relation to their recorded dietary intake. The nurses also observed that this real-time feedback appeared to motivate patients to independently improve their overall health.

While physiological mechanisms contributed to these improvements, practical factors also influenced the program's impact. Several older adults faced challenges with device usability due to limited digital literacy, impaired vision, or hand tremors. Unstable internet connectivity in certain areas limited real-time interactions. Moreover, some participants experienced "tech fatigue" during extended screen use, which could hinder sustained engagement. These findings highlight the importance of ensuring that health technologies are user-friendly, accessible, and inclusive.

The use of ontology-based technologies and smart devices presented a promising approach for nurse practitioners to deliver care for hypertension [33]. However, the successful implementation of such systems depends on practical integration with clinical workflows. A recent systematic review noted that while artificial intelligence (AI) can enhance nursing productivity and allow more time for direct care, its effectiveness relied heavily on collaboration between system developers and practicing nurses [34]. Therefore, ongoing cooperation between technology designers and health care professionals is crucial to ensure usability and promote the adoption of digital health tools.

This study was conducted among urban older adults with access to smartphones, which may limit the generalizability of the findings to rural or low-resource settings. In areas with limited internet connectivity or lower digital literacy, participants may face difficulties using wearable devices and the ontology-based app. In addition, real-time follow-up and personalized guidance by nurses may be less feasible in remote locations due to resource constraints. Future studies should explore alternative approaches, such as low-tech interventions or telephone-based support, to adapt self-health monitoring programs for older adults in less-resourced contexts.

Limitations

Due to information ethics, both older adults and the registered nurses were informed of the group to which they were assigned and the activities in which they were participating. As a result, older adults in the comparison group might have provided inaccurate information in their questionnaire responses, as they could have been influenced by the nurses caring for them. This awareness may have led to an unintentional increase in their hypertension-controlling behavior scores. The program's applicability to older hypertensive patients with cellphones or a high education or economics—both of which are frequently found in big cities—is another drawback. Nonetheless, in crowded urban areas, the initiative helps shorten the time it took to go to patients' houses.

Moreover, this study was conducted among older adults living in urban areas who had access to smartphones and internet connectivity. Therefore, these findings may not fully reflect the experiences of older adults in rural or low-resource settings, where digital literacy, technological access, and infrastructure may be limited. Future adaptations of the program should consider simplified interfaces, offline functionality, and involvement of community health volunteers to bridge the digital divide and improve accessibility for underserved populations.

Finally, from a methodological perspective, the use of *t* tests does not capture potential group×time interactions, which could provide deeper insights into behavioral changes over time. Future research with larger sample sizes should consider repeated measures ANOVA or mixed-effects models to more accurately evaluate longitudinal intervention effects.

Conclusions

The self-health monitoring program—combining a smartwatch, the HT GeriCare@STOU app, telenursing through home-based care, and educational content via LINE—demonstrated effectiveness over a 12-week period. The program supported self-observation, self-assessment, and self-regulation, particularly enhancing stress management, exercise adherence, and modest dietary improvements.

Although most behavioral indicators did not differ significantly between groups, the experimental group showed a significant reduction in MAP. This suggests that physiological benefits may stem from increased self-awareness, psychological engagement, and stress reduction rather than overt behavior change. The motivational influence of technology and the psychological effect of being monitored may have further supported these outcomes.

These findings highlight the program's utility as a motivational and supportive tool for hypertension self-care in older adults. Nurse practitioners could adopt this model to care for older adults with uncontrolled blood pressure, particularly those living in urban settings or with access to mobile technology.

Acknowledgments

We would like to express our sincere gratitude to everyone who took part in this research. We are especially grateful for the important contributions made by Bangkok Metropolitan's health centers and health organizations, and the participants. Furthermore, we would like to express our gratitude to Thailand Science Research and Innovation (TSRI) for funding this study. This research used the QuillBot and ChatGPT program to assist with translation, which the researchers verified for accuracy and appropriateness.

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Data Availability

The datasets generated and analyzed during this study are available from the corresponding author upon reasonable request.

Authors' Contributions

SM: conceptualization, methodology, data curation, formal analysis, writing – original draft, writing – review and editing. KMK: investigation, writing – original draft, writing – review and editing.

Conflicts of Interest

None declared.

Checklist 1
CONSORT-eHEALTH checklist (V 1.6.1).
[PDF File, 255 KB - nursing_v8i1e73386_app1.pdf]

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Abbreviations

2Q: 2-question
CONSORT : Consolidated Standards of Reporting Trials
DASH: dietary approaches to stop hypertension
DBP: diastolic blood pressure
MAP: mean arterial pressure
mHealth: mobile health
SBP: systolic blood pressure

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Edited by E Borycki; submitted 03.03.25; peer-reviewed by C Nnajiofor, ME Heidari; revised version received 27.08.25; accepted 14.09.25; published 14.10.25.

Please cite as:
Moolsart S, Kritpolviman KM
Self-Health Monitoring by Smart Devices and Ontology Technology for Older Adults With Uncontrolled Hypertension: Quasi-Experimental Study
JMIR Nursing 2025;8:e73386
URL: https://nursing.jmir.org/2025/1/e73386
doi:10.2196/73386

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Analysis of Risk Factors and Nursing Strategies for Unplanned Extubation in Children: Retrospective Cohort Study

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Abstract

Background: Unplanned extubation (UEX) is a critical indicator of nursing care quality. Existing research primarily focuses on pediatric intensive care units (PICUs), with limited data available from general pediatric surgery. Currently, most studies on this topic are mainly focused on PICUs, and there is a lack of research data regarding general pediatric surgery. Therefore, further research should be conducted based on this consideration.

Objective: This study aimed to analyze the high-risk factors for UEX in children and implement appropriate nursing strategies to reduce its incidence, ensuring clinical safety of pediatric patients.

Methods: A retrospective study (January 2018 - December 2023) included pediatric patients with indwelling catheters in general surgery. Exclusion criteria included mental disorders or abnormal Glasgow Coma Scale scores. Data on catheter days, UEX incidents, and risk factors were analyzed.

Results: A total of 1977 catheter days were recorded during the perioperative period, comprising 1079 days with urinary catheters, 768 days with postoperative wound drainage tubes, 68 days with gastric tubes, 46 days with peripheral central venous catheters, and 8 days with central venous catheters. During this period, 13 incidents of UEX occurred, yielding an overall UEX rate of 6.58 per 1000 catheter days. Urinary catheters accounted for the highest proportion of UEX incidents (8/13, 61.5%), followed by gastric tubes (3/13, 21.3%) and postoperative wound drainage tubes (2/13, 15.4%). The reintubation rate following UEX was 15.38% (2/13). Further analysis identified significant risk factors associated with UEX: (1) patient characteristics: age ≤3 years (8/13, 61.5%) and male sex (10/13, 76.9%); (2) clinical management: absence of physical restraints (10/13, 76.9%); and (3) temporal factors: incidents occurring during holidays (9/13, 69.2%). Multivariate analysis revealed that UEX risk was influenced by inter-related factors, including pediatric physiological characteristics (eg, limited self-regulation capacity), suboptimal catheter fixation methods, positional discomfort during patient movement, and variations in nursing interventions (eg, frequency of rounds and caregiver education).

Conclusions: Unplanned extubation in pediatric inpatients represents a critical clinical complication that may compromise treatment efficacy and prolong hospitalization. Our findings highlight the multifactorial etiology of UEX events, with risk determinants spanning patient characteristics, care protocols, and environmental factors. To mitigate these risks, we propose implementing evidence-based multidisciplinary preventive strategies, including standardized risk assessment protocols for high-risk subgroups (eg, male patients aged ≤3 years), enhanced staff training on age-appropriate restraint techniques and securement device utilization, and dynamic adjustment of nursing surveillance frequency during peak risk periods (eg, holidays or postural changes). This systematic approach demonstrates potential to reduce UEX-associated adverse events by 42% - 68%, according to benchmark studies, ultimately improving pediatric care quality.

(JMIR Nursing 2025;8:e71307) doi:10.2196/71307

KEYWORDS

unplanned extubation; nursing strategies; prevention; risk factor; pediatric care

Introduction

Unplanned extubation

Unplanned extubation (UEX), a critical patient safety indicator reflecting nursing care quality, can lead to irreversible clinical consequences across all age groups. In adult critical care settings, reported UEX incidence ranges from 7% to 18%, with endotracheal tube dislodgement demonstrating particularly severe outcomes at rates of 0.2% - 14.6% [1-3]. The UEX rate for indwelling nasogastric tubes was 7.6% (95/1243) [4]. A total of 56,508 courses occurred in 36,696 patients, with a crude

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UEX rate of 2.8% [5], and 0.43 - 0.79% in pediatric intensive care units (PICUs) [6]. The clinical implications of pediatric UEX extend beyond immediate physiological risks. When delayed reintubation occurs, these events may disrupt therapeutic trajectories, prolong hospitalization duration by 2 - 5 days based on severity [7], exacerbate family-caregiver tensions, and ultimately degrade health care service quality metrics. Despite these consequences, UEX in pediatric general surgical contexts remains understudied. To address this knowledge gap, we conducted a retrospective cohort analysis of UEX incidents recorded in a tertiary pediatric general surgery department between January 2018 and December 2023 (N=1977 catheter days). Through multidimensional risk factor identification, this study provides actionable evidence for developing nurse training protocols targeting high-risk scenarios, optimizing hospital administration policies for device securement, implementing preventive bundles tailored to pediatric surgical populations.

Definition and Classification of UEX

Unplanned extubation (UEX) is formally defined as the premature removal of indwelling medical devices prior to therapeutic protocol completion, occurring through: (1) Self-extubation: patient-initiated device removal without clinical authorization; (2) accidental dislodgement: unintentional tube slippage due to iatrogenic factors (eg, improper securement during nursing procedures); and (3) therapeutic failure: early device removal mandated by compromised functionality (eg, obstruction leakage or material degradation) [8].

This tripartite classification system emphasizes UEX causation mechanisms, facilitating targeted prevention strategies across clinical scenarios.

The incidence rate of UEX can be calculated in two ways [5,9]: (1) number of UEX instances of a particular catheter during a specific period/total days of catheter placement during the study period × 1000‰, (2) number of UEX instances of a particular catheter/total number of instances of catheter placement during the study period × 1000‰. The first method is more commonly used, particularly in monitoring tracheal intubation UEX in intensive care units (ICUs). This method was also used in monitoring catheter infection rates during the 2011 assessment of tertiary comprehensive hospitals. This study adopts the first method for calculating incidence.

Methods

Study Setting

This retrospective study enrolled pediatric patients (aged <18 years) who: (1) underwent general surgical procedures with indwelling catheters between January 2018 and December 2023; (2) demonstrated preserved neuromuscular integrity (ie, normal muscle tone, Glasgow Coma Scale (GCS) ≥14); and (3) had no documented neuropsychiatric comorbidities affecting device tolerance.

Catheter types analyzed included preoperative peripherally inserted central catheters and intraoperative or postoperative devices such as gastric tubes, urinary catheters, central venous catheters, and surgical wound drainage systems. Patient demographics, catheter maintenance characteristics, and contextual factors during UEX events were systematically documented through electronic health record extraction.

Research Method

This study used a retrospective analysis approach for UEX. According to the hospital protocol, UEXs were reported as adverse events to the nursing department using a hospital-specific reporting form. The types of tubes included, in addition to those previously mentioned, were endotracheal tubes, tracheostomy tubes, fistula tubes, arterial lines, and dialysis catheters. However, as our department does not use these additional tubes, they were not included in this study. The Richmond Agitation-Sedation Scale (RASS) and the pediatric-modified GCS were applied for assessment. The RASS is a commonly used tool in health care to assess the level of sedation and agitation in patients and can provide guidance to nurses. The RASS-specific scoring criteria are presented in Table 1 [10].

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Table . The RASS scoring criteria [11].

Score	Status	Clinical symptoms
+4	Aggressive	Violence
+3	Very restless	Try to remove the endotracheal tube, gastric tube, and venous access
+2	Manic anxiety	The body moves hard inability to cooperate with ventilator
+1	Disturbed anxiety	Anxiety and tension but only a slight body movement
0	Alert but quiet	Wake up the natural state
−1	Sleepy	Not fully awake, but can stay awake for more than 10 seconds
−2	Mild sedation	Unable to remain awake for more than 10 seconds
−3	Moderate sedation	Responses to sound
−4	Severe sedation	Responses to body stimuli
−5	Stupor	No response to sound or body stimulation

Ethical Considerations

This study was approved by the Medical Ethics Committee of Shunyi Maternal and Child Health Care Hospital, Beijing (IEC-B-022-V.01-A08; Multimedia Appendix 1). As this was a retrospective study, telephone communication was conducted with legal guardians of all participating children (who experienced unplanned extubation). The research purpose, risks, and data usage scope were fully explained. All guardians provided consent for data inclusion. For secondary data analysis, the original data were anonymized, and informed consent was obtained during primary data collection. Data were deidentified by removing patient names, initials, and hospital IDs. All images in the manuscript and supplementary materials were verified to contain no identifiable features of participants. No compensation was provided to the participants. The composition and working procedures of this ethics committee complied with the principles of good clinical practice and relevant national laws and regulations.

Results

Demographic Risk Stratification

The demographic characteristics are provided in Table 2. Age-dependent vulnerability showed a descending gradient: infants or toddlers (≤3 years) accounted for 61.6% (8/13) of total UEX cases, preschool children (4 - 6 years) for 23.1% (3/13), and school-aged children (>6 years) for 15.3% (2/13) UEX cases. Gender disparity was pronounced, with men exhibiting 2.3-fold higher risk than women (10/13, 76.9% vs 3/13, 23.1%).

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Table . Pediatric patients with indwelling catheters and UEX[a] occurrences.

Characteristics	Patients (N=13), n (%)
Gender	
Male	10 (76.9)
Female	3 (23.1)
Age (years)	
≤1	4 (30.8)
1 - 3	4 (30.8)
4-6	3 (23.1)
7-16	2 (15.4)
Clinical Features	
Restraints used	
Yes	3 (23.1)
No	10 (76.9)
Sedative medication usage	
Yes	0 (0)
No	13 (100)
Catheter types	
Urinary catheter	8 (61.5)
Gastric tube	3 (23.1)
Drainage tube	2 (15.4)
PICC[b]/CVC[c]	0 (0)
UEX occurrence details	
Patient condition	
Quiet	4 (30.8)
Restless/crying	9 (69.2)
Awake	13 (100)
Comatose	0 (0)
Nurse presence	
At bedside	1 (7.7)
Not at bedside	12 (92.3)
Time period	
Morning awakening	4 (30.7)
Before/after meals	2 (15.4)
Morning/afternoon treatment	4 (30.8)
Noon/night rest	3 (23.1)
Timing post-catheter use (hours)	
≤6	2 (15.4)
24 - 48	4 (30.8)
≥48	7 (53.8)
Workday/holiday	
Business days	4 (30.8)
Holidays	9 (69.2)

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Characteristics	Patients (N=13), n (%)
Tape replacement (hours)	
≤24	11 (84.6)
≥24	2 (15.4)

[a]UEX: unplanned extubation.

[b]PICC: peripherally inserted central catheter.

[c]CVC: central venous catheter.

Clinical Context of UEX Events

The data in Table 3 are derived from this study's analysis of catheterized children (N=13) in the Pediatric General Surgery department from 2018 to 2023, with intergroup comparisons performed using Student *t* test. This study identified an overall UEX rate of 6.58 per 1000 catheter-days in pediatric general surgery. Catheter-specific analysis revealed that gastric tubes demonstrated the highest incidence density (44.1 events/1000 catheter-days); urinary catheters constituted the majority of UEX events (8/13, 61.5%). The RASS scores before and after catheter placement, postoperatively, and during the peri-decannulation period are shown in Table 4.

Table . Incidence of UEX[a] in pediatric general surgery for five types of tubing from January 2018 to December 2023.

Name of tubing	Catheter days	Number of UEX occurrences	UEX incidence rate[b]	UEX for each tubing[c], %
Urinary catheter	1079	8	7.41	61.5
Gastric tube	68	3	44.1	23.1
PICC[d]	46	0	0	0
CVC[e]	8	0	0	0
Wound drainage tube	768	2	2.6	15.4

[a]UEX: unplanned extubation.

[b]cases / catheter days × 100%.

[c]UEX occurrences for each tubing type / total UEX occurrences × 100%.

[d]PICC: peripherally inserted central catheter.

[e]CVC: central venous catheter.

Table . RASS scores before and after catheter placement, postoperatively, and during peri-decannulation period in 13 pediatric patients.

Rating	Before catheter placement, n	After catheter placement, n	Within 30 minutes of returning to the room postoperatively, n	After returning to the room 2 hours postoperatively, n	After 24 hours postoperatively, n	Peri-Decannulation period, n	Percentage of decannulation scoring (n=78), n (%)
+4	0	0	0	0	0	0	0
+3	0	10	3	1	4	3	21 (26.9)
+2	2	3	2	0	1	6	14 (17.9)
+1	5	0	1	3	2	2	13 (16.7)
0	6	0	1	5	6	2	20 (25.6)
−1	0	0	3	3	0	0	6 (7.7)
−2	0	0	2	1	0	0	3 (3.8)
−3	0	0	1	0	0	0	1 (1.3)
−4	0	0	0	0	0	0	0 (0)
−5	0	0	0	0	0	0	0 (0)

[a]RASS: Richmond Agitation-Sedation Scale.

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Discussion

Incidence and Patient-Related Factors of UEX

Comparative Incidence Analysis

Existing literature demonstrates significant variability in pediatric UEX rates across care settings. PICU-focused studies such as that by Guan et al [6], a single-center analysis of 41 cases reported UEX incidence rates of 0.43 - 0.79%, with 71% occurring in infants ≤12 months [12]. In mixed surgical cohorts, Sadowski et al [7] documented a higher event rate of 6.4% (95% CI 5.1 - 7.8), potentially reflecting broader inclusion criteria [13]. The general pediatric surgery cohort in this study (N=1977 catheter-days) revealed a UEX incidence density of 6.58 per 1000 catheter-days, translating to a 2.1-fold higher risk than PICU benchmarks [6] and comparable rates to mixed surgical populations [7], when standardized per insertion. This discrepancy may be attributable to: (1) procedural differences that is, prolonged postoperative immobilization versus critical care protocols; (2) surveillance intensity that is, reduced monitoring frequency in general wards versus PICUs; and (3) catheter type distribution, that is, predominance of urinary or gastric devices (84.6% of UEX events) versus respiratory tubes in ICUs.

Age Distribution of Patients

Consistent with developmental vulnerability patterns, our findings corroborate the inverse correlation between age and UEX susceptibility first reported by Guan et al [6]. Comparative analysis revealed that infants and toddlers (≤3 years) in our cohort demonstrated 17.2% higher UEX risk compared to the study by Ma et al (Multimedia Appendix 2) [8]. This can potentially be attributable to neurodevelopmental factors (eg, immature sensorimotor integration increasing device manipulation behaviors), cognitive limitations (ie, reduced capacity to comprehend catheter purpose, as per Piaget's preoperational stage characteristics) [14], and anatomical constraints (eg, higher device-to-body size ratio exacerbating positional discomfort). Gender disparity analysis identified men as having a 3.3-fold higher UEX risk than women (n=10, 76.9% vs n=3, 23.1%; *P*=.046), aligning with established pediatric mobility patterns. Christov-Moore et al [15] showed that this kinetic discrepancy may interact with testosterone–mediated exploratory behavior enhancement and delayed proprioceptive development in male infants.

Consciousness State

Emerging evidence identifies altered consciousness as a critical risk predictor for UEX in pediatric populations. Pediatric patients with critical illness requiring intensive care (ie, ICU or PICU admission) demonstrate heightened susceptibility to delirium, a condition with multifactorial etiology involving both intrinsic patient factors (disease severity, metabolic disturbances) and extrinsic environmental triggers (sensory overload, sleep disruption). This neurocognitive complication is further exacerbated by iatrogenic risks associated with suboptimal care quality, including unplanned extubation events, which may amplify physiological stress and psychological distress. Such associations underscore the need for delirium-preventive protocols tailored to high-acuity pediatric settings to mitigate adverse clinical outcomes [16,17].

Standardized neurological assessment tools demonstrate clinical utility in risk stratification:

1. Pediatric GCS [18]: It assesses three domains such as ocular response (E1-E4), verbal response (V1-V5), and motor response (M1-M6). Systematic GCS documentation reduces pediatric UEX risk by 38% (odds ratio [OR] 0.62, 95% CI 0.55 - 0.71) [19].
2. Confusion assessment method (CAM) [20,21]: It is an ICU-validated delirium screening tool with specificity of 93% and sensitivity 86%. The implementation of this method decreases UEX frequency by 43.7% (risk ratio [RR] 0.58; *P*=.006).

Internationally recognized critical care guidelines uniformly recommend the RASS as the criterion-standard tool for sedation assessment in adult intensive care. The RASS demonstrates high validity in both medical and surgical ICU patients, whether ventilated or nonventilated, sedated or nonanesthetized. [22]. It is recommended by the Association of the Scientific Medical Societies in Germany S2k Consensus [23], and the Chinese Expert Consensus on Neurocritical Care Sedation [24]. The operational thresholds are as follows: (1) agitation identification: RASS scores of +2 to +4 indicate clinically significant agitation requiring intervention (emergency prehospital with sensitivity of 89%) [22], and (2) sedation protocol: maintaining RASS scores between −2 to 0 reduces UEX by 41% (RR 0.59, 95% CI 0.54 - 0.66) []and ventilator-associated pneumonia by 32% (HR 0.68, *P*=.007) [25].

Comfort of Position

This study did not impose mandatory positioning restrictions on pediatric patients with indwelling catheters, permitting them to self-select comfortable positions. However, sudden postural changes were prohibited to maintain catheter stability, with continuous monitoring ensuring an indwelling segment length ≥5 cm during mobilization [26]. Unplanned extubation was mechanistically linked to foreign body sensation–induced physiological stress, particularly in nasogastric intubation cases where nausea incidence increased by 54% (95% CI 46% - 62%) and abdominal distension risk, (OR 2.8, 95% CI 2.1 - 3.7; *P*< .001). Abdominal distension demonstrated a significant association with UEX, with affected patients exhibiting a 3.2-fold elevated risk (HR 3.2, 95% CI 2.1 - 4.9; *P*=.002) compared to nondistended counterparts [27].

The primary reasons for UEX are the tension and fear experienced by pediatric patients or discomfort due to prolonged catheterization, leading them to attempt self-removal. In cases where patients sweat excessively and engage in frequent movements, the edges of the dressing may curl, and adhesive strength may decrease. Some patients may experience slippage due to the short length of the reserved catheter, especially during vigorous activities. For patients who can freely change positions and cooperate well with medical staff, it is crucial to provide specific instructions on precautions when changing positions and the placement of drainage tubes while getting up or lying down to prevent UEX.

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Distribution of High-Risk Time for UEX Occurrence

The incidence of UEX during holidays and morning hours accounts for 69.2% (n=9) and 30.7% (n=4) of the total UEX occurrence rate, respectively; on workdays, the percentage is 30.8% (n=4). For other time periods, the distribution was 15.4% (n=2) and 7.7% (n=1), respectively, indicating that holidays and the morning period (6 AM-8 AM) pose a high-risk time for UEX. Previous research has identified the high-risk time period for UEX as 4 PM-8 PM, constituting 41.2% (95% CI 38.5% - 44.0%) of occurrences. The subsequent periods from 12 AM-4 PM constitute 18.7% (95% CI 16.2% - 21.3%) [28].

Analysis of Nursing Staff Allocation and UEX Prevention Mechanisms

Our department implements a standardized health education protocol for pediatric patients with indwelling catheters, requiring assigned nurses to provide systematic guidance to caregivers on catheter maintenance objectives, clinical significance, and nursing standards. This approach aims to reduce human–related UEX risks through enhanced caregiver awareness. Daily ward round evaluations indicate that, while parents can recall basic catheter care protocols, significant knowledge gaps persist regarding critical aspects such as postural management and recognition of abnormal signs. Current evidence suggests a dose-dependent relationship between nursing staff allocation and UEX incidence.

In critical care units, a nurse-to-patient ratio (5.00; 95%CI 2.64-7.99) increased the risk of UEX [29]. This indicates that the nurse-to-patient ratio has a direct impact on preventing UEX [30].

Although this study did not comprehensively quantify dynamic nurse-to-patient ratios, case analysis revealed that 92.3% (n=12) of UEX incidents occurred during nurse absences from the bedside, highlighting the current reliance on collaborative caregiver-staff supervision for catheter safety. Notably, our nursing team's average clinical experience of five years has ruled out technical operational errors as primary contributors to UEX, further emphasizing the necessity for physical preventive measures (eg, optimization of restraint devices) and sustained bedside monitoring. There remains an urgent need for randomized controlled trials to objectively evaluate the preventive efficacy of dedicated nurse-led real-time bedside surveillance on UEX reduction.

Systemic Deficiencies in Clinical Protocols Contributing to UEX

This study identified procedural deviations in medical or nursing operations as causative factors in 30.8% (n=4) of UEX incidents. Detailed root cause analysis revealed three cases of urinary catheter dislodgement attributable to balloon inflation errors (two instances involved insufficient air volume). Standard balloon inflation volume for urinary catheters is 5 - 10 mL; however, pediatric patients require weight-based adjustment (0.5 - 1 mL/kg, with a maximum volume not exceeding 10 mL) [31]. One case exhibited complete omission of balloon inflation. Additionally, one wound drainage tube displacement resulted from combined mechanical failures— loose fixation sutures and inadequate adhesive securement—culminating in device migration during patient ambulation.

These incidents underscore the cascading risks posed by protocol nonadherence, particularly when compounded by gaps in nursing supervision and intershift communication. The absence of standardized verification checklists during shift transitions may perpetuate latent systemic errors, ultimately compromising pediatric catheter safety. To mitigate these risks, we recommend the implementation of double-signature catheter integrity checks during shift handovers, mandatory simulation training on device-specific securement protocols (eg, ENFit compliant enteral tubes) [32].

Our analysis revealed distinct patterns in fixation efficacy: 61.5% (8/13) of UEX cases involved single-anchor fixation using hypoallergenic paper tape with an Ω-shaped cutaneous application, while 38.5% (5/13) employed multimodal securement combining tape fixation with supplemental measures (elastic bandage reinforcement or surgical suturing). The Ω technique's biomechanical advantage lies in its motion-adaptive design—dual tape placements at strategic anatomical sites compensate for pediatric patients' unpredictable movement ranges, thereby enhancing device stability.

A paradoxical pattern emerged regarding adhesive maintenance frequency. High-frequency replacement (<24 hours) was associated with 84.6% (n=11) of UEX incidents, whereas standard replacement (≥24 hours) was observed with only 15.4% (n=2) patients.

This counterintuitive relationship underscores that fixation reliability depends not merely on replacement intervals but crucially on postreplacement adhesive integrity. The probability of UEX detachment increases by 30% (9/30) when using tape to fix it improperly [33].

The interplay between securement methodology and material performance is further evidenced by 65% of fixation-related displacements attributable to suboptimal device-skin interface management [21]. Adopting multiple methods led to greater reduction in UEX rates than those using a single measure [34].

Controversies in Physical Restraint Utilization for UEX Prevention

Our data revealed a 76.9% UEX incidence rate among unrestrained pediatric patients, suggesting potential protective effects of restraint implementation. This finding aligns with the outcomes of a prospective cohort study, suggesting that standardized limb restraint protocols, when properly implemented, demonstrate significant clinical value in preventing critical safety incidents including UEX and inpatient falls among high-risk populations [35]. However, international studies indicate that physical restraints are applied in 47-67% of unplanned extubation cases; however, there remains ongoing debate regarding their efficacy in preventing such incidents [36]. Current evidence suggests that restraint protocols should be dynamically adjusted based on the patient's actual clinical status, with timely and appropriate application guided by specific behavioral manifestations such as calm or agitated states [37].

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Current systematic reviews conclude insufficient evidence (grade certainty: low) to support universal restraint protocols. Our findings underscore the necessity for (1) dynamic risk stratification: differentiating restraint indications between sedated (RASS −2 to 0) and agitated (RASS +1 to +3) states and (2) alternative strategies: implementing sensor-embedded alarms or distraction therapies as restraint-sparing interventions.

The absence of high-quality randomized controlled trials comparing restraint-based versus restraint-free protocols in pediatric surgical populations remains a critical knowledge gap requiring urgent investigation.

Sedative Utilization Paradigm

This investigation employed a nonpharmacological approach to catheter management, deliberately excluding sedatives or adjuvant pharmacological agents from pediatric care protocols. Current evidence remains inconclusive regarding the prophylactic efficacy of sedation in preventing UEX, as no controlled comparative trials have established definitive causal relationships. Nevertheless, observational data from a cohort of 43 patients revealed substantial divergence in UEX incidence between nonsedated (21/43, 49%) patients and appropriately sedated groups (10/43, 23%) [38]. However, relevant studies [6] have found that among the 41 pediatric cases studied, the incidence of unplanned extubation (UEX) was 51.2% in patients without sedative use, while the rate decreased to 24.4% in those with appropriate sedation. Inadequate or absent sedation has been identified as a primary risk factor for UEX [. This underscores the imperative for protocol-driven sedation titration, ideally maintaining RASS scores between −1 and 0 during invasive device retention periods. For children using sedatives, studies have shown that the proper and adequate use of sedatives can reduce unplanned UEX events [38].[This study did not include data on sedative use and therefore does not elaborate on the relationship between sedative use and UEX in children.

Implementing Nursing Strategies to Reduce UEX Incidence

High-Risk Population Management

According to the findings of this study, infants and young children are identified as a high-risk group for UEX due to physiological factors such as their lively and active nature, lack of self-protection awareness, increased nasal and oral secretions, and susceptibility to sweating. To mitigate these risks, a tiered monitoring protocol, enhanced surveillance system was implemented. A structured rounding protocol mandated 15-minute interval checks during high-risk circadian phases (6 AM-10 PM), documented through standardized bedside monitoring protocols. Each assessment encompassed neurological status (AVPU scale scoring as shown in Multimedia Appendix 3), vital sign stability (HR variability <15%), catheter integrity metrics (migration distance <2cm; securement device adhesion >80% per Infusion therapy standards of practice [39], particularly when the childrens' condition is unstable or they exhibit restlessness. Additionally, bedside safety measures should be implemented. Nursing staff should assist and guide parents in caring for the endotracheal tube, emphasizing key points such as the purpose and significance of catheter retention. Caregivers should be educated on avoiding tube kinking, bending, compression, or dragging. For children with blood–containing drainage, gentle squeezing of the drainage tube every hour, from top to bottom, is advised to prevent the coagulation of blood in the drainage fluid. Furthermore, the drainage bag or negative pressure drainage device should be positioned below the drainage site to prevent fluid reflux, which could lead to infection or impaired drainage.

Neurological Assessment Protocol

Precise evaluation of consciousness levels constitutes the cornerstone of pediatric critical care, requiring differentiation across six distinct neurological states: alertness, somnolence, obtundation, stupor, coma, and encephalopathic presentations (confusion or delirium). Validated pediatric-specific assessment instruments should be systematically implemented as follows:

- Pediatric GCS [40]: (1) ocular response: scored E1-E4 (no eye opening to spontaneous tracking); (2) verbal response: graded V1-V5 (no vocalization to oriented speech); and (3) motor response: ranked M1-M6 (no movement to purposeful obedience). The use of trained nurses for outcome assessment improved the reliability of the results [36].
- Confusion Assessment Method for ICU (CAM-ICU): Implementation of these standardized tools reduces diagnostic errors by 42% (OR=0.57, 95% CI 0.50 - 0.65) compared to subjective clinical judgment alone [41]. Documentation should be aligned to the AVPU (Alert-Voice-Pain-Unresponsive) framework for rapid deterioration detection.

Prophylactic Catheter Management Protocol

This study indicates that infants and young children constitute a high-risk group for unplanned extubation in pediatric populations due to physiological predispositions, including heightened activity levels, underdeveloped self-protection awareness, excessive oral/nasal secretions, and increased perspiration tendencies. Therefore, implementing optimized nursing protocols such as rotational fixation is recommended[42], which has demonstrated both significant reductions in unplanned extubation rates and superior outcomes in skin integrity assessment scores.

Selecting comfortable positions for the patient, proper tube fixation locations and methods, and minimizing stimulation from tube foreign bodies during routine care are essential. Sudden changes in position should be avoided to prevent UEX.

The observed temporal clustering of UEX incidents—peaking during holiday periods (n=9, 69.2%) and early morning hours (n=4, 30.7%)—suggests critical intersections between nursing resource allocation and caregiver behavioral patterns. Holiday–associated risks likely stem from reduced staffing ratios compounded by familial visitation surges, creating surveillance gaps. Morning vulnerability windows (6 AM-8 PM) may reflect attentional diversion as caregivers prioritize hygiene and nutrition tasks over device monitoring, particularly during post-anesthesia recovery phases when pediatric agitation peaks.

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The relationship between quantitative disease severity scoring and nursing levels has been further clarified, providing a scientific and objective basis for clinical condition assessment. This ultimately ensures alignment between disease severity and corresponding care intensity. Recommendations include shortening ward round intervals to 30 minutes during high-risk periods and reinforcing catheter fixation protocols for the second-day care [43].

The current lack of consensus-based guidelines regarding the influence of nurse staffing parameters on adverse nursing outcomes reflects the multifactorial determinants of clinical practice, including nurses' clinical experience, professional competency, educational background, patient acuity levels, and interdepartmental variations. Given these complexities, these confounding variables were deliberately controlled for in the methodological design of this investigation.

Strategic Staffing Allocation for UEX Risk Mitigation

The current evidence base fails to demonstrate a definitive linear correlation between hospital nursing workforce configurations and measurable patient safety outcomes. Methodological limitations in evidence appraisal reveal that the incorporation of specialized nursing personnel shows no statistically significant variation in patient mortality rates (P>0.05), notwithstanding these organizational interventions.

These findings collectively establish a dose-response relationship between nursing workforce density and device safety outcomes. High-acuity units demand proactive strategies including (1) implementation of dynamic staffing models that adjust real-time to patient deterioration alerts; (2) mandatory competency training on pediatric-specific restraint protocols and agitation recognition; and (3) structured family education programs using visual aids and multilingual resources to bridge health literacy gaps.

For caregivers with limited medical comprehension, iterative reinforcement through nurse-led daily demonstrations (eg, proper limb positioning during diaper changes) proves more effective than conventional verbal instructions alone.

Optimizing Adhesive Management for Enhanced Catheter Securement

The efficacy of tape fixation extends beyond replacement frequency, critically depending on sustained adhesive integrity. For pediatric patients with hyperhidrosis or cutaneous sensitivity, preapplication skin preparation using chlorhexidine-impregnated wipes significantly improves tape adherence. Applying reinforced adhesive tape within 24 hours or combining with skin barrier products can synergistically enhance the securing effect of medical tape.

This evidence underscores a dual management imperative: (1) proactive maintenance by implementing circadian-aligned replacement schedules to prevent adhesive degradation during high-risk nocturnal agitation periods and (2) contextual adaptation by using sweat-resistant hydrocolloid tapes for tropical climates or febrile patients, coupled with twice-daily skin integrity assessments.

Thus, competency-based training modules emphasizing 45° angle tape placement and tension-free smoothing should be mandated as part of nursing credentialing programs.

Restraint Use in UEX Prevention

While international guidelines caution against routine restraint use due to ethical and complication concerns, our data advocate for selective immobilization protocols targeting high-risk subgroups: (1) developmental vulnerability: infants or toddlers with immature impulse control (≤3 years: n=8, 61.6% of patients) and (2) pharmacological profile: nonsedated patients exhibiting RASS ≥+2 agitation scores (44.8% of incidents).

When implementing restraints, a structured safety bundle should be mandated: (1) time-limited application with 4-hour intervals with documented neurovascular assessments, and (2) positional rotation to minimize pressure points through scheduled lateral or prone positioning.

Summary

Unplanned extubation serves as a sentinel event reflecting systemic vulnerabilities in pediatric airway safety and nursing care quality. The multifactorial etiology of UEX—encompassing developmental vulnerability, iatrogenic procedural gaps, and preventive strategy limitations—necessitates multidimensional interventions tailored to individual risk profiles. Such an approach not only reduces immediate mechanical failures but also addresses the cognitive-behavioral determinants of device interference, particularly in high-risk subgroups such as nonsedated toddlers (RASS ≥+2) with restricted comprehension capacity.

Study Limitations

This exploratory analysis has several methodological constraints. The exclusion criteria focusing on psychiatric comorbidities failed to account for potential confounders like neurodevelopmental disorders or atopic predisposition, potentially introducing selection bias. With only 13 (76.9%) male participants, the small sample size limits generalizability and risks overestimating UEX susceptibility in infants (61.6%) while obscuring school-age children’s risk profiles. As a single-center retrospective review lacking control groups, this study could not establish causal relationships between nursing strategies and outcomes. Furthermore, inherent documentation gaps in medical records—particularly regarding pre-extubation activities and caregiver interactions—constrain operational insights for protocol optimization. Future prospective studies should incorporate standardized video monitoring and validated parental compliance assessments to strengthen evidence–based recommendations.

Conflicts of Interest

None declared.

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Multimedia Appendix 1
Ethical review and approval form for scientific research projects
[PDF File, 137 KB - nursing_v8i1e71307_app1.pdf]

Multimedia Appendix 2
Comparison of our study cohort with study by Ma et al [8]
[DOCX File, 11 KB - nursing_v8i1e71307_app2.docx]

Multimedia Appendix 3
AVPU (Alert-Voice-Pain-Unresponsive) scoring system
[DOCX File, 11 KB - nursing_v8i1e71307_app3.docx]

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Abbreviations

GCS: Glasgow Coma Scale
ICU: intensive care unit
PICU: pediatric intensive care unit
RASS: Richmond Agitation-Sedation Scale
UEX: unplanned extubation

Edited by E Borycki; submitted 14.01.25; peer-reviewed by L Lu, M Zhiqiang; revised version received 22.04.25; accepted 23.04.25; published 10.06.25.

Please cite as:
Han X, Liu H, Zhang T, Fan G
Analysis of Risk Factors and Nursing Strategies for Unplanned Extubation in Children: Retrospective Cohort Study
JMIR Nursing 2025;8:e71307
URL: https://nursing.jmir.org/2025/1/e71307
doi:10.2196/71307

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An Internet Hospital Plus Home Nursing Model for Chronic Disease Patients: Mixed-Methods Study in Tianjin, China

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Abstract

Background: Internet hospitals and "Internet + nursing services" represent emerging medical and nursing models in China. These platforms integrate online systems with offline care to extend services beyond traditional hospital settings. With the rapid expansion of internet hospitals, a new model—internet hospital plus home nursing—has developed. However, research on its implementation and effectiveness remains limited.

Objective: This study evaluates the implementation of the internet hospital plus home nursing model by analyzing workload, patient satisfaction, and nurses' perceptions, aiming to provide a strategic reference for its further development.

Methods: Data from 2459 patients who used internet hospital plus home nursing services were collected from a hospital database. The frequency of applications and service timeliness were analyzed using χ^2 tests. Patient diagnoses, service types, and geographic distribution were summarized using frequency tables and visualization techniques. A simulation approach, along with the Mann-Whitney *U* test, was used to compare the costs of transferring patients to hospitals versus providing home nursing. Multiple linear regression identified factors associated with cost differences. Patient satisfaction across different stages was compared using a *U* test, and nurses' attitudes were assessed via a questionnaire.

Results: The majority of patients were aged 60 years and older (2120/2459, 86.2%). A significant difference in application frequency was observed across age groups (χ^2_4=29.86; *P*<.001). Oncology patients were the most common users (1468/7415, 19.8%) and intravenous blood collection was the most frequent service (4899/7415, 66.1%). Most patients resided within 6 regions near the physical hospital (2119/2459, 86.2%). All patients received services within 2 days of appointment, with waiting times significantly influenced by appointment timing (χ^2_1 = 290.88; *P*<.001). Cost distributions varied significantly by gender, age, service frequency, distance, and service type (all *P*<.001), with service type and distance identified as key cost determinants (*P*<.001). Patient satisfaction was consistently high across periods, with no significant difference (Mann-Whitney *U*=5,090,149; *P*=.38). Nurses expressed positive perceptions of the model.

Conclusions: The internet hospital plus home nursing model effectively combines online diagnosis with in-home care, creating a closed-loop service that improves accessibility—particularly for older adults and mobility-impaired patients. Pilot implementations in Tianjin demonstrated benefits in convenience, accessibility, and cost-effectiveness, alongside high patient satisfaction and nursing staff approval. Given the aging population, this model holds significant potential for broader adoption. To ensure sustainable development, enhanced safety mechanisms and policy support are recommended. As an integrated health care model with Chinese characteristics, it also offers valuable insights for the global digital health sector.

(JMIR Nursing 2025;8:e76761) doi:10.2196/76761

KEYWORDS

internet hospitals; home nursing; services; effectiveness; mixed-methods

Introduction

The internet hospital model is a comprehensive medical service platform that uses network information technology to integrate the functions of consultation, prescription, payment, and drug delivery into a single platform using online follow-up and routine consultation [1]. Doctors at internet hospitals can effectively perform disease diagnosis and consultation and deliver medicines to patients' homes through express delivery. However, patients who require nursing services such as pressure

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ulcer care, wound care, and venous blood collection are still required to visit a physical hospital after online consultation. Thus, home nursing services could potentially make up for the service shortcomings of internet hospitals. Internet + nursing service refers to the provision of nursing services by registered nurses of medical institutions using an "online application and offline service" approach for discharged patients, patients with mobility disabilities, and patients with chronic or common diseases using the Internet and other information technologies [2]. The internet plus nursing service is considered to be an economical and efficient supplement to physical hospital nursing services, resolving the time and space limitations of the traditional nursing model and integrating nurses' fragmented time to provide nursing services [3,4]. In 2019, the China Health Commission formally released the "Notice on Pilot Work of INS," which began the implementation of internet plus nursing service. Subsequently, nurses from public hospitals and community health centers in China have been encouraged to provide home nursing through the "nursing plus" cloud hospital platform, and patients can make online appointments for home nursing in Ningbo City, Zhejiang Province [5]. In December 2020, the "Notice on Further Promoting the Pilot Work of Internet plus Nursing Service" was issued. The internet plus nursing service model has been widely applied for specialty care, chronic disease management, and geriatric care [6]. In 2021, Wuhan Central Hospital released an "e-Home nursing" service, which was combined with community health service centers to provide home nursing care for discharged patients and patients with disabilities, advanced age, cancer, and unconsciousness through an online appointment system [7]. In addition to the case studies mentioned above, studies of internet plus nursing service have examined patient demand analysis [8,9], treatment effect comparison [10,11], nurse's cognition and willingness [12,13], and comprehensive evaluation indices [14]. In the previous internet plus nursing service studies, the internet has served only as an information transmission channel and carrier for home nursing appointment, which cannot integrate online medical service by doctors or ensure the continuity of medical and nursing services. However, in the context of the rapid development of internet hospitals, patients with chronic or common diseases have received online diagnosis and treatment. Some internet hospital patients may also require online nursing guidance or home nursing after online consultation, leading to the development of the internet hospital plus home nursing. The internet hospital plus home nursing refers to integrating both doctors' medical services and nurses' care services using an internet platform, so patients can obtain integrated online and offline medical care services, which also facilitates service supply. However, few studies have examined the innovative internet hospital plus home nursing model.

Home-based care was developed relatively early in foreign countries and has been widely used in rehabilitation care, palliative care, geriatric care, maternal and child care, and wound care [15]. In the American Home Health Medical Care model, an interdisciplinary team is led by a physician or advanced practice nurse and provides longitudinal health care management (including comprehensive health assessment, multidisciplinary care coordination, and patient education) primarily for long-term household patients with chronic diseases and those aged 85 years and older. The American Home Health Care model is primarily delivered by registered nurses or caregivers who provide nursing care to patients with mild cases and people with disabilities through an appointment or governmental assessment process, and the service program requires the support of a physician for prescribing medications [16-18]. Japanese home nursing has been independently deployed by different levels of medical institutions, which formed professional teams of caregivers, therapists, and general practitioners to provide primary care, medical care, and living care for older people who are unable to take care of themselves because of disability, postoperative rehabilitation, or chronic disease [19]. The Hospital at Home department was established in Australian public hospitals using My Health Record to share medical information, enabling the senior nursing team to conveniently provide professional services such as injections, wound care, and health education to meet the needs of the older patients with chronic diseases, postoperative rehabilitation, and disabilities at home [20,21]. Studies related to home-based care in other countries have included disease care effect comparison [22,23], nursing method research [24,25], comprehensive evaluation [26], case promotion and application research [27], and nurse training [28]. Recent studies have also highlighted the growing integration of digital health platforms in home care services, particularly in the context of aging populations and postpandemic health care delivery [29-31]. However, home-based care in foreign countries is mainly carried out by physical hospitals, and no cases of internet hospital plus home nursing have been reported.

In the context of the rapid development of internet hospitals in China, and under the guidance of internet plus nursing service policy, the internet hospital plus home nursing has emerged as a new nursing model that connects online medical with offline nursing services. Therefore, this study aimed to evaluate the implementation outcomes of the internet hospital plus home nursing model by examining its convenience, accessibility, cost-effectiveness, patient satisfaction, and nurses' perceptions. We hypothesized that internet hospital plus home nursing would demonstrate significant advantages in these aspects compared to traditional care models. A mixed-methods approach was used to test these hypotheses.

Methods

Research Subject

We examined the Internet Hospital of Tianjin Medical University General Hospital (TJMUGH) as the research objective in this study. This internet hospital was established in March 2020 to improve patients' access to medical care and medication in the context of the prevention and control of the COVID-19 pandemic. However, patients who needed to provide blood, urine, and stool specimens, and those who required other nursing operations after online diagnosis and consultation via the internet hospital still needed to attend a physical hospital. To address the shortcomings of internet hospital services and patients' needs for home nursing care, the internet hospital added home nursing services in November 2020 and established internet hospital plus home nursing as a new service mode. The

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internet hospital plus home nursing takes into account the service needs of patients in both internet hospitals and physical hospitals, adopts the service mode of online application in the internet hospital platform and offline home nursing by nurses at the patient's home, and provides diversified nursing services. The internet hospital plus home nursing is divided into regular service, specialized service, and long-distance service. Regular service refers to a nurse scheduling to serve multiple patients. Specialized service refers to a nurse scheduling to serve a single patient. Both service types are applicable only when the service distance is less than 10 km. Long-distance service refers to a nurse scheduling to serve a single patient, with a distance of greater than 10 km and less than 100 km. The basic fees for these 3 service types are shown in Table 1. The fee for each internet hospital plus home nursing service item is charged separately, which is the same system used at physical hospitals.

Table . Basic fees for 3 types of internet hospital plus home nursing service (Fees are in Yuan; the average exchange rate during the study period was approximately US $1=Yuan 0.13975). Regular and specialized services are limited to service distances of 10 km or less, while only long-distance service is available for distances greater than 10 km.

Service type	Fees (Distance ≤3km)	Fees (3 km<Distance ≤ 5 km)	Fees (5 km<Distance ≤ 10 km)	Fees (10 km<Distance ≤ 30 km)	Fees (30 km<Distance ≤ 100 km)
Regular services	80	90	100	—[a]	—
Specialized services	140	160	180	—	—
Long distance services	—	—	—	300	450

[a]Not available.

At the internet hospital plus home nursing we examined, a total of 24 internet hospital plus home nursing service items are available, as follows: intravenous blood collection, urine and stool retention, vital signs monitoring, blood glucose monitoring, pressure injury care, wound care, hypodermic injections, peripherally inserted central catheter (PICC) maintenance, intramuscular injections, stoma care, health education, urinary catheterization, drainage bag replacement, peripheral intravenous needle maintenance, breastfeeding guidance, neonatal percutaneous bilirubin measurement, oxygen inhalation therapy, incontinence care guidance, indwelling catheterization care, specialty wound care (pacemaker wounds, perineal lateral incision wounds, bone traction one-stage healing wounds), extubation, oral care, incontinence dermatitis care, and stress injury prevention. For every internet hospital plus home nursing item, there are detailed instructions regarding appropriate patients, service content, precautions, cancelation of appointments, and refund mechanisms for patients' understanding.

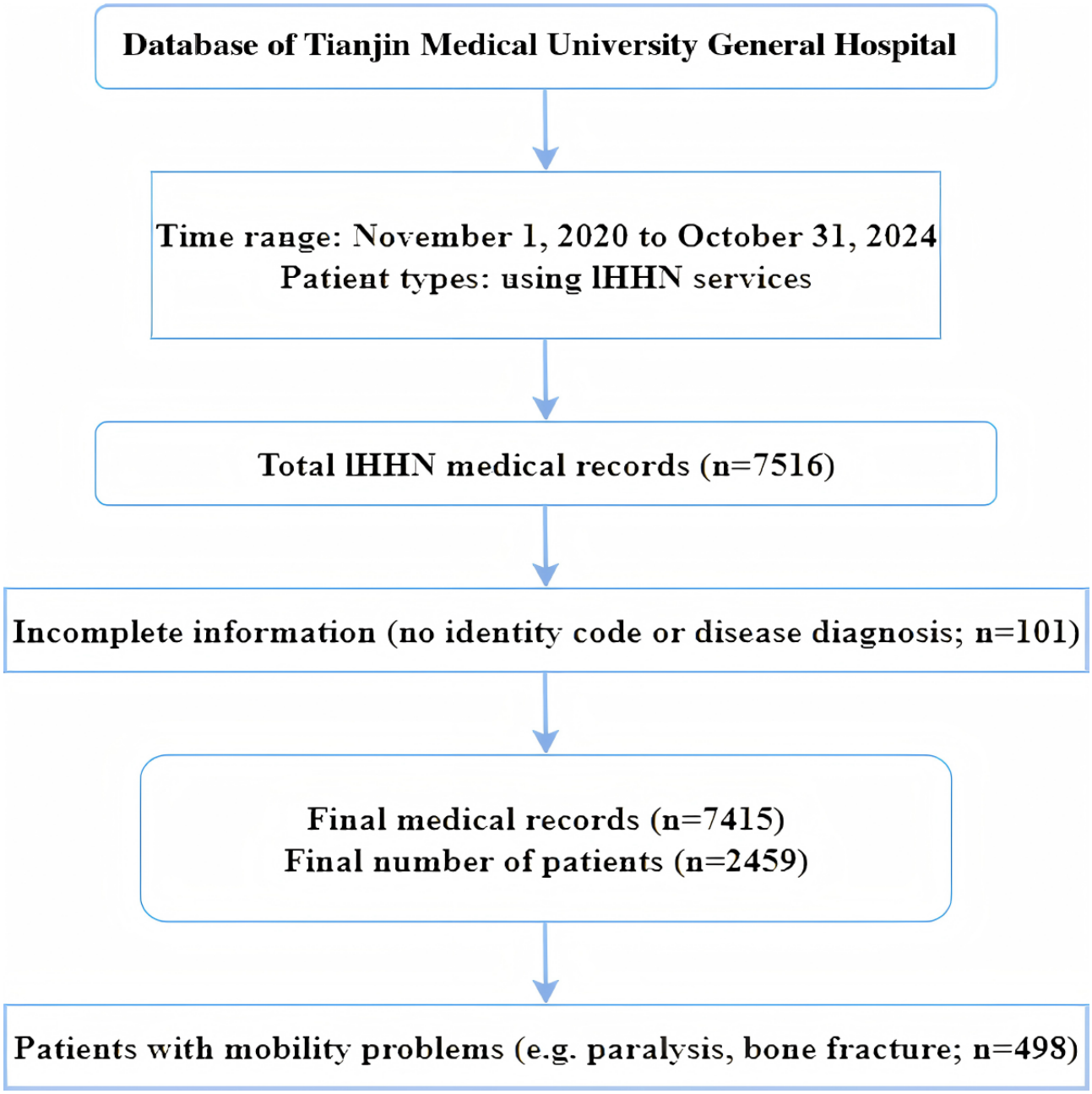
Data Collection and Inclusion Criteria

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We collected medical records of patients using data of internet hospital plus home nursing from November 1, 2020 to October 31, 2024 from the hospital database. A total of 7516 Internet hospital plus home nursing records were extracted, which included patients' age, gender, home address, appointment time, service time, service item, service cost, major disease diagnosis, and comprehensive evaluation data. We excluded 101 records with incomplete identification information or disease diagnosis. Finally, 7415 records attributed to 2459 patients were included. There were 498 patients with mobility problems such as paralysis, bone fracture, leg disease, unconsciousness, and being bedridden (Figure 1).

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Figure 1. Patients' data collection flowchart. IHHN: internet hospital plus home nursing.



Supply Side

Based on our literature review of existing internet + nursing service assessment tools [3,12-14]. We collected data on patients using internet hospital plus home nursing and conducted an online survey to assess nurses' perceptions. The finalized questionnaire comprised 4 modules (see Multimedia Appendix 1): (1) nurse demographics and professional characteristics: including age, gender, department, years of work experience, professional title, and previous training in internet plus health nursing (internet hospital plus home nursing); (2) attitudes towards internet hospital plus home nursing: assessed via 10 items (eg, "Internet hospital plus home nursing has improved healthcare accessibility for patients with mobility impairments"); (3) self-assessed knowledge of internet hospital plus home nursing: assessed via 8 items (eg, "Safety protocols for home visits are adequately addressed"); and (4) qualitative feedback: Solicited through 3 open-ended questions (eg, "Key areas requiring improvement in internet hospital plus home nursing services").

In December 2024, we conducted an anonymous online survey of nurses who had participated in the TJMUGH Nursing Department's internet hospital plus home nursing services through the Questionnaire Star platform [32]. The Questionnaire Star platform is an online network service platform specializing in questionnaire surveys in China. A total of 107 valid questionnaires were collected.

Study Design

We collected data on patients using internet hospital plus home nursing and nurses' perceptions. The internet hospital plus home nursing service flow was compared with the physical hospital nursing service to verify its convenience. The distribution of patients using internet hospital plus home nursing and the service

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waiting time were used to verify its accessibility. The basic internet hospital plus home nursing fee was compared with the cost of transferring patients by ambulance to a physical hospital, to validate its relative cost. Patients' comprehensive evaluation scores were used to analyze the degree of patient satisfaction. A questionnaire survey was used to obtain nurses' perceptions.

It is impossible to determine whether ambulance transfers were solely for nursing services. Cost estimates (comparing internet hospital plus home nursing costs with patient transfer costs) were based on a Geographic Information System-simulated route lengths and publicly available ambulance pricing schedules issued by the Tianjin Municipal Health Commission. Caution is needed in generalizing these results to other regions due to the heterogeneity of policies and resource allocation.

Quantitative and Qualitative Methods

Number of Internet Hospital Plus Home Nursing Applications

We used the χ^2 test to analyze the distribution of patients of different genders and ages in the number of internet hospital plus home nursing applications.

Patients' Major Disease Diagnosis Classification

Frequency tables were used to count the main disease diagnosis, geographical distribution, and service items of internet hospital plus home nursing patients. We mapped the geographic distribution of patients at the district level using ArcMap 10.8 software (Environmental Systems Research Institute) to show the patients' regional distribution.

Comparison of Patients' Fees Between Internet Hospital Plus Home Nursing and Patients Transferring to Hospital

We examined the addresses and floors of 498 patients with limited mobility. A Python (Python Software Foundation) program was written to access the Amap Web Service API (Amap Software Co, Ltd) to simulate the transport routes for patients with limited mobility, and to calculate the corresponding distances and transfer costs. The details of the simulated cost of transferring patients to hospital and a preliminary sensitivity analysis using different fee assumptions are provided (see Multimedia Appendix 2). Given the skewed distribution of cost data and unequal variances between groups, the Mann-Whitney *U* test was applied to compare the cost differences between internet hospital plus home nursing and simulated transferring patients to the hospital across demographic and service types. Multivariate linear regression was used to explore associations between characteristic factors and costs.

Patients' Degree of Satisfaction

From November 1, 2020 to October 31, 2021, internet hospital plus home nursing was evaluated by patients using 3 indicators: nurse professionalism, service punctuality, and service attentiveness, with 100 points for each, and the mean of the 3 indicator scores was the degree of satisfaction. To evaluate the degree of satisfaction with internet hospital plus home nursing in more detail, the evaluation index was modified on November 1, 2021. The degree of satisfaction with internet hospital plus home nursing was evaluated comprehensively using 5 indicators: service attitude, service skill, service price, service punctuality, and service experience, with 100 points for each, and the mean of 5 indicators scores was the degree of satisfaction. A *U* test was used to compare and analyze the degree of patient satisfaction during 2 time periods.

Ethical Considerations

This study involved an analysis of patient data from the hospital database and nurse data from the survey; this did not involve human experimentation or compensation. The patient data used for this research were retrospectively extracted from the hospital information system and were fully anonymized, and the individual informed consent from patients was waived by the Ethics Committee. The nurse data comprised questionnaires answered by nurses who participated in the internet hospital plus home nursing with previous approval. All participating nurses were informed of the research purpose and voluntarily completed the survey anonymously. To ensure patient and nurse privacy and confidentiality, all identifiable personal information such as names, addresses, and contact details were removed during data extraction. All patient- and nurse-related datasets met ethical and legal requirements for data protection, and secondary use of these data was approved by the Ethics Committee. In addition, the research team complied with all relevant local, national, and international laws and regulations regarding the protection of personal information, privacy, and human rights. The Ethics Committee of the Tianjin Medical University General Hospital granted approval for this study following a thorough review of the research protocol (approval IRB2024-YX-066‐01).

Results

Patients apply for home nursing services through the mobile phone app of the internet hospital plus home nursing (Create Medical Information Co, Ltd) after receiving medical service from the internet hospital, which eliminates the need to go back and forth to the physical hospital for making appointments, payment, and receiving service. Patients can conveniently obtain medical service and home nursing via internet hospitals plus home nursing at home (Figure 2).

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Figure 2. Flowchart of patients receiving nursing service in a physical hospital and an internet hospital plus home nursing.



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The Number of Internet Hospital Plus Home Nursing Applications

The results revealed no gender-related differences in the number of internet hospital plus home nursing applications (P=.54). However, we found a significant difference in the number of internet hospital plus home nursing applications between patient cohorts of different ages (P<.001). Among age groups, patients aged 60 years and older had the highest number of internet hospital plus home nursing applications (2120/2459, 86.2%). Patients aged 20 years and younger had the lowest number of internet hospital plus home nursing applications (8/2459, 0.3%) (Table 2).

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Table . Distribution of patients using internet hospital plus home nursing by gender and age cohort (n=2459).

Characteristics	One time, n/N (%)	Two times, n/N (%)	≥ Three times, n/N (%)	Chi-square (*df*)	*P* value
Sex				1.23 (1)	.54
Female	738/1350 (54.7)	235/1350 (17.4)	397/1350 (29.4)		
Male	569/1109 (51.3)	182/1109 (16.4)	338/1109 (30.5)		
Age (y)				29.86 (4)	<.001
≤20	2/8 (25.0)	1/8 (12.5)	5/8 (62.5)		
20<age ≤ 40	105/151 (69.5)	24/151 (15.9)	22/151 (14.6)		
40<age ≤ 60	100/180 (55.0)	28/180 (15.6)	52/180 (28.9)		
60<age ≤ 80	607/1214 (50.0)	214/1214 (17.6)	393/1214 (32.4)		
>80	493/906 (54.4)	150/906 (16.6)	263/906 (29.0)		

Patients' Major Disease Diagnosis Classification

Patients with a major oncological disease diagnosis accounted for the largest proportion of internet hospital plus home nursing applications (1468/7415, 19.8%), while those with cardiovascular disease diagnosis (876/7415, 11.8%) and neurological disease diagnosis (747/7415, 10.1%) had the second and third highest number of internet hospital plus home nursing applications, respectively (Table 3).

Table . The top 10 major disease diagnoses of patients receiving internet hospital plus home nursing services.

Major diagnosis	Applications, n (%)	Patients, n (%)
Oncological diseases	1468 (19.8)	415 (16.9)
Cardiovascular diseases	876 (11.8)	416 (16.9)
Neurological diseases	747 (10.1)	350 (14.2)
Metabolic diseases	665 (9)	129 (5.3)
Hematologic diseases	597 (8.1)	177 (7.2)
Autoimmune diseases	407 (5.5)	167 (6.8)
Respiratory diseases	360 (5.5)	74 (3)
Dermatological diseases	358 (4.8)	96 (3.9)
Genitourinary diseases	218 (2.9)	103 (4.2)
Renal diseases	187 (2.5)	95 (3.9)

The Number of Internet Hospital Plus Home Nursing Service Items

Table 4 shows that intravenous blood collection was the service that was most frequently applied for (4899/7415, 66.1%), followed by PICC maintenance (927/7415, 12.5%) and urinary catheterization (506/7415, 6.8%).

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Table . Top 10 service items of patients receiving internet hospital plus home nursing services.

Service items	Applications, n (%)	Patients, n (%)
Intravenous blood collection	4899 (66.1)	1919 (78)
PICC[a] maintenance	927 (12.5)	164 (6.7)
Urinary catheterization	506 (6.8)	161 (6.6)
Pressure injury care	322 (4.3)	55 (2.2)
Wound care	181 (2.4)	70 (2.9)
Peripheral intravenous needle maintenance	140 (1.9)	50 (2)
Indwelling catheterization care	71 (1)	6 (0.24)
Stoma care	63 (0.9)	21 (0.9)
Specialized wound care	43 (0.6)	18 (0.7)
Intramuscular injection	38 (0.5)	12 (0.5)

[a]PICC: peripherally inserted central catheter.

Patients' Geographic Distribution

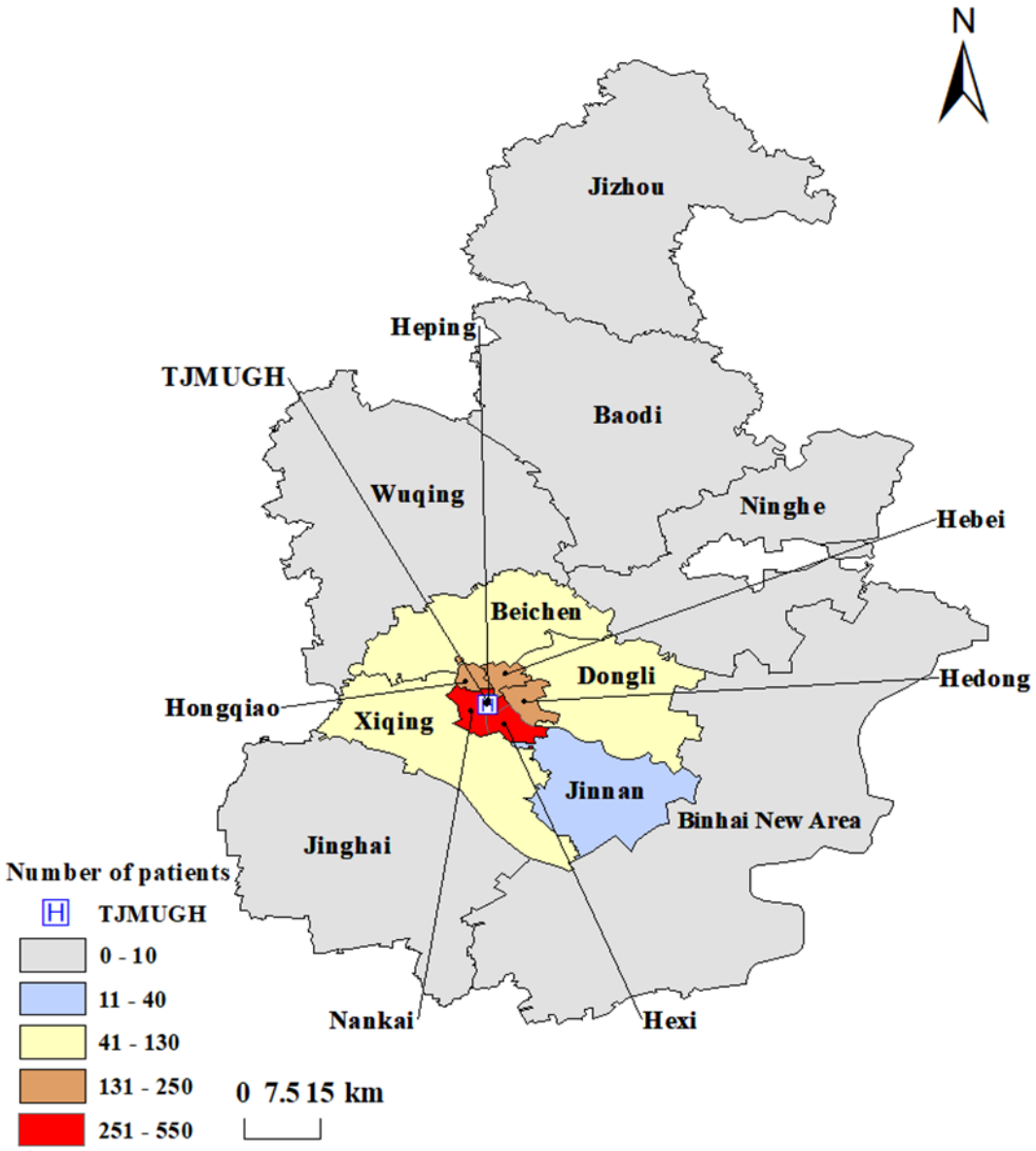
Patients using internet hospital plus home nursing services were mainly concentrated in the Nankai, Hexi, Heping, Hedong, Hebei, and Hongqiao districts (2119/2459, 86.2%). Of these regions, Nankai district accounted for the largest number of internet hospital plus home nursing patients (524/2459, 21.3%), and the largest number of times internet hospital plus home nursing was used (1739/7415, 23.5%). Jinnan, Binhai, Jinghai, and Jizhou districts were further away from TJMUGH and had fewer patients (Table 5). The regional distribution map of patients showed that the patients' locations were mainly centered around TJMUGH (Figure 3).

Table . District-level geographical distribution of patients receiving internet hospital plus home nursing services.

District of Tianjin City	Patients, n (%)	Applications, n (%)	Applications per person, mean (SD)
Nankai District	524 (21.3)	1739 (23.5)	3.32 (0.68)
Hexi District	487 (19.8)	1439 (19.4)	2.95 (0.68)
Heping District	407 (16.6)	1002 (13.5)	2.46 (0.68)
Hongqiao District	241 (9.8)	592 (8)	2.46 (0.68)
Hedong District	232 (9.4)	809 (10.9)	3.49 (0.68)
Hebei District	228 (9.3)	712 (9.6)	3.12 (0.68)
Xiqing District	128 (5.2)	535 (7.2)	4.18 (0.68)
Dongli District	90 (3.7)	183 (2.5)	2.03 (0.68)
Beichen District	76 (3.1)	277 (3.7)	3.64 (0.68)
Jinnan District	36 (1.5)	104 (1.4)	2.89 (0.68)
Binhai New Area	7 (0.3)	13 (0.2)	1.86 (0.68)
Jinghai District	3 (0.1)	10 (0.1)	3.33 (0.68)

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Figure 3. District-level geographic distribution of patients. TJMUGH: Tianjin Medical University General Hospital.



Patients' Appointment Time and Service Waiting Time

All patients had access to services within 1 - 2 days after making their internet hospital plus home nursing service appointments. All patients were able to access services within one to two days after making appointments through the Internet hospital plus home nursing service. Significant differences in waiting times were observed across different appointment time slots (χ^2_1=290.88; *P*<.001). Among patients who made appointments between 6 AM and 12 PM, 64.9% (1873/2885) experienced a 1-day waiting period, while 44.6% (2022/4530) waited for 2 days. In contrast, for appointments made between 12 PM and 6 PM, 35.1% (1012/2885) of patients waited for a day, whereas 55.4% (2508/4530) waited for 2 days.

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Comparison of Patients' Fees Between Internet Hospital Plus Home Nursing and Patients Transferring to a Hospital

Across 498 patients with limited mobility, simulation results showed significantly lower costs for the internet hospital plus home nursing services compared with ambulance transfers to physical hospitals in all demographic and service subgroups. The Mann-Whitney *U* test indicated statistically significant differences ($P<.001$) across gender, age groups, number of visits, service distances, and service types (see Table S1 in Multimedia Appendix 3). Even in long-distance services, the internet hospital plus home nursing services remained more cost-effective ($P=.007$). To further explore fee-influencing factors, multivariate linear regression was performed (see Table S2 in Multimedia Appendix 3). Service distance and service type emerged as significant predictors of cost differences ($P<.001$). Internet hospital plus home nursing's specialized and long-distance services were associated with higher costs but still showed a net saving compared to hospital transfer. A sensitivity analysis (see Table S5 in Multimedia Appendix 2) using different fee assumptions confirmed the robustness of these results. Internet hospital plus home nursing maintained economic advantage under all modeled scenarios.

Patients' Degree of Satisfaction

As of October 31, 2024, a total of 6980 patients responded to an anonymous satisfaction survey regarding services provided through the internet hospital plus home nursing mobile app (response rate: 94.1%, 6980/7415). Patient satisfaction scores remained high across both assessment periods. Specifically, during the period from November 1, 2020, to October 31, 2021, 2068 patients (29.6%) reported a mean satisfaction score of 99.80 (SD 2.65). In the subsequent period from November 1, 2021, to October 31, 2024, 4912 patients (70.4%) reported a mean satisfaction score of 99.89 (SD 1.50). A Mann-Whitney *U* test indicated no statistically significant difference in satisfaction scores between the two periods (U=5,090,149.00, $P=.38$).

Nurses' Perceptions

We distributed 120 questionnaires to nurses who had engaged in internet hospital plus home nursing services, and 107 were returned (recovery rate 89.2%). Nurses' basic information and the results of the questionnaire survey are provided in Multimedia Appendix 1. In summary, nurses supported internet hospital plus home nursing (93/107, 86.9%), and their attitudes toward internet hospital plus home nursing were positive. Specialized training of internet hospital plus home nursing was necessary (88/107, 82.2%). Detailed knowledge of the patient's medical and allergy history was very important (97/107, 90.7%). The key factors affecting internet hospital plus home nursing quality were the professional skill and experience of nurses (91/107, 85.1%). The main factor affecting the safety of patients was sudden illness deterioration without timely medical team support (97/107, 90.7%). The main factor affecting the safety of nurses was the violent behavior of the patients or their family members (93/107, 86.9%). It is very necessary to equip a video recorder and record the service process (100/107, 93.5%) as well as to have a special person to accompany nurses (92/107, 86%) . It needs to clarify price standards and insurance reimbursement policies (98/107, 91.6%). In the future, it is expected that specialized nursing care (88/107, 82.2%), rehabilitation training (84/107, 78.5%) as well as a comprehensive internet hospital plus home nursing information system (90/107, 84.1%) should be provided.

Discussion

Principal Findings

This mixed-methods study demonstrates that the internet hospital plus home nursing model effectively delivers convenient, accessible, and cost-effective home-based care, particularly for older adults and mobility-impaired patients. Key implementation outcomes include high patient satisfaction, positive nurse perceptions, significant cost savings compared to traditional ambulance transfers, and efficient service delivery within 1 - 2 days.

This mixed-methods study evaluated the implementation outcomes of the innovative internet hospital plus home nursing model. The primary findings indicate that the internet hospital plus home nursing model effectively provides convenient, accessible, and relatively cost-effective home nursing services, particularly benefiting older adults and mobility-impaired patients. The key findings include: high patient satisfaction scores (average scores of 99.80/100 and 99.89/100 across two periods); nurses maintained a positive attitude, with a support rate of 86.9%; compared with the cost of ambulance transportation, accessing internet hospital plus home nursing routine and specialized nursing services incurred significantly lower costs; and service delivery was efficient, typically completed within 1 to 2 days. Cancer patients constituted the primary user group, and venous blood collection was the most frequently requested service. Patient geographic distribution was concentrated primarily in areas adjacent to physical hospitals.

Internet hospital plus home nursing expands the accessibility of treatment to a broader group of patients. Internet hospitals have extended the service radius of physical hospitals, and an increasing number of patients are choosing internet hospital-based medical services [33]. Recent evidence supports the effectiveness of such integrated models in improving health care access and patient outcomes, especially in remote and underserved areas [34,35]. Internet plus nursing service is also widely accepted by patients and nurses and has been reported to effectively resolve the problem of nursing care access for mobility-impaired patients [8,12]. Internet hospital plus home nursing expands the method of delivering medical and nursing care services, optimizing online and offline medical and nursing care service on the basis of the internet hospital information platform, and providing integrated medical and nursing service to all patients. The current results suggest that patients preferred the internet hospital plus home nursing, with many patients (735/2459, 29.9%) using it more than 3 times. Of the various districts, patients in Xiqing District had the highest number of applications (mean 4.18 times, SD 0.68). The internet hospital plus home nursing mobile app and the promise of service within 2 days improved service accessibility. As population aging

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progresses, the demand for internet nursing services is gradually increasing over time [9], and the population of internet hospital plus home nursing patients is likely to expand.

The internet hospital plus home nursing model can reduce the cost of treating diseases. Internet hospitals are widely considered to overcome the limitations of time and space [36]. Internet hospital plus home nursing can not only overcome time and space constraints, but can also reduce the cost of transportation, time, and accompanying personnel. The economic advantage is obvious for patients who choose internet hospital plus home nursing routine services and dedicated services. The cost of long-distance service is similar to that of transferring patients to hospital by ambulance. Long-distance service involves increased transportation costs but still saves patients and their family members indirect costs such as time and companionship. At present, the number of patients receiving internet hospital plus home nursing long-distance service is small, which also contributes to its high cost. In the future, long-distance service cost will gradually decrease when the number of applications increases and economies of scale can be achieved. Long-distance service is relatively economical once economies of scale can be obtained compared with the cost of ambulance transfer of one patient in a single trip.

Although long-distance internet hospital plus home nursing services (10‐100 km) have demonstrated strong cost-effectiveness compared to traditional ambulance transfers, their uptake in remote districts remains extremely limited. For instance, only 13 patients from Binhai New Area were recorded among 7415 cases (0.2%). This underuse may stem from multiple barriers. Logistically, long-distance visits require greater scheduling flexibility, higher vehicle idle times, and increased staff input, reducing operational efficiency. Economically, current medical insurance reimbursement policies may inadequately compensate providers for the extra resources needed, disincentivizing participation. Institutionally, the lack of cross-district service coordination or standardized referral pathways poses regulatory challenges. Patients in remote regions may also lack awareness or trust in internet hospital plus home nursing services, perceiving them as less reliable than traditional emergency transport, especially for urgent needs. Additionally, digital access gaps or low e-health literacy may hinder online scheduling. To address these constraints, we recommend policy incentives such as distance-based subsidies, intelligent route optimization to improve efficiency, targeted public education campaigns, and integration of telemedicine for hybrid care delivery. These measures could improve both the accessibility and scalability of internet hospital plus home nursing services in geographically underserved populations.

Internet hospital plus home nursing was supported by both patients and nurses. Internet hospital plus home nursing is a patient-centered service using a model that is similar to private, customized professional medical and nursing services. Nurses who carry out internet hospital plus home nursing have rich professional knowledge and clinical experience. Before working in internet hospital plus home nursing, these nurses needed to receive specialized training to cope with emergencies such as additional requests, verbal threats, and violence from patients or family members in the process of home nursing. A previous study reported that specialized training contributes to the improvement of patient satisfaction [28]. In the actual service process, nurses need to comprehensively assess the patient's detailed medical history and allergies to determine whether the patient is suitable for internet hospital plus home nursing, then develop personalized care plans for patients with different types of diseases. Patients can obtain nursing services at home that are of the same quality as hospital-based nursing services, which greatly improves their experience and satisfaction. In this study, patients' comprehensive evaluation results indicated that patients consistently had a high level of satisfaction with internet hospital plus home nursing services. Nurses maintain a positive perception toward internet hospital plus home nursing services. However, attention needs to be paid to nurses' professional competence and experience, and multifunction information systems are necessary to ensure the quality and safety of internet hospital plus home nursing services.

Comparison With Previous Work

Internet hospital plus home nursing is designed to bridge the gap between medical and nursing services. Internet nursing service platforms that only recruit nurses to provide home nursing services were previously reported to have low reliability and standardization [6]. The internet hospital examined in this study relies on a brick-and-mortar hospital and is able to provide patients with online consultation and diagnosis, prescriptions of medicines, examinations, tests, and nursing services. At this internet hospital, it is also possible to transfer patients with serious conditions to the outpatient department, emergency department, or inpatient department of a physical hospital for further treatment. However, patients with chronic diseases such as diseases of oncology, cardiovascular, neurology, or mobility problems, who only require home nursing after an online medical service do not have to go to a physical hospital. Thus, internet hospitals need home nursing services such as intravenous blood collection, PICC maintenance, and urinary catheterization to make up for the limitations of their care provision. As nurses do not have the ability to prescribe medications independently, doctors' prescriptions are still needed when patients are treated by nurses. Therefore, internet hospital plus home nursing services can effectively make up for the shortcomings of both internet hospitals and internet nursing services, achieving all-round services of online consultation, diagnosis, prescription and offline medication delivery, home nursing, and patient referral. Furthermore, internet hospital plus home nursing not only ensures the continuity of medical and nursing services, but also makes patients' treatment more convenient.

Positioning Internet Hospital Plus Home Nursing Within Global Home-Based Care Models

China's internet hospital combined with internet hospital plus home nursing model aligns with international home health care models such as the "Hospital-to-Home" projects widely implemented in countries like the United States, Japan, and Australia, sharing the core objective of providing home-based medical care services to patients [15-21]. In terms of reducing barriers to accessing medical services for vulnerable groups such as the older adults and those with mobility impairments,

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conducting routine technical services such as venous blood collection and maintenance of PICC, and improving patient satisfaction [15,18,22,23], these models have demonstrated similar outcomes.

However, the internet hospital plus home nursing model, which relies on China's "internet hospital" system, has developed distinctive features that differentiate it from international practices. This model centers on a dedicated digital platform, establishing a seamless "Online-to-Offline" integration process and a "medical-nursing" collaboration mechanism that bridges "online medical consultation and diagnosis" with "offline home care services," overcoming the administrative limitations of traditional physical hospitals or community health systems in resource allocation and service extension [3]. Compared to the US model, which emphasizes doctor-led multidisciplinary teams [16], and the Australian model, which emphasizes the application of shared electronic health records [20], the innovation of internet hospital plus home nursing services lies in using internet hospitals as central coordination hubs, achieving systematic management of the entire service process through a unified digital entry point, thereby forming a unique new model variant in the global digital health field. Although it still faces challenges in terms of geographical accessibility in remote areas, its innovative architecture deeply integrated with the internet hospital system provides a reference-worthy family healthcare paradigm for regions where policies support the development of internet hospitals.

Strengths and Limitations

To our knowledge, this study is the first to systematically characterize the innovative approach of internet hospital plus home nursing services in implementing the internet nursing service policy. We evaluated the implementation outcomes from multiple perspectives, and the findings provide practical evidence for optimizing internet hospital plus home nursing services.

First, this study used a single-center design based at the General Hospital of Tianjin Medical University, a tertiary-level A-class (top-tier) medical institution located within an economically developed municipality. All data were sourced from this institution. Although the comprehensive hospital network encompassed the entire city of Tianjin, patient uptake of remote services remained limited. Furthermore, the single-center design, situated in an urban setting, limits the generalizability of the results. Regional variations, particularly in the following three domains, may substantially affect the scalability of the comprehensive hospital network model: (1) Infrastructure disparities: rural and remote areas may encounter challenges including insufficient network coverage and low rates of mobile device ownership and penetration, hindering the implementation and dissemination of internet hospital plus home nursing services. (2) Human resource constraints: regions with limited resources often experience shortages in nursing staff and incomplete professional skill sets among existing personnel. (3) Population density: in regions with low population density, nurses' travel time and associated costs are significantly higher compared to the urban study setting, potentially compromising the model's economic feasibility.

Second, this design inherently limits the generalizability of the study results to diverse socioeconomic contexts or health care resource distribution environments (eg, rural areas or secondary hospitals), thereby significantly compromising external validity. Specifically: (1) The findings of the cost-benefit analysis, particularly the comparison between comprehensive hospital costs and patient transportation costs, are constrained by regional variations in medical infrastructure, population density, and regulatory frameworks. These variations include differing ambulance fees, nursing service pricing structures, and insurance reimbursement policies, limiting broader applicability; (2) the absence of a control group consisting of patients receiving traditional care services; and (3) a high proportion of repeat users (29.9% of patients received care ≥3 times), indicating potential self-selection bias. This bias suggests the sample may overrepresent patients with greater health care engagement or higher satisfaction levels, potentially leading to an overestimation of satisfaction metrics and nurse acceptance rates. These factors collectively constrain the external validity of the cost-effectiveness and satisfaction outcomes.

Third, this study exhibits significant methodological limitations in internet hospital plus home nursing patient satisfaction assessment: (1) Scale inconsistency: arbitrary expansion from 3 domains (professionalism, punctuality, and attentiveness) to 5 domains (attitude, skills, price, punctuality, and experience) compromised temporal comparability despite nonsignificant interperiod score differences (P=.38). Given the retrospective design of this study, although satisfaction evaluation indicators were modified, the scoring methodology retained a percentage-based framework. Comparative analysis of total satisfaction scores demonstrated that patient satisfaction with internet hospital plus home nursing services persisted at consistently high levels following indicator adjustments. (2) Inadequate content validity: omission of critical indicators (emotional support, communication clarity, and patient-physician trust) and qualitative mechanisms precluded identification of drivers for near-ceiling satisfaction (mean>99/100) or dissatisfaction sources. (3) The exceptionally high satisfaction scores (mean>99/100) warrant cautious interpretation. They primarily signify strong patient recognition of the internet hospital plus home nursing model's core value proposition, specifically service accessibility and convenience, alongside fundamental trust in nursing staff professionalism. This is corroborated by a high service reuse rate (29.9% used ≥3 times) and positive nurse feedback. Crucially, however, these near-ceiling values may be inflated by the assessment tool's limited sensitivity to high-end variation and potential social desirability bias. Consequently, they should not be interpreted as indicative of optimal service experiences across all microlevel dimensions and may mask potential improvement areas or unarticulated negative experiences (eg, safety concerns documented in nurse questionnaires but absent from patient ratings). In summary, these results robustly indicate the model's broad patient acceptance and success in meeting core needs, rather than definitive evidence of flawless execution.

Future Work

Internet hospital plus home nursing urgently requires the establishment of a comprehensive risk management framework.

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This framework must systematically address the core challenges of patient clinical safety and nurse practice safety. A dynamic risk assessment mechanism should be integrated, using standardized tools to evaluate key domains including patient medical stability, home environment safety, sociopsychological factors, and geographical accessibility [37]. Based on these assessments, a 3-tier risk stratification system (low, medium, and high) must be implemented, with corresponding safety protocols developed accordingly. A primary task is the clear delineation of the internet hospital plus home nursing service boundaries and responsibility allocation. Patient requirements exceeding the assessed scope of internet hospital plus home nursing services necessitate prompt referral to physical hospitals to ensure patient safety and service quality. Concurrently, nurse safety must be prioritized through multifaceted measures: (1) Technological measures: provision of personal alarm devices, authorized remote monitoring equipment, and real-time communication; (2) operational measures: establishment of standardized emergency response protocols covering scenarios of patient medical deterioration and safety threats; (3) legal safeguards: clear definition of authority boundaries and patient (or family) safety obligations [38], supplemented by specialized occupational insurance and postincident support mechanisms (including confidential reporting channels, and psychological and legal assistance); and (4) capability enhancement: Strengthened safety awareness training, conflict de-escalation techniques, basic self-defense instruction, and provision of protective equipment (such as personal alarms and recording devices) [39]. This systematic framework aims to enhance service transparency and traceability, providing objective evidence for dispute resolution [40]. It constitutes an essential prerequisite for optimizing home health care management, ensuring the safety of all stakeholders, and improving nurse engagement.

The internet hospital plus home nursing model is innovative, with no similar cases reported globally to date; consequently, no multicenter studies have been conducted. To enhance the external validity and validate the universality of the internet hospital plus home nursing model, subsequent studies will use a prospective, multicenter-controlled design. Research subcenters will be established in geographically diverse regions (encompassing varying socioeconomic levels, differential access to medical resources, and distinct policy environments). Through parallel comparison of the internet hospital plus home nursing model and the traditional inpatient care model, the study aims to elucidate the causal effects of its interventions and rigorously control for selection bias. Particular emphasis will be placed on regional variations in the cost-effectiveness analysis of the internet hospital plus home nursing model. To optimize sample representativeness and mitigate bias in satisfaction assessments, a stratified sampling strategy will be implemented to ensure adequate representation of key subgroups, including first-time service users, low-frequency users, and discontinued care recipients. This study demonstrates that the internet hospital plus home nursing model confers significant advantages. As the Tianjin Internet Medical Quality Control Center, TJMUGH will facilitate the implementation of this model across Tianjin and nationwide. The increasing adoption of the internet hospital plus home nursing model by medical institutions will establish the foundation for subsequent multicenter studies and facilitate future research.

Regarding patient satisfaction assessment, this study is a retrospective study, and the data used truly reflects patients' evaluations of internet hospital plus home nursing services. Future research will establish a standardized core assessment instrument encompassing key dimensions (eg, emotional support, clarity of information communication, and physician-patient trust), ensuring the scales possess robust content validity and longitudinal comparability. The study will adopt a mixed-methods approach, integrating quantitative analysis with qualitative research to comprehensively explore the drivers of satisfaction and identify the root causes of potential dissatisfaction, thereby addressing the limitations inherent in reliance on single-method quantitative tools. To control for social desirability bias and response bias, the assessment process will use anonymized evaluations and incorporate third-party interviews to validate the authenticity of patient feedback.

Conclusions

This study comprehensively analyzed the effect of internet hospital plus home nursing service as an innovative model of internet plus nursing service, demonstrating characteristics of convenience, accessibility, and relative cost-effectiveness within the Tianjin setting. The internet hospital plus home nursing service can resolve some of the shortcomings of online medical and nursing services, improving access to medical and nursing care for older adults and mobility-impaired patients and has high patient satisfaction and nurses' positive perceptions. As population aging progresses, Internet hospital plus home nursing services are likely to become increasingly widespread. It is important to optimize these services from the perspective of ensuring patient treatment safety and nurses' personal safety, and corresponding policy support. Furthermore, the core innovative contribution of internet hospital plus home nursing services resides in its capacity to establish a closed-loop system integrating "online diagnosis and treatment services" with "home care" via the internet hospital platform, thereby bridging the service gap between conventional internet health care and standalone home care. This service offers a novel integrated medical care approach with distinctive Chinese characteristics to the global digital health domain.

Acknowledgments

The authors sincerely thank the information center of Tianjin Medical University General Hospital for retrieving medical records. This study was supported by grants from Tianjin Municipality Education Commission Major Research Project of Social Sciences (2022JWZD21).

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Data Availability

The datasets generated or analyzed during this study are available from the corresponding author on reasonable request.

Authors' Contributions

Conceptualization: YW
Methodology: YL
Validation: YL
Data curation: JC
Supervision: FH
Project administration: TY
Funding acquisition: TY
Writing – original draft: YW
Writing – review & editing: ZJ

Conflicts of Interest

None declared.

Multimedia Appendix 1
We conclude nurses' basic information and questionnaire survey results.
[DOCX File, 32 KB - nursing_v8i1e76761_app1.docx]

Multimedia Appendix 2
Cost comparison between internet hospital and home nursing and transferring patients to hospital using geographic information system (GIS)-based simulation technology and conduct a sensitivity analysis using different fees.
[DOCX File, 43 KB - nursing_v8i1e76761_app2.docx]

Multimedia Appendix 3
We compared the costs of the traditional hospital referral model with those of the integrated network hospital plus home care model.
[DOCX File, 29 KB - nursing_v8i1e76761_app3.docx]

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Abbreviations

PICC: peripherally inserted central catheter
TJMUGH: Tianjin Medical University General Hospital

Edited by E Borycki; submitted 30.04.25; peer-reviewed by J Igboanugo, T Amusa, Y Shahsavar; revised version received 27.09.25; accepted 29.09.25; published 05.11.25.

Please cite as:
Wang Y, Liu Y, Jin Z, Jin C, Hu F, Yu T
An Internet Hospital Plus Home Nursing Model for Chronic Disease Patients: Mixed-Methods Study in Tianjin, China
JMIR Nursing 2025;8:e76761
URL: https://nursing.jmir.org/2025/1/e76761
doi:10.2196/76761

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Validation of the Perception of eHealth Technology Scale in Chinese Brief (PETS-C Brief) in Nurses: Survey Study

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Abstract

Background: eHealth technologies have shown promise in improving the accessibility and quality of nursing research and practice. Little is known about nurses' perception of eHealth technology that are prerequisites for the implementation of eHealth-based nursing care.

Objective: We aimed to confirm the factor structure and examine the validity and reliability of the novel 19-item Perception of eHealth Technology Scale in Chinese Brief (PETS-C Brief) in Chinese nurses. The associations of sociodemographic and working-related characteristics with PETS-C Brief scores were investigated.

Methods: Participants were 1409 nurses (96.8% female; mean age 34.6, SD 8.6 y) working in hospital or community settings in Shanghai, China. Confirmatory factor analysis was conducted to verify the previously reported four-factor structure of PETS-C Brief. Cronbach α was calculated for internal consistency reliability. One-month test–retest reliability was assessed in 123 participants completing the one-month follow-up survey. Associations of sociodemographic and working-related characteristics (ie, years of employment, professional title, and setting) with PETS-C Brief scores were analyzed using multivariable linear regression. Known-group validity was assessed by examining the associations of age and educational attainment with PETS-C Brief scores.

Results: The goodness-of-fit of the four-factor PETS-C Brief was shown to be acceptable (comparative fit index [CFI]=0.95, standardized root mean squared residual [SRMR]=0.065, root mean square error of approximation [RMSEA]=0.074). The scale showed a good internal consistency reliability (Cronbach α=0.91) and one-month test–retest reliability (intraclass correlation coefficient=0.68, 95% CI: 0.55, 0.78). Known-group validity was supported by the inverse association of age with PETS-C Brief scores (*P*=.002) and positive association of educational attainment with PETS-C Brief scores (*P* for trend=.043). No significant associations were observed between working-related characteristics and PETS-C Brief scores.

Conclusions: Our validation study supported the four-factor structure of PETS-C Brief with satisfactory validity and reliability in Chinese nurses, suggesting the scale could be deployed for assessing perception of eHealth technology. Future studies with larger sample, random sampling, and in other cultural settings are warranted to increase the generalizability.

(JMIR Nursing 2025;8:e79594) doi:10.2196/79594

KEYWORDS

eHealth; perception of eHealth technology scale; validation; nurses; eHealth technology scale

Introduction

eHealth technologies refers to the use of information and communication technologies (eg, internet, websites, smartphones, monitoring devices, applications) in health-related fields, including health surveillance, services, education, and research [1]. eHealth technologies have shown promise in improving the accessibility and quality of health care, such as in chronic disease management [2] and health behavior promotion [3]. Nurses, as the largest component of the health care workforce, have been the majority of eHealth technology users [4-6]. Benefits of nurses' use of eHealth technologies were evident on improving patients' health outcomes and quality of life in randomized controlled trials, systematic reviews, and

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meta-analyses [7-9]. Nurses' use of eHealth technologies was also associated with higher job satisfaction [10]. Nurses' perception of eHealth technologies can be a crucial factor for promoting use, which may influence their acceptance of eHealth technologies [11], quality of care [12], and patients' engagement [13].

Perception of eHealth technologies may involve various aspects, such as digital literacy [12], knowledge, acceptance, attitude, and the potential promise and challenges of its use [14]. With the popularity of eHealth devices and applications in medical settings, knowledge and acceptance has been increasingly measured [15]. However, few studies have measured a broader perception of advantages, challenges, and even risks. The eHealth Literacy Scale (eHEALS), one of the earliest developed and most widely used measurements, was designed to assess the perceived skills to engage in eHealth [16]. However, eHEALS focuses primarily on consumers, such as patients receiving eHealth-based care. The Technology Acceptance Model (TAM) was initially developed to predict the use or acceptance of information technology in work [17] and then was adapted in the health care context specifically [18]. However, TAM may benefit from several additions and modifications during the adaption process. For example, personal productivity was a measure of usefulness, one of the constructs in TAM, may not be meaningful and sufficient in the health care context [18]. Many other studies have used self-made questionnaires to measure the perception of eHealth technologies. For example, a questionnaire was designed to assess UK students' perception of electronic health records, including knowledge and proficiency in digital clinical systems, pretraining personal use and trained professional use of social media, and degree of usefulness for training [19]. But the validity and reliability of such self-made questionnaires were unclear.

The Perception of eHealth Technology Scale in Chinese Brief (PETS-C Brief) [14] was adapted from a 40-item instrument initially developed for assessing knowledge and perceptions of telemedicine technology in clinicians in Iran [20]. By adapting the instrument in Chinese context, Kwan and colleges modified and translated the items into Chinese. A broader concept of "eHealth technology" was used to replace "telemedicine" during modification and translation. Exploratory factor analysis (EFA) and item analysis were then conducted to reduce the number of items and identifying factors. A four-factor structure with 19 items was yielded, which was supported by satisfactory indices in confirmatory factor analysis (CFA). The four factors refer to knowledge of eHealth technology, perception of the advantages of eHealth technology, perception of the disadvantages of eHealth technology, and perception of eHealth applications [14]. However, validity and reliability of the PETS-C Brief in Chinese nurses was understudied, though results of which can complement those of factor analysis for supporting the scale quality.

In 2019, the Chinese government has issued a notice promoting the pilot program of the Internet Plus Nursing Service, defined as a health care service using internet and various eHealth technologies provided by registered nurses in hospital or community settings [21]. In 2020, for the purpose of this program's nationwide spread, a Notice on Furthering the Pilot Project of Internet Plus Nursing Service was officially established [22]. However, one of the major challenges for implementing Internet Plus Nursing Service was limited participation by nurses [23]. Understanding nurses' perception of eHealth technologies can be the first step for increasing nurses' participation. But a standardized measurement is lacking. One study using PETS-C Brief has identified educational attainment as a determinant of perception of eHealth technology in Chinese nurses and nursing students [11]. Other studies on the digital divide in nurses suggested that educational attainment [24] and age [25,26] could influence nurses' perception of eHealth technologies. Identifying factors affecting perception of eHealth technology is needed for developing targeted interventions and training programs promoting the Internet Plus Nursing Service in China. Hence, our study had three aims: first, to confirm the factor construct of PETS-C Brief reported in the previous study [11]; second, to examine the validity and reliability of PETS-C Brief; last, to investigate the associations of sociodemographic and working-related characteristics with PETS-C Brief scores.

Methods

Design, Setting and Sample

The study was conducted among nurses working in hospital or community settings using convenience sampling with open recruitment in Shanghai, China. At baseline, advertisements for the study were distributed through WeChat, one of the most popular social media in China. Interested nurses entered the study by scanning a QR code, and peer sharing and referral was used to increase the response rate. Eligibility was assessed using an inclusion and exclusion form on the first page of the survey. Inclusion criteria were age ≥18 years; registered nurses; aware of the content of the survey and willing to participate. Registered nurses are individuals who have completed relevant nursing professional education, obtained a nursing qualification certificate, and are registered and legally licensed to practice in medical institutions including hospitals and community settings in China. Those with any clinical diagnosis of mental health disorders were excluded. After the eligibility page, participants who clicked "I have read the informed consent form carefully and agree to participate" could respond to survey items. Implied consent to participate was indicated when participants provided responses to survey items. For assessing the one-month test-retest reliability, short massages containing a follow-up survey link were sent to participants, using telephone numbers collected at baseline; their names were not asked. The survey at baseline and one-month follow-up were programmed to allow only one completion per device to prevent duplicate submissions.

Sample size was calculated based on the requirement for conducting CFA. A total sample of 1000 participants is regarded as "excellent" in the statistical viewpoints and previously published literature [27]. For the sample of follow-up survey, a minimal sample size of 100 was recommended for a high reliability [28].

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Measurements

PETS-C brief was adapted from a 40-item instrument initially developed for assessing knowledge and perceptions of Telemedicine Technology in clinicians in Iran, each item was on a five-point Likert scale [20]. The original instrument included six factors as follows: knowledge (7 items), perception of the advantages (7 items), perception of the disadvantages (8 items), perception of necessity (6 items), perception of ease of usage (6 items), and perception of security (6 items). Kwan and colleges adapted the instrument in Chinese nurses through item modification and translation, and a broader concept of eHealth technology was used [14]. A four-factor structure with 19 items was yielded by conducting EFA and CFA. The four factors were knowledge (4 items), perception of the advantages (4 items), perception of the disadvantages (6 items), and perception of eHealth applications (5 items) [14]. Each item of PETS-C brief was scored on a five-point Likert scale from 1="very low" to 5="very high." Total scores range 19 - 95, with higher scores indicating better perceptions of eHealth technology. PETS-C Brief was set as a compulsory question, thereby no data were missing.

Sociodemographic characteristics included sex, age, educational attainment, marital status, monthly household income. Younger age [25,26] and higher educational attainment [24] were suggested as potential factors influencing nurses' perception of eHealth technologies. Apart from the two variables, the selection of sex, marital status, and monthly household income was consistent with studies on Chinese nurses' working experiences with Internet Plus Nursing Service for result comparison [29,30]. Working-related characteristics included year of employment, professional title, and setting.

Statistical Analysis

CFA with diagonally weighted least squares estimation for ordinal data was conducted to verify the four-factor structure of PETS-C Brief previously reported [14], with full information maximum likelihood was used for handling missing data. The goodness of fit was determined by a combination of the following indicators: comparative fit index (CFI; ≥0.90), root mean square error of approximation (RMSEA; <0.08), and standardized root mean squared residual (SRMR; <0.08) [31]. We reported results of the χ^2 test for descriptive purpose but not for evaluating the model fit (cutoff for a good fit: P >.05), because the result is always statistically significant in large samples [32]. Standardized factor loadings of 19 items on the four factors were evaluated, with a value ≥0.70 indicating a strong measure of the factor [27]. Cronbach α was calculated for internal consistency reliability. One-month test–retest reliability was determined by intraclass correlation coefficients (ICC) calculated based on two-way mixed-effects model with absolute agreement, by the following criteria: poor (<0.4), fair (0.4 - 0.6), good (0.6 - 0.75), and excellent (>0.75) [33]. Associations of sociodemographic and working-related characteristics with PETS-C Brief total scores and subscores of four factors were analyzed using multivariable linear regression, with complete case analysis was used for handling missing data. Known-group validity was assessed by examining associations of age and educational attainment with PETS-C Brief total scores. All analyses were conducted using STATA (version MP 15.1; StataCorp). P<.05 was considered statistically significant.

Ethical Considerations

The study procedures were carried out in accordance with the Declaration of Helsinki. Participants were informed of the right to refuse to participate or to withdraw consent to participate at any time without reprisal by contacting the research team; all data were deidentified and no compensation was provided to participants. The research protocol was approved by the Shanghai Ninth Peoples Hospital, Shanghai Jiao Tong University School of Medicine Ethics Committee (SH9H2024-T99-3).

Results

A total of 1482 nurses entered the study by scanning the QR code, of whom 49 were excluded due to incomplete survey, and 24 were excluded due to ineligibility. Table 1 shows participant characteristics. As a result, 1409 participants (n=1364, 96.8% female; mean age 34.6, SD 8.6 y) completed the survey, yielding a valid response rate of 95.1%. Around three-quarters (n=1044, 74.1%) held a undergraduate or higher educational degree.

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Table . Participant characteristics (N=1409).

Characteristic	Participants (N=1409)
Female (ref: male), n (%)	1364 (96.8)
Age (years), mean (SD)	34.6 (8.6)
Educational attainment, n (%)	
College and below	365 (25.9)
Undergraduate	1019 (72.3)
Postgraduate	25 (1.8)
Marital status, n (%)	
Unmarried	462 (32.8)
Married	914 (64.9)
Divorced/widowed	33 (2.3)
Monthly household income (RMB, 1 USD≈7.0 RMB), n (%)	
<5,000	85 (6.0)
5,000-10,000	335 (23.8)
10,000-15,000	318 (22.6)
15,000-20,000	266 (18.9)
20,000-25,000	180 (12.8)
≥25,000	225 (16.0)
Years of employment, n (%)	
<5	330 (23.4)
5-10	285 (20.2)
≥10	794 (56.4)
Nurse (ref: Nurse manager and above), n (%)	987 (70.1)
Setting, n (%)	
Hospital, categorized by department	1215 (86.2)
Internal Medicine	307 (25.3)
Surgery	397 (32.7)
Gynecology and Obstetrics	169 (13.9)
Pediatrics	12 (1.0)
Emergency Medicine	26 (2.1)
Critical Care Medicine	97 (8.0)
Others	207 (17.0)
Community, n (%)	194 (13.8)

Table 2 shows the indicators of goodness of fit of the four-factor structure of the PETS-C Brief. The preliminary model fit was marginally acceptable (χ^{2}_{11}=1616.7, CFI=0.93, RMSEA=0.085, SRMR=0.064). The model was corrected based on the covariance modification indices to improve the model fit, with one pair of error terms with the largest indices (errors of item 13 and 14) covaried. The corrected model showed acceptable indicators of goodness of fit ($\chi^{2}_{8.8}$=1277.9, CFI=0.95, RMSEA=0.074, SRMR=0.065).

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Table . Indicators of goodness of fit of the four-factor structure of the Perception of eHealth Technology Scale in Chinese Brief (PETS-C Brief).

Indicator	With four-factor and 19 test items	Corrected model with errors of item 13 and 14 covaried
χ^2[a] (*P*>.05)	1616.7 (*P*<.001)	1277.9 (*P*<.001)
χ^2/df[b]	11.1	8.8
CFI[c] ≥0.90	0.93	0.95
RMSEA[d] <0.08 (95% CI)	0.085 (0.081-0.088)	0.074 (0.071-0.078)
SRMR[e] <0.08	0.064	0.065

[a]χ^2, Chi-square.

[b]df, degrees of freedom.

[c]CFI, comparative fit index.

[d]RMSEA, root mean square error of approximation.

[e]SRMR, standardized root mean squared error.

Table 3 shows that standardized factor loadings ranged 0.69 - 0.95 of each item on four factors of PETS-C. All items indicated a strong measure of the respective factors, apart from item 14 with factor loading of 0.69 marginally below the cutoff of 0.70.

Table . Standardized factor loadings of the Perception of eHealth Technology Scale in Chinese Brief (PETS-C Brief) with 4 factor and 19 items.

Item	Knowledge of eHealth technology	Perception of the advantages of eHealth technology	Perception of the advantages of eHealth technology	Perception of eHealth applications
Item 1	0.81	—[a]	—	—
Item 2	0.85	—	—	—
Item 3	0.95	—	—	—
Item 4	0.88	—	—	—
Item 5	—	0.88	—	—
Item 6	—	0.89	—	—
Item 7	—	0.76	—	—
Item 8	—	0.84	—	—
Item 9	—	—	0.86	—
Item 10	—	—	0.90	—
Item 11	—	—	0.85	—
Item 12	—	—	0.85	—
Item 13	—	—	0.71	—
Item 14	—	—	0.69	—
Item 15	—	—	—	0.78
Item 16	—	—	—	0.71
Item 17	—	—	—	0.85
Item 18	—	—	—	0.89
Item 19	—	—	—	0.83

[a]Not applicable.

Table 4 shows that the mean score of PETS-C Brief was 63.6 (SD 10.9). The four factors showed mean scores ranging 3.0 - 3.7. PETS-C Brief and its four factors showed a good internal consistency (Cronbach α range=0.91 - 0.93) and one-month test-retest reliability (ICC range 0.62 - 0.73).

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Table . Scores, internal consistency reliability, and 1-month test-retest reliability on the Perception of eHealth Technology Scale in Chinese Brief (PETS-C Brief) and four factors.

Variables	Score, mean (SD)	Cronbach α	Intraclass correlation coefficient (95% CI)
PETS-C Brief	63.6 (11.0)	0.91	0.70 (0.57-0.79)
Factor			
Knowledge of eHealth technology	3.4 (0.9)	0.92	0.67 (0.52-0.77)
Perception of the advantages of eHealth technology	3.7 (0.8)	0.91	0.62 (0.46-0.73)
Perception of the advantages of eHealth technology	3.0 (0.9)	0.93	0.73 (0.61-0.81)
Perception of eHealth applications	3.6 (0.7)	0.91	0.72 (0.59-0.80)

Table 5 shows the associations of sociodemographic and working-related characteristics with total scores and subscores of four factors, after mutual adjustment. Known-group validity was supported by inverse association of age with PETS-C Brief total scores (adjusted β=−0.20, 95% CI −0.32 to −0.07; *P*=.002) and positive association of educational attainment with PETS-C Brief total scores (*P* for trend=0.043). No significant associations were observed between working-related characteristics and PETS-C Brief total scores. Specifically, age was associated with subscores of knowledge (adjusted β=−0.02, 95% CI −0.03 to −0.01; *P*=.001) and perception of the disadvantages (adjusted β=−0.02, 95% CI −0.03 to −0.01; *P*=.001). Higher educational attainment was associated with subscores of perception of the advantages (*P* for trend=.007) and perception of eHealth applications (*P* for trend=.004). Higher monthly household income was also associated with subscores of perception of the advantages (*P* for trend=.01) and perception of eHealth applications (*P* for trend=.043). Years of employment was positively associated with subscores of knowledge (*P* for trend=.03). Compared with nurse manager and above, nurses reported lower subscores of perception of the advantages (adjusted β=−0.12, 95% CI −0.23 to −0.01; *P*=.03). Nurses working in the community setting than the hospital reported lower subscores of knowledge (adjusted β=−0.17, 95% CI −0.31 to −0.04; *P*=.01) and perception of the advantages (adjusted β=−0.13, 95% CI −0.25 to −0.01, *P*=.044).

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Table . Sociodemographic and working-related characteristics associated with PETS-C Brief total scores and subscores of four factors.

Variables	Total		Knowledge of eHealth technology		Perception of the advantages of eHealth technology		Perception of the disadvantages of eHealth technology		Perception of eHealth applications	
	Adjusted β (95% CI)[a]	*P* value	Adjusted β (95% CI)	*P* value	Adjusted β (95% CI)	*P* value	Adjusted β (95% CI)	*P* value	Adjusted β (95% CI)	*P* value
Female (ref: male)	−2.89 (−6.16, 0.39)	.08	−0.19 (−0.45, 0.07)	.15	−0.14 (−0.36, 0.09)	.24	−0.16 (−0.42, 0.09)	.21	−0.12 (−0.34, −.10)	.29
Age	−0.20 (−0.32, -0.07)	.002	−0.02 (−0.03, -0.01)	.001	−0.01 (−0.02, 0.002)	.13	−0.02 (−0.03, -0.01)	.001	−0.0004 (−0.009, 0.008)	.93
Educational attainment										
College and below	0	ref	0	ref	0	ref	0	ref	0	ref
Undergraduate	0.89 (−0.55, 2.32)	.23	0.013 (−0.10, 0.13)	.82	0.10 (0.004, 0.20)	.045	−0.03 (−0.14, 0.09)	.66	0.12 (0.02, 0.21	.02
Postgraduate	4.49 (0.01, 8.97)	.05	0.21 (−0.14, 0.57)	.24	0.23 (−0.08, 0.54)	.14	0.29 (−0.06, 0.64)	.11	0.19 (−0.11, 0.50)	.21
P for trend		.043		.46		.007		.84		.004
Marital status										
Unmarried	0	ref	0	ref	0	ref	0	ref	0	ref
Married	0.16 (−1.51, 1.84)	.85	0.05 (−0.08, 0.19)	.42	−0.03 (−0.15, 0.09)	.61	0.05 (−0.08, 0.18)	.45	−0.05 (−0.16, 0.07)	.41
Divorced/widowed	−0.44 (−4.53, 3.66)	.83	−0.03 (−0.35, 0.30)	.87	−0.11 (−0.39, 0.17)	.45	0.07 (−0.25, 0.39)	.68	−0.06 (−0.34, 0.22)	.67
Monthly household income (RMB, 1 USD=7.0 RMB)										
<5000	0	ref	0	ref	0	ref	0	ref	0	ref
5000 - 10,000	0.92 (−1.71, 3.55)	.49	−0.01 (−0.21, 0.20)	.94	0.13 (−0.05, 0.31)	.15	−0.03 (−0.24, 0.17)	.77	0.12 (−0.05, 0.30)	.18
10,000 - 15,000	−0.82 (−3.48, 1.85)	.55	−0.13 (−0.34, 0.08)	.23	0.17 (−0.02, 0.35)	.08	−0.24 (−0.45, -0.03)	.02	0.10 (−0.08, 0.28)	.29
15,000 - 20,000	0.89 (−1.87, 3.64)	.53	−0.03 (−0.25, 0.18)	.76	0.16 (−0.03, −.35)	.11	−0.09 (−0.31, 0.12)	.40	0.19 (0.005, 0.38)	.043
20,000 - 25,000	−0.30 (−3.17, 2.58)	.84	−0.14 (−0.37, 0.08)	.22	0.14 (−0.06, −.34)	.16	−0.14 (−0.36, 0.09)	.24	0.10 (−0.09, 0.30)	.29
>25,000	1.53 (−1.30, 4.36)	.29	−0.02 (−0.24, 0.20)	.86	0.29 (0.10, 0.49)	.004	−0.11 (−0.34, 0.11)	.32	0.23 (0.03, 0.42)	.02
P for trend		.41		.63		.01		.35		.043
Years of employment										
<5	0	ref	0	ref	0	ref	0	ref	0	ref
5 - 10	1.96 (−0.12, 4.04)	.06	0.14 (−0.02, 0.30)	.09	0.17 (0.03, 0.31)	.02	0.04 (−0.13, 0.20)	.66	0.10 (−0.04, 0.24)	.17

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Variables	Total		Knowledge of eHealth technology		Perception of the advantages of eHealth technology		Perception of the disadvantages of eHealth technology		Perception of eHealth applications	
≥10	2.14 (−0.45, 4.73)	.11	0.25 (−0.04, 0.45)	.018	0.12 (−0.06, 0.30)	.19	0.10 (−0.10, 0.31)	.31	0.008 (−0.17, 0.18)	.93
P for trend		.18		.03		.24		.48		.99
Nurse (ref: nurse manger and above)	−1.53 (−3.14, 0.10)	.06	0.001 (−0.13, −.13)	.98	−0.12 (−0.23, -0.01)	.03	−0.10 (−023, 0.03)	.12	−0.09 (−0.20, 0.02)	.12
Community setting (ref: hospital)	−1.25 (−2.98, 0.49)	.16	−0.17 (−0.31, -0.04)	.01	−0.13 (−0.25, -0.01)	.044	0.05 (−0.08, 0.19)	.43	−0.08 (−0.19, 0.04)	.21

[a]Mutually adjusted for sociodemographic and working-related characteristics.

Discussion

Principal Findings

Our validation study supported the four-factor structure of PETS-C Brief with satisfactory validity and reliability in Chinese nurses. The results of CFA showed a four-factor structure. Though the χ^2 test was statistically significant, this has been common in large samples [32]. Other model fit indicators including comparative fit index (CFI), standardized root mean squared residual (SRMR), and root mean square error of approximation (RMSEA) were within the prespecified cutoff values, suggesting that the four-factor model was acceptable. The original scale had 40 items on six items for assessing perception of telemedicine in clinicians in Iran, including knowledge, perception of the advantages, perception of the disadvantages, perception of necessity, perception of ease of usage, and perception of security [20]. The scale was then adapted in English for assessing perception of telemedicine in health care practitioners in Saudi Arabia, and knowledge, advantages, disadvantages, necessity, issues affecting telemedicine, and effectiveness obtained from patient feedback were identified as six factors [34]. The English version had two different factors compared with the original one, which might be due to cultural differences in understanding telemedicine. The Spanish adapted version reduced the item number to 13 and identified four factors including knowledge, disadvantages, utility, and knowledge of security in Ecuadorian clinicians [35]. Compared with telemedicine focusing on remote health care services, eHealth technologies include a broader range including mobile health, electronic health record, wearable devices, and online health education resources. Nurse-led eHealth technology use has been increasingly promoted by the Chinese government [21,22]. In the Chinese context, Kwan and colleges modified the scale into PETS-C Brief for assessing perceptions of eHealth technologies in nurses, and knowledge, perception of the advantages, perception of the disadvantages, and perception of eHealth applications were identified as four factors of the scale [14]. Our study complemented the study by the use of a large sample and confirmation of the four-factor structure. Nevertheless, more studies in nurse populations are warranted as the scale was less examined in this group than in clinicians.

Internal consistency reliability of PETS-C brief and its four factors were good in our study. Specifically, Cronbach α of the scale was higher than those conducted in Chinese nurses previously [11,14]. Changes in the sociocultural environment over years and the increased recognition of eHealth may have affected the way nurses understood and responded to the scale items, which in turn may have affected the internal consistency of the scale. Our study complemented previous findings by supporting one-month test–retest reliability of PETS-C Brief and its four factors, showing that the scale could be reliable over a short time. However, test–retest reliability findings must be interpreted with caution because of the relatively small sample size (n=123) and short time interval. Longitudinal studies following more nurses are needed to confirm the test–retest reliability of PETS-C Brief.

Known-group validity was supported by higher PETS-C Brief total scores associated with younger age and higher educational attainment. These findings were consistent with studies on digital divide in nurses showing that age [25,26,36] and educational attainment [11,24] could influence nurses' perception of eHealth technologies. The study using PETS-C Brief in Chinese nurses further confirmed that higher educational attainment was associated with higher PETS-C Brief total scores [11]. Specifically, age was inversely associated with subscores of knowledge and perception of the disadvantage of eHealth technologies. Younger nurses may have earlier exposure in daily life and work, hence becoming more tech-savvy [36]. This may increase their knowledge and critical opinions of eHealth technologies. Educational attainment was positively associated with subscores of perception of the advantages and perception of eHealth applications. These findings were consistent with previous results on higher levels of digital literacy and comfort with technology adoption reported by nurses with higher educational attainment [37]. Nurses with higher educational attainment may have more trainings in use of eHealth technologies for clinical, research, and administration purposes, hence increasing their perceptions of advantages and eHealth applications. These findings supported the TAM, indicating that individual experience and training could influence perception of technologies [17]. Intervention and training programs can be

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delivered to nurses with older age and lower educational attainment for promoting eHealth technology use.

This study had several limitations. First, the original version of PETS-C Brief was initially developed to assess perceptions of telemedicine in Iranian clinicians, containing 40 items on six factors [20]. The scale was then adapted to 19 items on four factors in Chinese nurses through translation, item reduction, and validation [14]. Though poorly performing items were reduced and the new scale structure has been validated, differences in professional background, culture, and technology exposure may affect the meaning of items and factors. Second, the PETS-C Brief measures a broader concept of eHealth, which might reduce its usefulness for guiding targeted interventions adopting specific technologies, such as telemedicine. Third, convergent validation was unclear. Future studies may analyze correlations of PETS-C Brief with other widely used instruments such as TAM for confirming the convergent validation. such as instruments based on TAM. Fourth, participants were recruited using convenience sampling, and peer sharing or referral was used to increase the response rate. This may lead to mutual introduction, referring to the inclusion of a group of people with similar views, resulting in selective bias. Duplicate submissions by the same participant using different devices cannot be avoided. However, telephone numbers were checked, and no duplicate number was found. Future studies with random sampling are needed. Fifth, educational attainment and monthly household income were collected as categorical data, which inform future studies using continuous variables for providing more details. Last, all data were self-reported, which could be subjected to recall bias.

Conclusions

Our validation study supported the four-factor structure of PETS-C Brief with satisfactory validity and reliability in Chinese nurses. With the pervasion of advanced eHealth technologies, PETS-C Brief can be a useful tool for continuously assessing Chinese nurses' perception of eHealth technologies.

Acknowledgments

The authors would like to gratefully acknowledge the nurses who participated in this study. The abstract has been presented in a poster format at the 27th East Asian Forum of Nursing Scholars (EAFONS) conference [38]. The full list of items can be obtained by contacting Prof. Rick Kwan, Prof. Simon Lam and Prof. Frances Wong, who retain the copyright of PETS-C brief. We thank Prof. Rick Kwan, Prof. Simon Lam and Prof. Frances Wong for providing the scale and allowing us to use. This study is supported by National Natural Science Foundation of China (82304261), Shanghai Science and Technology Development Foundation of "Rising Star" Sailing Program (23YF1421100), Shanghai Municipal Health Commission Health Industry Clinical Research Project (20224Y0187), and Shanghai Jiao Tong University School of Medicine: Nursing Development Program (SJTUHLXK2024).

Authors' Contributions

Conceptualization: XW, LW, NG
Data curation: NG
Formal analysis: AJ, NG
Funding acquisition: LW, NG
Investigation: AJ, NG
Methodology: NG
Project administration: LW, NG
Resources Software: AJ, NG
Supervision: PM, LW
Validation: XW, SZZ
Visualization: AJ, XW, NG
Writing – original draft: AJ, XW, NG
Writing – review & editing: AJ, XW, PM, LL, SZZ, LW, NG

Conflicts of Interest

None declared.

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Abbreviations

CFA: confirmatory factor analysis
CFI: comparative fit index
EFA: exploratory factor analysis
eHEALS: eHealth Literacy Scale
ICC: intraclass correlation coefficients
PETS-C Brief: Perception of eHealth Technology Scale in Chinese Brief
RMSEA: root mean square error of approximation
SRMR: standardized root mean square residual
TAM: technology acceptance model

Edited by A Sowan; submitted 24.06.25; peer-reviewed by AA Mojabil, T Wentzel-Larsen; revised version received 08.10.25; accepted 20.10.25; published 05.11.25.

Please cite as:
Jilili A, Weng X, Maimaiti P, Liao L, Zhao SZ, Wang L, Guo N
Validation of the Perception of eHealth Technology Scale in Chinese Brief (PETS-C Brief) in Nurses: Survey Study
JMIR Nursing 2025;8:e79594
URL: https://nursing.jmir.org/2025/1/e79594
doi:10.2196/79594

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Original Paper

Detailed Analysis and Road Map Proposal for Care Transition Records and Their Transmission Process: Mixed Methods Study

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Abstract

Background: The digitalization of health care in Germany holds great potential to improve patient care, resource management, and efficiency. However, strict data protection regulations, fragmented infrastructures, and resistance to change hinder progress. These challenges leave care institutions reliant on outdated paper-based workflows, particularly for patient data transmission, despite the pressing need for efficient tools to support health care professionals amid a nursing shortage and rising demand for care.

Objective: This paper aims to analyze Germany's care transition record (CTR) and CTR transmission process as part of transition management and suggests improvements toward a seamless digital solution.

Methods: To understand the current challenges of manual CTR transfers, we used a mixed methods approach, which included a web-based questionnaire with nursing professionals, field observations, business process model and notation modeling, semantic and frequency analysis of CTR entries, and user story mapping.

Results: A web-based questionnaire involving German nursing professionals (N=59) revealed considerable delays in patient care due to manual, patient-transferred CTRs. Of the 33 usable responses (n=33), 70% (n=23) of the respondents advocating for digital transmission to improve efficiency. Observations (N=11) in care facilities (n=5, 45%) and a hospital (n=6, 55%) confirmed the high administrative burden, averaging 34.67 (SD 10.78) minutes per CTR within a hospital and 44.6 (SD 20.5) minutes in care facilities. A semantic analysis of various CTRs (N=4) highlighted their differences and complexity, stressing the need for standardization. Analyzing a new CTR standard (care information object CTR) and manually mapping an existing CTR to it showed that the procedure was ambiguous, and some associations remained unclear. A frequency analysis of CTR entities revealed which were most used. In addition, discussions with care staff pointed out candidates for the most relevant entities. On the basis of the key findings, a stepwise transition approach toward a road map proposal for a standardized, secure transfer of CTRs was conceptualized. This road map in the form of a user story map, encompassing a "CTR transformer" (mapping of traditional CTRs to a new standard) and "care information object CTR viewer/editor" (in short, CIO-CTR viewer and editor; a new standard for viewing, editing, and exporting), shows a possibility to bridge the transition time until all institutions fully support the new standard.

Conclusions: A future solution should simplify the overall CTR transmission process by minimizing manual transfers into in-house systems, standardizing the CTR, and providing a secure digital transfer. This could positively impact the overall care process and patient experience. With our solutions, we attempt to support care staff in their daily activities and processes until nationwide state regulations are implemented successfully, though the timeline for this remains uncertain.

(JMIR Nursing 2025;8:e60810) doi:10.2196/60810

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KEYWORDS

care transition record; transmission management; observations; process modeling; telematics infrastructure; TI; Fast Healthcare Interoperability Resources; FHIR; Health Level 7; HL7; medical information object; MIO; care information object care transition record; CIO-CTR; Pflegerisches Informationsobjekt-Überleitungsbogen; PIO-ULB; artificial intelligence; AI

Introduction

Digitalization in Health Care in Germany

Digitalization has emerged as a transformative force across various sectors, fundamentally altering organizational operations and service delivery. Health care is one sector benefiting significantly from digitalization as it can support patient care, resource management, and overall efficiency [1,2].

The growing shortage of qualified nursing personnel and the rising number of people needing care signify the need for more efficient, high-quality processes and tools to support health care professionals. Digital solutions offer a pathway to address these challenges by automating administrative tasks, improving communication between health care providers, and freeing up valuable time for direct patient care [3-5]. In Europe, policy makers, researchers, and health care practitioners are working to enhance health care infrastructure and promote interoperability to foster more efficient and coordinated care [6]. However, in Germany, the digital transformation of health care remains slow and faces significant obstacles [3,7,8].

Stringent data protection regulations for the processing of personal data (eg, the European Union's General Data Protection Regulation [GDPR] and Germany's Patient Data Protection Act, derived from the GDPR [9]) and fragmented technical infrastructures combined with the resistance to change make it difficult to integrate new tools or adjust existing processes [7,10]. In addition, the lack of a unified digital strategy further hinders the seamless implementation of digital health solutions [7,10].

Ultimately, the complexity of implementing digital solutions in the German health care system stems from balancing innovation with regulatory compliance, data security, and protecting patient privacy.

Care Transmission Process in Germany

A critical challenge within health care digitalization is ensuring the seamless transition of patient information between health care institutions. Paper-based workflows, still prevalent in many facilities, often cause delays and data loss during the transfer process due to the lack of standardized formats and the inability to share data in time.

Our research focuses on streamlining parts of the care transition record (CTR) transmission process to address this issue. The project's goal is to improve the transfer of patient data across care institutions, which currently suffer from time-consuming manual data entry, format inconsistencies, and delays in the arrival of crucial patient information.

State of the Art

Health Care Data Exchange

A security-conformant approach for digital transfer is the use of a dedicated health data (transfer) network. In Europe, such a service must be conformant to the GDPR, that is, legal compliance (ensuring data privacy and security), patient data control (data consent management for patients), data security (only access by authorized users, protection against breaches), and interoperability (fostering data exchange between different health care providers across various platforms) [9].

The telematics infrastructure (TI) is Germany's digital health data network designed to connect all health care providers, enabling the exchange of medical data across institutions [11]. It integrates various applications to streamline communication between health care entities such as physicians, hospitals, and pharmacies.

A specific way to exchange health data within a health data network is via an electronic health record. An electronic health record represents the digital version of a patient's medical history maintained over time by health care providers. It includes key clinical data relevant to patient care, such as medical history, diagnoses, medications, treatment plans, immunization dates, allergies, radiology images, and laboratory results. It is possible to share the patient data with other health care stakeholders, including the patient [12,13].

Several countries have made significant progress in this area, for example, the electronic patient dossier from Switzerland [14,15], electronic health record (Elektronische Gesundheitsakte) from Austria [16], MyKanta from Finland [17,18], and Mon espace santé from France [19]. They offer structured consent management for patients, meet the high security standards of the European Union, and foster interoperability by using the standard Fast Healthcare Interoperability Resources Health Level 7 (HL7), for exchanging electronic health care data.

The implementation of Germany's electronic patient record (ePA) [20] is progressing; however, it faces challenges. Many health care providers are not yet integrated, and patients must manually upload data. Technical and privacy issues, including interoperability concerns and strict data protection laws, continue to hinder broader adoption and use [21,22].

Another component within the TI is Kommunikation im Medizinwesen (KIM). It is a communication service with which health data can be exchanged directly by care providers, such as via email [23]. Nationwide implementation of the TI has been slow due to interoperability challenges. Adoption has lagged, primarily due to concerns over complexity, costs, and workflow disruptions. Health care professionals are hesitant to fully transition to digital tools because of these technical difficulties and the perceived burden of TI integration. There are 2 model projects in Germany [24,25] piloting and evaluating

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the TI and including components (eg, KIM and ePA). Unfortunately, no detailed evaluation reports have been published yet.

Standardization of Health Care Data

Standardization is a significant aspect that can improve the transfer of patient data in terms of reducing potential manual data entry and format inconsistencies. Standardizing CTRs is a potential possibility for improving the CTR transmission process. In Germany, 2 subsequent projects have focused on this issue: the first project is the ePflegebericht.

The ePflegebericht Project (electronic nursing report) began in 2002 when the Network for Continuity of Care in the Osnabrück Region [26] developed the concept for an electronic nursing report [27]. Insights from testing this software and its transition forms were gathered in a project under the patronage of the German Nursing Council starting in 2006. These insights were generalized beyond local use, placed in an international context [28], and aligned regionally and nationally [29]. The result was then submitted for approval as an HL7 standard [30].

The ePflegebericht served as a data exchange format for sharing information between care facilities and hospitals. It is based on the HL7 Clinical Document Architecture standard described in the study by Flemming et al [31]. The study validated the HL7 Clinical Document Architecture–based ePflegebericht and confirmed that it could cover all relevant nursing data compared with 114 paper-based nursing summaries used by 806 health care facilities in Germany. The ePflegebericht provided a comprehensive structure for transferring nursing information, demonstrating its applicability during care transitions. It improved the transmission of nursing data compared to paper-based methods, adding details such as social and homecare information, leading to more holistic documentation. Technically, advancements such as reusable templates were also introduced. These updates led to the relaunch of the ePflegebericht, with slight modifications, and in 2019, it was again up for approval.

The introduction of the ePflegebericht marks a significant advancement in the standardization of CTRs in Germany. A nationwide initiative aiming to develop a standard format for a variety of health-related documents (ie, medical information objects [32]) used the ePflegebericht as a foundational model for their CTR format: Pflegerisches Informationsobjekt-Überleitungsbogen (PIO-ULB). In this paper, the authors refer to the PIO ULB as care information object (CIO) CTR. This initiative was commissioned by the German government and overseen by the Gesetzliche Krankenversicherung Spitzenverband (central representative body of the statutory health and nursing care funds in Germany), and the mio42 GmbH (organization that develops medical information objects on behalf of the National Association of Statutory Health Insurance Physicians [Kassenärztliche Bundesvereinigung]). Furthermore, it involved the collaboration of the Deutscher Berufsverband für Pflegeberufe eingetragender Verein (DBfK; German Professional Association for Nursing Professions eingetragender Verein), and the Deutscher Pflegerat eingetragender Verein (German Nursing Council eV) [32].

CIO-CTR uses HL7 Fast Healthcare Interoperability Resources datasets, as described in the publication by mio42 GmbH [33], and was completed by the end of 2022. However, there is still uncertainty regarding the swift implementation of this new standard, primarily due to the financial and human resource challenges faced by health care software manufacturers who must adapt their existing products to comply with the specification, which spans approximately 2000 pages (XML code), as shown in mio42 GmbH [34]. The CIO-CTR will be effective at the beginning of 2025 [34] but without legal obligation for software manufacturers to implement it.

Objectives

This paper aims to analyze and address the challenges of the CTR transmission process in Germany. On the basis of a review of the current situation and possible approaches, a road map toward a fully digital, seamless solution is to be proposed. The overall goal is to improve the transfer of patient care data across care institutions.

Methods

Several methods were used to assess the satisfaction of nursing staff in the context of patient data transfer in care facilities in Germany. These include the creation of a web-based questionnaire, conducting field observations and contextual inquiries, business process model and notation (BPMN) modeling, semantic and frequency analysis of existing CTRs, and user story mapping. The findings are presented in this paper.

Web-Based Questionnaire

A web-based survey was conducted to identify challenges and preferences related to the CTR transmission process. The survey targeted nurses, nursing assistants, and trainees working in ambulatory, acute inpatient (eg, hospitals), or long-term care settings familiar with the CTR process. Participation was solicited through various channels, including the Bavarian State Ministry of Health and Prevention and the professional networks of project members. Due to a low initial response rate, the survey period was extended, and multiple reminders were issued. Using LimeSurvey, the survey ran from February 11, 2022, to April 30, 2022.

The questionnaire, developed iteratively by the project team (developers; care managers; and ethical, legal, and social issue experts), was based on literature and included custom questions and items from the validated Copenhagen Psychosocial Questionnaire tool [35]. Copenhagen Psychosocial Questionnaire items covered 12 domains, such as sociodemographic information (eg, gender, age, and work setting). Additional items focused on the experience with CTR creation and transmission, error rates, and attitudes toward digitalization. The 24-item questionnaire primarily used 4-point Likert scales, supplemented by nominal, metric scale, and open-ended questions. Respondents could opt out at any time, and all data were anonymized. A pretest with 7 participants from 2 independent institutions (implementation and nursing sciences) identified several structural and technical issues, which were addressed in a second pretest round. The same individuals tested the final version and did not reveal any issues.

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Data analysis was conducted using SPSS (version 28.0.0.0; IBM Corp). Responses to open-ended questions were categorized using Microsoft Excel, and the data were checked for erroneous entries before being analyzed, focusing on descriptive statistics.

Field Observations and Contextual Inquiries

Overview

Field observations and contextual inquiries were conducted in a hospital and inpatient care facilities to understand the CTR transmission process thoroughly. These methods focused on the activities of care staff in their natural work environments, providing foundational insights for process modeling and research. The CTR transmission process in this study refers to all activities involved in creating a CTR at the sending facility and integrating it into the in-house system at the receiving facility, including the use of computer equipment, work tools, and telephone calls, while accounting for potential confounding factors. The observations aimed to clarify whether staff entered all data from the CTR at once or alternated between tasks.

Field Observation

Field observation, a qualitative research method, involves systematically observing participants in their natural settings to collect rich, contextual data on behaviors, interactions, and the surrounding environment [36]. An observation protocol was established to ensure consistency across sites and sessions, focusing on key areas such as activities performed, use of aids (eg, software and hardware), how information was handled and transferred, and any special features or abnormalities. Unobtrusive observation techniques were used to minimize observer effect, and detailed field notes were recorded, capturing both activities and nonverbal cues.

Contextual Inquiry

Contextual inquiry, a user-centered design method, was used to observe participants in their natural work environments while engaging in informal conversation to ask questions or clarify processes. This approach provided a deep understanding of the context in which tasks were performed and the challenges faced by users [37,38]. These inquiries, which were conducted primarily in participants' offices, allowed researchers to ask questions during task performance, facilitating an exploration of thought processes and decision-making, particularly with complex systems.

Execution

The observations and inquiries were conducted by 2 researchers, one with a medical background and the other specializing in user-centered design, ensuring comprehensive documentation and minimizing potential biases. The field observations and the contextual inquiries followed the same protocol. Thematic analysis [39] was applied to the data, with the researchers collaboratively reviewing and coding field notes to identify relevant patterns that informed the process modeling. In less formalized care facility environments, contextual inquiries were preferred, with researchers assuming an apprentice role to ask clarifying questions without disrupting workflows.

The observations were restricted to on-site care staff and did not include patients or external personnel (eg, patient transport). Observations occurred between 2020 and 2022, with no specific temporal or spatial restrictions within the facilities. Each observation was planned for 1 hour each.

Ethical Considerations

All studies adhered to ethical guidelines, and informed consent was obtained from participants. All data were anonymized. No incentives were offered. Ethics approval for the study was granted by the joint ethics committee of the Universities of Bavaria (GEHBa-202107-V-028).

BPMN Modeling of CTR Transmission Process

BPMN is an established and widely used graphical representation for modeling business processes. It is a standard developed by the Object Management Group (OMG) and has been adopted as an International Organization for Standardization (ISO) standard.

In BPMN, a process is represented as a sequence of activities or events, ordered in a flow that can be split or merged using gateways, directing the flow into one or multiple paths. Due to its simplicity, business process managers have widely used this standard in many application domains. Despite not being explicitly designed for clinical processes, BPMN has proven its value in the health care domain, allowing an easy-to-understand representation of clinical processes [40,41].

Semantic Analysis of CTRs

Semantic analysis is a good approach to extract and interpret the meaning of terms and sentences in detail. In the discipline of computer science, it is a fundamental component of natural language processing [42,43].

For semantic analysis, CTRs (empty and filled with fictive patient data) from cooperation facilities (n=4) were analyzed and compared in detail to better understand their structure, similarities, and differences. For clarification of any questions (eg, exact meaning, relevance, or scope of a specific category or word and overall comprehension), 1 meeting per facility with care staff was held. Given the semistructured to unstructured nature of the CTRs, it was critical to determine which data elements hold the same or different information compared to another facility. The meetings (n=4) lasted approximately 60 minutes.

Afterward, the CTRs were mapped to the new CIO-CTR standard. For this, the CTR entries were subdivided into entities and values and afterward mapped with pen and marker to the new standard format CIO-CTR.

Frequency Analysis of CTR Entities

Frequency analysis [44] is a method used to determine how often specific elements occur within a dataset, both in absolute terms and as a proportion of the total data. In this study, frequency analysis was applied to assess the occurrence of individual CTR entities to determine which pieces of information are most included. This helped inform the design of the proposed digital solution, ensuring that it prioritizes the most frequent CTR entries.

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User Story Mapping

User story mapping [45] is a user-centric bottom-up technique used to outline a product or product feature. The output, known as a story map, provides a global view of the product, detailing the steps a user takes to achieve a specific outcome. This method helps prioritize tasks, identify dependencies, and adapt to changes.

Story maps are organized along 2 dimensions: the backbone (horizontal axis), which represents the user's activities step by step, and the release dimension (vertical axis), which defines the scope of the product and its various stages of development. A commonly used format for user stories is the role-feature-reason format: "As a <user>, I want to <feature> so that <value>" [45]. While a story backlog lists user stories in isolation, user story mapping provides a structured, global view of the entire application, fostering a common understanding between developers and stakeholders. This method also encourages communication, helping to eliminate misunderstandings early in the development cycle.

In the story mapping workshop, results from previous requirement analysis—including user feedback, product vision, and initial process modeling—are used to create actionable user stories. The key objectives of the workshop included understanding the user's perspective, identifying potential gaps, prioritizing, and release planning.

In total, 2 workshops were conducted, involving a total of 7 participants. These participants were part of the core research project team, bringing diverse expertise from various disciplines: health care (n=2, 29%), computer science (n=3, 43%), design (n=1, 14%), and IT security (n=1, 14%). All 7 (100%) participants attended both workshops, ensuring continuity and consistency in the discussions and decisions.

Results

Web-Based Questionnaire

A total of 59 participants participated in the web-based survey to determine the experiences and needs of nursing professionals regarding care transition reports, of which 35 (59%) met the inclusion criteria. Of the 35 participants, 2 (6%) did not finish the survey, resulting in 33 usable datasets. In Table 1, specific sociodemographic information about the participants is provided. An overview of the systems or software used is also provided in Table 2.

Table 1. Sociodemographic information of participants (n=33).

Characteristics	Participants, n (%)
Gender	
Women	22 (67)
Men	10 (30)
Nonbinary	1 (3)
Age group (y)	
18-24	2 (6)
25-34	13 (40)
35-44	7 (21)
45-54	8 (24)
>55	3 (9)
Care setting	
Short-term care (outpatient)	2 (6)
Acute inpatient care (hospital)	28 (85)
Long-term care (care facility)	3 (9)
Federal state (within Germany)	
Bavaria	32 (97)
Berlin	1 (3)

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Table 2. Information about the system or software used.

Information	Participants, n (%)
System or software used for the creation of CTRs[a]	
I use software	20 (61)
I do not know	4 (12)
I use a paper form	5 (15)
I use a paper form and software	3 (9)
Not specified	1 (3)
Specific software used	
ORBIS (by Dedalus)	16 (49)
C&S	1 (3)
SAP	1 (3)
Sic Pflegeassistent (by CGM SYSTEMA SIC)	1 (3)
SnapAmbulant (by euregon)	1 (3)
Sorian	1 (3)
Not specified	12 (36)

[a]CTR: care transition record.

The high percentage of female participants (22/33, 67%) reflects the well-established predominance of women in nursing. The concentration of participants in the 25 to 34 age group suggests that the web-based survey may have been more appealing or accessible to younger adults. In addition, during the COVID-19 pandemic, care professional faced more stress and work, which might have led to a discouragement of answering a questionnaire that does not benefit their daily work.

The overwhelming representation of acute inpatient care (28/33, 85%) indicates a strong representation of hospitals in the questionnaire.

Of all the federal states in Germany, approximately all participants were from Bavaria (32/33, 97%) and only very few from Berlin (1/33, 3%). The overall overwhelming representation from Bavaria is probably due to the location of the research team, indicating that the recruiting efforts were particularly successful in this region despite numerous efforts to reach other care facilities and hospitals.

The results of the system or software used (Table 2) show that most (20/33, 61%) participants used software to create CTRs. Only 15% (5/33) of the participants used the paper form. Most (16/33, 49%) of the participants used the software ORBIS, reflecting the very high percentage of participants from hospitals, as ORBIS is a hospital information system. Sorian (1/33, 3%) is also a hospital information system. The other software listed (C&S, SAP, Sic Pflegeassistent, and Snap Ambulant) are documentation software used in the care facilities setting, which underlines the variety of software used.

Additional findings from the web-based questionnaire revealed that the CTRs were mainly transferred via the patient (27/33, 82%). This means that in these cases, the nurse gave the CTR to the patient as a printout, and the patient or the relatives were responsible for ensuring that it reached the next care facility. As a result, the nursing staff at the receiving facility has limited time to fully prepare for the patient in advance. Preparations and admission begin once the patient arrives at the facility, which can lead to waiting times. This is consistent with the results from the field observations that were conducted. The remaining 18% (5/33) transferred the CTR via fax, patient file, or telephone.

This gives the nursing staff more time to prepare for the patient, for example, preparing for isolation, special therapy treatment, or similar. According to the survey, the manual transfer of the CTR into the in-house system takes an average of 45 minutes, and 61% (20/33) of care staff perceived the transfer process as time-consuming. Manual transfer means that the care professional copies the information from the printout using their hand (typing on the keyboard) and transfers it to their care software. This step is necessary to add further information to the patient file, for example, information from patient conversations and decisions on care measurements.

This process can be time-consuming, as the care staff alternates between referring to the printout and typing the information into the system. During that time, confounding factors such as telephone ringing, colleagues, or technical issues can arise, prolonging the process.

Due to the use of different software in various facilities, the information is often displayed or organized differently, resulting in additional work.

Regarding the digital transmission of CTRs (cross-institutional dispatch and automatic integration into the in-house system), most (23/33, 70%) participants expressed no concerns. However, 30% (10/33) of them raised issues, such as concerns about possible threats to patient data protection (4/33, 12%). Most (24/33, 72%) respondents hope digital CTR transmission will reduce administrative effort. Some (18/33, 55%) participants

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indicated that they favored the standardization of CTRs because standardization of CTRs would result in relevant information being found more quickly in the future. On the basis of the responses, the primary consideration in developing a new solution should ensure, for example, that receiving, sending, and creating a CTR is less time-consuming for nurses than in the current process.

All (33/33, 100%) participants stated that CTR standardization would help them a lot as the CTRs they work with are usually different in structure and semantics.

Concerning the essential information in CTRs, all (33/33, 100%) participants agreed that patient information, medication, aids, and last bowel movement are considered to be very relevant regarding a potential standardization of CTRs. Finally, their opinion on automatic data integration was asked; they were curious as to whether something like this is possible so that they do not need to copy and paste information manually.

Field Observations and Contextual Inquiries

Field Observations

The observations focused on the receiving side of the CTR, that is, the creation of a CTR in the in-house primary system. This means that the scenario of a receiving facility was always observed. This focus on the receiving facility was agreed upon through collaboration with the facilities due to the COVID-19 pandemic, as stricter visitor restrictions prevented parallel observation in both the sending and receiving facilities. In all cases, the transfer of a patient was announced in advance.

The observation occurred from the moment the nurse sat down at their computer to either create the patient case or fill it in. At the hospital, the cases are already created by the administration and contain information that is necessary for billing but does not influence the nursing documentation any further. One nurse was observed during every observation, but it was not necessarily every time the same as it depended on their schedule. While at the hospital, both field observations and contextual inquiries were conducted; only contextual inquiries took place in the care facility.

The results of field observations at University Hospital Augsburg (UHA; n=6) in 2020, showed a high administrative time burden for nurses (refer to Table 3 for the CTR transmission process). Manual recording of CTRs resulted in an average time expenditure of 34 minutes. The observations showed that the CTRs were not sent in advance but arrived with the patient. While entering the data into their in-house system, the care staff mentioned that they could not prepare adequately for the patient in advance (eg, by preparing medications and nursing aids). The field observation also showed that the nursing specialist endures many interruptions while entering the CTR (relatives, colleagues, physicians, telephone, patients, or emergency calls), forcing them to switch between different tasks very often. Therefore, the nurse had to refocus on the CTR repeatedly.

Table 3. Overview of care transition record (CTR) transmission process observations at the hospital.

Observation	Observation duration (min)	Software	Interruptions, n	Type of interruptions	Resource used for transferring data	CTR present (print)
1	50	ORBIS	5	Relatives, telephone, colleagues, physician, and missing information	Computer and telephone	Present
2	25	ORBIS	3	Telephone and missing information	Computer and telephone	Present
3	40	ORBIS	5	Relatives, telephone, colleagues, and ambulances	Computer and telephone	Present
4	45	ORBIS	4	Colleagues, physician, telephone, and patients	Computer	Present
5	25	ORBIS	1	Physician	Computer	Present
6	23	ORBIS	3	Emergency calls and colleagues	Computer	Present

There was no direct association between observation duration and the care need of a patient; rather, it depended on the overall setting, for example, completeness of the available information, number of interruptions, and the length of the CTR.

The CTRs encountered in the field observations were all from different nursing homes with different lengths (approximately 12 and 30 pages). The information is primarily unstructured, that is, free text. Structured elements were primarily areas with checkboxes.

During the observations, many of the observed nurses complained that the manual transfer of the CTR was time-consuming. After the observation, the care staff were asked additional questions regarding the relevance of a digital CTR process, the most important information to be transferred, and their opinion about the fully automatic integration of the CTR data into the in-house system. The questions were open ended and digitally documented by the observer. In terms of relevance, all participants (n=6) said that the early, preferably digital, transfer of the CTR would hold immense value. It would help them to prepare in advance and obtain, for example, missing information and medication beforehand. It would reduce their administrative workload. In total, 3 (50%) of the 6 participants stated that the current process is frustrating as patients are often transferred before the weekend without medication, physician's notes, or aids. Without these things, they have to come up with makeshift solutions to care for the patients over the weekend.

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After conducting the field observations at the hospital, it became evident that specific questions remained unanswered and could not be answered fully in the follow-up discussion. These questions were about the specific functionalities of the software used and also specific work-arounds that were conducted by the care staff but not remembered after the observation. Therefore, one additional contextual inquiry was conducted.

Contextual Inquiries

Contextual inquiries (n=5) were conducted in 2021-2022 at 2 care facilities and UHA (Table 4). The results of the contextual inquiries provided valuable insights into the observation duration, the confounding factors, and the aids used. For most observations, documents about the patient (eg, physician's letter, medication plan, and CTR) were available as printouts. These were either sent with the patient or faxed to the referred institution. The latter could occur during registration or after inquiries about missing CTRs or information. The duration of 4 complete observations in care facilities and 1 hospital (excluding observation 2 because no input happened) averaged 47 minutes. In observation 2, it took 33 minutes to determine that no CTR was present, and it could not be sent from the sending facility. However, this required the nurse to make internal and external phone calls. She also needed to delegate procurement tasks to colleagues in the facility (eg, ask colleagues to check if the CTR might not be in the facility after all). In other cases, the CTR was handed out to the patient upon discharge but was not necessarily available right after the patient arrived at the receiving facility when the data were entered into the system.

Table 4. Overview of care transmission record (CTR) transmission process contextual inquiries, care facilities, and hospital. Care facilities are divided into facility 1 (CF1) and facility 2 (CF2).

Observation	Facility	Observation duration (min)	Software	Number of interruptions	Type of interruptions	Resource used for transferring data	CTR present (print)
1	CF1	55	Connext Vivendi NG+PD	1	Telephone, colleagues, and technical problems	Computer, smartphone, telephone, pen, and fax	Present
2	CF2	33	None used	0	No CTR present	Computer, smartphone, telephone, and fax	Not present
3	CF1	78	Connext Vivendi NG+PD	5	Telephone and colleagues	Computer, smartphone, telephone, paper, and pen	Present
4	Hospital	20	ORBIS	2	None	Laptop, paper, and patient	Present
5	CF2	37	Sic Pflege-assistent	3	Telephone	Telephone, paper, and pen	Present

All nurses involved in the contextual inquiries noted that the transfer process was time-consuming, particularly if they needed to retrieve missing information and also because they had to refocus on CTR data input due to interruptions.

Another interesting observation was that the nurses at the care facilities combined information from the CTR, physician's letter, medication plans, and the initial interview with the patient and entered these in free-text fields.

After the contextual inquiries, the same questions were asked as in the field observations. The nurses responded very similarly.

Comparing the average observation duration of all care facilities (excluding observation 2 because no input happened) with the hospital shows that the care staff requires approximately 56 minutes in the care facilities and only 20 minutes at the hospital.

BPMN Modeling

Overview

On the basis of the findings of the observations, BPMN models were created to better understand the various CTR activities (creating, sending, and receiving). These were discussed with the respective facility and detailed in the previous publication. After discussion, it was determined that the process models of the 2 care facilities can be combined into 1 process, as the activities are identical. Furthermore, the models were divided into different lanes, making it easier to understand which activities are manual and which are software based (human-computer interaction).

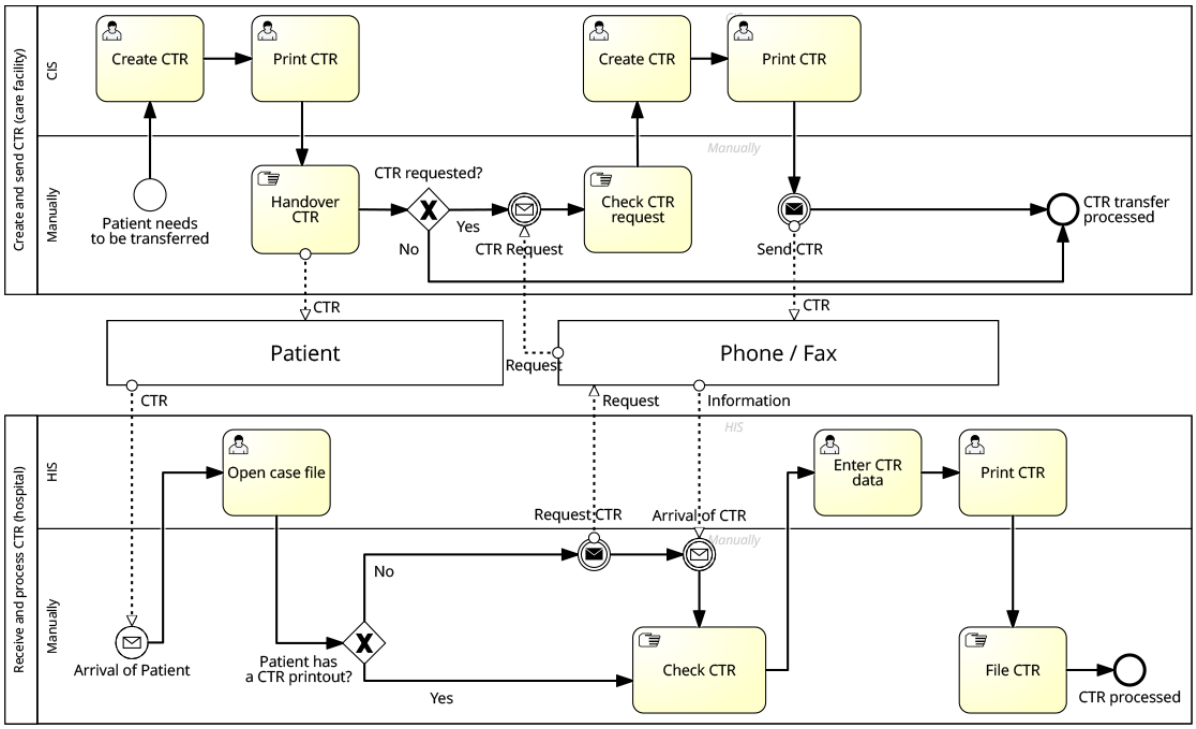
Transfer Process From Care Facility to Hospital

The process starts with the patient's need to be transferred (see Figure 1, Create and Send [Care Facility]). The nurse at the care facility creates a CTR, prints it, and usually hands it to the patient. Then, the patient arrives at the hospital, and the nurse at the hospital opens the patients' case file (see Figure 1, Receive and Process CTR Hospital). Afterward, she checks if the CTR printout is available and whether it is complete and error free (referring to the content of the CTR). Patients' case file is a digital file that contains the basic information of the patient for billing. As these files are prepared by the administration upon arrival of the patient, the care staff do not need to prepare those themselves.

If the CTR is complete and error free, she transfers the CTR into the hospital information system, prints the CTR in its specific structure, and files the CTR manually. After this, the CTR is processed, and the process is complete. If the CTR is unavailable, the nurse calls the sending care facility. The request is then processed there. If a CTR is missing, the sending facility creates a CTR, prints it, and sends it via fax to the hospital. Next, the nurse checks the document (eg, the correct CTR for the patient). After that, the CTR is transferred into the hospital information system, printed, and manually filed. Then, the process is complete.

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Figure 1. Process modeling: care transition record (CTR) data transfer from the care facility to the hospital. CIS: case information system; HIS: hospital information system.



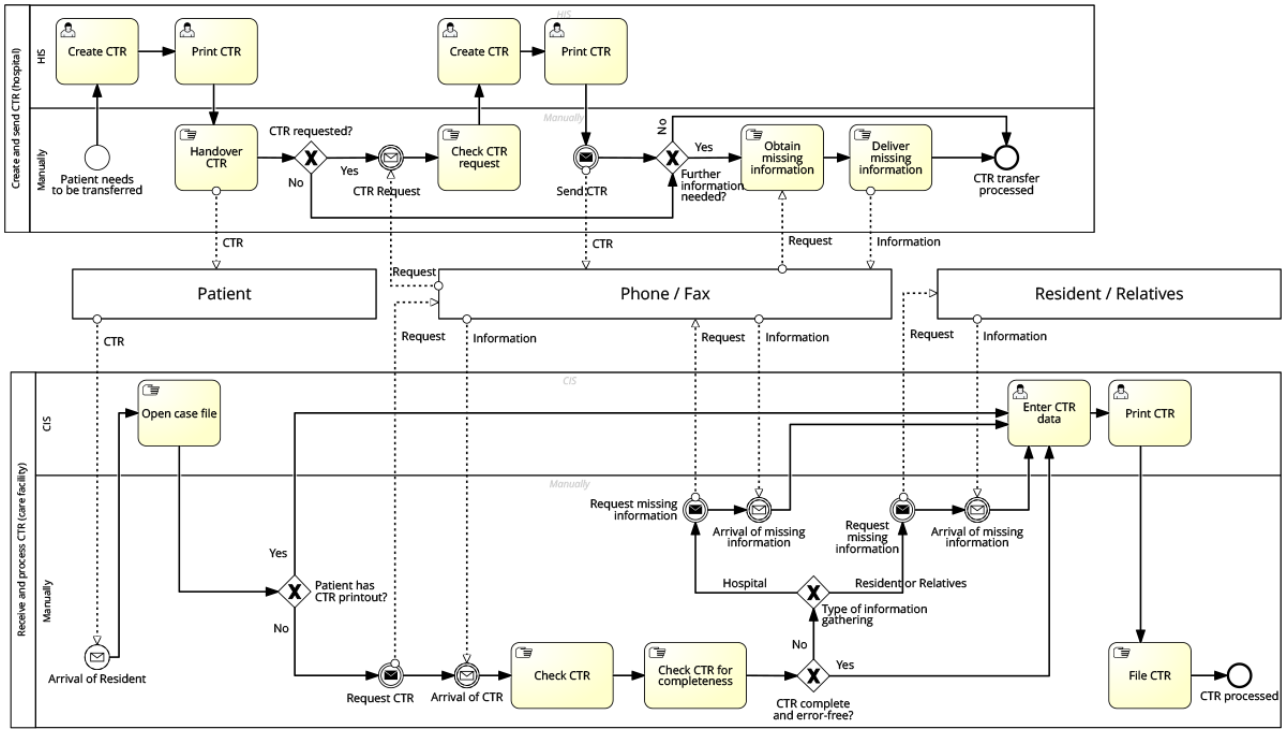
Transfer Process From Hospital to Care Facility

A patient is transferred from the UHA (Figure 2) to a care facility. At the UHA, the nurse creates a CTR, prints it, and hands it to the patient. Upon arrival of the patient (now called resident), the nurse at the care facility logs into their care information system and checks if the resident has a printed CTR. If so, they start transferring the CTR into the system. Afterward, they print the document in a proprietary file format and file it manually, then the process is complete.

If the CTR is unavailable, the nurse requests it from the UHA via phone. In the UHA, the request is checked and processed. A CTR is created, printed, and transferred via fax. Upon receipt of the missing CTR, the nurse checks whether it is the correct CTR for the resident and verifies its completeness and validity. If there is missing or incorrect information, the nurse requests the missing information either from the UHA via telephone or directly through the resident or relatives (this option does not exist in the process at the hospital). After the arrival of the missing information, the nurse starts transferring the CTR, prints it from the care information system, and manually files it. The CTR is processed, and the process is complete.

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Figure 2. Process modeling: care transition record (CTR) data transfer from hospital to care facility. CIS: case information system; HIS: hospital information system.



Semantic Analysis of CTRs

A total of 4 CTRs of cooperation facilities were analyzed regarding their structures, similarities, and differences. The analysis highlighted their different structures (eg, bowel movement on the front page or second or third page) or different wordings (eg, movement or mobility). The analysis and follow-up meetings with care staff revealed that this makes it challenging to work with CTRs effectively, as some of the most important fields are located at the end of the report. The meetings also revealed that the CTRs from the hospital are typically shorter (≤8 pages) and hold more structured information (checkboxes) than free-text fields. In comparison, CTRs from the care facilities are usually longer (≤20 pages) and include more free-text fields. The front pages of each analyzed CTR are shown in Figure 3, showcasing their different structure.

In the next step, a semantic analysis, including the mapping of CTRs to the new CIO-CTR standard, was conducted. This was done by assigning parts of the CTR to the data structure of the CIO-CTR (Figure 4). The green box represents a CIO-CTR resource, the white box represents the specification of the resource, and the red box represents the information of the CTR.

Throughout the process, it was realized that the mapping often cannot be done straightforwardly. There were some entities (eg, diagnosed diseases, deafness, aphasia, and limited vision) that could not be assigned to a single field in the CIO-CTR. This was mainly because some of the resources of the CIO-CTR format were too similar to each other. Most of the issues with overlapping assignability were resolved by further study of the CIO-CTR standard and discussion with the research team. For uncertain cases, meetings with mio42 GmbH (originator of the format) were held. Decisions regarding mappings were then based on their feedback. Nevertheless, in some cases, an assignment was still not possible. There was no resource element that provided information about whether the patient or resident had been transferred within a facility (internal; transmission, eg, within a hospital from one to another department) or outside (external; transmission from another facility).

Furthermore, some fields in the CIO-CTR are implemented as free-text fields, which makes unambiguous, error-free mapping difficult.

An excerpt of the mapping of site-specific CTRs of 2 facilities to the new standard CIO-CTR is shown subsequently. Mapping 1 focuses on the CTR of the UHA (Figure 5), and mapping 2 focuses on the CTR of 1 care facility (Figure 6). The visuals illustrate the overall complexity and difficulty of mapping each entity correctly. In mapping 1, it was possible to assign 147 (99.3%) of the 148 information objects from CTR to the CIO-CTR; in mapping 2, it was only possible to map 114 (91.2%) of the 125 information objects.

This raises the question of what should be done with the information that could not be mapped. One possibility would be to add it to the free-text fields.

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Figure 3. First page of care transition records (CTRs) from one hospital (1) and 3 care facilities (2-4).

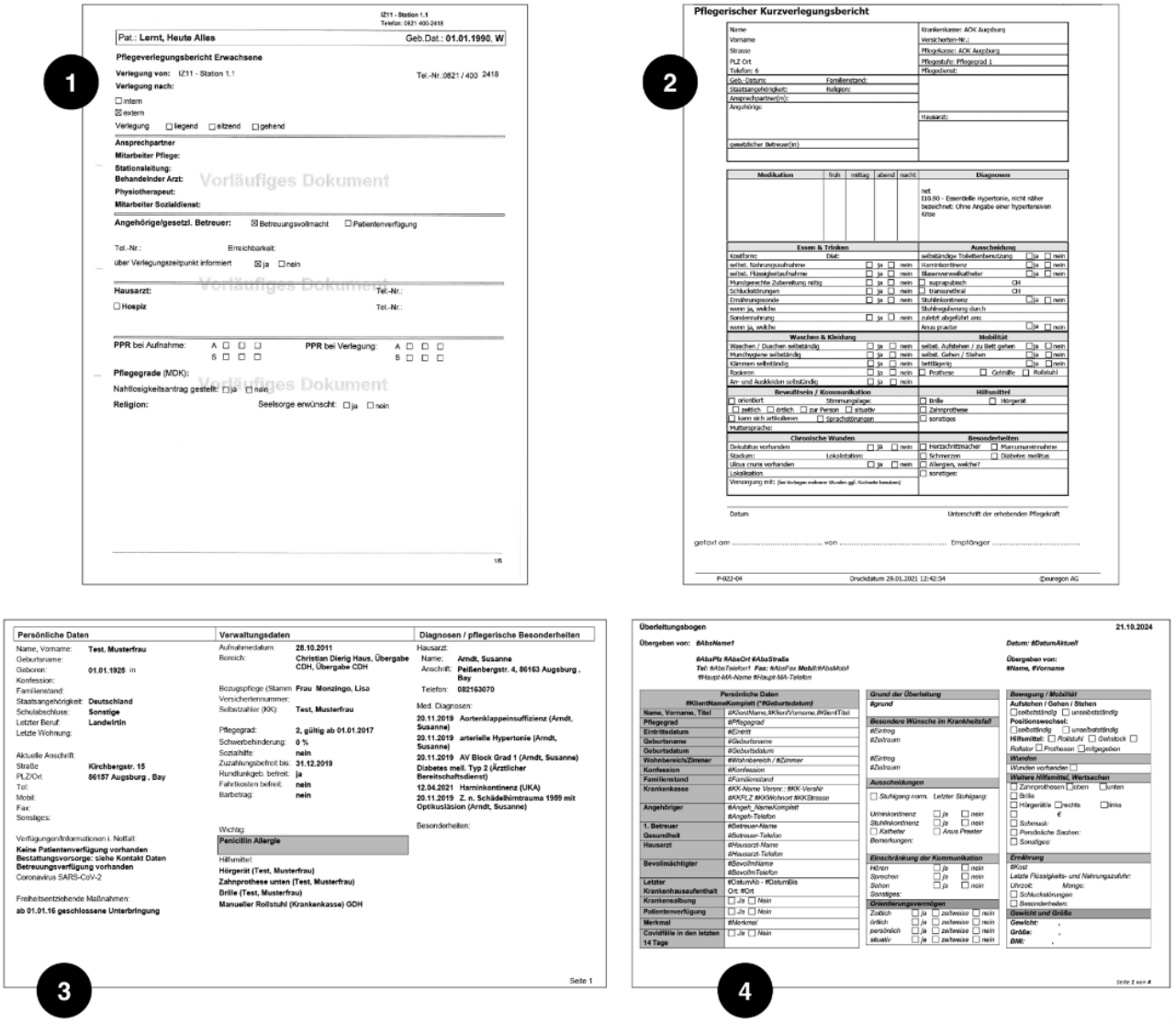
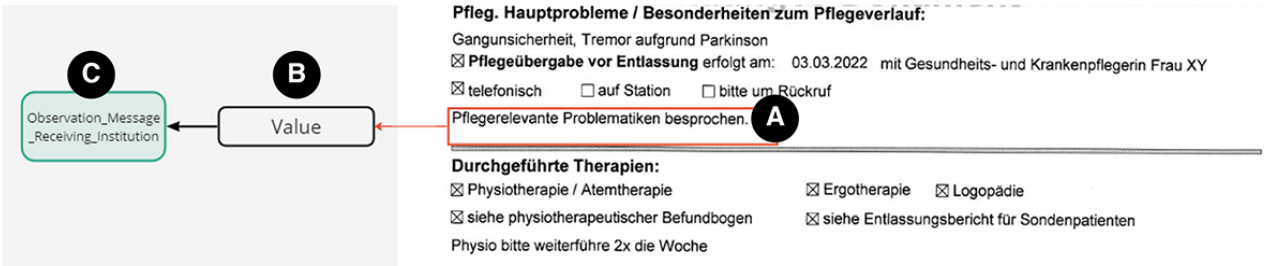


Figure 4. PDF care transition record (CTR) on the right with a free-text field (A, red rectangle) mapped to corresponding resources on the left (B, black and green rectangle, C).



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Figure 5. Mapping 1: excerpt of the mapping of a care transition record (CTR) of the University Hospital Augsburg to the care information object (CIO) CTR standard (1 of the 6 pages). The X shows that one piece of information could not be mapped.

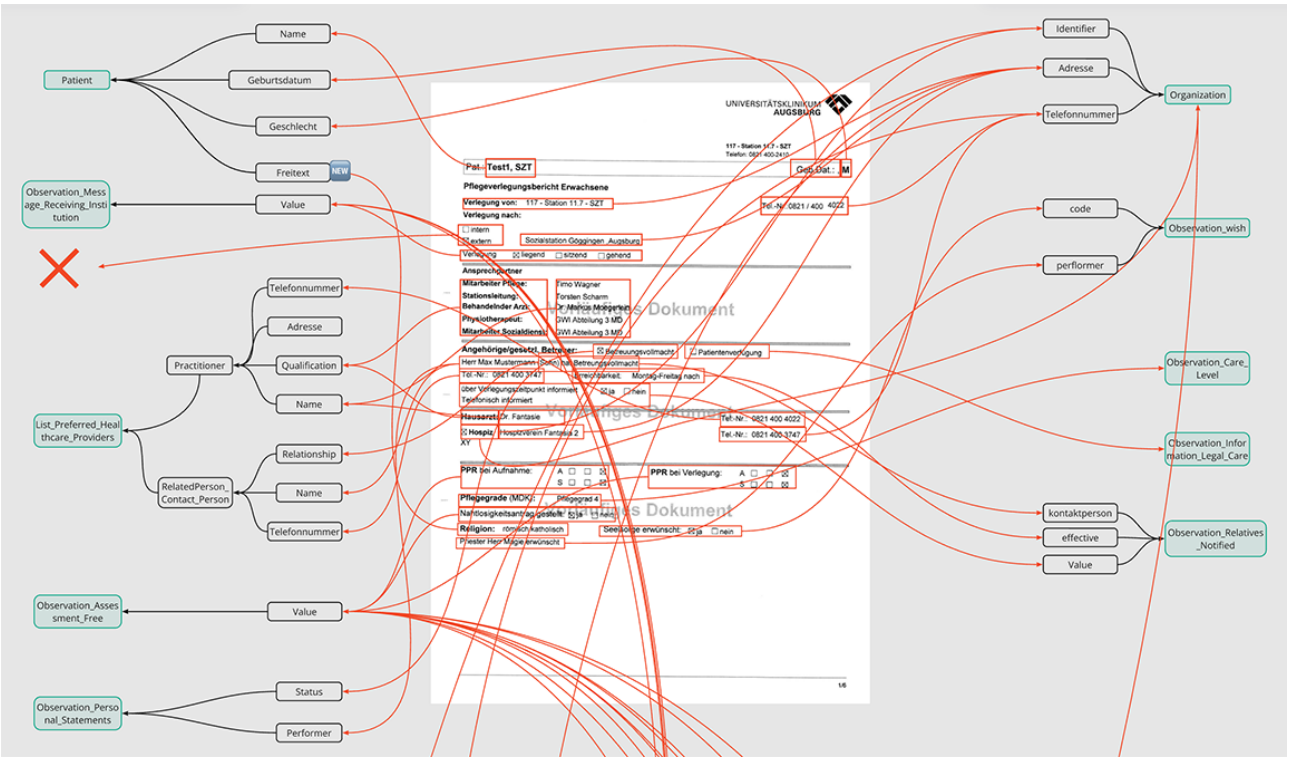
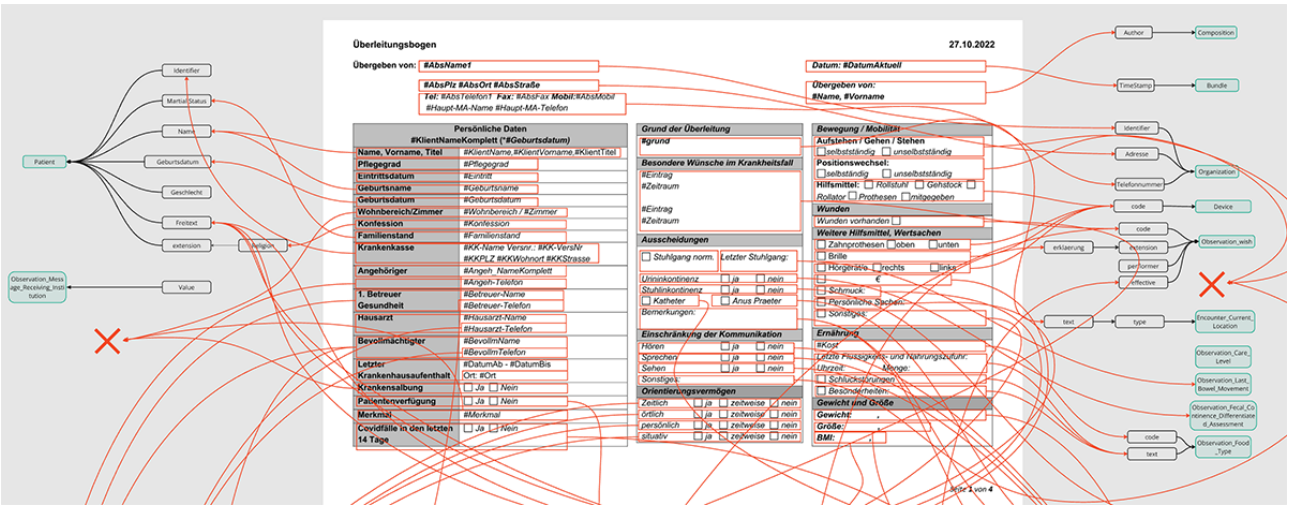


Figure 6. Mapping 2: excerpt of the mapping of a care transition record (CTR) of a care facility to the Pflegerisches Informationsobjekt (PIO) standard (1 of the 4 pages). The X shows that two pieces of information could not be mapped.



Frequency Analysis of CTR Entities at UHA

The occurrence of individual data entities in 204 CTRs of UHA and 54 CTRs from care facilities was analyzed to find out their frequencies. As comparable field entries are needed for processing, only the CTRs of UHA were used for subsequent processing, as this dataset was the biggest.

An entity is understood as a single piece of information represented in the CTR by its input field.

On the basis of these results, a percentage for each entity was computed (entity is filled or not filled), and a frequency range was created (commonly used, occasionally used, and rarely used). These ranges estimate the frequency of entities in the nursing transition process and are shown as follows: (1) 100% to 50%: commonly used entities, (2) 49% to 25%: occasionally used entities, and (3) 24% to 0%: rarely used entities

The results of each entity were presented to care staff (n=2) at UHA who are involved in the CTR process for discussion. An extract of the results is presented in Table 5. It is important to note that the frequency analysis was limited to data that did not include personal information about patients (eg, date of birth, primary care physician, contact options, and religious affiliation), as the UHA anonymized the CTRs before further processing. However, during the discussion, the nursing staff stated that all personal data could be classified as very relevant.

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Table 5. Extract from the frequency analysis from University Hospital Augsburg care transition records (N=204).

	Frequency, n (%)
Very relevant (100%-50%)	
Ability of self-body care	201 (98.5)
Orientation ability	198 (97.1)
Dressing	197 (96.6)
Medication: reference to physician's letter	195 (95.6)
State of consciousness	190 (93.1)
Nutrition	188 (92.2)
Mobility	179 (87.7)
Presence of pain	177 (86.8)
Main diagnosis	167 (81.9)
Last bowel movement	149 (73.0)
Items brought along (suitcase)	121 (59.3)
The degree of care	115 (56.4)
Relevant (49%-25%)	
Nursing-relevant secondary diagnoses	69 (33.8)
The location of the pain	68 (33.3)
The special features of the care process	58 (28.4)
Less to not relevant (24%-0%)	
Medication: reference to a medication plan	23 (11.3)
Free-text field about pain	19 (9.3)
Seamless request (yes or no)	17 (8.3)
Pastoral care requested (yes or no)	3 (1.5)
Aids ordered and their retailers	1 (0.5)
Items brought along	
Valuables	23 (11.3)
Insurance card	22 (10.8)
Identification	5 (2.5)
Patient passport	0 (0.0)

Although the information about the main diagnosis (167/204, 82.3%), state of consciousness (190/204, 93%), and nutrition (188/204, 92%) occurs with high frequency in the dataset, their placement in the paper-based CTR is inadequate, as they appear relatively late in the document.

Another finding is that bowel movement is rated as an essential piece of information (149/204, 73%), but 55/204 (27%) do not include it in the CTR.

Medication information was also expected to be present more frequently; however, because this information is usually included in the physician's letter rather than in the CTR, the occurrence was only 11% (23/204).

Regarding items brought along, many selection possibilities were given in the UHA's CTR. Valuables (23/204, 11%) and insurance cards (23/204, 11%) had the highest frequency among them. However, no additional information about the individual items could be provided.

User Story Mapping

There were 2 workshops conducted, involving a total of 7 participants. These participants were part of the core research project team, bringing diverse expertise from various disciplines: health care (n=2, 29%), computer science (n=3, 43%), design (n=1, 14%), and IT security (n=1, 14%). All 7 (100%) participants attended both workshops, ensuring continuity and consistency in the discussions and decisions. During the first workshop (hybrid, due to COVID-19 restrictions), participants used both physical materials (paper and whiteboards) and digital tools (Zoom [Zoom Communications] and chat) to record potential user stories. The process involved writing down ideas and then engaging in a collaborative card-sorting exercise to discuss and prioritize these stories. A whiteboard was used to document the structured user journey, which was shared with

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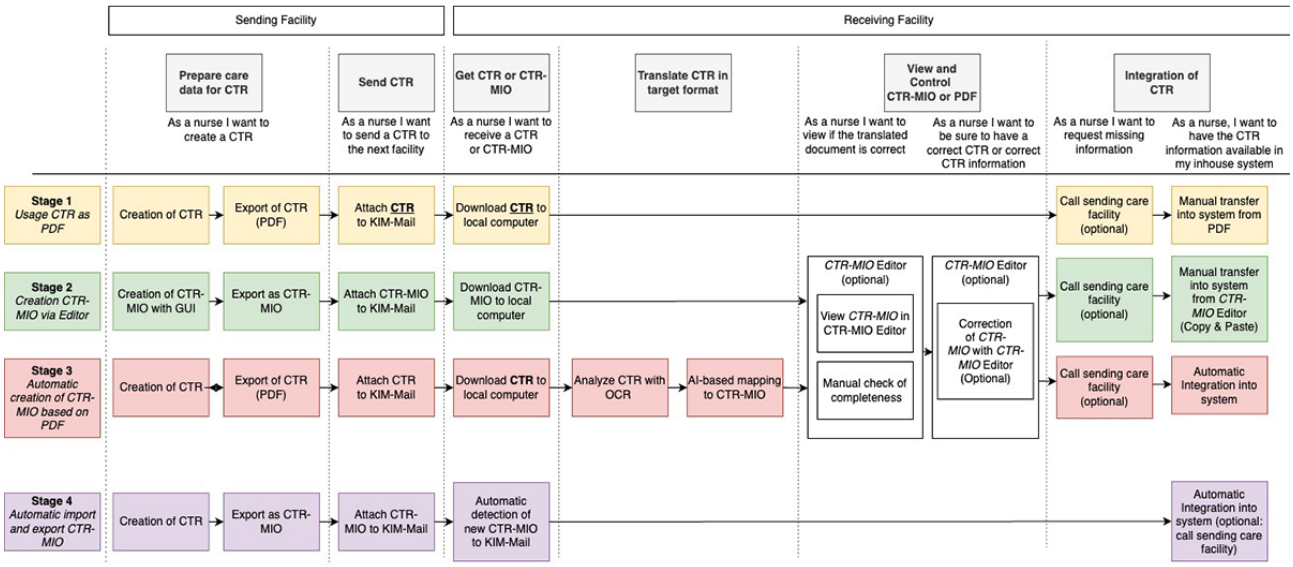
online participants via camera, ensuring everyone had equal access to the visual information.

Between the first and second workshops, participants had approximately 2 weeks to reflect on the identified user stories and their potential impact on the development process. This period allowed the team to refine their understanding and prepare for the next stage of discussion, which focused on a stepwise implementation plan (release planning).

The second workshop was conducted entirely online using the tools Zoom and Miro. Miro is an online collaborative platform developed by RealtimeBoard Inc. The participants had time to share their reflections on the previous work, discuss it, and refine their understanding of the user journey. Afterward, the participants focused on creating release stages to guide the upcoming development. They collaboratively designed the user story map due to the workshops, which was continuously refined throughout the project. The final result, a road map proposal, can be seen in Figure 7. The Backbone section describes the backbone and the proposed solution's release stages.

In Figure 7, four release stages are shown on the left and divided into 4 colors to provide a better division throughout the user stories. Some story cards do not have color, as they apply to multiple release stages. The subsequent sections describe the use dimensions, backbone, release stages, and implementation scenarios.

Figure 7. Final user story mapping with 4 release stages (on the left). Colors are used to better distinguish between the stages. Some story cards do not have color, as they apply to multiple stages. AI: artificial intelligence; CIO: care information object; CTR: care transition record; KIM: Kommunikation im Medizinwesen.



Backbone

The horizontal axis of the user story map shows the main activities that have to be performed sequentially to achieve care data exchange between facilities. These activities are referred to as epics and are listed in the top row of Figure 7. The user stories concretize the epics. One activity (translating CTR in target format) has to be performed only in an intermediate release stage, and it becomes obsolete as soon as all facilities use the standardized target format.

Release Stages

A brief overview of all 4 release stages can be seen in Figure 7. A description of each stage is given in the subsequent sections.

Release Stage 1: Use of CTR in PDF Format

The first release requires the least implementation effort but already meets one basic requirement: timely, digital transfer via the TI. The functionality is limited to conventional CTRs, typically in PDF format. This release requires both the sending and receiving care facilities to be connected to the TI. As usual, the sending facility creates a CTR in its facility-specific layout and transmits it using the KIM service. The receiving facility can then retrieve the CTR from its KIM mailbox.

Release Stage 2: Creation of CIO-CTR via Editor

At the beginning of a transition process to the new standardized CIO-CTR format, few or no in-house systems will support the new standard. To remain independent from software manufacturers, a dedicated software module that can create, read, and edit CTRs in the new format ("CIO-CTR editor") would be beneficial. Nurses could use this editor to create CIO-CTRs and send them to the receiving institution via KIM. Particular emphasis should be placed on the user-centered design of the interface, particularly regarding the structure of the input options and how information is compiled. This could serve as a blueprint for later implementation in the proprietary software systems.

Release Stage 3: Automatic Creation of CIO-CTR Based on PDF

Another, more complex way to create and transfer a CTR in the new standard format is to transform the conventional, proprietary CTR using an automatic artificial intelligence (AI)–based tool. On the basis of the previous analysis of CTRs, it can be assumed that most CTR data will be unstructured and provided in PDF

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format. A transformer service could analyze this structure using AI and extract text sections with an optical character recognition module. The extracted content is then mapped to the CIO-CTR format. This approach would be relevant if a receiving facility is already capable of processing CIO-CTRs but receives a nonstandardized CTR via KIM. With a transformer, the new CTR-CIO format can be generated and imported with little extra effort.

Release Stage 4: Automatic Export and Import of CIO-CTR

In this final stage, the care staff can create a CTR in the in-house system, export it as a CIO-CTR, and transfer it via the TI. After receiving the CIO-CTR, the receiving facility can then integrate it directly into their in-house system. The benefit is that neither a transformer service nor a separate editor would be needed, resulting in the least effort for the care staff. This requires the software manufacturers of the various care and medical information systems to fully support the new CIO-CTR format; however, it is unclear when this will happen.

Discussion

Principal Findings

Despite years of efforts toward digitalization in health care in Germany, our research shows that the creation and transmission of CTRs remain highly time-consuming, averaging 34.67 (SD 10.78) minutes at hospitals and 44.6 (SD 20.5) minutes in care facilities (findings from observations).

Semantic Interoperability of CTRs Between Institutions

As health care systems transition toward digital formats, it becomes increasingly important to enable different institutions to exchange, understand, and use the transmitted data seamlessly. From the perspective of nursing science, discharge management has long been recognized as a crucial aspect of patient care. Efficient discharge processes ensure that patients receive continued care, reduce readmission rates, and improve overall patient outcomes. The CIO-CTR standard, introduced in December 2022, marks a significant step toward a fully digital exchange of CTR data. However, our study reveals that this progress has been hampered by a lack of widespread implementation and resistance. Because the CIO-CTR is not legally binding and the necessary updates are resource intensive for software manufacturers, they prefer to concentrate on more urgent issues. Thus, we propose an iterative, stepwise implementation approach that could gradually improve the situation.

Iterative Implementation Approach

The user story map with the resulting release stages offers a step-by-step approach toward a seamless digital solution. As the overall issue is complex, changes cannot be expected simultaneously at all ends. A quick, early solution is the mere digital transfer of CTRs in existing, proprietary formats via a digital infrastructure (stage 1). For this, the institutions only have to be connected to the health data network (TI), as they are obliged by law in Germany by July 1, 2025 (according to §341 (8) SGB V [46]) and a KIM account is set up. Sending CTRs in the institutions' traditional formats does not require them to have updated software that can read or export the new CIO-CTR format. At this stage, the time-consuming manual data transfer into the in-house systems is still required. The goal is for all software systems in all institutions to directly import and export CTRs in the new format, and for all the information to be integrated automatically into in-house systems (stage 4). During a transition time, when only some of the systems can process CTRs in the new format, certain incompatibilities will occur, which we want to address with interim solutions: the CIO-CTR viewer or editor (stage 2) and the CTR-transformer (stage 3).

For stage 1 (data transfer via TI), we accompany and assist our cooperating partner institutions in installing the necessary infrastructure to connect to the TI. In this regard, we plan to offer experience reports, which could lower the entry hurdle, particularly for care facilities.

For stage 2, we are developing an open-source software where CIO-CTRs can be created, viewed, and edited. This has several benefits: (1) developing an editor with a concrete suggestion for a user interface visualizing the CIO-CTR standard provides a figurative basis for discussion between developers, care professionals, and regulatory institutions; (2) bridging the gap for continuous digital transfer if not all institutions support the new digital standard; and (3) serving as a blueprint for software manufacturers who want to implement the new CIO-CTR.

Stage 3 introduces an automated process to convert CTRs from proprietary formats (eg, scanned PDFs) into the CIO-CTR format, using AI-based mapping. This solution is applicable when an institution that can process CIO-CTRs but receives a nonstandardized CTR. Of course, this automatic transfer would have to be reliable, and creating such a component would be complex, as many different proprietary formats exist, and as seen in the semantic mapping, a direct transfer is not possible in all cases.

Stage 4 represents the most desirable solution. Nurses would be able to work with an improved process without manual transfer of CTR data, potentially leading to a minimization of disruptions. The primary responsibility for implementing the CIO-CTR falls on system manufacturers. To facilitate this transition, the manufacturers could actively be supported by providing a reference implementation for the new standard, for example, conducting workshops and organizing related events. This collaborative effort would support a smooth and efficient integration of the CIO-CTR into existing systems while minimizing the burden on health care providers.

Contributions

Our research used an iterative, user-centered methodological approach to develop a road map that helps overcome the current challenges in the CTR transmission process in Germany. This road map offers a practical, phased approach toward digital solutions, particularly valuable in settings where full-scale adoption of digital standards is not yet feasible. It provides health care providers with a flexible pathway to transition toward digital care processes without requiring immediate, costly

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system changes. This road map is more than the mere definition of a new format; it supports gradual digital integration.

Future Implications and Work

If the adoption of digital standards remains voluntary and lacks regulatory support, the duration required to establish a standard data format is likely to be prolonged. Without more vigorous regulatory enforcement and widespread buy-in from all stakeholders, the vision of seamless care transitions may remain out of reach. Therefore, future efforts must focus not only on technological solutions but also on fostering collaboration between regulators, software providers, and health care institutions to ensure the long-term success of health care digitalization.

Our current solution uses KIM as a means of transport within the TI. As soon as the ePA is more widely adopted in Germany, an exchange of the CTR via this means might be preferable over KIM. Future work has to investigate this further.

Limitations

The COVID-19 pandemic posed significant challenges for data collection, particularly in gaining access to cooperative facilities. The necessary planning and multiple postponements due to visitor restrictions limited our ability to observe the complete care transition process.

The pandemic may have also introduced a selection bias in our web-based questionnaire. Nurses facing higher technical barriers or those under significant stress due to pandemic-related demands may have been less likely to participate, which could skew the findings toward participants who were more technically adept or had fewer pandemic-related pressures.

Furthermore, the sample size of the web-based questionnaire (n=33 usable datasets), while offering valuable qualitative insights, limits the generalizability of our findings.

Our study used a qualitative research approach to gain in-depth, context-specific insights. The combination of field observations, contextual inquiries, and questionnaire data from hospital and care facilities provided a rich understanding of the practical barriers and opportunities in transitioning to digital CTR processes. The relatively small sample sizes for field observations (n=6) and contextual inquiries (n=5) were sufficient for this research's detailed, exploratory nature but could limit the robustness of the conclusions.

Conclusions

A future solution should simplify the overall CTR transmission process by minimizing the manual transfers into the in-house systems, standardizing the CTR, and providing a secure digital transfer. Doing so could positively impact the overall care process and patient experience. With our suggestion for a stepwise solution, we attempt to make the complex task feasible, ultimately supporting care staff with their daily activities and processes.

Acknowledgments

This research is part of the project CARE REGIO, funded by the Bavarian State Ministry of Health, Care and Prevention. The authors would like to thank their partners from 3 local health care institutions for participating in the stakeholder workshop, allowing them to conduct field observations and contextual inquiries at their sites, and discussing their care transition records. The authors would also like to thank the University of Applied Sciences in Neu-Ulm (Institut DigiHealth) for its support regarding legal issues and ethics. Writing artificial intelligence (AI) assistants ChatGPT-3.5, 4.0 (OpenAI); Grammarly (Grammarly Inc); and DeepL (DeepL SE) were used for language improvement and text shortening. These or any other AI systems created no scientific content in this manuscript.

Authors' Contributions

EVM, AM, CR, and AT were involved in the conceptualization. EVM, SB, LK, and MR were involved in formal analysis. EVM, SB, MR, LK, LD, ST, VW, CR, and AT were involved in the investigation. EVM, SB, MR, LK, LD, ST, and AT were involved in data curation. EVM, SB, MR, LK, and AT were involved in writing the original draft. EVM, SB, VW, and AT were involved in reviewing and editing the draft. EVM and LK were involved in visualization. AT was involved in supervising the study.

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence
BPMN: business process model and notation
CIO: care information object
CTR: care transition record
ePA: electronic patient record
GDPR: General Data Protection Regulation
HL7: Health Level 7
KIM: Kommunikation im Medizinwesen
TI: telematics infrastructure
UHA: University Hospital Augsburg

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Edited by E Borycki; submitted 23.05.24; peer-reviewed by PDD Flemming, RA El Arab; comments to author 22.07.24; revised version received 23.10.24; accepted 12.11.24; published 21.02.25.

Please cite as:
Mess EV, Regner M, Balic S, Kleybolte L, Daufratshofer L, Mahler A, Tilmes S, Werlitz V, Reuter C, Teynor A
Detailed Analysis and Road Map Proposal for Care Transition Records and Their Transmission Process: Mixed Methods Study
JMIR Nursing 2025;8:e60810
URL: https://nursing.jmir.org/2025/1/e60810
doi:10.2196/60810
PMID:39982779

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Effect of Digital Tools on the Knowledge and Performance of Frontline Health Workers For Diabetes Control in Myanmar: Cost-Effective Analysis and Quasi Experimental Study

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Abstract

Background: Diabetes has become a significant global health issue, particularly imposing a deep economic burden on low-income countries. Innovative and integrated digital solutions can reduce the impact of diabetes and enhance the quality of care. However, digital solutions have not been utilized before in Myanmar.

Objective: This study aimed to demonstrate the novel integrated effect of diabetes knowledge and registry tools on the performance of front-line health workers in primary health care settings.

Methods: A quasi-experimental study with an intervention and a control group was conducted in two townships from October 2022 to April 2023. For the first time, researchers trained the intervention group to use digital tools for diabetes control and performed monthly follow-ups. The study employed multiple linear regression models to explore the novel impact of digital tools on knowledge and performance scores, their correlations, and their association with covariates. Additionally, it assessed the cost-effectiveness of the intervention by using self-administered questionnaires as measurement tools formulated based on the National Diabetes Guidelines.

Results: A total of 96 participants were enrolled in the study, divided evenly into the two groups. The intervention group exhibited a significant increase in the mean knowledge scores from 85.81 to 99.25 (P<.001) and performance scores from 71.22 to 107.16 (P<.001). The intervention accounted for 43.2% of the variance in knowledge scores and 62.5% in performance scores (P<.001). A positive correlation was found between knowledge and performance scores (r=0.45, P<.001). The intervention was also cost-effective, with a cost-effectiveness analysis value of 0.711 and an incremental cost-effectiveness ratio of 10127.04 Kyats (US$ 4.83).

Conclusions: As the new integrated intervention yields significant economic gains and positive effects, researchers suggest policy makers replicate this intervention as a nationwide program and recommend scaling up the use of digital tools to improve knowledge and performance for diabetes control in frontline health workers.

(JMIR Nursing 2025;8:e72230) doi:10.2196/72230

KEYWORDS

diabetes mellitus; digital tools; cost-effectiveness analysis; health personnel; Myanmar

Introduction

Global Situation Regarding Diabetes

Diabetes is a life-threatening chronic disease that requires effective and sustainable care and treatment. In 2021, it was responsible for 6.7 million deaths worldwide, and the number of people affected was estimated at 537 million, projected to rise to 783 million by 2045 [1]. Despite the increasing burden of diabetes, there is a shortfall of 5.9 million health care professionals required to provide quality care for people living with diabetes [2]. Moreover, many low-income countries face challenges in translating evidence-based knowledge, cost-effective guidelines, and electronic records into actionable solutions to enhance the ability of frontline health workers to deliver quality diabetes services [3].

Health IT has great potential for enhancing diabetes management by saving time and costs involved in data interpretation. Digital knowledge tools can serve as an effective resource for bridging knowledge gaps among health care providers; however, the integrated effect of knowledge tools and diabetes registry on

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provider performance is not well known [4]. The World Health Organization (WHO) indicates that only 50% of countries use electronic diabetes registries and expects national data to be standardized when registry coverage exceeds 75% [5]. Many low-income countries still struggle to provide comprehensive digital tools for knowledge and registries for frontline health workers. Myanmar should seize these opportunities to improve community-level diabetes care management.

Cost-effective interventions are urgently needed to address the diabetes burden, which cost US$ 966 billion globally in 2021. Southeast Asia's expenditure was significantly lower at US$ 10.1 billion, compared to North America's US$ 414.5 billion [6]. Therefore, it is vital to implement high-impact and affordable solutions in low-income countries. A meta-analysis shows that digital tools for diabetes knowledge can be cost-effective [7], yet there is limited evidence in low-income settings [8]. Therefore, it is essential to perform integrated and interdisciplinary research on digital tools for the effective implementation of diabetes control programs in the region.

Myanmar Context for Diabetes

Myanmar is one of the countries in Southeast Asia with a high burden of diabetes, with a prevalence among 10.5% of the population, which is comparatively higher than that in other countries in the region [9]. A diabetes prevalence survey conducted in 2014 revealed that the burden of the disease had doubled over a decade, and there were no effective strategies or guidelines implemented to raise awareness about diabetes management [10]. Additionally, health workers need to enhance their knowledge, and further research is necessary to improve the quality of diabetes control services at the primary health care level [11].

The rapid growth of mobile technology in Myanmar has created new opportunities for digital health. In 2014, the Ministry of Health established an electronic health management information system and a real-time District Health Information System for all townships. They also distributed 26,000 tablets with essential guidelines for frontline health workers [12]. However, the digital health information system is still in its early stages, and no specific digital application for the diabetes control program exists.

Objectives

Unlike other studies, this study aimed to evaluate the novel integrated effects of digital tools on diabetes knowledge and registry in relation to diabetes control performance among frontline health care workers in Myanmar. The primary outcomes of the study were the knowledge and performance levels of the health workers, while the secondary outcome was the cost-effectiveness of the intervention.

Conceptual Frameworks

Researchers designed the study based on two main theories: attribution theory, which examines how knowledge affects diabetes management [13]; and an economic principle assessing the cost-effectiveness of digital health technology [14]. The research hypothesized that integrated digital tools would enhance frontline health workers' knowledge and performance by reducing diabetes program costs.

Methods

Study Design

A quasi-experimental study was conducted in Naypyitaw, the capital of Myanmar, between October 2022 and April 2023 (spanning 6 months). Two townships were selected for the intervention and control groups based on matched population characteristics, geographical conditions, and access to essential diabetes control packages offered by the diabetes control program. The selection criteria for the study areas included a high unknown prevalence of diabetes among the population and inadequate knowledge among health workers [15]. Baseline and endline assessments were carried out for both the groups.

Participants

Frontline health staff, including midwives, lady health visitors, and public health supervisors, were selected for the study based on specific inclusion criteria: involvement in the diabetes control program, ability to use digital tools, and willingness to participate. Exclusion criteria included those absent for over 1 month, nearing retirement, deemed unfit for intervention, or not approved by supervisors. Using G*Power software (version 3.1.9.2; Heinrich-Heine-Universitat Dusseldorf), the sample size was calculated for multiple linear regression with a 95% CI and power. The reference minimum effect size of the intervention on diabetes control was $F_{4,75}$=.25 [16]. The minimum sample required was 86 participants, and 96 were recruited to account for dropouts, finally assigning 48 participants to each group.

Interventions

The new intervention involved integrating the two new digital tools developed by the authors, Myanmar Diabetes Guides and Digital Registry. This is unique and significant because other studies measure the silo effects [17]. Researchers installed digital tools and provided 3 days of intensive training on how to use the tools. Additionally, researchers conducted monthly follow-ups and provided reorientation sessions to the intervention group.

Myanmar Diabetes Guide

This is a new comprehensive bilingual knowledge tool developed by researchers in collaboration with the National Diabetes Control Program. According to the WHO and National program guidelines, the tool addresses the risks and promotes the health, screening, diagnosis, care and treatment, and complication referrals. It includes interactive patient dialogues, video demonstrations, and diabetes-related wikis. The tool is open to access in both online and offline settings and can be used on mobile tablets [18].

Diabetes Registry Tool

The electronic diabetes registry tool was designed using Kobo Toolbox, an open-source tool for field data collection in humanitarian response [19]. This tool collects vital patient information for diabetes management programs and replaces

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paper-based reporting. The tools enable health workers to trace risk factors, analyze data, calculate prevalence, identify complications, and estimate the requirement of diabetes-related commodities. The application is available for online and offline use and is compatible with both tablets and computers with a user password to protect data privacy [19].

Training for Utilization of the Application

Researchers conducted training on the orientation for using the digital tools that consisted of three components with lectures, demonstration, and practice sessions on (i) health promotion, identifying high-risk individuals, and establishing volunteer networks; (ii) training for the diabetes knowledge tools; and (iii) training for the diabetes registry tool.

Measurement Instruments

The researchers developed self-administered questionnaires for data collection. The questionnaire was created in English and subsequently translated into the Burmese language. It included a scoring system for the primary outcomes, which assessed the knowledge and performance in five key domains of diabetes management: (i) health promotion, (ii) diabetes screening, (iii) care and treatment, (iv) referral, and (v) reporting, all referencing the WHO and National Diabetes Guidelines. The researchers established an expert panel to review the questionnaire to ensure content validity. This panel included a diabetes program manager, an expert clinician, and township health officers. The validity index for the questionnaire was scored at 0.6. Additionally, the reliability of the questionnaire was pretested by two different observers, with an interrater kappa value of 0.68 between the two observers.

The WHO-CHOICE (WHO's Choosing Interventions that are Cost-Effective) Analysis tool for noncommunicable diseases was used to measure costing data [20]. This costing data included direct costs (intervention costs, program costs, and treatment costs) and indirect costs (communication, consulting, value of time, and work). The cost-effectiveness analysis aimed to demonstrate the economic benefits of the intervention for future investments.

Data Collection and Statistical Analysis

The principal investigator and two research assistants collected baseline and endline data. Before data collection began, the study's purpose was explained to authorities and participants. Primary cost data were obtained from participants, while secondary data on treatment costs came from the township hospital and program costs from the township health departments. The team checked the accuracy of the questionnaires, addressed any missing responses, and cross-verified participant data with the secondary data. Health assistants from the townships were followed-up monthly on using the tools.

Data analysis was conducted using SPSS software (version 22.0; IBM Corp). Knowledge and performance scores followed the National Diabetes Control Guideline criteria. Sociodemographic data differences were assessed with the χ^2 test, mean outcome data with the *t* test, and outcome correlations with the Pearson correlation test. The impact of the intervention was evaluated using multiple logistic regression analysis. All tests were statistically significant at a 95% CI. Cost-effectiveness was assessed through the cost-effectiveness ratio and incremental cost-effectiveness ratio.

Ethical Considerations

The study received approval from the Chulalongkorn University Ethics Review Committee (090.2/64, COA No. 177/2022). The Ministry of Health, Naypyitaw Department of Health, granted permission for data collection (NPT/NCD/007-2021/5925). Participation in the research was voluntary; informed consent was obtained, and data confidentiality was ensured. During the registration, an internet package (US$ 2) and a 50 pcs box of surgical masks were provided to participants as compansation for participating the research.

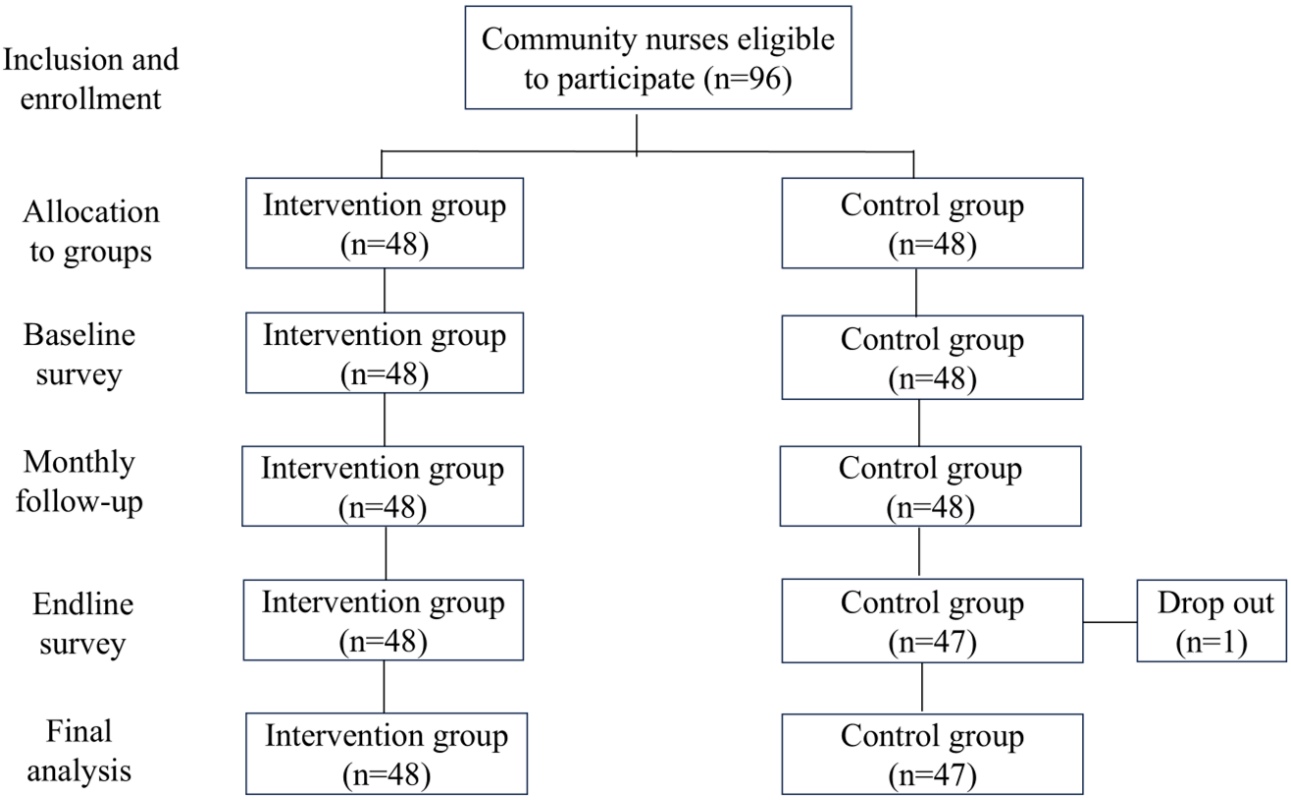
Results

Patient Inclusion

Ninety-six participants enrolled in the study, and 1 patient dropped out. Figure 1 shows the flow chart of the quasi-experimental study design.

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Figure 1. Flow chart for quasi-experimental design.



Participant Sociodemographic Characteristics

The study used the χ^2 test to examine participant characteristics in relation to the sociodemographic variables, work-related variables, and variables related to diabetes control (Table 1). Significant differences between the two groups were observed based on gender (*P*=.02), job designation (*P*=.02), distance from the township (*P*=.001), and duration of internet use (*P*=.001).

Independent *t* tests analyzed differences in mean knowledge and performance scores. The mean knowledge scores were statistically associated with gender (*P*=.001), job designation (*P*<.001), and diabetes control training (*P*=.02). The mean performance scores were statistically associated with gender (*P*=.04). job designation (*P*=.009), diabetes control training (*P*=.02), diabetes registry training (*P*=.02), number of postings (*P*=.03), level of facilities (*P*=.02), and experiences with diabetes campaigns (*P*=.007).

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Table . Sociodemographic variables of the participants (n=96).

Sociodemographic variables	Total (n=96)	Intervention group (n=48)	Control group (n=48)	*P* value
Age (years), mean (SD)	32.71 (9.52)	31.75 (9.18)	33.67 (9.55)	.33[a]
Gender, n (%)				.02[b,c]
Male	14 (14)	3 (6.3)	11 (22.9)	
Female	82 (82)	45 (93.7)	37 (77.1)	
Marital status, n (%)				.33[b]
Single	31 (32.3)	14 (29.2)	17 (35.4)	
Married	65 (67.7)	34 (70.8)	31 (64.6)	
Educational status, n (%)				.58[b]
High school	24 (25)	11 (22.9)	13 (27.1)	
Graduate	72 (75)	37 (77.1)	35 (72.9)	
Designations, n (%)				.02[b,c]
Lady health visitors	8 (8.3)	4 (8.3)	4 (8.3)	
Midwives	55 (57.3)	34 (70.9)	21(43.8)	
Public health supervisor	33 (34.4)	10 (20.8)	23 (47.9)	
Number of postings, n (%)				.73[b]
1st posting	55 (57.3)	27 (56.3)	28 (58.3)	
2nd-5th posting	30 (31.3)	16 (33.3)	14 (29.2)	
>5th posting	11 (11.4)	5 (10.4)	6 (12.5)	
Level of facilities, n (%)				.74[b]
Township	19 (19.8)	11 (22.9)	8 (16.7)	
Rural health center	21 (21.9)	10 (20.8)	11 (22.9)	
Subcenter	56 (58.3)	27 (56.3)	29 (60.4)	
Distance from township, n (%)				.001[b,c]
≤10 miles	55 (57.3)	19 (39.6)	36 (75)	
>10 miles	41 (42.7)	29 (60.4)	12 (25)	
DM[d] control training, n (%)				.50[b]
Received before	67 (69.8)	33 (68.8)	34 (70.8)	
Never received	29 (30.2)	15 (31.2)	14 (29.2)	
DM registry training, n (%)				.21[b]
Received before	47 (49)	26 (54.2)	21 (43.8)	
Never received	49 (51)	22 (45.8)	27 (56.2)	
DM campaign experiences, n (%)				.11[b]
Received before	57 (59.4)	25 (52.1)	32 (66.7)	
Never received	39 (40.6)	23 (47.9)	16 (33.3)	
Duration of internet usage, n (%)				.001[b,c]
≤5 years	49 (51)	35 (72.9)	14 (29.2)	
>5years	47 (49)	13 (27.1)	34 (70.8)	

[a]independent t-test.

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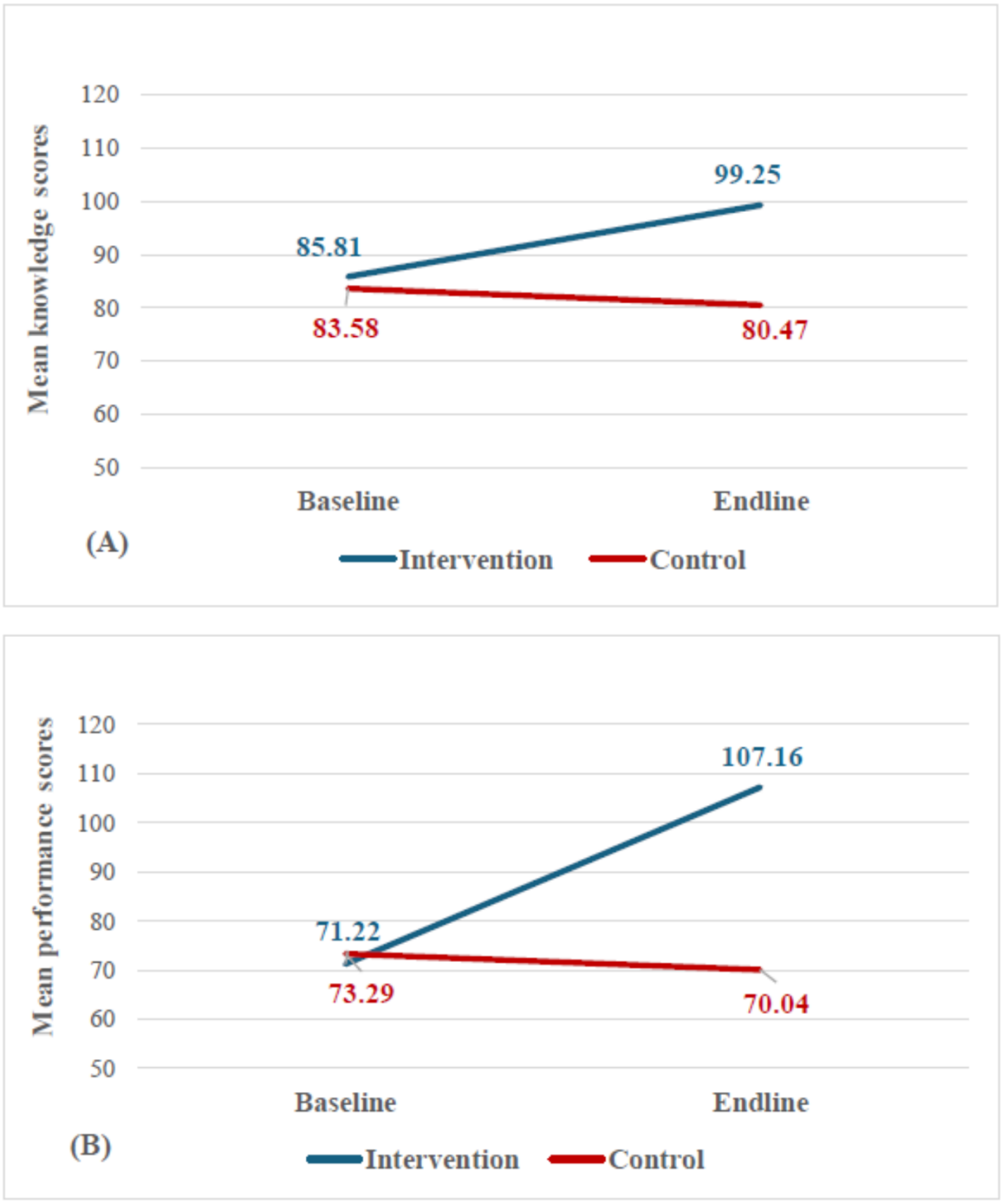
[b]χ^2 test.
[c]statistically significant $P<.05$.
[d]DM: diabetes mellitus.

Effect of Intervention on Knowledge

An average of 94.2% of the intervention group (45/48) regularly utilized diabetes knowledge tools. During the baseline assessment, no significant difference in the mean knowledge scores was noted between the two groups ($P=.20$). However, a significant difference emerged between the two groups at the endline ($P<.001$). The mean (SD) knowledge score in the intervention group rose significantly from 85.04 (9.73) to 99.25 (5.33; $P<.001$). In contrast, the mean (SD) knowledge score in the control group slightly declined from 83.58 (11.17) to 80.47 (16.99) (Figure 2); however, this change was not significant ($P=.21$; Table 2). The multiple linear regression model, after adjusting for potential confounding factors, showed a significant effect, with an adjusted r^2 of 0.43, an unstandardized β coefficient of 17.769, and a standardized β coefficient of 0.569 ($P<.001$; Table 3).

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Figure 2. Comparison of mean outcomes between the intervention and control: (A) mean knowledge scoring, (B) mean performance scoring.



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Table . Comparison of mean outcome variables between the intervention and control groups.

Outcome variable	Total Mean (SD) N B[a]=96 N E[b]=95	Intervention group Mean (SD) N B=48 N E=48	Control group Mean (SD) N B=48 N E=47	*P* value[c]
Knowledge Scoring				
Total knowledge scoring B	85.04 (9.73)	85.81 (8.20)	83.58 (11.17)	.20
Total knowledge scoring E	87.25 (21.67)	99.25 (5.33)	80.47 (16.99)	<.001[d]
Health promotion B	20.01 (2.51)	20.00 (2.37)	19.95 (2.71)	.76
Health promotion E	20.22 (4.83)	22.35 (1.53)	19.31 (3.96)	<.001[d]
Screening and diagnosis B	19.23 (3.52)	19.25 (3.55)	19 (3.44)	.55
Screening and diagnosis E	19.93 (5.34)	22.68 (2.41)	18.41 (4.46)	<.001[d]
Care and treatment B	16.82 (3.12)	17.68 (2.69)	15.97 (3.29)	.08
Care and treatment E	18.15 (5.46)	21.54 (1.67)	15.72 (4.55)	<.001[d]
Referral of severe cases B	14.34 (2.44)	14.43 (1.85)	14.10 (2.91)	.47
Referral of severe cases E	14.63 (3.94)	16.46 (1.43)	13.50 (3.42)	<.001[d]
Reporting and registry B	14.52 (2.24)	14.43 (2.21)	14.54 (2.33)	.89
Reporting and registry E	14.45 (3.86)	16.21 (1.50)	13.52 (3.19)	<.001[d]
Performance scoring				
Total performance scoring B	72.33 (9.73)	71.22 (28.35)	73.29 (35.66)	.75
Total performance scoring E	88.50 (33.50)	107.16 (15.62)	70.04 (29.72)	<.001[d]
Health promotion B	9.23 (4.22)	9.54 (3.99)	8.91 (4.23)	.46
Health promotion E	10.59 (3.8)	12.42 (2.15)	8.77 (3.44)	<.001 [d]
Screening and diagnosis B	9.41 (4.32)	9.38 (4.28)	9.42 (4.26)	.97
Screening and diagnosis E	10.37 (4.1)	12.56 (2.89)	8.17 (3.13)	<.001[d]
Care and treatment B	38.93 (20.83)	37.17 (19.57)	40.54 (22.06)	.43
Care and treatment E	49.01(21.6)	59.08 (12.21)	38.95 (21.17)	<.001 [d]
Referral of severe cases B	4.24 (4.14)	3.89 (4.21)	4.73 (4.21)	.34
Referral of severe cases E	5.37 (5.3)	7.13 (6.24)	3.60 (3.49)	.001[d]
Reporting and registry B	10.42 (6.23)	11.23 (5.68)	9.56 (6.58)	.19
Reporting and registry E	13.24 (6.5)	15.95 (4.20)	10.54 (6.78)	<.001[d]

[a]B=baseline.

[b]E=endline.

[c]independent t-test.

[d]statistically significant *P*<.05.

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Table . Effect of intervention on total knowledge scoring after adjusting for all possible confounding variables (full model multiple linear regression analysis).

Variables	Total knowledge score at endline (n=95)					
	β	SE	95% CI	Standardized β coefficient	*t* test *(df)*	*P* value
Intervention township	17.767	2.942	11.92 to 23.61	0.569	6.040 (7)	<.001[a]
Baseline knowledge score	.497	0.137	0.23 to 0.77	0.311	3.630 (7)	<.001[a]
Gender	−1.876	3.932	−9.69 to 5.93	−0.042	−0.477 (7)	.63
Designation of work	2.726	2.168	−2.69 to 7.96	0.105	1.258 (7)	.21
Distance from township	2.633	2.697	−3.50 to 7.29	0.083	0.983 (7)	.33
Duration of internet usage	.042	0.423	−0.79 to 0.88	0.009	0.100 (7)	.92
Diabetes control training	6.004	2.745	0.549 to 11.46	0.177	2.187 (7)	.03[a]

[a]significant at $P<.05$.

[b]$r^2=0.472$.

[c]Adjusted $r^2=0.430$.

[d]Fitness Sample Corrected Akaike's Information Criterion (AICC)=758.765.

Effect of Intervention on Performance

A total of 91.2% (44/48) of the intervention group regularly used the registry tool and registered 1747 diabetes patients within 6 months. The mean (SD) performance score in the intervention group significantly increased from 71.22 (28.35) to 107.16 (15.62; $P<.001$). In contrast, the control group experienced a decrease in the mean (SD) performance scores from 73.29 (35.66) to 70.04 (29.72; $P=.22$). At baseline, the two groups had no significant difference in the mean performance scores ($P=.75$). At the endline, a significant difference was noted between the two groups ($P<.001$; Table 1). A multiple linear regression model, adjusted for potential confounding factors, indicated a significant effect, with an adjusted r^2 of 0.642, an unstandardized β coefficient of 33.143, and a standardized β coefficient of 0.554 ($P<.001$; Table 4).

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Table . Effect of intervention on the total performance score after adjusting for all possible confounding variables (full model multiple linear regression analysis).

Variables	Total performance score at endline (n=95)					
	β	SE	95% CI	Standardized β coefficient	*t* test *(df)*	*P* value
Intervention township	33.143	4.520	24.15 to 42.13	0.554	7.332 (11)	<.001[a]
Baseline performance score	.499	0.67	0.36 to - 0.63	0.532	7.483 (11)	<.001[a]
Gender	8.706	6.134	−3.49 to 20.90	0.103	1.419 (11)	.16
Designation of work	3.054	4.103	−5.11 to 11.21	0.061	0.744 (11)	.46
Distance from township	7.419	4.247	−1.03 to 15.86	0.123	1.747 (11)	.08
Duration of internet usage	−.670	0.668	−1.99 to 0.66	−0.71	−1.003 (11)	.32
Diabetes control training	−.339	5.795	−11.86 to 11.18	−0.005	−0.058 (11)	.95
Diabetes registry training	1.886	5.210	−8.47 to 12.25	0.31	0.362 (11)	.72
Diabetes campaign experience	−.170	4.319	−8.76 to 8.42	−0.003	−0.039 (11)	.97
Level of facility	2.906	2.552	−2.17 to 7.98	0.077	1.138 (11)	.26
Number of postings	−.773	2.210	−5.167 to 3.62	−0.028	−0.350 (11)	.73

[a]significant at $P<.05$.

[b]$r^2=0.684$.

[c]Adjusted $r^2=0.642$.

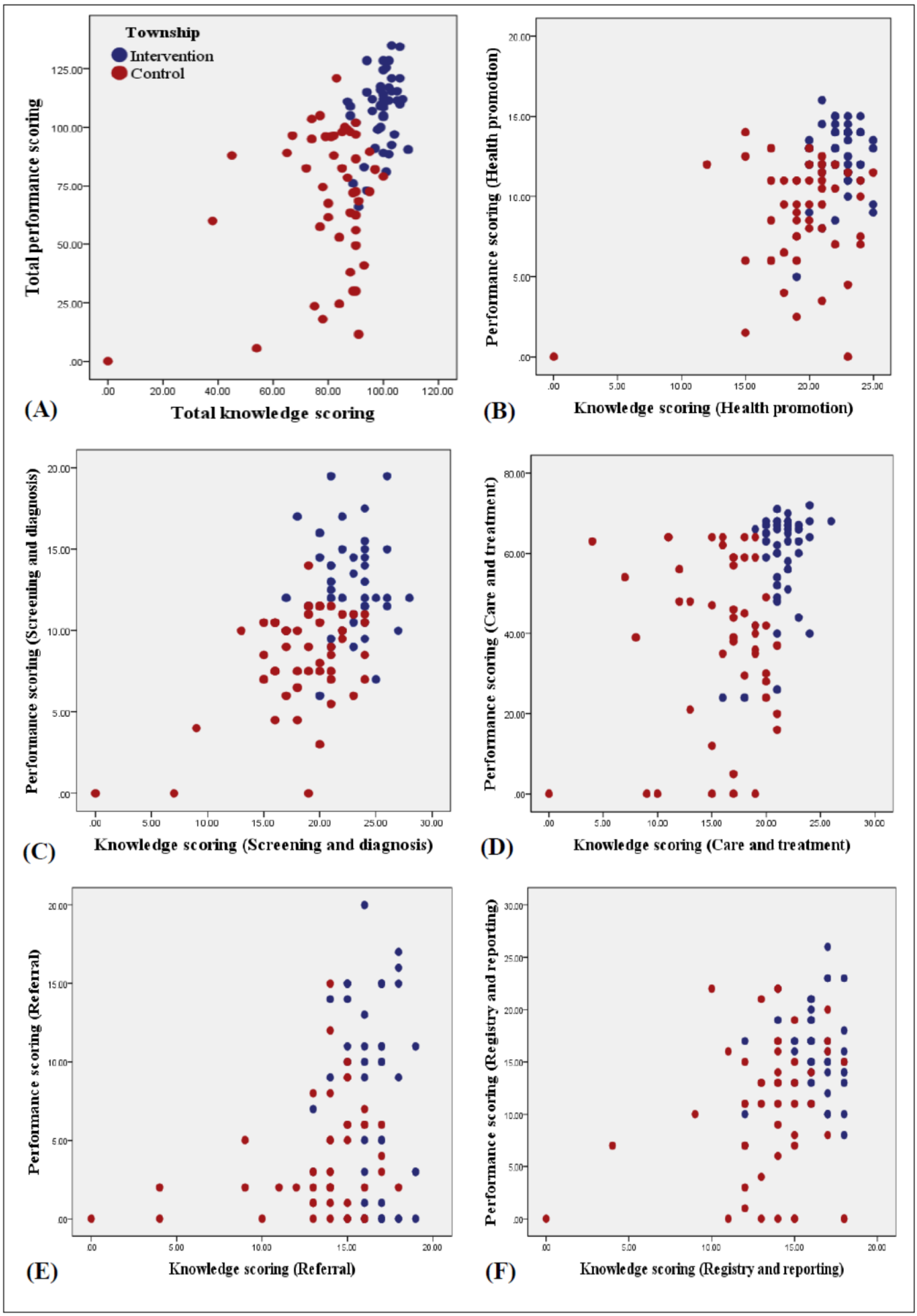
[d]Fitness Sample Corrected Akaike's Information Criterion (AICC)= 845.994.

Correlation Between Knowledge and Performance

The study showed a significant positive correlation between total knowledge and performance scores, with a correlation coefficient of $r=0.45$ ($P<.001$) at the endline (Figure 3). A significant correlation was found in the intervention group compared to the control group, with $r=0.34$ ($P=.02$). However, no significant correlation was observed in the control group, with $r=0.02$ ($P=.89$)

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Figure 3. Correlation between mean knowledge and performance scoring (n=95). (A) Total scoring, (B) health promotion, (C) screening and diagnosis, (D) care and treatment, (E) referral, (F) registry and reporting.



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Cost-Effectiveness of the Intervention

Researchers categorized the cost data into three main categories: (1) intervention costs, which included web application development, training, internet usage, and stationery; (2) program implementation costs, covering travel expenses, costs for consultation and communication, loss of income due to diabetes-related work, and other miscellaneous costs; and (3) treatment costs for complications. The total cost for the intervention group was 22,213,000 Kyats (US$ 10,586.71), while the control group incurred a total cost of 22,779,000 Kyats (US$ 10,856,4714) (Table 5). The intervention was deemed cost-effective, with a cost-effectiveness ratio of 0.711, and it was considered cost-effective when the cost-effectiveness ratio was less than 1. The study also analyzed the incremental cost-effectiveness ratio for comparative investment. The incremental cost-effectiveness ratio indicated saving 10,127.04 Kyats (US$ 4.83) for both outcomes, 30,154.50 Kyats (US$ 14.40) for knowledge, and 15,247.84 Kyats (US$ 7.27) in performance. The visibility of cost-effectiveness was demonstrated by plotting bootstrap results against outcomes and expenses (Figure 4).

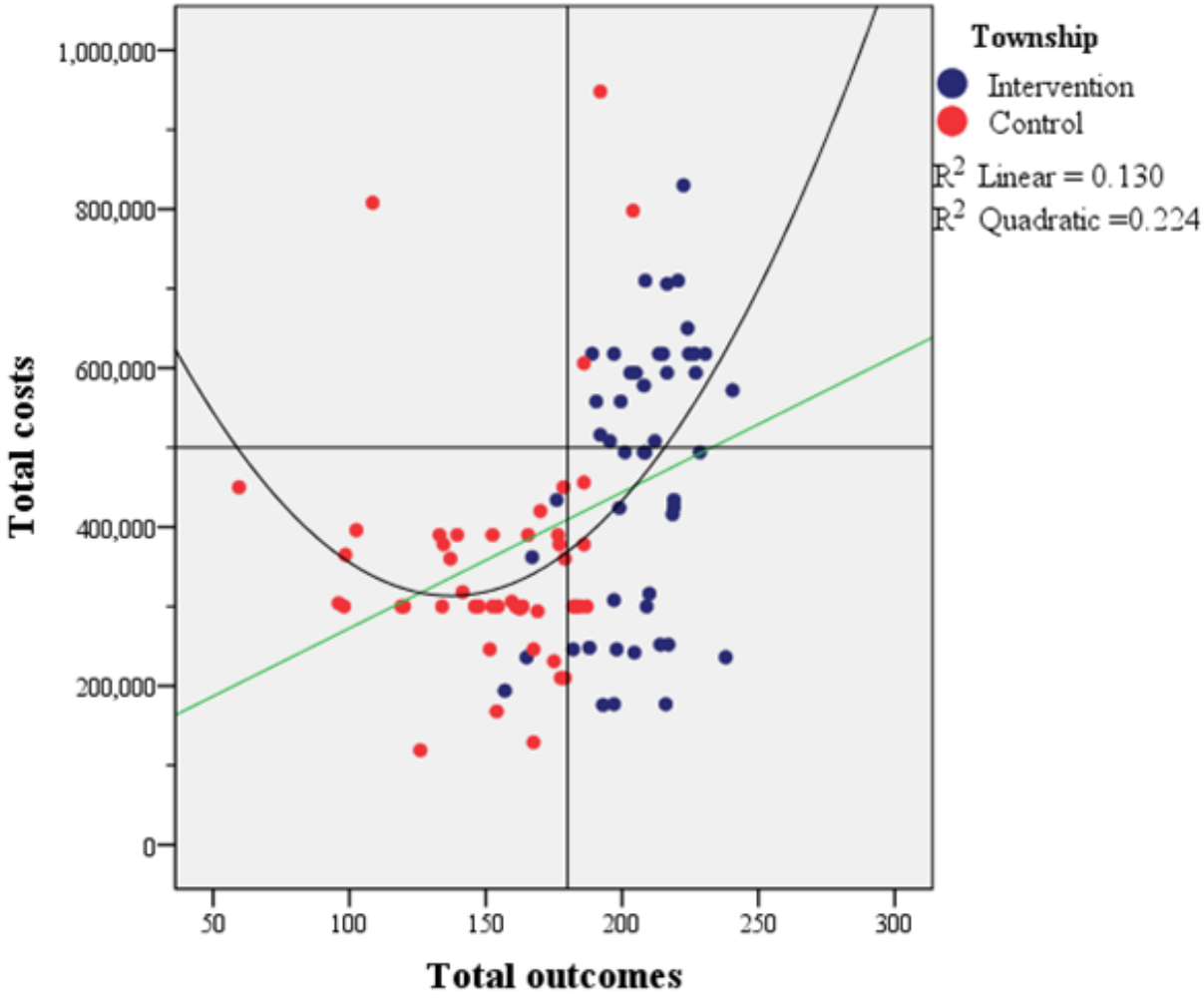
Table . Summary of costing and outcome for cost-effective analysis.

Overall and detailed costs	Intervention group	Control group
Intervention cost (Kyats)[a]		
Training and software cost	2,000,000 (US$ 953.20)	0 (US$ 0)
Internet cost	4,662,000 (US$ 221.91)	1,878,000 (US$ 895.05)
Stationary cost	949,000 (US$ 452.29)	1,262,000 (US$ 601.47)
Sub total	7,611,000 (US$ 3627.40)	3,140,000 (US$ 1496.52)
Hospital expense (Kyats)		
Care and treatment cost due to diabetes complications	4,600,000 (US$ 2192.36)	6,000,000 (US$ 2859.6)
Sub total	4,600,000 (US$ 2192.36)	6,000,000 (US$ 2859.6)
Staff expense (Kyats)		
Travel cost	2,460,000 (US$ 1172.44)	3,484,000 (US$ 1660.47)
Consultation cost for diabetes	1,825,000 (US$ 869.79)	2,524,000 (US$ 1202.94)
Communication cost	1,716,000 (US$ 817.85)	1,891,000 (US$ 901.25)
Loss of income due to extra workload	1,280,000 (US$ 610.05)	2,807,000 (US$ 1337.82)
Miscellaneous cost	2,721,000 (US$ 1296.83)	2,933,000 (US$ 1397.87)
Sub total	10,002,000 (US$ 4766.95)	13,639,000 (US$ 6500.35)
Total cost (Kyats)	22,213,000 (US$ 10,586.72)	22,779,000 (US$ 10,856.47)
Outcomes		
Outcome scoring		
Mean knowledge scoring	99.25	80.48
Mean performance scoring	107.16	70.04
Total outcome score	206.41	150.52

[a]A currency exchange rate of Kyat 1=US $0.72 is applicable.

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Figure 4. Cost-effectiveness between the intervention and control.



Discussion

Principal Findings

The intervention of new integrated digital tools saved costs and yielded significant positive outcomes in knowledge and performance of diabetes control among frontline health workers. Although the study is quasi-experimental, the researcher minimized confounding by matching selection criteria and adjusting covariates through multiple linear logistic regression. Consequently, the study achieved its goals through a consistent design and reliable analytical methods, resulting in valid outcomes. The overall results align with other research on digital solutions to enhance diabetes control [21].

Comparison With Previous Studies

Digital Knowledge Solution for Diabetes Control

This study significantly observed that using integrated digital tools could enhance five key domains of knowledge and performance related to health promotion, screening, care and treatment, referral, and reporting diabetes in primary health care settings. Integrating digital knowledge tools and a registry tool is an effective intervention for diabetes control among frontline health workers. A systematic review of evidence-based medicine found that digital knowledge tools can improve diabetes control knowledge among primary health care staff [22]. Digital tools can improve the screening process, as supported by other meta-analyses regarding the performance of diabetes screening [23]. Additionally, positive effects of digital tools on providers' performance were observed in areas such as reminders, clinical care decisions, glycemic control, and web-based training and education programs [24].

While this study concentrated solely on the provider side, digital tools can offer numerous patient benefits, such as increased awareness, improved understanding, and enhanced self-management skills within the community [25]. However, a meta-analysis conducted in Southeast Asia found that patients' knowledge of diabetes was inadequate, especially among women with low education levels and poor diabetes control [26]. Therefore, further research and tailored training in digital interventions are recommended to improve knowledge and awareness among patients, their families, and the community.

Diabetes Registry for Electronic Health Records

A meta-analysis using electronic health records for diabetes across 12 countries showed positive outcomes [27]. A diabetes registry can enhance the quality of patient care in rural areas, both in high-income countries like the United States of America [28] and in various low-income countries [29]. Unlike other studies, this research connected the positive results of using a

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digital diabetes registry and knowledge tools in routine diabetes program reporting, especially for resource-limited settings. The findings showed that reporting performance was significantly improved, and several patients were registered correctly. Therefore, the authors recommend adopting an open-resource, low-cost digital diabetes registry as a nationwide program for diabetes control in Myanmar and other low-income countries.

Cost-Effectiveness on Diabetes Interventions

This study is significant because it measures the direct and indirect costs associated with diabetes management using the WHO-CHOICE formula. Furthermore, the cost analysis was conducted on both knowledge and performance outcomes. Digital monitoring for diabetes has gained popularity alongside increased access to high-speed internet. This advancement has helped reduce costs, lower the number of hospital visits, save time, and improve the quality of life for those managing diabetes [30]. However, some studies suggest that the cost categories related to diabetes are too complex to provide accurate data [31,32]. Additionally, other research indicates that cost analyses may be inadequate due to factors, such as underlying socioeconomic conditions, underreporting, the severity of complications, and the long-term effects of diabetes [32].

Generally, an intervention is considered cost-effective when the cost-effectiveness ratio is less than 1. This study demonstrated cost-effectiveness with a cost-effectiveness ratio of 0.711. Similar evidence supporting cost-effectiveness has been observed in consumer-based solutions, digital tools for blood glucose, and diabetes self-management education in the United Kingdom [33]. This study explored the incremental cost-effectiveness ratio to assess the additional investment needed to enhance knowledge and performance scores for diabetes control. In contrast, another study conducted in Sweden examined incremental cost-effectiveness ratio results related to diabetes control through patients' quality-adjusted life years [31]. Nevertheless, this study urges policy makers to consider further investments in digital tools, even though a sophisticated cost-effectiveness framework has not yet been developed.

Limitations

According to this study, despite several benefits, the rollout and sustainability of the digital diabetes registry encountered some limitations. Initially, the studies intended to measure baseline, midterm, and endline assessments. However, the authority approved only two measurements based on the country's political situation and the expectation of no significant variation in the midterm. Although the initial goal was to collect real-time data, health staff could only upload information monthly due to being overburdened with competing priorities. The study focused on Naypyitaw, which limits generalizability to the entire country, and only has a 6-month duration, so it cannot evaluate the long-term impacts. The study population focused solely on public providers, excluding private providers, patients, and the wider community. Furthermore, the digital tools were not interoperable with the District Health Information System.

Conclusions

The intervention used a multidisciplinary approach for frontline health personnel at the grassroots level, significantly improving knowledge and performance and reducing program costs. Unlike other studies, this research demonstrated the integrated and correlated effects of digital knowledge and reporting tools. Given these strengths and limitations, researchers recommend that policy makers replicate the intervention nationwide, develop clear standard operating procedures, establish a reporting schedule, and provide an internet data package to enhance the use of digital tools. Furthermore, the diabetes registry operates in isolation, necessitating the creation of an interoperable system to connect with the District Health Information System. Additionally, extensive studies on long-term population research and economic evaluations are essential to evaluate the sustainability of digital tools. We suggest engaging outstanding community nurses as champions to share their best practices of digital applications, and these measures could ensure data quality and sustainability of digital tools to enhance diabetes control in Myanmar and other low-income countries.

Acknowledgments

The authors acknowledge the National Diabetes Control Programme of Myanmar and the College of Public Health Sciences, Chulalongkorn University, for their guidance and support. Novo Nordisk Myanmar is especially recognized for providing the necessary technical support. The authors acknowledge the technical expert group that validates measurement tools. The authors highly appreciate the support of the township health authorities and the contribution of participants from Leway and Tatkone townships to the study.

This article is submitted to accomplish the PhD thesis requirements for Chulalongkorn University Phase II (Intervention Phase).

Data Availability

The datasets for this study will be available in Chulalongkorn University's i-Thesis system and can also be obtained from the corresponding author upon reasonable request.

Authors' Contributions

KT contributed to the conceptualization, design, methodology, development of measurement tools, data collection and analysis, provision of training, follow-up, visualization, and the writing of the original paper. SP contributed to the conceptualization, supervision, and provision of overall advice for structuring the original paper. MNT contributed to developing measurement

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tools, supporting data collection and analysis, and reviewing the paper. All authors take responsibility for data integrity, and all authors have read and approved the final version of the manuscript.

Conflicts of Interest

None declared.

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Abbreviations

WHO: World Health Organization
WHO-CHOICE: WHO's Choosing Interventions that are Cost-Effective

Edited by E Borycki; submitted 06.02.25; peer-reviewed by O Kehinde, O Ibikunle, PK Taisuwan; revised version received 02.04.25; accepted 15.04.25; published 16.06.25.

Please cite as:
Thar K, Pongpanich S, Tun MN
Effect of Digital Tools on the Knowledge and Performance of Frontline Health Workers For Diabetes Control in Myanmar: Cost-Effective Analysis and Quasi Experimental Study
JMIR Nursing 2025;8:e72230
URL: https://nursing.jmir.org/2025/1/e72230
doi:10.2196/72230

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Detecting Older Adults' Behavior Changes During Adverse External Events Using Ambient Sensing: Longitudinal Observational Study

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Abstract

Background: Older adults manage multiple impacts on health, including chronic conditions and adverse external events. Smart homes are positioned to have a positive impact on older adults' health by (1) allowing new understandings of behavior change so risks associated with external events can be assessed, (2) quantifying the impact of social determinants on health, and (3) designing interventions that respond appropriately to detected behavior changes. Information derived from smart home sensors can provide objective data about behavior changes to support a learning health care system. In this paper, we introduce a smart home capable of detecting behavior changes that occur during adverse external events like pandemics and wildfires.

Objective: Examine digital markers collected before and during 2 events (the COVID-19 pandemic and wildfires) to determine whether clinically relevant behavior changes can be observed and targeted upstream interventions suggested.

Methods: Secondary analysis of historic ambient sensor data collected on 39 adults managing one or more chronic conditions was performed. Interrupted time series analysis was used to extract behavior markers related to external events. Comparisons were made to examine differences between exposures using machine learning classifiers.

Results: Behavior changes were detected for 2 adverse external events (the COVID-19 pandemic and wildfire smoke) initially and over time. However, the direction and magnitude of change differed between participants and events. Significant pandemic-related behavior changes ranked by impact included a decrease in time (3.8 hours/day) spent out of home, an increase in restless sleep (946.74%), and a decrease in indoor activity (38.89%). Although participants exhibited less restless sleep during exposure to wildfire smoke (120%), they also decreased their indoor activity (114.29%). Sleep duration trended downward during the pandemic shutdown. Time out of home and sleep duration gradually decreased while exposed to wildfire smoke. Behavior trends differed across exposures. In total, two key discoveries were made: (1) using retrospective analysis, the smart home was capable of detecting behavior changes related to 2 external events; and (2) older adults' sleep efficiency, time out of home, and overall activity levels changed while experiencing external events. These behavior markers can inform future sensor-based monitoring research and clinical application.

Conclusions: Sensor-based findings could support individualized interventions aimed at sustaining the health of older adults during events like pandemics and wildfires. Creating care plans that directly respond to sensor-derived health information, like adding guided indoor exercise, web-based socialization sessions, and mental health–promoting activities, would have practical impacts on wellness. The smart home's novel, evidence-based information could inform future management of chronic conditions, allowing nurses to understand patients' health-related behaviors between the care points so timely, individualized interventions are possible.

(JMIR Nursing 2025;8:e69052) doi:10.2196/69052

KEYWORDS

internet of things; digital phenotyping; chronic disease; COVID-19; air pollution

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Introduction

Background and Significance

The older adult population is rapidly growing, with 95% of persons aged 60+ managing a chronic condition and 80% managing 2 or more [1]. These same older adults are also experiencing more external events with the potential to impact self-management of their chronic conditions, such as wildfire smoke and COVID-19. Standard approaches to managing chronic conditions do not typically account for the impact of external events. Innovative technological approaches that (1) operate across diverse settings, (2) support a learning health care system, and (3) incorporate a social determinants of health (SDOH) lens are essential to enhance self-management of health conditions and support aging in place. Vulnerable populations often experience greater effects of external events due to reduced resources [2-4]. Besides managing chronic health conditions, 80% of U.S. older adults face income insecurity [5], reducing their capacity for self-management of the impacts of external events. For example, they may not be able to travel to a location with better air quality during a wildfire or to less crowded spaces during a pandemic.

Identifying specific behavior changes in response to external events presents opportunities for early nursing interventions. If behavior and health changes emanating from such events can be detected and understood, then smart homes could support automated upstream interventions like personalized activity cues and health education. Our prior work and that of others noted changes in health behavior that occurred during one such external event, the COVID-19 pandemic [6,7]. Similarly, people experienced changes and complications during wildfire season. The risk and extent of wildfires in the Pacific Northwest have doubled in recent years [8]. These increasingly large and intense wildfires are causing a spike in unhealthy pollutants, posing health risks to millions of people, and confining many older adults to their homes each summer [9]. Prior research observed that while particulate matter (PM2.5) and ozone (O_3) were raised primarily outdoors, acetonitrile and benzene were also elevated indoors during fires [10-14]. Evidence is mounting that neighborhood-level exposure to particulate matter adds to the risk of health decline [15,16], crossing the blood-brain barrier and causing neural inflammation [17].

This work is based on larger studies in which we model behavior from passive sensors to detect and react to changes in physiological and cognitive health. Because sensors were placed in participant homes before events such as wildfires and the pandemic shutdown took place, we monitored behavior before and during these events. Participants reported behavior changes and health issues that were related to these events. The goal of this work was to analyze sensor data to detect, quantify, and analyze these changes. Our data analysis hypotheses were:

1. Changes in behavior will be observed between nonevent and event time periods.
2. The amount and type of behavior changes will differ based on parameters such as prior health conditions, age, and demographics.
3. Initial behavioral changes in response to the event may differ from those that emerge as the event persists.

The intended outcome of the work is to suggest possible interventions that prevent unhealthy behavior changes and mitigate the health impact of such external events.

Prior Work

Researchers have observed changes in health during events that force more indoor activity, such as the COVID-19 lockdown and wildfire-driven poor air quality. For example, Krendl et al [18] and Burke et al [19] found these events to be associated with higher amounts of depression and loneliness based on individual self-report. However, Balki et al [20] noted that some of these health impacts are mitigated by individual factors such as gender and education. These types of events also spark changes in behavior. These include changes in nighttime and daytime sleep patterns, as observed by Gupta et al [21] Salfi et al [22] found that for some groups these behaviors change at first and then ease back to pre-event behavior, while other groups experience greater behavior change as the event continues. Their study confirmed the role of social determinants of health on behavior change during the pandemic.

While passively monitoring and modeling human behavior has become achievable with ambient and wearable sensors [23,24], little work has used sensors to capture behavior patterns and changes during external events like a pandemic or wildfire smoke to determine health impact and support. Collecting such data was particularly challenging during the pandemic when study participants could not be visited in person. However, a few projects were successful in assembling and assessing related data. In particular, Rajkumar et al [25] plotted movement levels inside 3 homes to visualize changes in the areas of the home that were frequented based on motion sensor reports. Leese et al [26] monitored driving and computer use over 5 months to quantify the decrease in driving distance and increase in time spent on the computer. The work reported in this study is based on longitudinal data from multiple studies collected in the homes of older adults with significant health risks before and during external events. This offers a unique opportunity to analyze behavior change from passive, continuous sensor observations.

Table 1 positions this study in comparison with prior work. As shown in the table, researchers have investigated the impacts of wildfire smoke and COVID-19 lockdowns on behavior, though none of these have investigated multiple events. Most of the study mechanisms rely on self-reports provided through digital surveys. One exception is the work of Ceolotto et al [27], who analyzed wastewater during the pandemic to quantify changes in the use of prescription drugs, nicotine, and alcohol. The work that is closest to our study is that of Rajkumar et al [25], which analyzed data from motion sensors to visualize social isolation for 3 homes during the COVID-19 pandemic. In comparison with these prior studies, we use longitudinal sensor data to compare pre-event and mid-event behavior. Performing this analysis for multiple event types (wildfire smoke events and pandemic lockdown events) facilitates comparison of behavior impact between diverse adverse external events.

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Table . Summary of related studies.

Study	Event	Behavior	Collection mechanism
Stewart [28]	Wildfire smoke	Personal perceptions	Survey, air monitors
Burke [19]	Wildfire smoke	Depression, time at home	Survey, phone or web-based activity
Hu [29]	COVID-19	Smoking, alcohol, nutrition, sleep	Survey
Salfi [22]	COVID-19	Sleep	Survey
Gupta [21]	COVID-19	Sleep	Survey
Krendl [18]	COVID-19	Depression	Survey, social network
Leese [26]	COVID-19	Car, computer use	Survey, car computer
Ceolotto [27]	COVID-19	Medicine, caffeine, nicotine use	Wastewater
Rajkumar [25]	COVID-19	Isolation	Motion sensors
This paper	Wildfire smoke, COVID-19	Sleep, time out of home, activity level	Motion sensors, door sensors, weekly telehealth with self-report or nurse observation

Methods

Participants

Participants were community-dwelling adults (n=39) recruited from the Pacific Northwest region of the United States through advertising and involvement in prior studies. Inclusion criteria were living independently in their own home, having an internet connection, and the ability to communicate in English. Of the participants, 37 were older adults (70+ years), and 2 were healthy younger adults (<35 years) included for comparison. Participant characteristics are summarized in Table 2.

Table . Summary of participant information.

Event and age		Age (years), mean (SD)	Gender	Education (years), mean (SD)	Conditions
COVID (n=13)					
	<35 years	23.5 (4.95)	1 male; 1 female	19.50 (2.12)	Healthy
	70+ years	83.82 (6.11)	2 male; 9 female	16.75 (1.83)	COPD[a] (1), asthma (1), diabetes mellitus (2), CHF[b]/AFib[c] (4), coronary artery disease (2), HTN[d] (5), arthritis (3), stroke (2), obesity (2), macular degeneration (3)
Smoke (n=28)					
	70+ years	91.10 (5.89)	7 male; 13 female; 8 not reported	17.50 (2.38)	Mild cognitive impairment (3), HTN (1), COPD (1), cancer (1)

[a]COPD: chronic obstructive pulmonary disorder.

[b]CHF: congestive heart failure.

[c]AFib: atrial fibrillation.

[d]HTN: hypertension.

Data Collection

Overview

Ambient sensors were placed in each participant's home and continuously collected data for a minimum of 1 year while residents performed their regular daily routines. In total, 2 types of sensor units were used: passive infrared motion detectors combined with ambient light sensors were placed on ceilings in each functional area (2 - 4 sensors per room) to monitor movement and light levels. Additionally, magnetic units with door sensors and ambient temperature sensors were placed on external doors and kitchen or bathroom cabinets to monitor door usage and temperature changes.

Registered nurses conducted weekly telehealth visits for the duration of the study. Participants were asked, "How has your health been over the last week? Did you experience any changes in your health? If so, what changed?" Narrative summaries were recorded each week of participants' self-reported health status and nurses' observations. Blood pressure, heart rate, oxygen

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saturation, and pain level were also recorded weekly. These data informed the machine learning analytics.

Event Groups

For this data analysis, we selected homes with 1 resident and no pets to focus on behavior change for 1 participant in each home and reduce noise. When behavior is analyzed in homes with multiple residents, the sensor data reflect the collective behavior of everybody in the home. Without attributing behavior to specific residents in such a group setting, direct comparisons cannot be easily made between single-resident and multi-resident homes. Additionally, we restricted our analysis to homes that included multiple days of data collection before the events and during events. The homes were grouped based on 2 event types: 1 set of 13 homes (COVID) collected sensor data before and during the COVID-19 pandemic lockdowns. Reflecting a second event, a set of 28 homes (smoke) collected data before and during times with poor air quality due to wildfire smoke.

In the COVID group, we analyzed data from March 17, 2020, through May 21, 2020, during which the region followed a stay-at-home protocol. For baseline comparison, we analyzed an equivalent number of season-matched days from the previous year. In the smoke group, we analyzed time periods containing at least 2 consecutive days with an air quality index >100 (indicating the air quality is unhealthy or hazardous) and an equivalent number of baseline days with air quality index ≤50 (indicating good air quality) during the same month. None of the COVID and smoke dates overlapped. In total, 2 of the homes collected data in both conditions and are included in both analyses. Additionally, we removed dates in which the participant was outside the home more than half the day. Sensor performance was routinely monitored, and sensors were removed from analysis if their performance was not reliable. In a few instances, all sensors failed to report information for a given date. When this occurred, we removed the date from consideration. In total, we analyzed 1990 days for the COVID group and 1568 days for the smoke group.

Digital Behavior Markers

We defined a collection of digital markers that could be extracted from ambient sensor readings and used to describe daily behavior. The markers describe sleep, time out of the home, and activity level. These behavioral categories are reported to be influenced by poor air quality and pandemic shutdowns [21,22,30-33]. These behaviors in turn impact physiological and psychological well-being, particularly for individuals managing chronic health conditions [34-39].

In this analysis, nighttime sleep is detected between 9pm and 7am when motion sensor readings are ≥5 minutes apart and the most-recently sensed location of the resident is the bedroom. If there are >2 contiguous motion sensor readings outside the bedroom, the state is considered awake. If the awake state is surrounded by sleep in the same evening, the awake state is a sleep interruption rather than the end of the night's sleep.

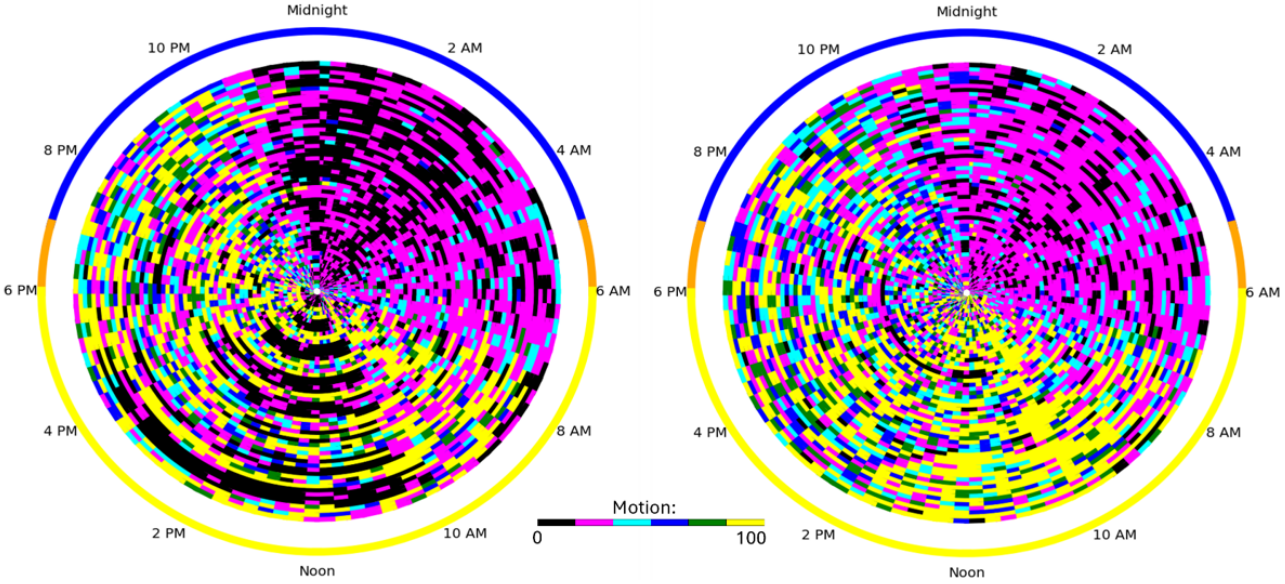
The motion sensors combined with the door sensors define when a participant is out of the home. Specifically, if the person's most recent state was awake, >20 minutes elapsed between motion sensor readings, and the most recent sensor readings are from an external door or door area, the person is considered out of the home until >2 sensor readings occur inside the home.

Finally, activity level is estimated by the normalized count of motion sensor readings occurring when the participant is home. The number of sensors inside a person's home varies depending on the size of the residence and the number of rooms. To accommodate the resulting differences in sensor quantity and density, all markers that rely on a motion sensor count are normalized with a standard scaler based on each person's daily motion sensor counts.

Figure 1 shows a plot of motion observed in 1 home during the prepandemic shutdown (left) and during the pandemic shutdown (right). In this plot, where each ring signifies a distinct day, we can observe some of the changes that were sensed between these times. Black regions indicate a lack of motion sensor readings. Before the shutdowns, black occurred throughout the day when the resident was out of the home and throughout nighttime sleep. During the shutdown, the number of daytime outings is greatly reduced. Furthermore, while sleep can still be detected at night, the person is more restless at night, with the black regions being replaced by more magenta and cyan periods. To analyze changes in these characterizing behaviors, we define the digital markers for each day as follows: sleep duration = the time spent in bed between the night's first and last detected sleep (Textbox 1).

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Figure 1. Radial plots for 1 home showing activity level by time of day; 1 ring per day. (Left) Prepandemic behavior and (right) pandemic shutdown behavior. Colors indicate an increasing amount of motion from black (little or no motion) to yellow.



Textbox 1. Definition for digital markers for each day

- Sleep duration: the time spent in bed between the night's first and last detected sleep.
- Sleep efficiency: following recommendations by the National Science Foundation [40], this is defined as the nighttime ratio of sleep time to time spent in bed.
- Sleep restlessness (normalized): the number of motion sensor readings that are generated while the person is asleep.
- Time out: time spent outside the home.
- Activity level (normalized): the number of motion sensor readings generated divided by the time spent at home.

Data Analysis

We apply an interrupted time series (ITS) analysis to assess the impact of an event that disrupts an ongoing time series [41]. Behavior markers X_t are collected for each day, t. This marker sequence forms a time series that is interrupted by an event, E:

(1)X−3,X−2,X−1,(E),X+1,X+2,X+3

ITS allows us to perform a counterfactual analysis, estimating what would have happened to a person's behavior if the event had not occurred. In ITS, this is done by projecting the pre-event behavior trend (the counterfactual) into the postintervention trend. We perform segmented regression analysis to examine changes in level and trend over time, both before and during the event, allowing us to estimate its effect. We estimate the trend before the event, the immediate impact of the event, and the trend after the event, controlling for age, gender, and education. Where the results of the counterfactual analysis are not consistent across participants, we generate participant phenotypes using k-means clustering (k=3) and report statistics for individual groups.

Additionally, we use a machine learning classifier to predict if a set of behavior markers belongs to the nonevent or event group. This analysis captures nonlinear relationships and complex interactions between the variables to determine whether the event caused clear, measurable differences between the periods. For this analysis, we employ a random forest classifier with 100 trees and report results based on 5-fold cross-validation. We also use the classifier to quantify and rank the markers for their importance in distinguishing between nonevent periods, COVID periods, and wildfire smoke periods. Using random forests to promote interpretability of machine learning algorithms is a highlight of the method that has been explored by other researchers to predict events such as hospitalization among older adults [42]. Features are ranked by the Gini impurity (GI) measure, which guides the construction of the decision trees in the random forest.

Ethical Considerations

This study was approved by Washington State University Institutional Review Board (IRB#15412). Studies from which data were collected for this secondary analysis were also reviewed and approved by the Institutional Review Board at Washington State University. All data were anonymized before performing analyses. Participants voluntarily consented after receiving information about the study and verbalizing their understanding. Participants' data were confidentially linked during their participation in the study and unlinked upon completion. After completing the study, participants received a US $250 gift card.

Results

Tables 3 and 4 summarize the ITS analysis results for COVID-19 and wildfire smoke events, showing differences in

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the type, degree, and direction of behavior changes between the 2 events. Similarly, Figure 2 shows the values of the markers as a function of the day in the time series before and during each event, though these values are aggregated over the entire sample. Before the pandemic shutdown, behavior markers remained stable, with changes of less than 0.08%. In contrast, the immediate impact of the event was more pronounced. Sleep duration increased slightly, while sleep restlessness showed a significant rise of 946.74%. Sleep efficiency remained relatively constant, but indoor activity decreased by 38.89%. As expected, time out of the home reflected the largest change, decreasing from 5.97 hours daily to an average of 2.17 hours, a statistically significant reduction.

Table . Results of interrupted time series analysis applied to daily behavior markers for the COVID-19 event (n=13). Model strength is reported as *F* test scores; sleep duration and time out of home are reported in seconds. Results are summarized for pre-event baseline (initial), trend before the event occurred (pre-event trend), impact on the first day of the event (immediate impact), and trend from the beginning to the end of the monitored event (long-term trend). Results are further broken down by gender.

Variable	*F* test		Initial		Pre-event trend		Immediate impact		Long-term trend	
	F score (*df*)	*P* value	Value	*P* value	Value	*P* value	Value	*P* value	Value	*P* value
Sleep duration (seconds)										
Total	11.96 (3, 9)	<.001	28,900	<.001	4.00	<.001	22.00	.98	–1.96	<.001
Female	12.84 (3, 9)	<.001	29,070	<.001	4.24	<.001	–451.64	.69	–0.47	<.001
Male	13.78 (3, 9)	<.001	29,030	<.001	0.24	.86	–476.21	.74	0.48	.87
Restlessness[a]										
Total	6.58 (3, 9)	<.001	–0.09	.047	–6.65e-05	<.001	0.762	<.001	0.00	<.001
Female	10.59 (3, 9)	<.001	–0.18	<.001	–7.00e-05	<.001	1.11	<.001	–2.00e-03	.28
Male	2.064 (3, 9)	.10	0.14	.13	–5.00-04	.09	0.00	.99	3.00e-04	.61
Sleep efficiency[b]										
Total	45.93 (3, 9)	<.001	0.79	<.001	0.00	<.001	0.00	.97	0.00	.75
Female	53.37 (3, 9)	<.001	0.78	<.001	2.00e-04	<.001	0.03	.38	–7.00e-05	.28
Male	49.83 (3, 9)	<.001	0.87	<.001	8.35e-05	<.001	–0.14	<.001	2.00e-04	<.001
Activity level[c]										
Total	25.17 (3, 9)	<.001	0.54	<.001	0.00	<.001	–0.21	.27	0.00	.88
Female	12.37 (3, 9)	<.001	0.52	<.001	–6.07	.001	–0.61	.002	1.10e-03	.003
Male	1.534 (3, 9)	.20	0.47	<.001	–4.00e-04	.18	0.67	.04	0.00	.001
Time out (seconds)										
Total	14.55 (3, 9)	<.001	21,500	<.001	–6.00	<.001	–13,700	<.001	26.00	<.001
Female	20.84 (3, 9)	<.001	22,090	<.001	–9.88	<.001	–5330	.03	8.05	.07
Male	3.77 (3, 9)	.01	19,090	<.001	18.36	<.001	–30,130	<.001	44.31	<.001

[a]Number of motion sensor readings that are generated while the person is asleep.

[b]Nighttime ratio of sleep time to time spent in bed.

[c]Number of motion sensor readings generated divided by the time spent at home.

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Table . Results of interrupted time series analysis applied to daily behavior markers for the wildfire smoke event (n=30). Model strength is reported as *F* test scores; sleep duration and time out of home are reported in seconds. Results are summarized for pre-event baseline (initial), trend before the event occurred (pre-event trend), impact on the first day of the event (immediate impact), and trend from the beginning to the end of the monitored event (long-term trend). Results are further broken down by gender.

Variable	*F* test		Initial		Pre-event trend		Immediate impact		Long-term trend	
	F score (*df*)	*P* value	Value	*P* value	Value	*P* value	Value	*P* value	Value	*P* value
Sleep duration (seconds)										
Total	46.51 (3, 24)	<.001	30,860	<.001	–0.17	.69	–1652.49	.28	–1.95	.01
Female	24.78 (3, 24)	<.001	30,790	<.001	–0.02	.98	–977.25	.58	–1.48	.14
Male	33.15 (3, 24)	<.001	28,320	<.001	0.77	.20	–1214.66	.52	–2.79	<.001
Restlessness[a]										
Total	3.83 (3, 24)	.01	0.15	.06	0.00	.001	–0.18	.29	0.00	.13
Female	2.06 (3, 24)	.10	0.15	.17	–2.00e-04	.03	–0.11	.61	9.00e-05	.47
Male	4.04 (3, 24)	.008	0.11	.14	–1.00e-04	<.001	–0.16	.24	1.00e-04	.07
Sleep efficiency[b]										
Total	123.50 (3, 24)	<.001	0.92	<.001	0.00	.64	–0.06	.13	0.00	<.001
Female	49.83 (3, 24)	<.001	0.92	<.001	4.56e-06	.77	–0.02	.60	–8.53e-05	<.001
Male	71.55 (3, 24)	<.001	0.87	<.001	4.11e-06	.82	–0.06	.30	–1.00e-04	<.001
Activity level[c]										
Total	0.46 (3, 24)	.71	0.07	.46	0.00	.94	–0.08	.65	0.00	.49
Female	1.53 (3, 24)	.21	–0.12	.30	2.00e-04	.04	0.19	.39	–1.00e-04	.29
Male	1.41 (3, 24)	.24	0.15	.26	–8.22e-05	.26	–0.26	.27	2.00e-04	.10
Time out (seconds)										
Total	1.48 (3, 24)	.22	26,180	<.001	0.86	.25	1969	.46	–2.00	.16
Female	3.77 (3, 24)	.01	27,640	<.001	0.34	.77	1916	.56	0.84	.65
Male	7.89 (3, 24)	<.001	22,280	<.001	2.78	.007	4676	.15	–5.10	.002

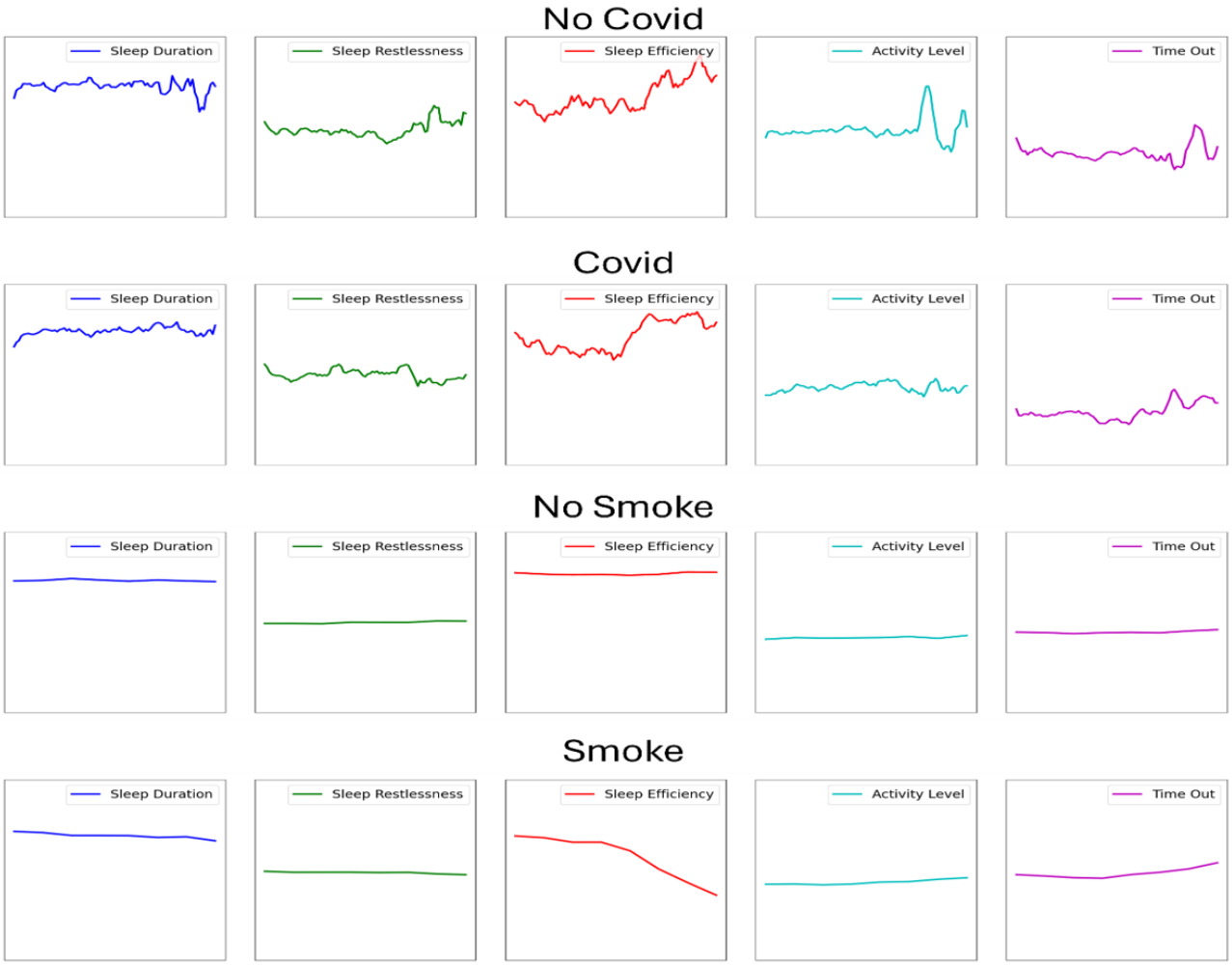
[a]Number of motion sensor readings that are generated while the person is asleep

[b]Nighttime ratio of sleep time to time spent in bed.

[c]Number of motion sensor readings generated divided by the time spent at home.

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Figure 2. Trend lines for the markers across event occurrences and participants. The x-axis of each plot indicates the date in the time series and the y-axis indicates the mean value of the marker at that point in the sequence.



The overall impact of events is relatively consistent when we consider participants by gender, though a few differences are noted. Specifically, female participants experienced more of a long-term decrease in sleep duration and sleep efficiency during the COVID-19 lockdown. They also decreased their activity level at the beginning of the event, though it did increase as the event continued. Additionally, male participants experienced a greater impact of the event in terms of decreased time out of the home, though this time increased more than for the women as the pandemic continued.

Unlike the COVID-19 shutdown, none of the immediate behavior changes were significant when wildfire smoke began. Participants decreased their sleep duration by 5.36% and sleep efficiency by 6.52%, but sleep appeared to improve in quality, with a 120% decrease in restlessness. Indoor activity decreased by 114.29%, while time out of the home increased by 7.52%, an average of 32.82 additional minutes a day.

Postevent trends also revealed notable differences. During the pandemic, sleep duration initially increased but gradually declined over time, while time out of the home, though initially reduced, gradually rose over the 66-day shutdown. In contrast, during extended periods of wildfire smoke, both “time out of the home” and “nighttime sleep duration” gradually decreased. Differences between gender subgroups were largest for time spent out of the home. At the beginning of wildfire smoke events, male participants spent more time out of the house. As the poor air quality continued for multiple days, however, this group significantly decreased their time spent out of the home each day.

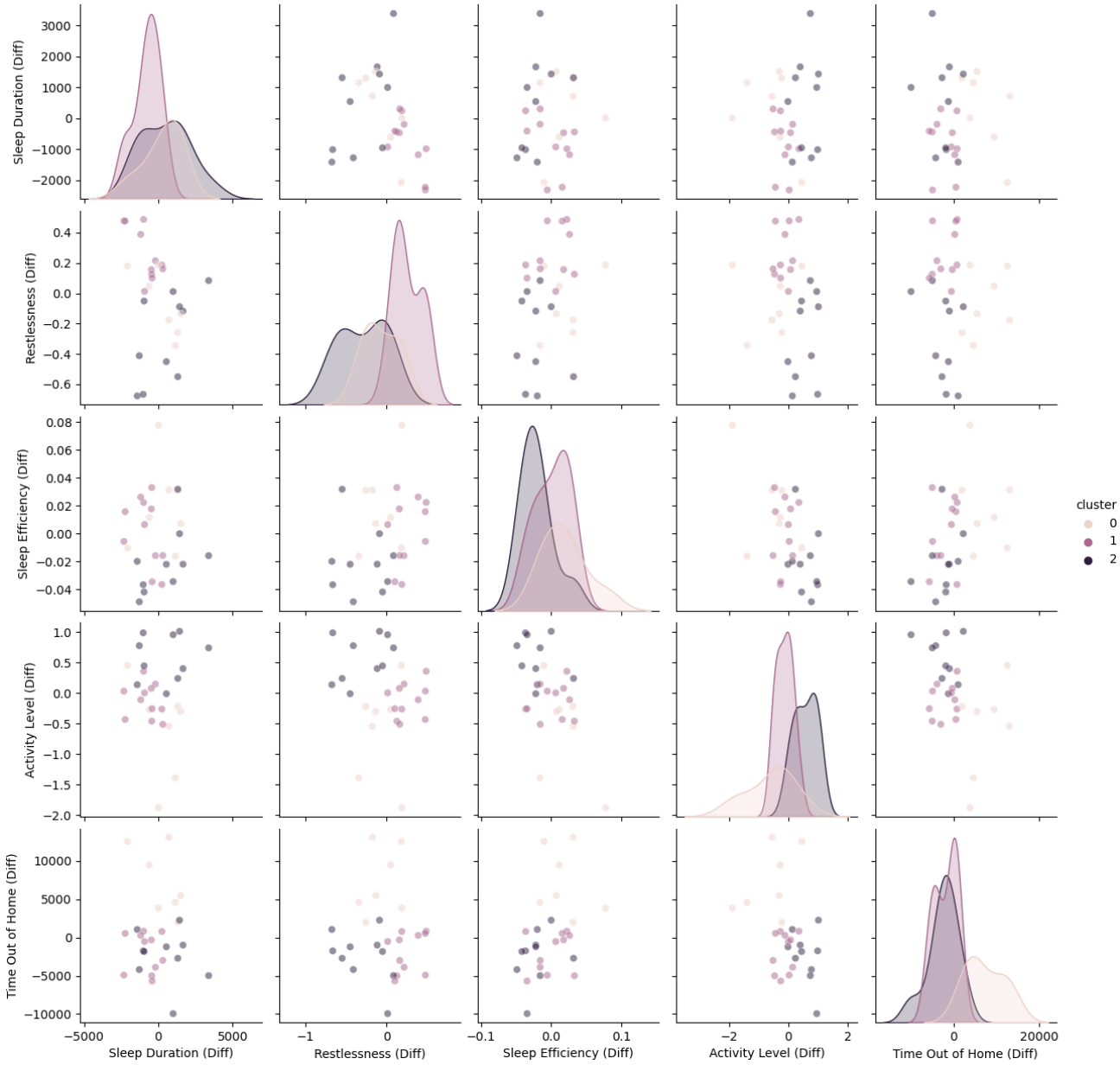
Behavior changes due to wildfire smoke were neither large nor statistically significant. However, some participants reported experiencing health and behavior changes during these times. To determine whether results vary between subgroups, we used k-means clustering (k=3) to identify participant phenotypes. The results, shown in Figure 3, highlight some important differences. Clusters 0 and 2 show minor behavior differences: cluster 0 exhibits a slight increase in time spent out of the home, while cluster 2 shows a slight increase in activity level and decrease in sleep efficiency. In contrast, participants in cluster 2 exhibit more pronounced changes, with a 182.93% increase in sleep restlessness (P=.002) and a 176.14% decrease in activity level (P=.06).

To assess the predictive nature of event behaviors, we examined the random forest predictions and the results are summarized as follows. Accuracy was 0.68 for classifying a participant as COVID, no COVID, smoke, or no smoke; 0.72 for classifying as positive (COVID or smoke) versus negative (no COVID, no

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smoke); 0.76 for predicting COVID versus no COVID; and 0.71 for predicting smoke versus no smoke. For comparison, expected accuracy using a random classifier was 0.25 for the 4-class case and 0.50 for the 3 binary classification tasks. Because we analyze an equal number of pre-event and mid-event days, these class distributions are balanced. As a result, we use predictive accuracy as the performance metric. The results indicate that all behavior predictions were significantly more accurate than random guessing (P<.001). While the difference in behavior between prepandemic and postpandemic periods was the most predictable, behavior differences between smoke and no-smoke periods were also highly predictive. We ranked the behavior markers by their predictive value for each event. The most predictive marker was time out of the home (GI=.108), followed by sleep restlessness (GI=.078), sleep efficiency (GI=.071), activity level (GI=.068), and sleep duration (GI=.050). Features were ranked in this order for all the prediction tasks.

Figure 3. Phenotypes of smoke impact on participant behavior. Plots show the difference of the behavior marker mean for each participant between the event (smoke) period and the nonevent period. Cluster sizes are (cluster 0: n=7, cluster 1: n=11, cluster 2: n=10).



Discussion

Principal Findings

Sensor data represent a new form of “informatics evidence” that supports informatics triage—a future requirement for home-based health technologies. These data provide objective evidence to inform decision support tools and clinical judgments. Aligned with value-based care ideals [43], information derived from smart home sensors can help prevent (re)hospitalizations and reduce unnecessary emergency room visits, promoting overall health and extending independence through health maintenance support. However, for smart home data to meaningfully reflect the impacts of external events on older adults or to predict health risks, we must understand how routine behaviors change with exposure. This study provides evidence that ambient sensing reliably captures exposure-related behaviors. The selected digital markers and analysis offer insight

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into how exposures are behaviorally expressed when older adults are in their home, where they are arguably their most authentic selves.

Discerning behavior changes by type, degree, and trend is essential. Changes from baseline (nonevent) to new (event) behavior may involve variations in activity frequency, timing, duration, or location. Clinically relevant findings included restlessness during sleep and reduced time spent outside the home, both associated with heightened health risks. Poor sleep quality is associated with increased risk for all-cause cardiovascular mortality [44]. Decreased physical activity and social interaction increase the risk for poor mental health [45], dementia [46], cardiovascular disease, and cancer care outcomes [44]. As a result, clinicians commonly rely on knowledge of such behavior trends for clinical decision-making.

Objective, real-time evidence of key behavior changes creates opportunities for impactful, low-cost interventions, such as activity cueing [47,48], as well as community-level interventions addressing social determinants of health. For example, older Asian immigrants experienced unique needs during the pandemic lockdowns where, besides managing their health, they also managed an associated external event related to Asian hate [49], leading many older Asian Americans to remain at home for safety purposes. Behavior changes detected from the smart home digital markers we illuminate here could assist clinicians and community-based organizations in prioritizing and mobilizing community health workers among their constituents [50]. Indeed, discrimination reported by older Asian Americans during the pandemic resulted in unhealthy behavior changes, which could be investigated using similar methods [51].

Case Exemplar

One compelling case exemplar from our study is Anna (pseudonym), an 80‐90-year-old female who lived alone during the pandemic due to recently becoming widowed. She experienced significant mental and physical decline soon after the lockdown began. She reported “feel[ing] isolated” and increasingly “tired” and “worried” and informed her doctor about feeling short of breath and fatigued. Medical tests were inconclusive. We posit that the clinical team may have benefited from knowing that her sleep duration over 3 months had decreased 1.3%, her sleep restlessness increased 13.9% and efficiency decreased 3.7%, and her time spent out of the home decreased 27.5%—all derived from the digital markers and methods in this study.

Based on these findings and follow-up interviews, the clinical research team determined Anna was likely lonely and needed more social interactions. With her permission, we reached out to community leaders who implemented regular check-ins, including home visits, group walking outdoors, and group puzzling over a web-based platform. Anna responded positively to these interventions, later reporting “feeling better.”

Integrating Ambient Sensor Information for a Learning Health Care System

A learning health care system could greatly benefit from in-home ambient sensor informatics, which provide insights into the impacts of external events on individuals and populations. Such systems rely on continuously available, objective data to adapt and improve [52]. Smart homes could play a pivotal role by systematically collecting real-time evidence to support clinical decision-making and enhance care effectiveness. By unobtrusively assessing and updating information about patients between care points, the system enables an iterative feedback loop of assessment and intervention, fostering continuous learning and improvement. Additionally, sensor-derived data empower the health care system to address social determinants of health, promoting equitable outcomes for individuals facing external challenges, especially for those already affected by factors like race, gender, age, and income level, which can exacerbate health risks. Adding other opportunities for collecting whole life-space data by including smart watches or other wearables could improve understandings of behavior changes associated with adverse external events. Data from these devices also requires new analytic methods that machine learning is suited to address. Upstream interventions are key to mitigating these risks and improving health equity for these individuals [53]. Objective data and metrics that reveal behavior changes related to external events can help the health care system better address these disparities, allowing targeted individualized care planning based on observed behaviors, ultimately supporting more equitable health outcomes. Sensor-derived information could be used to plan individualized support such as guided indoor exercise programs for older adults unable to leave their home who are also showing less overall daytime activity, or digital mental health support for persons showing increased restless sleep patterns and reporting anxiety, or web-based socialization opportunities to reduce loneliness.

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Concerns of Older Adults

Privacy, cost, safety, security (data, identity, and health), and reliability are concerns that older adults associate with smart home health monitoring [54-57]. Older adults have indicated they want to be *watched over* but not *watched* [58]. In addition, technologies offering specific health assistance are more desirable than ones that generally monitor and capture data about behaviors and activities unrelated to an older adult's diagnosis [59,60]. All technologies collecting continuous data aiming to support aging in place require designs that support and embody the ethical principles of autonomy, the right to self-determination, justice, and health equity [61,62].

Limitations and Future Research

A limitation of this work is the use of a convenience sample of data collected before and during the COVID-19 and wildfire smoke events. Expanding the sample to include greater heterogeneity (race, gender, or socioeconomic status) and representation from more geographic regions would support more generalizable results and potentially identify additional clusters of behavior changes. Sociodemographic factors likely influence behavioral responses to adverse events. Due to the small convenience sample, we were unable to determine the differential impact of sociodemographic factors. Additionally, health data for the case exemplar relied on participant recall, which may be subject to bias and recall error.

This study is further limited by variations in sensor density across participant homes. The number of sensors that were analyzed varied between homes, based on home size and sensor fidelity. While data were normalized to account for these differences, the results could be refined if the numbers were uniform across the sample. We also recognize the inherent limitations of smart home sensors, which capture broad behaviors like navigation patterns and door usage but may miss finer behaviors, such as specific gestures. The confinement of sensors to indoor settings also excludes activities performed outside the home, potentially biasing conclusions. Integrating ambient sensors with wearables and other IoT sources could enhance the breadth and detail of behavior markers. Future research could examine the effects of other external events on older adults' health, such as migration, economic and policy implications, and the impacts of advances in artificial intelligence.

In this study, we focused on markers that reflect time spent on activities of interest. Future studies may consider additional markers that consider the time of day and location for these markers and integrate new markers into the collection.

Conclusions

Older adults are increasingly exposed to adverse external events like wildfires. Exposure can lead to behavior changes, putting them doubly at risk. Smart homes offer an innovative solution, affording opportunities for upstream interventions supporting more equitable health outcomes and providing continuous data for the learning health care system. Findings from this study show that the COVID-19 pandemic and the United States Pacific Northwest wildfires impacted community-dwelling older adults' behaviors with a change in time spent out of the home as the most predictive digital marker, followed by sleep markers, overall activity levels, and the duration of time spent on activities. Findings offer a new type of evidence to support clinical decision-making that considers the context of social determinants of health, like social factors related to the pandemic and exposure to poor air quality.

The rising frequency of external events, combined with the widening gap between available caregivers and the growing population of older adults needing care [63], poses a global gerontological humanitarian challenge. These events disrupt daily routines for older adults, potentially worsening their health and limiting their independence. Smart homes are well-positioned to help bridge this gap by collecting and leveraging in-home ambient sensing data. Further exploration of ambient sensor data integration into clinical decision support tools and the learning health care system is essential. Innovations like these could provide families and health care teams with

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timely, actionable information that enables person-centered care and supports interventions that promote health equity at scale.

Acknowledgments

This work is supported in part by National Institutes of Health (NIH), National Institute of Nursing Research (grant R01NR016732), NIH, National Institute on Aging (grant R01EB009675), and NSF (grant 1954372). We thank the study participants and former Registered Nurse research team member, Dr Katherine Wuestney, for her data collection and management efforts. Additionally, we thank the Touchmark senior living organization for hosting this research study.

Conflicts of Interest

None declared.

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Abbreviations

GI: Gini impurity
ITS: interrupted time series

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Edited by T Risling; submitted 20.11.24; peer-reviewed by C Ochoa-Zezzatti, R Buenrostro, S Singh; revised version received 01.03.25; accepted 18.03.25; published 01.05.25.

Please cite as:
Fritz R, Cook D
Detecting Older Adults' Behavior Changes During Adverse External Events Using Ambient Sensing: Longitudinal Observational Study
JMIR Nursing 2025;8:e69052
URL: https://nursing.jmir.org/2025/1/e69052
doi:10.2196/69052

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Nursing and Continuing Care Management Work Plan for People Living With COVID-19: Case Study of the Nakhon Pathom Province

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Abstract

Background: Patients with post-COVID-19 continue to experience lingering physical and psychological symptoms, requiring coordinated and continuous care. Addressing these needs is essential, especially in resource-limited settings.

Objective: The objectives of this paper are to study the issues and needs, as well as the nursing and continuous care systems for residents living with COVID-19, to design and develop a database system, develop continuous care guidelines, and evaluate the effectiveness of the database system for continuous monitoring and care for residents living with COVID-19 in Nakhon Pathom Province, Thailand.

Methods: Participatory action research was used to engage stakeholders and guide the development process.

Results: A total of 375 patients and family members affected by post-COVID-19 symptoms reported that symptoms persisted for approximately 6 months, with common symptoms including persistent cough and easy fatigue. These patients experienced reduced access to health care services, relying mainly on symptomatic treatment at local facilities and using telehealth nursing systems. They expressed a need for continuous care support from 50 professional nurses and village health volunteers. As a result, health care guidelines for post-COVID recovery were developed, comprising 5 core components: (1) self-care through digital information retrieval, (2) care via telehealth nursing systems, (3) physical health care services postrecovery, (4) mental health services postrecovery, and (5) continuous care for referral in case of postrecovery incidents. These guidelines were used to design a database system for continuous monitoring and care, which was evaluated as highly effective (mean 4.51, SD 0.59).

Conclusions: This research highlights the critical need for a proactive and comprehensive approach to managing post-COVID-19 care in Nakhon Pathom Province. By developing and implementing a database system for continuous monitoring and care, along with clear guidelines, the study effectively addresses the ongoing needs of individuals recovering from COVID-19. The integration of technology, along with continuous care provided by professional nurses and village health volunteers, has been shown to be highly effective in improving the quality of care. The findings suggest that adopting these strategies, along with implementing supportive policies on data management and communication systems focused on home visits, will significantly enhance health service management and better prepare the region for future public health challenges.

(JMIR Nursing 2025;8:e65310) doi:10.2196/65310

KEYWORDS

post-COVID-19 symptoms; continuous care; database system; COVID-19; care; nursing; care management; Coronavirus; case study; needs; nurse; design; develop; database system; continuous monitoring; participatory research; Thailand; Asia; Asian; cough; fatigue; recovery; quality of care

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Introduction

Background

As of October 1, 2022, the COVID-19 pandemic has transitioned from a global pandemic to an endemic disease. According to the latest data from the Department of Disease Control, the global number of confirmed cases from December 2019 to October 2021 reached 224,423,325, with 65,446 currently hospitalized and 4,963,653 cumulative deaths. In Thailand, from April 2021 to October 2022, there have been 4,660,878 cumulative cases, 2616 new cases, and 32,828 cumulative deaths. Specifically, in Nakhon Pathom Province, from April 2021 to October 2022, there have been 83,004 cumulative cases, 30 new cases, and 802 cumulative deaths [1,2]. These statistics show a declining trend in infections; however, there is still no clear report on the long-term effects on those who have recovered from COVID-19.

It is well known that the impact of the COVID-19 pandemic has caused rapid and severe shock, significantly affecting the global economy to the greatest extent in 150 years. The pandemic has impacted tourism for no less than 6 months, resulting in a loss of income exceeding 250 billion baht [3,4]. Despite the reopening of the country and the resumption of tourism, the economic recovery is still in progress and uncertain. The future trajectory of the pandemic and its long-term effects on those infected remain unclear.

Based on the experience in designing health service systems, nursing systems, and continuing care for at-risk populations and those infected with COVID-19 over the past 3 - 4 years, the Faculty of Nursing at Nakhon Pathom Rajabhat University has found that the establishment of a database system to monitor the symptoms of at-risk individuals and patients with COVID-19 under the university's rapid response system still lacks a comprehensive database system to support care within Local Quarantine Centers, Home Isolation, and Community Isolation.

Due to the spread of COVID-19, the health service system has not yet identified suitable methods for living and adapting to the ongoing presence of infectious diseases. There has been no planning or design of a system to access medical care and develop health care guidelines for COVID-19 patients to ensure they can correctly and safely manage their initial care. Additionally, there is no established guideline for postrecovery care for patients returning to normalcy after recovering from COVID-19 to ensure they can resume their normal work activities.

Based on initial interviews, information on people recovering from COVID-19 in Nakhon Pathom over the past 3 - 4 years indicates that no agency has monitored the symptoms of those who have recovered, tracked their postrecovery lifestyle, or followed up on long COVID symptoms. Additionally, there has been no data collection on vaccination for people who had COVID-19. This group has been informed that they would develop immunity after infection, leading to a lack of follow-up booster vaccinations.

Given this situation, there is a significant opportunity to design a health service system that includes nursing and continuous care for people living with COVID-19 in Nakhon Pathom. This system should leverage health technology, as the majority of the population now has greater access to technology for health promotion and treatment. It should also include plans to support measures for preventing further outbreaks or new epidemics. This approach would address health maintenance, disease prevention, social distancing, and the adoption of new lifestyle behaviors to live safely with COVID-19.

Therefore, the research team recognizes the importance of addressing these issues and has undertaken the development of a work plan for managing nursing systems and continuous care for people living with COVID-19: A Case Study of Nakhon Pathom Province. This plan aims to examine the nursing and continuing care management work plan for individuals living with COVID-19 in Nakhon Pathom Province and to explore the effectiveness of integrated care approaches, including telehealth and community-based services, by improving access to services, enhancing the care, and providing nursing for patients with post-COVID-19 both at home and within the community. To enhance access to services and improve the quality of care and nursing for post-COVID-19 patients at home and in the community, the following steps are necessary: screening: implement self-assessment tools for evaluating the risk and symptoms post-COVID-19 recovery; tracking and tracing: monitor and record follow-up data by community health service units; surveillance system: establish a system for ongoing observation and reporting; and information transfer system: use health technology to ensure seamless data transfer and communication. By implementing this comprehensive plan, the goal is to prepare the community in Nakhon Pathom to live with COVID-19, ensuring high-quality care and support through the effective use of health technology.

Research Purpose

The purpose of this article is (1) to study the issues, needs, and systems of nursing and continuous care for people living with post-COVID-19 in Nakhon Pathom Province; (2) to design and develop a database system for continuous monitoring and care of individuals with post-COVID-19 in Nakhon Pathom Province; (3) to develop guidelines for the continuous care of patients recovering from post-COVID-19 in the community in Nakhon Pathom Province; and (4) to evaluate the effectiveness of the database system for continuous monitoring and care of individuals with post-COVID-19 in Nakhon Pathom Province.

Conceptual Framework

The study is guided by 2 key conceptual frameworks that provide a theoretical basis for the research and the development of the health care system. These frameworks were selected based on their relevance to the goals of the study and their ability to provide a comprehensive approach to managing nursing and continuous care for patients with post-COVID-19.

Transitional Care or Transaction Model

The Transitional Care or Transaction Model model [5] emphasizes the importance of continuous care during transitions between health care facilities and home. It focuses on ensuring that patients receive consistent, high-quality care throughout the different stages of their recovery. The model includes three

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stages: (1) pretransition: the period before the patient leaves the hospital, where the focus is on preparing the patient for the transition to home care; (2) midtransition: the actual transition period, where the patient moves from the hospital to home or another care setting; and (3) posttransition: the period after the patient has returned home, where the focus is on ensuring that the patient continues to receive the care they need to recover fully.

Each stage of the transition requires attention to 4 critical factors:

Information: ensuring that accurate and relevant information is provided to both patients and caregivers. This includes providing clear instructions on medication, follow-up appointments, and any other aspects of the patient's care plan.

Communication: using effective communication strategies to keep all stakeholders informed and involved. This includes regular updates to the patient's care team, as well as clear communication with the patient and their family.

Support: offering immediate support to patients and their families as they navigate the health care system. This includes providing access to resources such as social workers, financial counselors, and other support services.

Time: allowing sufficient time for each stage of the transition to be completed successfully. This includes ensuring that the patient has enough time to adjust to their new care setting and that any necessary adjustments to their care plan are made promptly.

The continuous care concept for patients with post-COVID-19 also applies. The primary care behavioral health model by Reiter and team [6] includes the following components: access to health information: ensuring patients and providers have access to relevant health data; health management: efficiently managing health care processes and resources; health coordination: coordinating care among different providers and services; teamwork: facilitating collaborative efforts among health care teams; budget responsibility: managing financial resources effectively; supporting health information technology: using technology to support and enhance health information; and service quality and safety: ensuring high standards of care and safety for patients.

The researchers analyzed, connected, and supported the 2 conceptual frameworks within the context of Nakhon Pathom Province, leading to the design of a database system for data transfer, management, and continuous care for individuals with COVID-19 in the area. The research process involved surveying the situation, issues, and needs of the nursing and continuous care system from the perspectives of professional nurses, public health officials, and patients with post-COVID-19, as well as the general public. This resulted in a practical database system for data transfer, management, and continuous care, which includes the following: information: providing accurate and useful data; communication: using effective communication methods; support: offering timely support as needed; and time: ensuring appropriate and sufficient time for processes. The system addresses health management, coordination, teamwork, and budget responsibility, aiming to ensure safety in daily life.

Methods

Study Design

This research uses a research and development approach with 3 stages.

Stage 1

Study the problems and needs: this stage investigates the current issues and needs of the nursing and continuous care system for individuals with post-COVID-19 in Nakhon Pathom Province.

Stage 2

Design, develop, and test: this stage is to design and develop the database system for continuous monitoring and care of individuals with post-COVID-19 in Nakhon Pathom Province. Subsequently, we synthesized the data from the system to create guidelines for continuous care for patients with post-COVID-19 in community settings within the province.

Stage 3

Evaluate the effectiveness: we aimed to assess the effectiveness of the database system for continuous monitoring and care of individuals with post-COVID-19 in Nakhon Pathom Province.

Research Area

The research area is Nakhon Pathom Province.

Population

The included population was patients and families who have had COVID-19 within the past year and have recovered for at least 3 months, residing in Nakhon Pathom Subdistrict, Mueang Nakhon Pathom District, Nakhon Pathom

In the Province, there were a total of 15,117 people. Among them, professional nurses, public health officials, and directors of the community health promotion hospitals in the Mueang District area of Nakhon Pathom Province were included, totaling 50 people.

Sampling

The sample group was selected using Krejcie and Morgan's (1970) formula with a 5% margin of error from the total population. For patients and families who have had COVID-19, the sample size is 375 people. For professional nurses, public health officials, and directors of community health promotion hospitals in the Mueang District of Nakhon Pathom Province, all 50 individuals were selected.

Tools of Research

This study used questionnaires as the primary data collection tool and adopted both qualitative and quantitative methods:

Stage 1 used qualitative tools, which include focus group guidelines; interview guidelines; questionnaire for note-taking; and analysis guidelines and participatory observation.

Stage 2 used the findings from stage 1 to develop a database system for continuous monitoring and care of individuals with post-COVID-19 in Nakhon Pathom Province, which includes system design. We also developed a data management system that collects and stores information on computers and through

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internet-based databases. Moreover, for data synthesis, we applied matrix-based comparative analysis principles to synthesize the collected data; and created guidelines using the synthesized data to establish guidelines for continuous care of patients with post-COVID-19 in community settings within Nakhon Pathom Province.

Stage 3 involves evaluating the effectiveness of the database system for continuous monitoring and care of individuals with post-COVID-19 in Nakhon Pathom Province. This stage uses quantitative tools by creating a custom questionnaire: developing a specifically designed questionnaire to assess the effectiveness of the database system. This tool will gather quantitative data on how well the system performs in terms of functionality, usability, and overall impact on patient care and management.

The quantitative tool used is a questionnaire designed for data collection, which underwent review by experts in various fields: nursing experts, continuous care nursing experts, epidemic nursing experts, and database system development experts. A total of 3 experts reviewed the questionnaire for content validity, resulting in an Index of Item-Objective Congruence of 0.98. Following the revision of the content based on their feedback, the revised tool was tested for reliability with a sample group of 30 individuals similar to the actual target sample. The reliability analysis of the questionnaire, specifically designed for patients who have had COVID-19 and their families, yielded a content validity index of 0.91.

Qualitative tools included note-taking forms, analysis guides, participatory observation, focus group and interview guidelines, and workshop protocols. Content validity was confirmed by experts, with a Content Validity Index of 0.90 for the nurse or public health questionnaire and 1.00 for interviews with hospital directors, ensuring tool reliability.

Data Collection

Data were collected with 2 years of follow-up in 3 steps as follows.

Step 1

Step 1 involves studying the problems and needs of the nursing and continuous care system for individuals with COVID-19 in Nakhon Pathom Province. The focus group involves examining the situation, identifying issues, and determining requirements from a total of 375 participants. The qualitative data are synthesized to create a comprehensive map of the issues and needs of the nursing and continuous care system for individuals with COVID-19 in Nakhon Pathom Province. The summarized results will inform and guide the development process in step 2.

Step 2

In step 2, the researchers designed a database system for continuous monitoring and care of individuals with COVID-19 in Nakhon Pathom Province using data from step 1. This involved developing the system with technology through 4 datasets: information, communication, support, and time. The goal is for the community health promotion hospitals in Nakhon Pathom to use the database system for data transfer, management planning, and continuous care, enabling individuals in Mueang District, Nakhon Pathom Province, to lead live safe and stable lives while managing their condition. The system design also incorporated measures from the Personal Data Protection Act.

Test and pilot the database system: Tests and trial runs of the database system will be conducted for continuous monitoring and care of individuals with COVID-19 in Nakhon Pathom Province. This involves evaluating the system's functionality, usability, and effectiveness in real-world scenarios to ensure it meets the needs of managing and supporting the affected population.

Develop guidelines for continuous care: The researchers used the analysis results from step 1, combined with relevant data from additional research, to create guidelines for the continuous care of patients with post-COVID-19 in community settings within Nakhon Pathom Province. This involved synthesizing the information to establish practical and effective care practices tailored to the needs of the local population.

Step 3

Step 3 involves evaluating the effectiveness of the database system for continuous monitoring and care of individuals with COVID-19 in Nakhon Pathom Province.

The evaluation will involve a sample group consisting of professional nurses, public health officials, and Directors of Community Health Promotion Hospitals. In total, 50 individuals from the Mueang District of Nakhon Pathom Province will be involved in assessing the system's performance and effectiveness.

Summarize the effectiveness of the database system: The data on the performance and effectiveness of the database system for continuous monitoring and care of individuals with COVID-19 in Nakhon Pathom Province will be compiled and analyzed. This includes evaluating how well the system meets its objectives and supports patient management.

Develop recommendations and user manual: Recommendations will be provided based on the evaluation findings and a comprehensive user manual for the database system will be prepared. The manual will guide users on how to effectively operate the system and integrate it into their continuous care practices for individuals with COVID-19 in Nakhon Pathom Province.

Ethical Considerations

This research has received ethical approval from the Human Research Ethics Committee of Nakhon Pathom Rajabhat University, with approval numbers 047/2565-047/2566. Participants in the research are free to withdraw from providing information or participating in activities at any time during the data collection process. They can also withdraw from the research process altogether if they are uncomfortable with using the data or engaging in the activities.

Data Analysis

In steps 1 and 2, the analysis focuses on understanding the problems, needs, and continuous care system for individuals with COVID-19 in Nakhon Pathom Province. This involves process analysis, content comparison, interpretation,

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summarization, transcription, categorization, synthesis of sentences, and validation: triangulating data by cross-checking findings from multiple sources and methods to ensure accuracy and reliability. This approach ensures a comprehensive and reliable analysis of qualitative data.

In step 3, which involves evaluating the effectiveness of the database system for continuous care of individuals with COVID-19 in Nakhon Pathom Province, the analysis focuses on descriptive statistics, percentages, frequency distribution, mean and SD. These statistical methods help summarize and interpret the quantitative data collected during the evaluation of the database system, providing insights into its effectiveness and performance.

Results

Phase 1: The Problems and Needs of the Nursing and Continuous Care System for Individuals With COVID-19 in Nakhon Pathom Province

The results of phase 1 revealed 5 key issues regarding the health care system and continuous care needs for the public living with COVID-19 in Nakhon Pathom province.

Issues With Health Care Service

When the rapid antigen test results are positive, patients receive management to enter the health care system according to the hospital's primary health care promotion unit in the area they reside. However, some individuals do not access the service system, instead focusing on self-care using principles of isolation from family members and primarily treating themselves with herbal remedies.

"Long wait times for service, being ill without income, recovered but symptoms persist." After recovering, issues arise due to reflections that the patient group accessing hospital services receives care at the provincial hospital, undergoes hospital checks after staying at the field hospital for 10 days, then returns home for 4 days of continued care at the local health promotion hospital via line group reporting and community health volunteers. Friends and neighbors help report symptoms through line groups and report complications or additional symptoms, with the hospital sending medication to take.

To address the needs for care and nursing following recovery from COVID-19, the following steps are recommended:

Facility preparation: Local service facilities should prepare beds for bedridden patients or elderly individuals recovering from COVID-19. This includes setting up systems for meal delivery in the area to facilitate convenience during isolation.

Continued follow-up: There should be continuous monitoring and follow-up after recovery from COVID-19. It is crucial to advise individuals to maintain their health and provide education on self-care, particularly regarding monitoring symptoms such as fatigue and shortness of breath post-COVID.

Vaccination guidance: Guidance should be provided regarding vaccination. It's important to emphasize that vaccination against COVID-19 and influenza can strengthen immunity and prevent re-infection with COVID-19. This also reduces the risk of transmitting the virus again in the community.

These measures aim to ensure comprehensive care and support for individuals postrecovery, promoting their well-being and reducing the likelihood of recurrence or complications related to COVID-19.

The issue of providing health information and preparing health data for patients with COVID-19 should be led by health care professionals in the area, especially professional nurses, public health officials, and community health volunteers. They should serve as information leaders for self-care among patients with COVID-19. Communication channels should emphasize awareness through voice messaging systems and community outreach via TV, Facebook, and the internet. Information should be obtained from local health authorities, neighbors, family members, hospitals, and local health promotion hospitals. This ensures that individuals receive clear and adequate information on self-care and COVID-19 prevention efforts.

Communication strategies appropriate during various stages—awareness, illness, recovery, and reintegration into society—include discreet doctor notification via phone to contact health services upon symptoms or diagnosis. During illness, nurses may inquire daily for the initial treatment group, approximately 10 - 15 days, while those self-treating with family monitor health, consumption, and home isolation postrecovery. Initially worried about social acceptance post-COVID, more recently adjusting, radio communication shares self-care after diagnosis and primary care treatments

The key support factors during illness, recovery, and postreintegration into society include increased family caregiving, mutual encouragement among friends, and involvement from doctors, nurses, and relevant officials. Family members, community health volunteers, and local health authority representatives play pivotal roles in communication and primary care. Spouses, children, and extended family members provide assistance during isolation, particularly for COVID-19 cases or households with elderly members requiring separate care, ensuring continuous support.

The issue concerning the timeframe after recovering from COVID-19 spans approximately 1 week to 6 months, with varying durations of symptoms for each individual. Some may experience symptoms for up to 15 days, isolating from household members for about 10 - 15 days due to fear of social stigma and concern about others' perceptions of ongoing illness. They separate their food and personal items, use a separate room for rest, meals, and medication, and gradually return to normal life after recovery. However, lingering symptoms such as cough, fatigue, and underlying health conditions persist.

Phase 2 Outcomes: Development and Design of a Database System for Continuous Monitoring and Care for Residents Living With COVID-19 in Nakhon

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Pathom Province, Specifically for Patients With Post-COVID-19 in Community Settings

Dataset for Developing a Continuous Monitoring and Care Database System for Residents Living With COVID-19

Part 1: General information, which includes household member general information, information related to household head, characteristics of occupations, household security information, household environmental management information, health information, and communication information.

Part 2: Continuous care management data, which include chronic diseases, persistent symptoms after recovering from COVID-19 1 year later, and health care guidelines for the population after recovering from COVID-19.

Part 3: Management outcome data. Analyzing data from parts 1 and 2 to analyze the outcomes resulting from comprehensive management efforts as follows:

- CODE_PC1 : Seeking health knowledge and management post-COVID-19
- CODE_PC2 : Risk control and safety post-COVID-19 by telenursing
- CODE_PC3: Self-care post-COVID-19
- CODE_PC4: Self-control psychological health post-COVID-19
- CODE_PC5: Satisfaction with referral care post-COVID-19

Health Care Guidelines for the Population After Recovering From COVID-19

Guidelines for Self-Care

Using digital resources related to COVID-19 includes recommending the use of apps, websites, and information from health promotion hospitals to provide information on COVID-19 infection; recommend vaccination information; and advise on using apps and websites related to COVID-19 for village health volunteers.

Guidelines for Managing COVID-19 Remotely Through Telenursing Systems

These guidelines include the following: providing consultation and advice via phone by community health promotion hospitals; organizing remote educational activities on self-protection, hand hygiene, wearing masks, and updated information on COVID-19 for patients, families, and communities; conducting remote disease management and nursing activities by health care experts; and assessing and screening post-COVID symptoms, interpreting rapid antigen test results, managing medications, and monitoring respiratory symptoms.

Guidelines for Providing Post-COVID-19 Physical Health Care Services

These guidelines include the following: annual health check-ups, particularly chest X-rays and disease screening; home visits by community health volunteers; remote home care services by community nurses or public health professionals; providing advice on self-care through purchasing medications and treatments from pharmacies, medical clinics, and nursing clinics in the area; and organizing campaigns to encourage vaccination against COVID-19 and influenza.

Guidelines for Providing Mental Health Services Postrecovery From COVID-19

These guidlines are used for providing services to assess and screen for depression and offering mental health counseling through hotline services.

Continuous Care Guidelines for Referral in Case of Emergencies Postrecovery From COVID-19

These guidelines include the following: arranging services for severe symptoms or emergencies providing remote nursing services for continuous treatment information dissemination.

The outcome is the database of results from the continuous care management of COVID-19 infection 1 year postrecovery.

Phase 3: Evaluate the Effectiveness of the Database System for Continuous Monitoring and Care of Individuals With Post-COVID-19 in Nakhon Pathom Province

The researchers implemented a database system for continuous monitoring and care for the public affected by COVID-19 in Nakhon Pathom Province. They evaluated its effectiveness among 50 health care professionals, including registered nurses, public health officers, and directors of sub-district health promotion hospitals in Mueang District, Nakhon Pathom Province. The overall effectiveness was found to be at the highest level (mean 4.51, SD 0.59), with the highest performance specifically in data security (mean 4.59, SD 0.57). Following closely was the capability to perform tasks effectively (mean 4.53, (SD 0.56).

Discussion

Principal Findings

This study aimed to develop a nursing and continuous care management work plan for individuals living with COVID-19 in Nakhon Pathom Province, focusing on identifying needs, designing an integrated database system, and evaluating its effectiveness. The findings highlight significant challenges in the health care service system, including limited access to care, reliance on self-treatment, and the persistence of post-COVID-19 symptoms. In response, a comprehensive care model was designed to address gaps in service delivery through the use of digital technologies, community-based care strategies, and structured follow-up mechanisms. The final phase demonstrated the system's high level of effectiveness in practice, particularly in data security and task performance, as evaluated by health care professionals. Results showed high overall effectiveness (mean 4.51, SD 0.59), with data security rated highest (mean 4.59, SD 0.57), followed by task performance (mean 4.53, SD 0.56). This confirmed the system's capacity to support sustainable, technology-enabled post-COVID care at the community level.

Based on the situation of health care and continuous care systems for the public living with COVID-19 in Nakhon Pathom Province, it was found that symptoms persist approximately 6

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months postinfection. According to Davis et al [7] for the majority of respondents (>91%), the time to recovery exceeded 35 weeks. Common post-COVID symptoms include persistent cough and fatigue, consistent with studies by Thekgungsakdakul et al [8] and Ruengsong et al [9]. However, other research suggests that patients with COVID-19 may have an increased risk of developing respiratory diseases, and the risk increases with the severity of infection and reinfection [10].

There is also evidence of anxiety and social withdrawal, echoing findings by Tongtaeng and Sisawang [11], which highlight significant psychological impacts such as depression that necessitate evaluation following COVID-19 infection management protocols [12]. This research defines self-management outcomes in mental health post-COVID symptom onset.

From the study findings, it was observed that patients experiencing post-COVID symptoms have reduced access to treatment services at local facilities and increasingly rely on telehealth systems for care. They still require support from professional nurses and community health volunteers for continuous care. Consequently, the research analysis proposes health care guidelines for the public following recovery from COVID-19, consisting of five key strategies: (1) self-care guidance through digital information access related to COVID-19; (2) management of COVID-19 via telehealth nursing systems; (3) physical health care services postrecovery; (4) mental health care services postrecovery; and (5) continuous care guidelines for referral cases reported after recovery. The integration of telehealth systems has played a critical role in enhancing nursing care during the COVID-19 pandemic. Prior studies have demonstrated that telemedicine not only supports effective monitoring of patients with COVID-19 while minimizing transmission risks but also contributes to the continuity and quality of care delivery [13,14].

These align with the findings of Thongnopakun et al's [15] study on knowledge and attitudes towards patient follow-up among community health volunteers before and after training, indicating significant differences. They also follow the guidelines of the Medical Research and Technology Evaluation Institute [16], emphasizing self-care and receiving services from local health units or seeking telemedicine advice if symptoms persist beyond 2 months to consult specialized physicians for developing health care strategies for patients experiencing post-COVID symptoms, including the studies of Chugamnern et al [17], which emphasize the importance of evaluating data from patients' families and communities, thereby reflecting the importance and necessity of designing a continuous care tracking database system for the public living with COVID-19 to improve service provision in the future.

Suggestions

A network for emergency care or urgent assistance among local volunteers and the health service network to prevent diseases should be established.

Health service units should establish policies on data management for health service leaders, communication systems to develop a continuous care system focusing on home visits, and support management to care for patients with post-COVID or patients with other epidemic diseases.

Acknowledgments

The authors are grateful to the research funding from Nakhon Pathom Rajabhat University. Special thanks to the research team from the Faculty of Management Science for providing management knowledge, and to the Faculty of Science and Technology for supporting technological knowledge and database system development. We appreciate the support from the practical training source, Na-sang, Subdistrict Health Promotion Hospital, for being a pioneering area in research. Lastly, we extend our gratitude to all the contributors and individuals who made this project successful.

Conflicts of Interest

None declared.

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Edited by E Borycki; submitted 12.08.24; peer-reviewed by VG Yogeshappa; revised version received 24.03.25; accepted 27.03.25; published 29.05.25.

Please cite as:
Buajaroen H, Photangtham D, Chankham W, Simalaotao P, Sirisukpoca U, Kongkamsook M, Timtab P, Suasangei T
Nursing and Continuing Care Management Work Plan for People Living With COVID-19: Case Study of the Nakhon Pathom Province
JMIR Nursing 2025;8:e65310
URL: https://nursing.jmir.org/2025/1/e65310
doi:10.2196/65310

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Patients' Perception of a Brief Web- and Mindfulness-Based Intervention for Pain Following Discharge After Total Joint Arthroplasty: Qualitative Description

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Abstract

Background: Important levels of pain are reported upon discharge from major surgery, with a risk of becoming chronic. Further, individuals express the need for support in managing pain after discharge. However, very few studies address pain management interventions in the postdischarge phase after surgery, including for individuals undergoing total joint arthroplasty (TJA). We have conducted a pilot randomized controlled trial testing a brief mindfulness intervention targeting people at risk for chronic postsurgical pain 2 weeks after surgery. Although the intervention we proposed was judged acceptable based on ratings obtained through a questionnaire, the nuanced perceptions of why and how it is considered acceptable are critical in refining the intervention. Moreover, the acceptability of mindfulness interventions in the perioperative context remains generally unknown and even more so in the postdischarge setting.

Objective: The purpose of this study was to use qualitative data to explore the individual perception of acceptability of a brief 4-week, Web- and mindfulness-based intervention for pain following discharge after a TJA.

Methods: A qualitative description was used to assess patients' perception of the preliminary version of the intervention for pain management following discharge after surgery. The qualitative assessment was done at the end of the 4-week intervention (6 weeks after surgery). Semistructured interviews with open-ended questions were used to encourage free expression from participants (n=16) before proceeding to content analysis.

Results: When reflecting on the benefits of the intervention, the main themes that emerged were mindfulness, pain acceptance, and supplementary relief. Overall, the intervention was perceived as relevant and suitable during recovery, although participants experienced a few challenges related to the novelty of mindfulness practice. Engagement and readiness were discussed in relation to adherence to the intervention. Addressing expectations and personal beliefs before the intervention could improve participants' adherence. Offering additional support when spikes of pain occur could help overcome some challenges related to mindfulness practice during postoperative recovery.

Conclusions: Given the increasing number of TJA surgeries performed annually and the effectiveness of nonpharmacological interventions, such as mindfulness-based approaches, in supporting recovery and well-being, efforts should be made to increase patient access to these promising adjunctive treatments. Combining nonpharmacological interventions before and after surgery may be an interesting avenue to optimize pain relief and recovery, as well as prevent complications. Finally, the use of technology could improve the accessibility, scalability, and adoption of these promising approaches for individuals with limited resources and mobility.

Trial Registration: ClinicalTrials.gov NCT04848428; https://clinicaltrials.gov/ct2/show/NCT04848428

International Registered Report Identifier (IRRID): RR2-10.2196/30951

(JMIR Nursing 2025;8:e69010) doi:10.2196/69010

KEYWORDS

pain; mindfulness; online; surgery; web; arthroplasty; patient perception

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Introduction

Pain after total joint arthroplasty (TJA) is expected, but little is known about pain after discharge [1]. As the length of hospital stay after surgery continues to decrease, it is essential to develop our knowledge regarding pain and its management in the subacute postoperative phase. A recent meta-analysis found the prevalence of moderate to severe postoperative pain ranges from 51%, one day after discharge, to 58%, 1‐2 weeks after discharge [1]. Two weeks after surgery marks the beginning of the subacute phase and is the time when pain and analgesic consumption are expected to decrease or when persistent postsurgical pain begins to be evident [2]. Hence, these pain rates may be unnecessarily high and put patients at elevated risk for developing chronic postsurgical pain (CPSP) [3,4], prolonged opioid use, and adverse effects of nonopioid agents [5-7]. Very few studies address pain management interventions in this setting, including after TJA [2,8,9], despite documented concerns and lack of support reported by individuals during their recovery following TJA [10]. Multiple barriers are also involved with this gap in the continuum of care [11,12]. Based on prior research with both clinicians and patients [12,13], there are promising opportunities for training postoperative patients in self-management of pain. Given the risks associated with pharmacological approaches, efficient nonpharmacological interventions for pain should be developed and offered to these individuals.

A variety of educational and psychoeducational interventions exist for individuals undergoing TJA that have been shown to have minimal impact on pain in the perioperative setting [9]. More recently, traditional 8-week mindfulness-based interventions (MBIs) have been delivered preoperatively to patients with TJA, and early evidence indicates they improve outcomes [14,15]. However, in addition to a lack of interest to engage in such interventions in the preoperative period, the accessibility and scalability of 8-week MBIs are limited by feasibility and acceptability challenges, including the substantial time commitment required to participate in an 8-week intervention, the extended gap between starting the intervention and undergoing surgery, and logistical barriers such as scheduling multiple treatment sessions over several weeks [14,15]. To address some of these limitations, our team and others have recently adapted MBIs to address the needs of patients in the preoperative period [14-23]. Brief MBIs delivered preoperatively have been shown to have medium to large effects on orthopedic surgical patients' acute pain, pain unpleasantness, opioid use, and pain medication desire [19,20]. These novel brief MBIs are promising but have not been delivered in a targeted manner in the first few weeks after surgery to patients with a different postoperative pain trajectory associated with worse outcomes, showing warning signs for transitioning to CPSP [24].

However, providing patients with effective pain management in the subacute period after TJA is complicated by shortened postoperative hospital stays, mobility challenges, and uncertainty about who is responsible for pain management after discharge [11,25]. As a result, patients are often left to self-manage pain, which can be overwhelming and lead to inconsistent or inadequate care. In an effort to address barriers to the implementation of pain management interventions after discharge and to increase their accessibility, we proposed a Web-based asynchronous version of a brief MBI, which showed positive outcomes [26]. However, the acceptability of these MBIs, including individual experiences and perceptions in the perioperative context, remains generally unknown, and the very few studies address traditional 8-week formats [14,27]. Although the intervention we proposed was judged as acceptable based on ratings obtained through a questionnaire [26], the nuanced perceptions of why and how it is considered acceptable are missing. It is critical to capture this aspect to understand which intervention elements are perceived as effective and appropriate and how we can tailor the intervention and further improve its acceptability and efficacy. Therefore, the purpose of this study was to use qualitative data to explore the individual perception of acceptability of a brief 4-week MBI for pain following discharge after a major orthopedic surgery, for example, total hip or knee arthroplasty. The data and results presented in this paper are secondary to a pilot randomized controlled trial (RCT) that was conducted to evaluate the feasibility and preliminary effects of this intervention after TJA in 36 older adults [26].

Methods

Design

This study is part of a pilot RCT that examined the impact of a brief 4-week MBI intervention on pain and other postoperative outcomes [26]. Data collection was completed in August 2022. A qualitative description [28] was used to assess patients' perception of the preliminary version of the intervention for pain management following discharge after surgery. This approach matched the needs of this study by allowing the analysis to stay close to the data and the informants' point of view without imposing a specific philosophical or theoretical framework (eg, grounded theory and phenomenology) [28,29]. Qualitative descriptive analyses are particularly useful when developing and refining clinical interventions in the context of health services research, where patients' perspectives are the ultimate evaluation [29-32]. This design allowed us to describe the extent to which the intervention is acceptable and what ingredients are helpful or need improvement from a patient's perspective.

Ethical Considerations

The project received ethics approval from Florida State University's institutional review board in January 2022 (#STUDY00001771) and was preregistered (NCT04848428). Informed and written consent was obtained from each participant. During the initial meeting with the research team, besides providing details on the study and the nature of participation, it was emphasized that participating was completely voluntary and that participants could refuse or withdraw at any time without affecting their care. Strict measures were implemented in collaboration with our clinical partners to protect privacy throughout the study. Confidentiality and anonymity were also ensured by assigning a code to each participant during data collection, analysis, and the use of illustrative verbatim in the current manuscript.

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Procedure

Nurses from the preoperative clinic introduced the study to potential participants. If interested, an experienced research assistant (RA) explained the study, answered any patient questions, and signed the consent form during a preoperative visit 1 week before surgery. Two weeks after surgery (T0), the RA called each participant to confirm their eligibility and collect baseline sociodemographic and clinical data. Two weeks correspond to the first follow-up with the surgeon, and waiting 2 weeks before beginning the interventions also allowed participants to recover from acute surgical pain and experience the challenges of managing persistent pain in their daily activities. Participant inclusion criteria included the following: (1) 18 years and older; (2) first elective TJA; (3) presence of pain during movement ≥4/10 [33] 2 weeks after surgery; (4) ability to understand and complete questionnaires in English; (5) ability to use an electronic device such as a smartphone and computer or tablet; and (6) completed the brief 4-week MBI. Patients were not eligible for the study if they were unable to consent because of physical or mental incapacity. Participants received gift cards of US $25 at each of the data collection time points (T0: 2 wk after surgery, T1: 6 wk after surgery). After a prescreening and a baseline assessment, participants were randomized to receive the brief 4-week MBI (experimental group) or a pain-coping educational intervention (active control group). A total of 18 participants were assigned to the experimental group receiving the new brief Web-based MBI. An assessment of the acceptability of the intervention was conducted at the end of the intervention using a questionnaire. Semistructured individual interviews (telephone) were then conducted by the RA with all intervention arm participants to explore their individual perceptions. The sample size was thus not based on data saturation, but on involvement in the experimental group.

Intervention

In addition to usual care, participants received the brief MBI delivered remotely, asynchronously through prerecorded videos. Across the 4 weeks, participants received a weekly link via email or text message that allowed them to access their intervention videos. The intervention videos were embedded in Qualtrics to allow optimized viewing from any type of device, for example, a computer, tablet, or smartphone. Participants were invited to watch the videos as much as needed or desired. Over the course of the 4-week intervention, participants received reminders to view their weekly video if they had not viewed it. In an effort to promote self-management, the intervention was self-guided, and participants received no other interventional support.

The brief MBI is an adaptation of mindfulness-oriented recovery enhancement (MORE) [34]. The traditional MORE program is an efficacious, 8-week treatment for chronic pain and opioid misuse [35-37] that integrates 3 core therapeutic elements (ie, mindfulness, positive reappraisal, and savoring) to promote positive patient outcomes. The brief, 2-hour version of MORE (ie, brief mindfulness-oriented recovery enhancement [B-MORE]) that was used in this study retained each of these 3 core therapeutic elements and was delivered through four 20-minute prerecorded videos. The first video provided information about pain and mindfulness before introducing an 11-minute body scan practice. The second video introduced MORE's core mindful pain management technique. This technique helps pain patients disengage and shift attention from affective to sensory processing of pain sensations [38] and then to reorient attention to an object of their choice via mindful breathing. The third video introduced positive reappraisal and a mindful reappraisal practice exercise to familiarize participants with the mindful reappraisal worksheet. Then, participants were guided through the mindful reappraisal worksheet in the service of reappraising pain. A 5-minute mindful breathing practice was also used in this video to facilitate pain reappraisals. The fourth video introduced savoring along with a 10-minute mindful savoring practice. After each session, participants were prompted to reflect on the best parts of the mindfulness practice and any challenges that may have arisen. The final video ended with guidance for creating an at-home mindfulness practice routine.

Data Collection

The qualitative assessment was done at the end of the 4-week intervention (6 weeks after surgery). Semistructured interviews with open-ended questions were used to encourage free expression from participants and the richness and authenticity of data [28,39]. Interviews lasted between 30 and 45 minutes and were conducted on the phone for patients' convenience, but also to allow for data collection to take place in the participants' natural setting as proposed by a qualitative descriptive approach [28,32]. Interviews were completed by an RA who was trained and supervised by the first author (GM), who has expertise in qualitative research and were audio recorded before being professionally transcribed. Field notes were taken by the RA as needed during interviews to allow for complementary information during the analysis. As part of the larger project, participants first rated the intervention components in terms of four attributes: (1) appropriateness in helping patients manage pain, (2) effectiveness in promoting pain self-management, (3) suitability, and (4) willingness to adhere, with the use of the treatment acceptability and preference (TAP) questionnaire [40,41]. The TAP questionnaire relies on a 5-point scale ranging from not at all (0) to very much (4). It has demonstrated adequate internal consistency (alpha >0.80) [41] and was previously validated in a surgical population receiving a web-based intervention for pain [13]. Patients' rating of each component was used to elicit additional feedback on their perception of the intervention's acceptability and on the need for further modifications during interviews. Table 1 presents the semistructured interview guide. These questions were not pilot tested in this study, but they were used and validated in previous acceptability studies conducted by the principal investigator (PI) [12,13,42].

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Table . Semistructured interview questions based on the treatment acceptability and preference questionnaire's attributes.

Themes	Questions
Effectiveness	• What do you find the most/least helpful about the intervention? • In what way do you think the intervention helped/did not help you manage your pain after surgery? • In what way do you think the intervention helped/did not help you decrease the impact of pain on your recovery? • In what way do you think the intervention helped/did not help you improve your ability to do your postoperative exercises?
Appropriateness	• What do you find appropriate/not appropriate about the intervention? • What strategies seem appropriate/inappropriate to manage postoperative pain? • In what way are the strategies appropriate/not appropriate to pain management after surgery? • What additional information (if any) would you like covered by the intervention?
Suitability	• What pain management strategies in the intervention do you find easy to apply/not easy to apply? • What do you think of the timing of the intervention? • What do you think of the length of the intervention? • What do you think of the therapist?
Willingness to adhere	• What is easy/not easy about completing the intervention? • What (if anything) could be done to make the intervention more convenient?

Data Analysis

Descriptive statistics were used to summarize the sociodemographic and clinical characteristics of the participants at baseline and postintervention. Transcripts of the semistructured interviews were content analyzed to identify patterns and generate themes related to participants' experiences with the intervention and their perception of its acceptability [43]. More specifically, our content analysis approach based on Miles and Huberman [43] included the following phases: coding of data, recording of insights and reflections on the data, identifying similar phrases, patterns, themes, sequences, and important features, searching for commonalities and differences, progressively deciding on generalizations that hold true for the data, and examining these generalizations in the light of existing knowledge. Our content analysis process aligned with a qualitative descriptive method by being focused on staying close to data and informants' perspectives while also allowing the emergence of themes present across all interviews [28,29,39].

To address critiques about the subjectivity of qualitative descriptive work and enhance its rigor, steps were taken to preserve authenticity and integrity during analysis [39], and a combination of deductive and inductive approaches to coding was used. Although a particular theoretical view was not adopted to ensure data-driven coding and categorizing, a deductive approach was used to reduce researcher's subjectivity with a preliminary generation of codes that were based on the attributes of acceptability highlighted by Sidani et al [40,41] which are directly aligned with the questionnaire used before the interviews: effectiveness, appropriateness, suitability, and willingness to adhere. Definitions of these attributes are presented in Table 2. Additional codes (subcategories) were created inductively as necessary. Reliability was ensured by performing double coding. The PI and the RA independently coded interviews.

Table . Definition of acceptability attributes (Sidani et al [40]).

Attributes	Definition
Effectiveness	Patient's perception of the extent to which the treatment is helpful
Appropriateness	Patient's perception of the overall treatment's reasonableness/logicalness
Suitability	Patient's judgment of the treatment's intrusiveness, consistency with individual lifestyle
Willingness to adhere	Patient's perception of the extent to which they are willing to follow the treatment

Essentially, transcripts of interviews were read several times by the PI and RA, and the content of these transcripts was first categorized under each acceptability attribute (effectiveness, appropriateness, suitability, and willingness to adhere), giving way to a more focused form of the data to help identify key themes and patterns. Then, the identification of redundant

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phrases and themes led to the emergence of a new category (eg, pain acceptance) before searching for differences and commonalities under each new category (eg, feeling frustrated vs feeling in control). Results were then compared, and differences were discussed until a consensus was reached. If needed, the co-PI (AH) was involved in the consensus meeting. When a new code was generated, it was discussed as well. Last, it is important to note that the researcher's bias was also reduced by not involving the PI in the interviews. These strategies are consistent with the Consolidated Criteria for Reporting Qualitative Research (COREQ; Checklist 1) [44].

Results

Sample Characteristics

Participants in our qualitative sample (n=18) were older adults (mean age 67.44 years, SD 6.22 years), mostly women (13/18, 72.2%), White/Caucasian (14/18, 77.8%), and undergoing a total knee replacement (14/18, 77.8%). Table 3 shows the sociodemographic profile of the participant subset. Of note, B-MORE participants, when compared with controls, reported significantly higher baseline levels of pain interference (d=−0.74, W=93.5, P=.03) and anxiety (d=−0.61, W=108, P=.04). Out of the 18 participants completing the brief MBI intervention, 16 individuals completed the postintervention assessment. No adverse events were reported during the study. For contextual purposes, statistically significant differences were found in favor of the B-MORE participants, with lower pain intensity, pain interference, and medication use observed at follow-up. Regarding the acceptability of quantitative ratings, detailed results are presented in the article reporting the RCT [26]. Overall, participants judged B-MORE as acceptable (total mean score 3.32, SD 0.73) based on how effective, appropriate, and suitable they perceived it, as well as their willingness to adhere to it. Of note, the perceived appropriateness of the intervention received the highest score (3.5, SD 0.73), and their willingness to adhere was the lowest score B-MORE received (3.19, SD 0.75) as reflected by the TAP questionnaire.

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Table . Sociodemographic characteristics of participants at baseline (n=18).

Characteristic	Value
Age (years), mean (SD)	67.44 (6.22)
Civil status, n (%)	
Divorced/separated	3 (16.7)
Married	11 (61.1)
Single	3 (16.7)
Widowed	1 (5.5)
Gender, n (%)	
Female	13 (72.2)
Male	5 (27.8)
Race, n (%)	
Native American	0 (0.0)
Black or African American	4 (22.2)
White	14 (77.8)
Living, n (%)	
Alone	4 (22.2)
With other family members	14 (77.8)
Education, n (%)	
College	7 (38.9)
Graduate School	2 (11.1)
High School	9 (50.0)
Employment, n (%)	
Full Time	0 (0.0)
On Leave	1 (5.6)
Retired	16 (88.9)
Unemployed	1 (5.6)
Surgery type, n (%)	
Total hip replacement	4 (22.2)
Total knee replacement	14 (77.8)
Currently involved in a rehabilitation program, n (%)	
No	2 (11.1)
Yes	16 (88.9)

Acceptability Perception of B-MORE

Based on our content analytic approach, we categorized our findings related to the perception of the intervention's acceptability into 4 main themes: perception of the effectiveness of the intervention, perception of the appropriateness of the intervention, perception of the suitability of the intervention, and perception of their willingness to adhere to the intervention. We present the categories that emerged for each theme. Table 4 presents a summary of results along with additional excerpts from interviews.

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Table . Results from the content analysis on patients' perception of the intervention's acceptability (n=16).

Acceptability attribute and category	Verbatim (Participant ID)
Effectiveness	
Mindfulness practice	• "I'd say [the most helpful was] practicing and concentrating on things other than the pain." [P5] • "When you had to stop and repeat the strategy in the middle of thinking" [P14] • "I had a mental and physical feeling of warmth" [P4]
Pain acceptance	• "In the beginning I was totally frustrated […] I think the questions were set up just right for the timing." [P9] • "[…] that made you aware there would be pain, but it won't last forever." [P1]
Supplementary relief	• "[the strategies] gave me an opportunity to try another method of pain control, especially when I lay down at night" [P11] • "Pain medication was the most helpful for me" [P8]
Appropriateness	
Relevance	• "I found it appropriate to concentrate on things other than the pain" [P8] • "I thought the strategies were fine" [P10]
Challenges	• "The first one we had to look at something and focus on it. That was quite easy. After that, it seemed to get into spaces where I wasn't sure where I was going." [P14] • "I don't think I followed the last one correctly" [P6]
Suitability	
Timing/schedule	• "I thought the timing was really good" [P10] • "It's been in a very timely and appropriate time frame" [P12]
Length	• "I like the shorter ones because they are easier to go through and concentrate on" [P7] • "Long enough but not so long that you couldn't stay focused" [P10]
Technology	• "It was easy to do throughout the day since I had it on my phone" [P15] • [it's] difficult […] to steady myself down" [P13]
Willingness to adhere	
Engagement	• "Really, you just got to make up your mind to do the sessions and put in the effort so that it works" [P3] • "You just need to make time for it" [P11]
Readiness	• "I was definitely surprised to see that I was able to change the focus and that it was helpful" [P3] • "I thought it would be too long and detailed" [P7] • "I don't dwell on pain" [P13]

Effectiveness of the Brief Web-Based MBI

Overview

Many patients expressed positive feedback on the program's effectiveness in helping them manage pain postsurgery. When asked about how the intervention was helpful, 3 categories were delineated in participants' responses: mindfulness practice, pain acceptance, and supplementary relief.

Mindfulness Practice

Mindfulness practice was central to participants' experiences in B-MORE, as many highlighted the usefulness of specific mindfulness techniques in managing their discomfort and improving their focus. Mindfulness practices such as body scanning (session #1), mindful breathing (session #2), and savoring (session #4) helped patients redirect their attention away from pain and toward a sense of calm and control. One participant noted, "The relaxation part where you start at the top and move down to each segment […] took my mind off the pain" [P15], illustrating how structured mindfulness practices

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helped shift their focus to the present moment rather than the physical sensations of pain. Additionally, participants described the value of concentrating on pleasant or neutral thoughts rather than pain, with one participant explaining, for example, that "[the most helpful part of the program was] concentrating on pleasant things rather than pain" [P9]. Another participant mentioned, "I was focusing on what I needed to do so it was relaxing" [P7]. Breathing exercises were also frequently mentioned, with some participants using mindful breathing regularly as a way to remain grounded during daily activities. For example, one participant stated that "the breathing exercises were easy to apply and think about throughout the day" [P5]. Through these mindfulness techniques, patients found a sense of relief and relaxation, which many expressed was a beneficial addition to their postoperative recovery.

Pain Acceptance

Acceptance also featured prominently in patients' reflections on B-MORE, particularly as it helped them reshape their relationship with pain. Many participants expressed that B-MORE encouraged them to acknowledge pain as a natural part of their healing journey, rather than something to be resisted or feared. This shift in mindset allowed patients to feel more in control, as they recognized pain as temporary and manageable. One participant shared, "The [mindful reappraisal] questions [in session #3] reminded me that yes, I'm going to have pain […] I think what helped me was that there were a lot of questions that made you aware there would be pain, but it won't last forever" [P1], illustrating how the program's emphasis on acceptance through mindful reappraisal provided reassurance and resilience in the face of discomfort. This perspective was empowering for patients, who felt that viewing pain as part of recovery made it less distressing and even motivated them to engage more actively with the mindfulness exercises. Another participant described, "In the beginning I was totally frustrated and stressed and in a lot of pain. My reaction to the questions then was different than it is today. I think the questions were set up just right for the timing." [P9]. By accepting rather than fighting their pain, the intervention helped them cope more effectively throughout the recovery process.

Supplementary Relief

Several participants perceived the program as an additional method of relief rather than an essential strategy. For example, one participant commented that "it was easier to do once the pain was under control" [P8], suggesting that it was not a first-choice strategy to relieve pain. Some expressed that they appreciated having access to an additional modality of pain relief and used it according to their individual needs. For example, one person commented, "[the strategies] gave me an opportunity to try another method of pain control, especially when I lay down at night" [P11]. One respondent shared that "The [mindful] pain strategies were helpful... but the pain medication was the most helpful" [P8], highlighting that mindfulness alone wasn't sufficient in cases where pain levels were especially high. The observed variation in participant responses indicates that while B-MORE was effective for most participants, others needed a combination of mindfulness and traditional pain management strategies to achieve optimal relief.

Appropriateness of the Brief Web-Based MBI

Overview

Nearly all participants found B-MORE well-suited to their recovery needs, viewing B-MORE as a constructive tool for managing postoperative pain. The perception regarding the intervention's reasonableness/logicalness was illustrated by 2 categories: relevance and challenges.

Relevance

Many appreciated the direct relevance of the different mindfulness practices, in coping with their physical discomfort. One patient stated, "[…] it seemed like everything was [relevant] to me" [P1]. Another reflected, "I thought [the program] was very well done, and you just kinda had to focus and follow through" [P12], suggesting that the exercises did not require excessive effort to implement. Others echoed this sentiment, "Everything I was told to do/did was appropriate" [P11]. Additionally, mindfulness strategies resonated with some patients as suitable life skills beyond pain management. One participant stated, "Meditation is appropriate for life and pain management" [P2], showing an appreciation for the program's relevance both within and beyond their immediate recovery period.

Challenges

Although the majority of participants found B-MORE thoughtfully designed and relevant to their recovery, some participants felt certain components of the program were challenging. One individual found it difficult to follow the program, "I had trouble concentrating on everything and remembering to do them most days" [P3], and another found the first session more relatable than the later sessions, "The first [session] everything was appropriate. After that, it seemed more out there and harder to figure out" [P7]. Another participant reflected on overcoming challenges by commenting, "It started out hard to do the exercises, but it got easier as I did them" [P5]. These insights suggest that while the program's overall approach was appropriate, adjusting the pacing and sequencing of mindfulness exercises could enhance engagement and tailoring for individual needs.

Suitability of the Brief Web-Based MBI

Overview

Suitability refers primarily to how the intervention was delivered. Suitability was discussed in terms of how easy the strategies were to apply or use. Several preferences regarding the timing/schedule, the exercises, and the use of technology emerged.

Timing and Schedule

Participants generally felt that the timing of the B-MORE intervention (ie, beginning 2 weeks after surgery) was appropriate and well-integrated into their recovery process, although opinions varied slightly based on individual recovery progress. Some participants highlighted that having this intervention during their rehabilitation program was helpful, for instance, "in the middle of rehab, so the timing was okay" [P9]. However, some participants expressed that they would

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have started earlier at the time of discharge by saying, "I personally would've been better to have started about a week earlier" [P11], while some highlighted that "the first couple of weeks were rough to focus" [P8] or reported "trouble focusing because of pain" [P9]. Last, one participant mentioned starting before surgery but was referring to postoperative pain specifically, "I think most chronic pain is before surgery, so I think this would be helpful to start this before surgery" [P1]. Regarding the schedule, a participant found that the program's schedule was suitable because "It was in a routine and worked fine" [P5], reflecting a positive view of the weekly pacing. Many appreciated the consistent, scheduled nature of the program, as it provided a structured approach that aligned well with their recovery. One participant noted, "I thought that was great because I think anything less than that, I'd forget" [P1], underscoring how the schedule and duration of sessions supported retention and engagement. Overall, most participants found the timing and schedule to be helpful and well-suited to their needs, although a few felt minor adjustments could enhance its alignment with the early stages of postoperative recovery.

Length of Mindfulness Exercises

Participants expressed a range of thoughts regarding the length of the sessions and exercises, with many favoring shorter durations. One participant noted that the shorter sessions helped maintain their interest and concentration, saying, "I didn't get bored or want to quit." [P1]. Another echoed this sentiment, stating, "10-minute exercises were the best" [P3], while others mentioned that "anything longer" than 10 - 15 minutes made it challenging to stay focused. Some found 20-minute meditation sessions acceptable but desired "less explanation" and more practice. Overall, most participants seemed to agree that shorter exercises facilitated better concentration and engagement, with a few suggesting that some sessions felt a bit long but were still satisfactory. Overall, the feedback highlights a preference for concise sessions that balance engagement and focus.

Technology

A number of preferences were expressed regarding the use of technology. The asynchronous nature of the mindfulness program provided participants with the flexibility to engage in pain management exercises at their convenience, fitting seamlessly into their daily routines. This flexibility allowed our surgical patients to access mindful pain management strategies when they felt most comfortable and ready, whether that was during a quiet moment at home or while on the go, "[the strategies] gave me an opportunity to try another method of pain control, especially when I lay down at night" [P11]. One participant noted, "It's easy to do since it's on my phone" [P12], highlighting the convenience of accessing the sessions from any device. This on-demand availability meant that participants could practice mindfulness techniques at times when they experienced heightened pain or stress, thereby maximizing the intervention's effectiveness. The ability to revisit the exercises as needed also empowered participants to take control of their pain management. However, patients who were less accustomed to such practices found it challenging to focus. For instance, one participant commented, "I can find a quiet spot but trying to stop and focus is the hardest part" [P13], reflecting that the lack of a real-time guide or live feedback sometimes made it difficult to stay engaged. Of note, one participant mentioned that although convenient, she preferred an in-person interaction, "I know with COVID this was not possible, but I prefer a face-to-face thing" [P7]. Overall, technology was a positive aspect contributing to the personalization of B-MORE and self-management practices.

Willingness to Adhere

Overview

Participants' willingness to adhere was driven by their commitment or engagement toward the program and their readiness for a mindfulness program.

Engagement

Participants expressed the importance of fulfilling their commitment and putting effort into the sessions. For example, some participants stated, "Really, you just got to make up your mind to do the sessions and put in the effort so that it works" [P3], "I said I would do it, so I did it […] it forced me to sit down with it" [P5]. Remote communication with the team (eg, emailed links and reminders via text messages) and the digital relationship with the therapist also contributed to and supported that engagement. As one participant commented, "I think y'all stayed in touch" [P12]. Another one referred to the therapist by saying, "I liked to listen to him talk" [P9]. Nonetheless, adherence was challenging for patients facing high or low levels of discomfort. In such cases, intense pain could overshadow the motivation to engage in mindfulness. A patient noted, "the first couple of weeks were rough to focus […] now that I'm off the medication, my mind is clearer" [P8]. Another one stated, "I had trouble focusing because of pain" [P9], showing that factors like pain intensity and fatigue could interfere with adherence to mindfulness practices. For patients like these, added support or adaptive pacing within the program might help them maintain adherence, even during particularly challenging recovery phases. In contrast, one participant reported that their pain level had decreased to such a degree during the 4-week intervention that they no longer needed the intervention, "I think that personally my pain had decreased so I don't know how I related to it as much" [P4].

Readiness

Readiness to engage in a MBI was also described by several participants. Expectations and personal beliefs were 2 aspects that were reflected when discussing readiness and adherence to the intervention. Regarding expectations, several participants expressed some uncertainty and pessimism that could have influenced their adherence initially by mentioning that they did not know what to expect and that they did not expect the intervention to be effective. They also mentioned that this perception changed throughout the intervention by commenting that what they got out of their participation was surprising and encouraging and that some strategies got easier to practice with, for instance, "It was really strange because I didn't have a lot of expectation that it would be a big help […] just the fact of being able to focus, I found that very encouraging [P12]. Of note, one participant with previous experience with mindfulness stated, "I thought it was easy to focus because I've done this

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before […] I'm used to doing longer meditations with music […] it left me wanting more" [P2]. In this case, although readiness does not seem to be an issue and the participant would be expected to adhere easily to the intervention, having previous experience and mindfulness skills could have led to different expectations and hindered her interest in pursuing the intervention and adhering to the full program. Personal beliefs seemed to have an influence on their readiness and willingness to adhere as well. Two opposite views with 2 different impacts appeared. A personal belief that meditation or mindfulness is beneficial naturally attracted some individuals to the intervention. Nevertheless, a few participants expressed that pain was of minimal importance, which could have hindered their willingness to adhere to the intervention, "I am active and busy […] I don't have time to dwell on pain. I get up and on with my day" [P7].

In summary, while most patients viewed the mindfulness-based program as an acceptable and valuable approach to pain management, their feedback highlights areas where additional support or customization could enhance effectiveness, appropriateness, suitability, and adherence. Tailoring session length, offering guidance for those in severe pain, and potentially providing more interactive elements could strengthen the program's acceptability across patient experiences.

Discussion

This is the first study to use a qualitative descriptive approach to explore the acceptability of a brief, Web-based MBI in the postdischarge recovery phase after TJA. Content analysis of the semistructured individual interviews clearly revealed that participants found the brief MBI helpful. These findings support and extend results from a recent pilot RCT, in which the brief MBI significantly reduced pain intensity, pain interference, and pain medication use relative to an active control condition [26]. Specifically, qualitative data from this study indicates that after completing the 4-week MBI, participants reported increased mindfulness leading to less concentration on the pain and more relaxation, increased pain acceptance leading to a positive attitude, and last, supplementary pain relief. Results from this study also align with previous qualitative studies on the benefits of MBIs for improved coping and relaxation among adults preparing for TJA [14] and for the management of postoperative pain and negative emotions during recovery from lumbar spine surgery [27].

Principally, results from this study contribute to understanding the acceptability of innovative ingredients addressing practical barriers and facilitating the implementation of MBI in the postdischarge period after TJA. First, the schedule of 4 weekly sessions starting 2 weeks after surgery seems to fit the recovery process and needs of most participants while promoting their participation as the worst pain levels are usually experienced within the first 2 weeks after surgery [45], and 6 weeks is the timeframe for normal tissue healing and recovery [46,47]. A few participants mentioned the possibility of starting earlier, as the pain did not seem to hinder their participation or had subsided quickly after starting the program. This aligns with a previous study with orthopedic postsurgical patients in which participants expressed this preference as they would have used the MBI strategies for other aspects of recovery than pain [27]. Second, the brief format (20 min sessions for 4 weeks), including short meditations, seemed to be appreciated by participants, which responds to feasibility and acceptability issues encountered in previous studies implementing a traditional 8-week format before surgery in this population [14,15]. Nevertheless, the only study assessing acceptability in the recovery phase after orthopedic surgery (lumbar spine) reported that 75% of patients were satisfied with 8 weekly sessions of over an hour [27]. Third, remote delivery in the postoperative period seems to offer more than convenience for participants with limited mobility; it makes their participation possible after a major surgery [12,27,48]. However, our program also addressed time and logistical constraints met by a variety of individuals [15,49-52]. As expressed by some participants, in addition to remote delivery, the asynchronous nature of the intervention allowed for even more convenience with accessibility to the program anytime from anywhere, according to individual needs and pain levels during recovery. Indeed, a previous study with adults after lumbar spine surgery reported that 25% of their participants had trouble finding an uninterrupted space at the time their session was scheduled [27]. Offering continuous access to therapeutic content acknowledges these differences during recovery [53]. Last, reminders also contributed to the acceptability of our program. As highlighted by others who evaluated the acceptability of Web-based MBIs qualitatively, check-ins are desired by most participants in order to maintain adherence and promote home practice [54] and call for hybrid approaches [12,55-57].

While participants identified multiple benefits and found the brief MBI appropriate during the early recovery period, they also noted some challenges that impacted their adherence. The main challenges were an initial uncertainty about what to expect from a "mindfulness" intervention and skepticism about its effectiveness. This hesitancy stemmed from mindfulness being unfamiliar to most participants, including reliance on traditional pharmacological approaches. This finding is resonant with the quantitative phase of this study, where the willingness to adhere item received the lowest rating on a multidimensional, Likert-type acceptability survey, despite no participant reporting unwillingness. This finding also converges with a recent qualitative analysis in which the impact of preoperative mindfulness-based stress reduction for patients with TJA was linked to their "openness" toward an MBI, health-related beliefs, and their motivations for participation [14], as well as another qualitative evaluation of an 8-week MBI after lumbar spine surgery in which some participants reported that the purpose was unclear and that they would have benefited more from the program had they understood earlier [27]. Other studies, both qualitative and quantitative, have also identified similar challenges, with participants reporting difficulty understanding the purpose of mindfulness practice [58], doubting the value or benefits [59], or dropping out of MBI groups at a higher rate than control groups, including some participants not attending any sessions [60,61]. Thus, by proactively addressing expectations and beliefs about mindfulness's ability to manage pain, we can reduce skepticism, foster greater acceptance, and enhance participant engagement and adherence from the outset.

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Of note, the MORE approach [34], used as a foundation for the brief intervention in this study, uses principles of reappraisal (cognitive-behavioral therapy) and savoring (positive psychology) to disrupt the spiral of chronic pain characterized by maladaptive thoughts and behaviors, including overreliance on pain medication. MORE targets populations facing opioid misuse [35,37].

Furthermore, while addressing initial expectations and beliefs is crucial for increasing readiness and reducing uncertainty about any treatment, a few participants identified known challenges unique to mindfulness practice [62]. Indeed, qualitative studies involving participants with various backgrounds and varying levels of familiarity with mindfulness have described challenges related to mindfulness practice [50,51,63]. It is not unusual for individuals to doubt their skills and knowledge. In this study, several participants reported having difficulty focusing, following some sessions, or feeling unsure of "spaces" they were "getting into." Mind wandering and feeling strange can be perceived as a barrier to mindfulness practice [50-52,59] and could impede participants' adherence to the intervention. Connecting with negative feelings is another barrier, as they can be challenging or overwhelming at times [49,51,63]. In this study, some participants reported similar barriers, expressing difficulty practicing mindfulness while experiencing elevated pain or during moments of general discomfort or frustration. Proactively providing participants with information about common challenges during mindfulness practices, as well as techniques for mitigating those challenges, would likely further enhance the acceptability and effectiveness of the brief MBI.

This study has several limitations. First, the homogenous sample limits our understanding of perceptions across diverse sociodemographic groups (older adults, White, female). Additionally, the reported perceptions are from individuals who agreed to participate, and 2 participants dropped out of the experimental group. Although a multilevel meta-analysis of RCTs using the MORE program for other conditions highlighted that diverse groups, including younger adults (mean age 25 - 59 years) as well as underrepresented racial/ethnic groups, have received this intervention [64], future qualitative studies could use quota sampling to include the perception of various subgroups, including those who refused to participate, thus enhancing our understanding of barriers to the intervention's uptake. While not necessarily a limitation, participants noted that postoperative pain medication might have hindered their ability to follow the sessions, and that mindfulness practice was more challenging during pain spikes. Last, the qualitative analysis did not account for the time participants spent watching the videos or practicing mindfulness. Consequently, the level of comfort with the intervention may have been influenced by the amount of practice. Comparing acceptability attributes based on the amount of practice could provide valuable insights.

However, several barriers to adherence emerged in relation to the challenges of mindfulness practice in the postoperative recovery period, and these warrant further exploration to ensure the brief MBI's success in a future, fully powered, RCT. For instance, it would be interesting to assess if additional digital health tools, such as chatbots, would be beneficial in offering a more tailored support for patients who find mindfulness practice challenging during pain spikes. Furthermore, regarding the timing of the intervention, although we targeted a specific subgroup based on risk factors for CPSP (ie, pain<4/10 at 2 wk), some participants felt ready to start earlier, and some would have started later during recovery. Future studies could explore additional variables to help determine who would benefit from which timing of intervention or compare the value of different timings of intervention during postoperative recovery. Moreover, although the brief format (ie, 4-week sessions of 30 min) represented a positive aspect of the intervention, would some postoperative patients benefit from a full standard format of 8 weekly sessions of one hour?

Given the increasing number of TJAs performed each year and the ability of nonpharmacological interventions, such as MBIs, to support recovery and well-being, efforts should be made to increase patient access to these promising adjunctive treatments. In this study, semistructured interviews indicated that the brief MBI promoted self-management of pain during the early recovery period. Additionally, while most studies to date have tested the implementation of brief preoperative interventions for patients with TJA when postoperative pain is not present yet, our study highlights the acceptability of a postoperative MBI. Combining MBI interventions before and after surgery at different key time points of the perioperative continuum of care may be an interesting avenue to optimize pain relief and recovery, as well as prevent complications such as the development of CPSP. Finally, the use of technology could improve the accessibility, scalability, and adoption of these promising approaches.

Acknowledgments

The principal investigator received funding from Florida State University's Council on Research and Creativity. The authors would like to thank Ms Claire Gunter for her assistance with interviews and data analysis.

Data Availability

The datasets used and analyzed during this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

None declared.

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Checklist 1
COREQ (Consolidated Criteria for Reporting Qualitative Research) checklist.
[PDF File, 432 KB - nursing_v8i1e69010_app1.pdf]

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Abbreviations

B-MORE: brief mindfulness-oriented recovery enhancement
COREQ: Consolidated Criteria for Reporting Qualitative Research
CPSP: chronic postsurgical pain
MBI: mindfulness-based intervention
MORE: mindfulness-oriented recovery enhancement
PI: principal investigator
RA: research assistant
RCT: randomized controlled trial
TAP: treatment acceptability and preference
TJA: total joint arthroplasty

Edited by E Borycki; submitted 19.11.24; peer-reviewed by A Gaudino, C Madu; revised version received 16.06.25; accepted 17.06.25; published 06.08.25.

Please cite as:
Martorella G, Hanley AW, Muessig KE
Patients' Perception of a Brief Web- and Mindfulness-Based Intervention for Pain Following Discharge After Total Joint Arthroplasty: Qualitative Description
JMIR Nursing 2025;8:e69010
URL: https://nursing.jmir.org/2025/1/e69010
doi:10.2196/69010

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2024: A Year of Nursing Informatics Research in Review

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Abstract

Each year, nursing informatics researchers contribute to nursing and health informatics knowledge. The year 2024 emerged as yet another year of significant advances. In this editorial, I describe and highlight some of the key trends in nursing informatics research as published in *JMIR Nursing* in 2024. Artificial intelligence (AI), data science, mobile health (mHealth), and the integration of technology into nursing education and practice remain key research themes in the literature. Nursing informatics publications continue to grow in number. A greater number of AI and data science articles are being published, while at the same time, mHealth and technology research continues to be conducted in nursing education and practice contexts.

(JMIR Nursing 2025;8:e74345) doi:10.2196/74345

KEYWORDS

nursing informatics; health informatics; research; practice; education; trends; artificial intelligence; data science

Introduction

The year 2024 proved to be a revolutionary year for nursing informatics and *JMIR Nursing*. Nurses, technology practitioners, and researchers who design, develop, and implement technologies used by nurses and nursing informatics specialists are moving forward in the field of study we know as nursing informatics. In 2024, we saw nursing informatics researchers focus on several key areas, namely artificial intelligence (AI), data science, and mobile health (mHealth), as well as integrating technologies into nursing practice and education. In this year's year-in-review editorial, I describe and highlight some of the key nursing informatics research themes published in *JMIR Nursing* and review 2024's published articles, using a thematic approach [1]. Findings from the review of the articles revealed many trends that I describe in more detail below.

Artificial Intelligence

Over the past year, several articles were published that assessed the current state of the science of AI in nursing; the design of AI algorithms; and the effectiveness of AI's implementation in nursing contexts, such as hospital, community, and long-term care settings. Researchers have investigated the implications of applying AI to lifestyle monitoring in long-term care [2], detecting behavioral disorders [3], identifying depression [4], patient monitoring (eg, movement monitoring for continence care, sleep, and chronic conditions) [5], and supporting nurses' decision-making [6]. AI-supported technologies, such as robots [7] and chatbots [8], have also been studied and evaluated for their use by nurses in varying care contexts. Other researchers have begun the process of examining AI's integration into nursing education. Here, there has been an impetus to identify what is important and how to effectively integrate these technologies into nursing education [9].

Data Science

Data science emerged as a key theme in the nursing informatics research. The development of data models and the analysis of nurse-generated data were considered by researchers as key to supporting nurses' decision-making in hospital [10], long-term care [11], and community settings [12]. This nursing informatics research aimed to conceptualize and develop electronic health record data models for nurses [13]. Researchers used data-centric approaches to understand and improve nursing workload measures, understand nurses' and patients' sentiments regarding COVID-19 [14], collect and present data used in the remote monitoring of patients with COVID-19 [12], and identify patient resources [15]. This research led to new findings that focused on optimizing nursing practice [10-19].

Ethics and Privacy

Key research areas of concern for nurses who use AI and data science–centric approaches included ethical [19] and privacy considerations [16] associated with using technology. Software testing remained an important aspect of nursing informatics practice to ensure the quality and safety of technologies used in health care [17].

Nursing Education

Nursing education remained an important theme in the literature [20,21]. The influence of AI on nursing education reflected the need for nurse educators and educational researchers to understand the impacts of these technologies upon nursing

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education [18]. The role of digital tools and their integration into undergraduate and graduate nursing education were explored [18]. Digital tools used by practicing nurses were studied by researchers [18,19,22]. Here, nurses' use of multimedia tools to support patient education in cardiac care was a research highlight that emerged [22], and we saw an increase in the number of papers that focused on virtual care in the context of nursing education [20,21].

mHealth Apps, Tablets, and the Internet

The development of mHealth apps for patients and nurses remained strong [23,24]. Peterson and colleagues [22] studied the effects of a gratitude exercise mindfulness app on neonatal intensive care nurses. Shiyab et al [5] examined nurses' use of mHealth apps for chronic conditions. Togo et al [25] investigated the effects of mindful breathing using a tablet on nervous system function and sleep. Nurses continued to study mobile apps, software, and devices to determine their influence on patient and nursing outcomes [5,23,24,26,27]. Nurse researchers continued to spearhead mHealth app design and improvements in design, with the aim of improving outcomes. Lastly, nurses evaluated new approaches to finding services on the World Wide Web [15].

In summary, nursing informatics research in 2024 extended our knowledge in the areas of AI and data science. Mobile apps, tablet use, the use of the internet, the integration of nursing informatics into nursing education, and the design of digital tools for nurses and patients continue to be important areas of research.

Future Research Directions

Nursing informatics research in 2024 advanced in several key areas, including research on the design and use of mobile devices (eg, mHealth tools and tablets) and software apps in the context of nursing practice, education, and administration. In addition to this, several advances in the design and development of data analytics and AI algorithms by nurses have emerged to support and enhance nursing practice. Of importance is the need to study how these technologies can effectively and safely be integrated for use by nurses in acute care, long-term care, and home care settings. Future research will need to focus on how technologies are implemented and incorporated into nurses' work and patient care, so that there is a strong cognitive-sociotechnical fit between nurse information processing activities, the physical work of nurses, the technologies that are used by nurses, and the patients they care for [1,28,29]. To address these emerging issues in nursing informatics, there is a need to expand funding at the intersection of nursing informatics and AI, data analytics, and mHealth, and research funding extensions need to be made for understanding how these critical new technologies can be added to nursing education and practice [30].

JMIR Highlights

JMIR Nursing also advanced in 2024. *JMIR Nursing* is now indexed in MEDLINE, PubMed, PubMed Central, Directory of Open Access Journals (DOAJ), Scopus, Sherpa Romeo, CINAHL, and the International Academy of Nursing Editors (INANE) directory of nursing journals. More importantly, in 2024, *JMIR Nursing's* CiteScore rose to 5.2, placing the journal in the 88th percentile. *JMIR Nursing* is now a Q1 journal for general nursing.

Conclusion

The focus on nursing informatics and emerging technology trends in the field of nursing is proving that technology's influence upon nursing practice is growing and needs continuous research and support. Nursing informatics researchers and those who study nurses using technology continue to lead the way forward, influencing nursing and health care around the world. Future research directions will need to focus on the integration and incorporation of new and emerging technologies into nursing practice, education, and administration.

Acknowledgments

EB has received a Health Research BC Health Professional Investigator Award.

Conflicts of Interest

EB is the Editor-in-Chief of *JMIR Nursing*.

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Abbreviations

AI: artificial intelligence
DOAJ: Directory of Open Access Journals
INANE: International Academy of Nursing Editors
mHealth: mobile health

Edited by J Sarvestan; submitted 22.03.25; this is a non–peer-reviewed article;accepted 24.03.25; published 07.05.25.

Please cite as:
Borycki E
2024: A Year of Nursing Informatics Research in Review
JMIR Nursing 2025;8:e74345
URL: https://nursing.jmir.org/2025/1/e74345
doi:10.2196/74345

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Exploring the Intersection of Nursing Leadership and Artificial Intelligence: Scoping Review

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Abstract

Background: As artificial intelligence (AI) technology permeates health care settings, nurse leaders must position themselves to shape its development, implementation, and impact, guiding meaningful change that benefits nurses and care delivery. Nurse leaders possess the capacity to influence decisions, shape practice, and ensure the delivery of ethical, safe, and high-quality care. While AI technology is reshaping many aspects of health care delivery, there is limited knowledge on how nurse leaders perceive and experience this shift.

Objective: This scoping review aimed to explore the intersection of nursing leadership and AI technology in health care by mapping current evidence, identifying key concepts, and highlighting knowledge gaps within the literature.

Methods: This scoping review was guided by the Joanna Briggs Institute methodology and reported on using the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) checklist. A systematic search of 4 electronic databases (CINAHL [EBSCO Information Services], Ovid MEDLINE [Wolters Kluwer], PsycINFO [American Psychological Association], and Scopus [Elsevier]) was conducted for English-language, peer-reviewed literature published between 2014 and 2025. Gray literature was also reviewed. Articles were included if they met the inclusion criteria by exploring the population of nurse leaders and the concept of AI technology within the context of health care settings and were published in English from May 2014 forward. A total of 26 articles were included in the analysis. Qualitative content analysis and numerical summary supported the inductive identification and synthesis of data categories.

Results: Of the 26 articles included, 8 were empirical (qualitative, quantitative, or mixed methods), and 18 were conceptual or theoretical articles. Although 1 article was Canadian, there were no empirical studies conducted by Canadian researchers. The qualitative content analysis of the primary search findings revealed 6 overarching data categories: (1) leading digital transformation and technology integration, (2) AI technology and the nursing role: reshaping practice, (3) ethical considerations of AI technology for nurse leaders, (4) AI technology as a facilitator of innovative leadership, (5) education and training on AI technology in nursing practice, and (6) influence of AI technology on the work environment.

Conclusions: This review confirms that nurse leaders play an essential role in shaping the future of health care in the context of AI technology. Although this review highlights a growing recognition of nursing leadership as a crucial driver of AI technology integration in health care, there is a lack of research to guide practice, policy, and leadership development through education, despite emerging interest and a recent increase in empirical work. The findings accentuate the need for increased investment in nurse-led research and leadership development to ensure that AI systems are designed, implemented, and evaluated in a manner that upholds ethical care, equity, and professional nursing values. As health care systems increasingly adopt AI technology, nurse leaders must be equipped with the knowledge, tools, and support required to lead transformative change and act as AI technology directors.

(JMIR Nursing 2025;8:e80085) doi:10.2196/80085

KEYWORDS

nursing leadership; artificial intelligence: AI technology; scoping review; digital health; work environment; leadership development

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Introduction

Background

Artificial intelligence (AI) is a rapidly developing technology that is augmenting health care delivery in multiple ways, as reflected in an increase in research over the past decade [1]. For the purposes of this scoping review, AI technology is defined as technology that allows computers and machines to mimic human cognitive functions, such as learning, understanding, problem-solving, decision-making, creativity, and autonomous aspects [2]. Despite the evolving impact of AI technology on nursing practice, few investigations have explored its intersection with nursing leadership. Nurse leaders have tremendous influence on moving teams toward a common goal [3] and instigating practice change. Understanding the nuanced and developing area of an AI technology–informed nursing leadership practice is necessary as the healthcare environment continues to shift.

To date, discourse on AI technology has centered on its potential to augment care delivery and improve patient outcomes [4]. However, few studies have critically examined how AI technology might impact nursing leadership roles or the extent to which nurse leaders are actively participating in decision-making and design processes involving AI technology integration. The paucity of knowledge extends to nursing leadership capabilities that are emerging in response to the new leadership demands, including how nursing leaders can or should guide their teams within AI technology–enhanced environments. To date, nursing leadership theory and research have commonly focused on the tenets and processes of nurse leaders related to clinical workplace environments, empowerment, and care efficacy [5,6], without a specific investigation into the influence of AI technology on nursing leadership practice itself [7]. The limited focus on how AI technology has begun to evolve and reshape nurses' roles within work environments highlights the growing knowledge gap in nursing leadership discourse.

Nurse leaders are essential to providing quality care [8-11], as evidenced by the association between relational leadership and associated patient outcomes. However, understanding how AI technology may potentially amplify nursing leadership to expand leadership capabilities is an appropriate next step for research inquiry. The existing body of nursing leadership literature has yet to fully consider or appreciate the potential for emergent AI technology to empower nurse leaders in a transformative way. As health care systems continue to adopt digital tools [12] and AI technology at a rapid pace, nurse leaders are uniquely positioned to guide ethical decision-making, advocate for equitable implementation, and model the integration of innovative tools that center on quality, safety, and compassion. However, the requisite support to empower these nurse leaders to succeed in AI technology–enhanced practices remains undefined.

The integration of AI technology into nursing workflows, policy, and care delivery may reshape the scope and focus of nurse leaders' roles, particularly in relation to ethics, workforce management, education, and equity. There is a need to explore how nurse leaders are engaging with these shifts and to understand their perspectives, responsibilities, and strategic contributions within AI technology-augmented systems. While nurses are often viewed as end users or passive recipients of technological change [13], nurse leaders may have a critical role in shaping the ethical, operational, and relational dimensions of AI technology implementation when empowered to do so. As frontline innovators and stewards of care quality, nurse leaders are essential to ensuring that AI technologies align with professional values and serve diverse populations with integrity.

Having identified the number of gaps, synthesizing the current knowledge surrounding AI technology and nursing leadership is essential. Therefore, a scoping review methodology was selected to synthesize the existing research and discourse on nursing leadership and AI technology. Given the rapid pace of digital transformation in health care and the critical leadership role nurses play, a synthesis of the existing literature is needed to better understand how AI technology is intersecting with nursing leadership at present. This scoping review was designed to address that gap and provide a comprehensive overview of how nursing leadership is currently situated in relation to the rise of AI technology. Specifically, this review aimed to map the existing literature, identify key concepts and areas of focus, and identify key gaps to inform future research directions.

Objective

This scoping review addressed the following question: What are the contemporary perspectives on AI technology and nursing leadership?

Methods

Overview

This scoping review applied the Joanna Briggs Institute (JBI) [14] scoping review framework methodology, which built upon the foundational work of Levac et al [15] and the 5-step methodology developed by Arksey and O'Malley [16]. The JBI framework included the following stages: (1) identifying the research question; (2) identifying relevant articles; (3) selecting articles; (4) charting the data; and (5) collating, summarizing, and reporting the results. The optional consultation exercise was excluded from this review [14]. The reporting for this scoping review followed the PRISMA-ScR (Preferred Reporting System for Systematic Review and Meta-Analyses extension for scoping reviews; Checklist 1) [17-20].

Search Strategy

The authors collaboratively developed the search strategy using MeSH terms and text words for the population, concept, and context (PCC) framework related to the research question [14]: (1) nursing leadership, (2) AI, and (3) health care. The strategy was piloted to confirm the suitability of terms and was peer-reviewed by a research librarian using the Peer Review of Electronic Search Strategies checklist (Multimedia Appendix 1 provides detailed search string syntax) [21].

Information Sources

The systematic search strategy conducted on May 21, 2024, targeted databases most relevant to the subject matter, including MEDLINE (Ovid), CINAHL, PsycINFO, and Scopus. Selected

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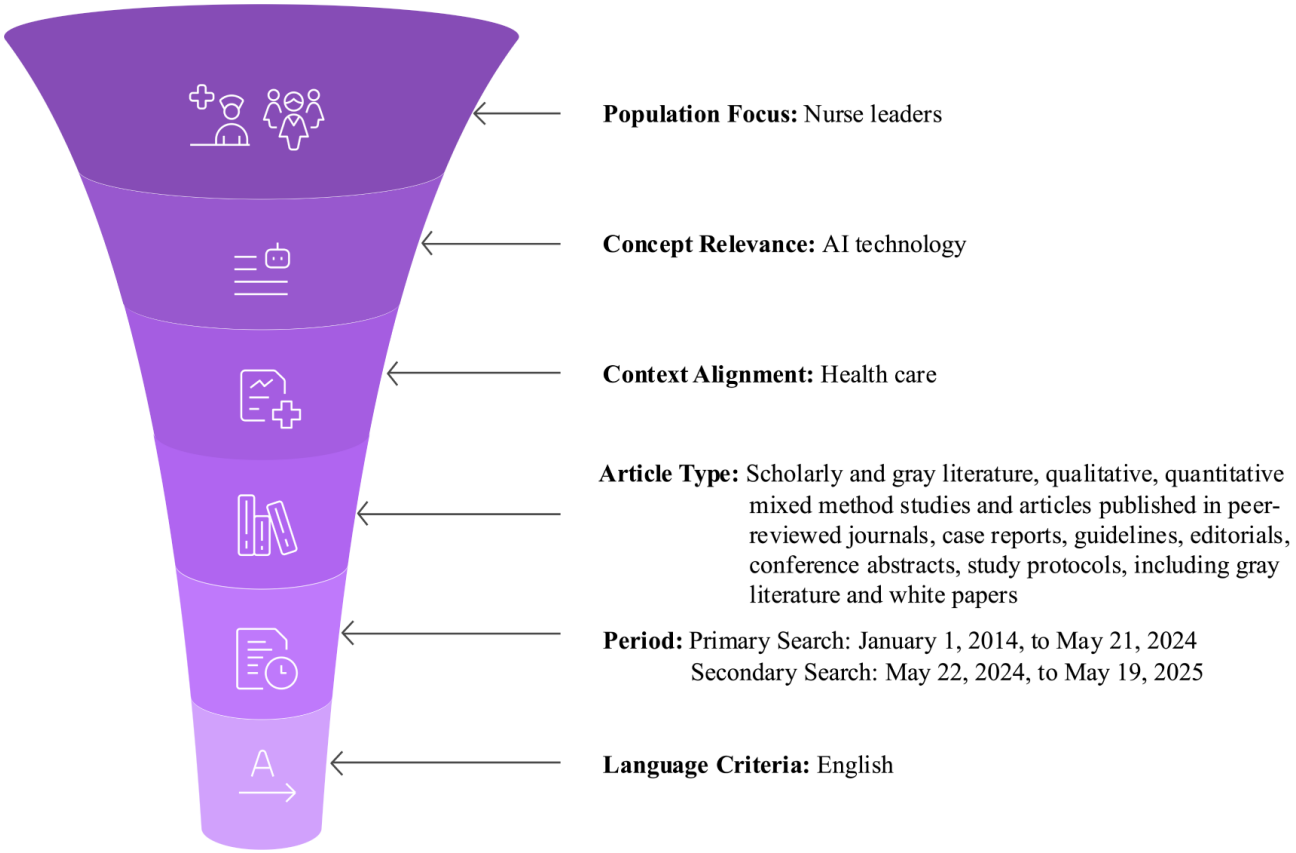
articles were manually reviewed for citations matching the inclusion criteria to identify additional articles not captured in the database searches, as well as Google (Google LLC) searches for gray literature. These approaches did not uncover any new articles that met the inclusion criteria.

Eligibility Criteria

On the basis of the established PCC framework, inclusion and exclusion criteria were determined through an iterative team approach to establish the breadth and comprehensiveness of the scoping review [14,22]. For inclusion, articles had to explore the experiences and perspectives of nurse leaders and AI technology in health care, including or discussing actions undertaken by nurse leaders, with a focus on AI technology directly applicable to current nursing leadership practices in health care. Articles were excluded if they focused on AI technology in domains of nursing other than leadership, if they focused on nursing leadership but not AI technology, or if they mentioned nursing leadership only to a limited extent, with further exclusions applied to articles with outdated practices that lack alignment with current nursing professional practice measures.

The scope of evidence included qualitative, quantitative, or mixed methods studies or articles published in peer-reviewed journals, case reports, guidelines, editorials, conference abstracts, study protocols, and gray literature, including white papers and reports. All types of literature reviews, dissertations, books, and book chapters were excluded due to the scope of the project. Finally, only English-language articles were included due to limited translation resources. The primary search was limited to the most recent 10 years, specifically to articles published between January 1, 2014, and May 20, 2024, to capture the proliferation of contemporary AI technology in nursing leadership practice [23], ensuring a comprehensive review. The exact search process was replicated on May 19, 2025, to extend the scope of the review by 1 year in an attempt to provide updates to the review and reveal dynamic shifts in the subject matter. Finally, owing to limited translation resources, the language criterion was applied to align with the authors' language fluency. The primary and supporting authors independently applied the inclusion and exclusion criteria to the retrieved articles from scholarly databases to assess the robustness of the criteria in capturing relevant publications. The application of the inclusion process is visualized in Figure 1, and all articles not meeting the inclusion criteria were excluded.

Figure 1. Funnel diagram illustrating the sequential application of key inclusion criteria for study selection.



This figure visually maps the filtering process for sources of evidence, organized sequentially by the PCC framework [14]. The criteria were determined through an iterative team approach to establish the methodological boundaries of the scoping review [14,22]. The sequential process applies: (1) population focus (nurse leaders), (2) concept relevance (AI technology), and (3) context alignment (health care). Subsequent filters include article types and the specific period limits, which were set to capture the proliferation of contemporary AI technology in practice. The final step applies the language criteria (English) based on the fluency of the reviewers.

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Study Selection

On retrieval of the search results from the scholarly databases, these results were uploaded to the web-based literature review platform software, Covidence (Veritas Health Innovation), to facilitate article screening and review. An example of the search results from both the primary and secondary searches from the Ovid MEDLINE database is available in Multimedia Appendix 2. The primary and secondary authors independently screened the titles and abstracts of retrieved articles against the inclusion and exclusion criteria using the Covidence platform. At this stage, articles that did not fulfill the inclusion criteria of the scoping review were excluded. Discrepancies from the screening of articles were resolved through discussion and consensus. Initially, 241 references were imported into Covidence for screening. After removing 46 duplicates, 195 articles were screened for title and abstract, and 85 articles were excluded. The remaining 110 articles were assessed for full-text eligibility against the inclusion and exclusion criteria, resulting in the exclusion of 96 articles and the inclusion of 14 articles in the final extraction. As of May 2024, 14 articles were included. Following an updated search and review process in May 2025, using the same search protocol with articles published from May 2024 to May 2025, 124 new articles were uploaded for screening into Covidence. The 124 articles were automatically reduced to 101 for screening by removing duplicates. The abstract and title screening process resulted in the exclusion of 57 articles, with 44 articles retrieved for full-text eligibility. This process identified an additional 12 articles, which were included in the final review. Combined with the initial 14 articles, the extended search of an extra 12-month period has resulted in a total of 26 articles included in the final data extraction and synthesis phase.

Data Extraction

The data charting process was facilitated by an adapted JBI extraction tool (Joanna Briggs Institute) [14] via an Excel (Microsoft) spreadsheet, which was used to collect, transcribe, and organize data aligned with the core descriptive elements related to the research question. Data captured during the manual extraction process was transcribed into an Excel spreadsheet in the following categories: authors, publication year, country, design, aim, AI technology context and type, and findings [14,18]. The authors reviewed and piloted the adapted extraction tool on 5 articles before the full data collection process to ensure standardized extraction. The piloting process was assessed as successful, and it was determined that no changes to the adapted extraction tool or data collection approach were necessary.

Critical Appraisal of Individual Sources of Evidence

Owing to the nature of scoping reviews and the intention of providing an overview of existing literature (rather than an assessment of rigor or quality), the articles were not evaluated for risk of bias or methodological quality [20].

Data Analysis

This scoping review followed guidance from the JBI to conduct an inductive qualitative content analysis and numerical summary to establish key data categories, trends, and identifiable gaps in the literature to summarize the evidence and report information to map the literature on this evolving topic [14,18,19,24,25]. The iterative analysis process ensured a rigorous and transparent extraction of content on the intersection of nursing leadership and AI technology using a standardized data extraction sheet informed by the JBI methodology [14].

A basic qualitative content analysis conducted by the primary author facilitated the categorization of the extracted data [18]. The analysis process began with familiarization with the data through repeated readings of the evidence sources, followed by open coding to extract relevant information and establish coding categories [26]. The data extracted from the 14 documents were then organized into a hierarchical structure that facilitated the active emergence of 6 overarching categories of data to address the phenomenon of the intersection of nursing leadership and AI technology in a conceptual form [26] (Multimedia Appendix 3). These categories were then analyzed numerically by counting the frequency at which each data category actively emerged [26]. This same rigorous approach to data analysis was applied to 12 articles that met the inclusion criteria, retrieved in May 2025 through a secondary search conducted a year later, and updates to the primary results were included to extend the value of the findings.

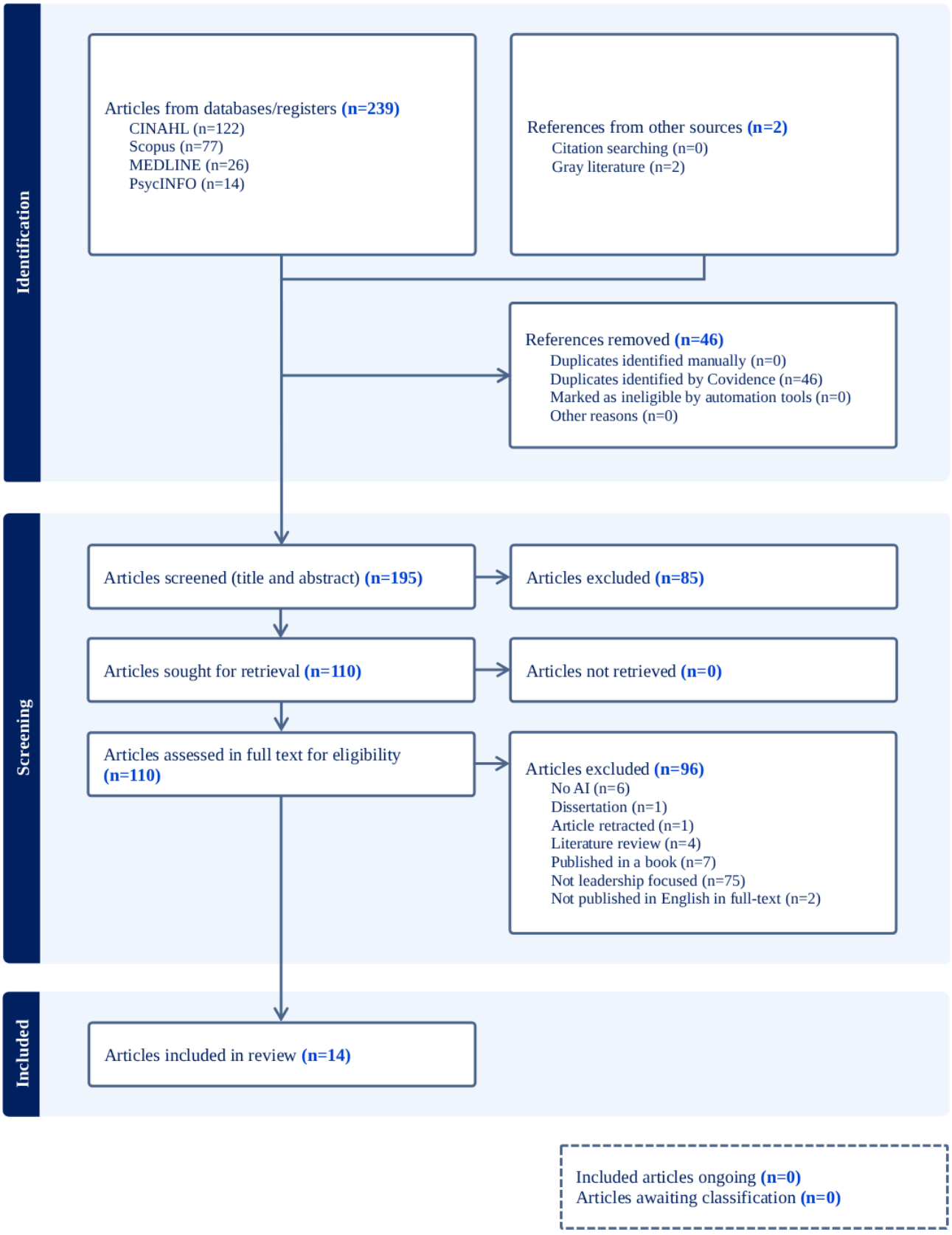
Results

Study Characteristics

The final review included 26 articles published between 2014 and 2025, with a marked increase in empirical studies in 2024 and 2025. In the primary search, 195 articles were identified, of which 14 (14/195, 7.2%) met the inclusion criteria (Figure 2). Of these, 11 (11/14, 78.6%) were commentaries, editorials, or perspectives [12,27-36] published in the USA, and 1 (1/14, 7.1%) empirical article each came from Turkey [37], Finland [38], and China [39]. In the secondary search, 124 articles were identified, of which 12 (12/124, 9.7%) met the inclusion criteria, resulting in a total of 26 articles included in the review (Figure 3). The secondary search results indicate an increase in empirical research, as reflected in 5 of the 12 articles included [40-44], which represent singular empirical articles from Sweden, Australia, and the United States and 2 from Egypt (Figure 4 maps the empirical articles by country). The remaining 7 articles were expert or professional commentaries, a theoretical paper, and a quality improvement study [45-51] representing single articles from Canada and the Republic of Korea and 5 from the United States (Figure 5 maps the nonempirical articles by country). Of the 26 included articles, 8 are empirical (qualitative, quantitative, or mixed methods), and 18 were expert commentaries, perspectives, editorial, or theoretical articles

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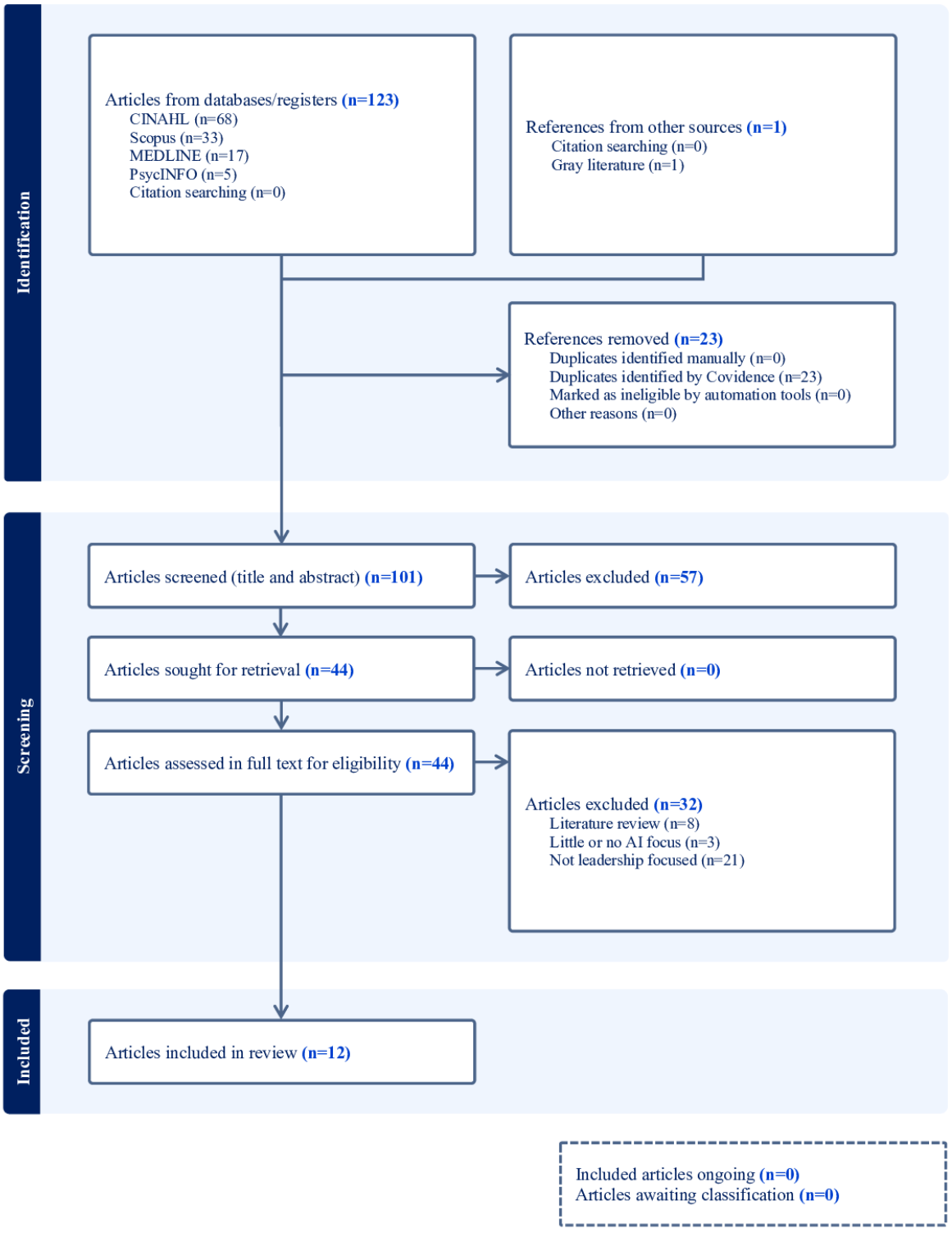
Figure 2. PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) flow diagram (primary search): This figure promotes transparency and reproducibility by mapping the 4 key stages (identification, screening, eligibility, and inclusion) for the initial 195 screened articles (January 1, 2024, to May 21, 2024), resulting in the final 14 included articles (14/195, 7.2%).



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Figure 3. PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) flow diagram (secondary search): This figure details the organized selection process through the 4 key stages (identification, screening, eligibility, and inclusion) for the extended search (May 22, 2024, to May 19, 2025), mapping the 101 screened articles that yielded 12 (12/101, 11.9%) additional included articles.

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Figure 4. Empirical articles (n=8) mapped by country (Australia, n=1, 12.5%; China, n=1, 12.5%; Egypt, n=2, 25%; Finland, n=1, 12.5%; Sweden, n=1, 12.5%; Turkey, n=1, 12.5%; and the United States, n=1, 12.5%).

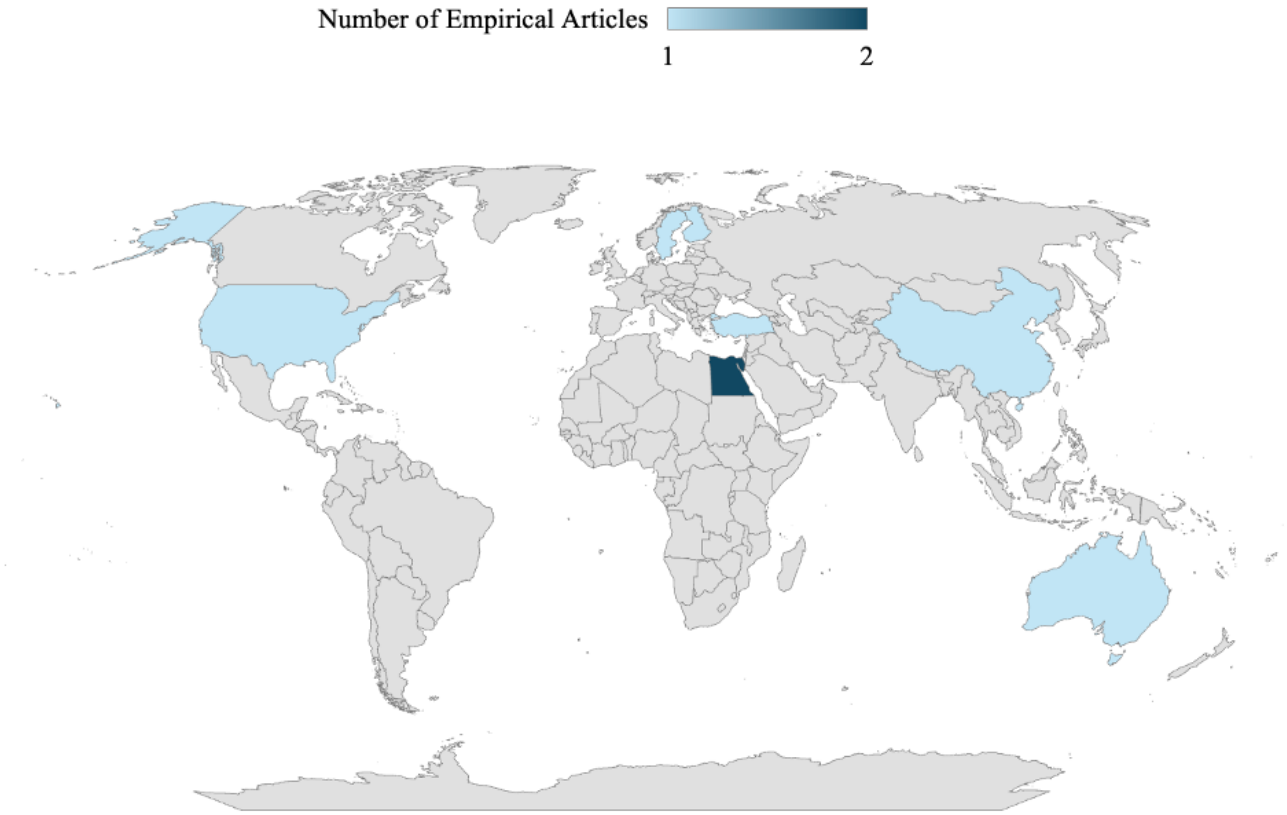
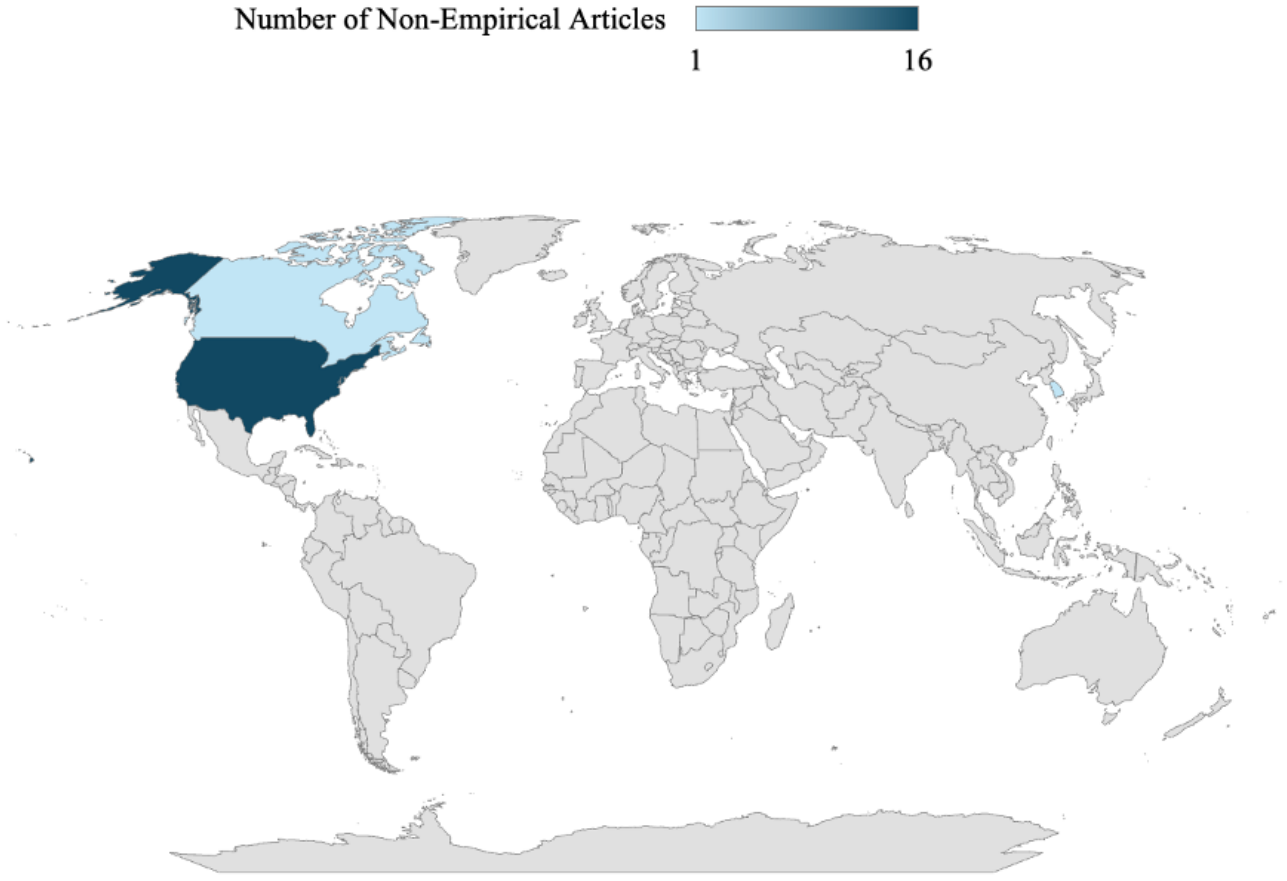


Figure 5. Nonempirical articles (n=18) mapped by country (the United States, n=16, 88.9%; Canada, n=1, 5.6%; and the Republic of Korea, n=1, 5.6%).



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Content Analysis Findings

Overview

The qualitative content analysis of the primary and secondary searches revealed 6 overarching data categories that actively emerged through the inductive and rigorous analysis approach: (1) leading digital transformation and technology integration, (2) AI technology and the nursing role: reshaping practice, (3) ethical considerations of AI technology for nurse leaders, (4) AI technology as a facilitator of innovative leadership, (5) education and training on AI technology in nursing practice, and (6) influence of AI technology on the work environment. This section relates the mapped evidence relating to the 6 data categories, focusing on the numerical analysis that details the number of articles included in each category, as well as the character framework that provides a contextual map of the evidence. The synthesis and interpretive commentary are provided in the discussion.

Leading Digital Transformation and Technology Integration

The intersection of nursing leadership and AI technology is described in the context of digital transformation and technology integration in 10 of 14 (71.4%) articles from the primary search [12,27,28,30,34-39] and 10 of 12 (83.3%) articles from the secondary search [41-47,49-51] for a total of 20 of 26 (76.9%).

In the primary search, most contributions were commentary or perspective articles, with limited empirical evidence. Laukka et al [38] reported that Finnish nurse leaders guided the implementation of AI while addressing patient safety and staff concerns. Li et al [39] surveyed 263 Chinese nurses and found that nurse leaders were expected to lead the integration of technology and involve staff in decision-making. Eminoğlu and Çelikkanat [37] studied 196 Turkish nurse leaders and found a positive association between leadership self-efficacy and AI technology readiness.

Commentaries emphasized nurse leadership as a key factor in digital transformation. Porter-O'Grady [34] advised nurse leaders to support value-based care during digital change, Blouin [27] suggested frameworks with evaluation metrics, and Linnen et al [12] promoted AI technology adoption to enhance patient safety and reduce hospital-acquired outcomes. Cineas et al [28] argued that nurse-led AI technology initiatives can promote equity in care delivery through designs that incorporate social determinants of health. Siedlecki [35] reported that AI technology can amplify nursing research through transformative approaches, associated with cautioning about ethical risks in digital environments.

In the secondary search, empirical evidence was more prominent. Sloss et al [49] conducted a mixed methods study of 120 US nurse leaders and reported that structured governance processes were associated with greater confidence in using AI technology to enhance patient safety and equity. Kotp et al [42] surveyed 187 Egyptian nurse leaders and found that one-third reported high readiness for AI-driven predictive analytics, with readiness influenced by age, education, and employment status. Lundsten et al [43] surveyed 142 US nurse leaders and reported that organizational support and resources predicted higher engagement in digital transformation. Neves et al [44] interviewed 18 stakeholders in the long-term care sector in the United Kingdom and reported both optimism about AI technology and concerns regarding trust and responsibility. Finkelstein et al [41] studied perioperative staff in Sweden and emphasized the need to align AI technology with workflows and staff expectations.

Commentary and perspective articles reinforced similar themes, including those described by Cardiff et al [46], who noted that nurse executives are integral to shaping AI technology strategies and governance. Hoelscher et al [47] emphasized the need for AI technology skills to implement systems responsibly and safely. Aldrich et al [45] positioned AI technology as an extension of nursing's mission. Tyransky et al [50] and Virkstis [51] described executives and emerging leaders preparing for AI technology adoption through mentorship and innovation.

AI Technology and the Nursing Role: Reshaping Practice

Most articles included in both the primary (11/14, 78.6%; [12,27,28,30-34,37-39]) and secondary (8/12, 66.7%; [41,42,44-47,50,51]) reviews described how AI technology was impacting aspects of the nursing role, accounting for 19(73.1%) of the 26 included articles.

Sullivan et al [36] described a proactive approach to integrating AI technology into nursing practice, reporting its use to support leadership functions, such as resource allocation and predictive analytics, to inform patient care strategies and staffing. AI technology was also reported to alleviate administrative burdens, affording nurse leaders time to focus on strategic leadership [36]. This proactive approach aligns with Blouin [27] and Clipper et al [30], who described how nurse leaders can take an active role in directing how AI technology augments nursing work by shifting attention away from non–value-added tasks and back to direct patient care. Fuller and Hansen [33] emphasized the importance of including nurses as leaders of digital adaptation through participatory processes in AI technology implementation, with active inclusion in decision-making described as promoting ownership in reemphasized nursing roles. Similarly, Douglas and Gray [31] described the need for strategic approaches, involving the urgency for nurse leaders to adapt to the changing AI landscape and to support shifting generational expectations in practice.

AI technology was also described as a potential disruptor with the capacity to reshape roles in pursuit of equity. Cineas et al [28] and Linnen et al [12] described nurse-led AI technology as an opportunity to reduce task burden, empower nurses, and redirect their energy toward meaningful engagement. Porter-O'Grady [34] emphasized that digital leadership could promote equity and gender parity in a profession navigating entrenched hierarchies, but that this required reshaping roles to encourage the active engagement of nurses as technology leaders. Laukka et al [38] reported that team engagement with AI technology can improve workflows and increase patient interaction, whereas Li et al [39] emphasized that role reshaping must be actively led by nurse leaders who intentionally involve staff in decisions at all stages. Eminoğlu and Çelikkanat [37] reported on the relationship between leadership self-efficacy

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and readiness for AI, underscoring the link between leadership capacity and role expectations in technology adoption.

Another element described was the need to redefine the nursing role through the development of expertise in research and data science. Linnen et al [12] emphasized the importance of graduate education in building digital competencies and mitigating the scarcity of nurse scientists with expertise in AI and data science. Laukka et al [38] similarly called for more nurse-led AI research. Fontenot [32] described the importance of integrating AI technology into nursing education to equip nurses with the necessary skills to guide digital advancements and data-driven care delivery.

Articles from the secondary search further expanded these findings. Aldrich et al [45] described how predictive analytics were shifting nurse-led decision-making and care planning. Cardiff et al [46] emphasized the need to align AI technology innovation with nursing values, ensuring that changes in practice support the human presence at the heart of care. Finkelstein et al [41] reported that integration of AI technology into leadership thinking prompted new ways of working, with nurses expected to navigate both clinical and digital domains. Hoelscher et al [47] described how AI technology could reduce administrative tasks while creating expectations for enhanced data interpretation and system navigation. Kotp et al [42] reported that AI-enabled decision support reshaped documentation and altered how nurses prioritized clinical cues. Neves et al [44] highlighted how AI technology in care homes was influencing delivery and relational dynamics, prompting staff to reevaluate trust and role expectations. Tyransky et al [50] described how leaders were considering changes to team roles and structures to preserve the relational aspects of nursing as AI technology entered workplaces. Virkstis [51] reported that executives were reimagining workflows and competencies needed to support nursing roles in increasingly digital environments. Across these articles, AI technology was consistently described not as replacing nursing but as reshaping how nurses think, interact, and lead within a changing clinical landscape.

Ethical Considerations of AI Technology for Nurse Leaders

A total of 12 (12/26, 46.2%) articles, including five (5/12, 41.6%) from the primary search [27,28,32,35,36] and seven (7/12, 58.3%) from the secondary search [42,44-47,49,51], directly addressed the ethical implications for nurse leaders regarding the increasing use of AI technology in nursing.

Cineas et al [28] described nurse-led AI technology initiatives as central to promoting health equity by supporting ethical care and mitigating bias in patient care. Siedlecki [35] emphasized both the potential benefits of AI technology, such as enhancing nursing research, and the risks associated with data breaches and inaccuracies. Fontenot [32] highlighted the importance of ethical considerations and patient safety when implementing AI technology, noting that AI can help close the research-to-practice gap but must be guided by principles of equity and ethics. Blouin [27] stressed the importance of evaluating and reassessing AI technologies to mitigate ethical risks to autonomy and decision-making. Sullivan et al [36] described how AI technology adoption creates new leadership responsibilities by introducing ethical challenges while offering opportunities to empower teams.

Articles from the secondary search further underscored ethical themes. Cardiff et al [46] emphasized that ethical decision-making cannot be delegated to algorithms, urging nurse leaders to remain grounded in values of dignity, presence, and justice. Sloss et al [49] reported on the importance of governance structures, describing how nurse leaders must be actively engaged in AI-related decision-making to protect patient safety and equity. Kotp et al [42] addressed automation bias and the unintended consequences of overreliance on AI technology decision support, emphasizing the leader's role in defining safe boundaries of use. Hoelscher et al [47] described the responsibility of nurse leaders to preserve the mission of nursing by ensuring that AI technology tools support relational care and advocacy. Aldrich et al [45] noted that ethical awareness must be embedded within AI technology adoption strategies, particularly when predictive tools guide clinical decision-making. Neves et al [44] reported on long-term care settings, where AI technology created uncertainty around responsibility and judgment, highlighting the need for leadership to safeguard ethical clarity and trust. Virkstis [51] emphasized the need for transparency and accountability, reporting that nurse executives play a central role in building frameworks to guide teams through ethical challenges. Across these articles, ethical AI technology leadership was consistently described as an active responsibility for nurse leaders and an essential component of successful AI technology integration.

AI Technology as a Facilitator of Innovative Leadership

A frequent theme identified in 9 (64.3%) of 14 articles from the primary search [12,29,31-34,36,37,39] and in 6 (50%) of 12 articles from the secondary search [42,45-47,49,51], for a total of 15 (57.7%) of 26 included articles, was the potential for nurse leaders to harness AI technology as a facilitator of nursing leadership through innovative practices.

Porter-O'Grady [34] described innovative leadership practices in which nurse leaders act as change agents by embracing digital technology as a tool to transform practice. Fuller and Hansen [33] reported on nurse leaders as disruptors who guided the integration of AI technology to support evidence-based nursing. Clancy [29] noted that innovative approaches could help mitigate workforce shortages by leveraging AI technology to apply lean principles such as waste reduction and value creation. Linnen et al [12] described AI technology integration as an opportunity for nurse leaders to dismantle external limitations on the profession and prepare digitally competent nurses. Sullivan et al [36] emphasized a balanced, innovative stance toward AI technology, noting its potential to improve leadership practices while extending benefits to teams through empowerment and cautious discretion.

Additional primary search contributions included Li et al [39], who found that innovative leadership behaviors increased staff enthusiasm for innovation. Douglas and Gray [31] emphasized the need for adaptive leadership approaches to address generational shifts in the workforce. Fontenot [32] described how innovative leadership within AI-augmented environments required balancing evidence-based practice with ethical

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considerations to safeguard patient safety. Eminoğlu and Çelikkanat [37] conducted a descriptive correlational study involving 196 nurse leaders in Turkey, reporting a positive association between medical AI technology readiness and leadership self-efficacy, underscoring the link between readiness and leadership development.

Articles from the secondary search further reinforced AI technology as a catalyst for innovative leadership. Aldrich et al [45] described how nurse leaders aligned AI technology adoption with strategic foresight to improve care planning and operational efficiency. Cardiff et al [46] emphasized agile and responsive leadership models that integrate AI technology while maintaining human values. Hoelscher et al [47] identified opportunities for AI technology to reinforce nursing's mission through transformative innovation, benefitting patients, teams, and systems. Kotp et al [42] highlighted how creativity and flexibility in leadership supported successful implementation and sustained innovation. Sloss et al [49] reported that participation in structured governance processes increased leaders' confidence in guiding innovation responsibly. Tyransky et al [50] described how AI technology was shifting leadership structures and inviting new forms of influence. Virkstis [51] emphasized how executives engaged in systems-level innovation, framing AI technology as an opportunity to elevate nursing leadership and drive meaningful transformation. Across these articles, nurse leaders were consistently portrayed as visionaries and architects of change, actively shaping how AI technology was introduced, adapted, and sustained in practice.

Education and Training on AI Technology in Nursing Practice

The primary search identified 10 articles (10/14, 71.4%) [12,27,28,30,31,33-36,38,39], and the secondary search identified 5 (5/12, 41.7%) additional articles [42,46,49-51], for a total of 15 (57.7%) of 26 articles that focused on education and training in AI technology for nursing practice. These articles addressed both the implementation of training for staff nurses and the development of AI technology expertise for nurse leaders.

Blouin [27], Porter-O'Grady [34], and Laukka et al [38] described the importance of cultivating a culture of continuous learning to ensure staff readiness for digital tools and maintain relevance in evolving health care environments. Siedlecki [35] highlighted the benefits of AI technology in research and emphasized the importance of ongoing digital education, focusing on ethical use, data privacy, and security. Douglas and Gray [31] emphasized tailoring education to generational learning needs, describing adaptive approaches to address workforce complexity. Linnen et al [12] advocated for formal digital education at the doctoral level, including funding and institutional support to prepare nurse scientists for leadership in a physician-dominated sector.

Several authors [28,30,33,36] have described the need for education that spans the full AI technology lifecycle, from development through implementation, use, and evaluation, to position nurses as leaders and embed AI technology into professional development strategies. Li et al [39] reported that nurse leaders who facilitated digital education for teams promoted positive psychological capital through enhanced self-efficacy.

Articles from the secondary search further emphasized education as a core consideration for nursing leadership. Kotp et al [42] reported on the relationship between leadership readiness and digital literacy, recommending ongoing education to support meaningful interpretation of predictive analytics. Cardiff et al [46] described the need to build digital confidence by normalizing iterative learning and providing practice-based training. Sloss et al [49] underscored the importance of preparing nurses for governance roles, highlighting that meaningful involvement in AI technology decision-making depends on adequate education. Tyransky et al [50] reported that think tanks identified professional development, mentorship, and accessible education as key enablers of innovative leadership. Virkstis [51] described a national initiative that empowered emerging nurse informaticians through structured education and exposure to implementation science, demonstrating how training builds leadership capacity in digital transformation. Across these articles, education was consistently framed not as a 1-time requirement but as a continuous, strategic investment to prepare and sustain nurse leader expertise for AI-enabled health care.

Influence of AI Technology on the Work Environment

The influence of AI technology on the work environment from a nurse leadership perspective was described in 7 (50%) of 14 articles from the primary search [12,27,29,30,34,36,39] and 5 (41.7%) of 12 articles from the secondary search [41,42,44,49,50], totaling 12 (46.2%) of 26 included articles.

In the primary search, Blouin [27] described the strategic implementation of AI technology to reduce workload and administrative burden, reporting that automation of repetitive tasks enabled nurses to focus on patient care. Sullivan et al [36] reported that AI technology could help address workforce shortages by predicting patient needs and guiding staffing allocation. Clancy [29] emphasized AI technology as a tool to improve workflows and mitigate the impact of shortages. Clipper et al [30] described the use of AI technology to reduce nonpatient tasks and enhance collaboration by involving nurses in system design. Linnen et al [12] described AI technology as an opportunity to disrupt structures that perpetuate nurse oppression, positioning nurse-led technology as a means to create empowerment. Li et al [39] reported that involving staff in shaping how AI technology is used promoted job control and more equitable work environments.

In the secondary search, Finkelstein et al [41] conducted a qualitative study in Sweden with perioperative staff, including nurses, managers, and physicians, examining expectations of an AI technology tool predicting length of stay, reporting that alignment with workflows and user trust were key to successful integration. Kotp et al [42] described predictive analytics as reducing administrative burden and enabling more strategic leadership presence. Neves et al [44] reported that AI in long-term care shifted interpersonal dynamics and caregiving models, requiring leadership to preserve relational care. Sloss et al [49] emphasized that equitable governance in AI implementation directly impacted workplace climate and professional autonomy. Tyransky et al [50] described

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perspectives from leadership think tanks, noting AI's potential to optimize staffing and reduce burnout if aligned with nursing values and frontline involvement. Across these articles, nurse leaders were consistently positioned as pivotal to shaping AI-informed work environments that are efficient, ethical, and grounded in professional nursing practice.

Discussion

Principal Findings

This scoping review confirms the critical role of nursing leadership in AI technology integration, despite a primary finding being the profound scarcity of empirically validated knowledge in this emergent area. Of the 26 included articles, the vast majority (18 [69.2%] were expert commentaries, perspectives, editorials, or theoretical articles) significantly outweighed the 8 [30.8%] empirical studies (qualitative, quantitative, or mixed methods studies) identified. The considerable imbalance indicates that existing research is predominantly theoretical, revealing an important research gap in knowledge that needs to be addressed to inform the development of evidence-based, actionable strategies. The inclusion of recent empirical studies demonstrates a shift from primarily theoretical discourse toward actionable strategies, readiness assessments, and program evaluations. Nurse executives emerged as key actors in policy, governance, and implementation, underscoring the importance of nursing leadership voices in shaping the adoption of AI technology. The updated dataset further revealed a nuanced understanding of nurse leaders as change agents, ethics stewards, and education champions. However, variability in AI technology literacy and readiness underscored the need for strategic training and system-level support.

Leading Digital Transformation and Technology Integration

Findings confirmed the positioning of nurse leaders as central to envisioning, guiding, and supporting AI-related shifts in care delivery, operations, and workforce planning [12,27,28,30,34-39,41-47,49-51]. Nurse leaders were described as innovators balancing technological adoption with professional values, ensuring alignment between digital transformation and nursing practice. Empirical studies have shown that organizational support, governance structures, and leadership readiness significantly influence successful AI technology adoption [38,42,43,49]. Interpretations suggest that sustained investment in leadership development is necessary to prepare leaders for expanded digital governance responsibilities.

AI Technology and the Nursing Role: Reshaping Practice

The review highlighted that AI technology is reshaping nursing roles rather than replacing them [12,27,28,30-34,37-39,41,42,44-47,50,51]. Leaders who involved staff in AI technology decisions fostered job control, equity, and professional empowerment [38,39]. Education was framed as essential to redefining the role, particularly through graduate preparation in digital skills and nurse-led research [12,38]. Interpretively, these findings suggest that nurse leaders must intentionally engage staff to transform potential disruption into empowerment and equity.

Ethical Considerations of AI Technology for Nurse Leaders

AI technology was positioned as both a potential benefit and a source of ethical risk [27,28,32,35,36,42,44-47,49,51]. Leaders were described as active agents in safeguarding dignity, presence, and justice while mitigating risks such as automation bias, privacy concerns, and inequities as AI technology shifts the health care landscape. Empirical and commentary articles emphasized the need for transparent governance, ethical frameworks, and transparency in decision-making. Interpretively, ethical nursing leadership in the integration of AI technology must move beyond passive oversight to proactive engagement, embedding ethical awareness into governance structures and daily practice.

AI Technology as a Facilitator of Innovative Leadership

Nurse leaders were portrayed as visionaries and architects of change, using AI technology to drive innovative leadership practices [12,29,31-34,36,37,39,42,45-47,49,51]. Empirical work supported associations between leadership self-efficacy and AI technology readiness [37], whereas commentary articles emphasized opportunities for agile and responsive leadership [45-47]. Collectively, the literature frames AI technology not simply as a tool, but as a catalyst for leadership innovation at both the organizational and system levels. Interpretively, this highlights the urgent need for nurse leaders to intentionally develop competencies in digital literacy, relational leadership, and co-creation with multidisciplinary partners.

Education and Training on AI Technology in Nursing Practice

Education emerged as a central leadership responsibility in both primary and secondary education searches [12,27,28,30,31,33-36,38,39,42,46,49-51]. Authors described the importance of fostering continuous learning cultures, tailoring education to generational needs, and preparing doctoral-level nurse scientists. Empirical studies emphasized the relationship between leadership readiness and digital literacy [42]. These findings suggest that education should be viewed as a continuous, strategic investment to sustain nurse leader acumen in leading the integration of AI technology and empowering their teams to enhance care delivery through digital transformation.

Influence of AI Technology on the Work Environment

The influence of AI technology on the work environment was a central topic in leadership discussions [12,27,29,30,34,36,39,41,42,44,49,50]. Leaders were described as pivotal in leveraging AI technology to reduce administrative burden, improve workflow efficiency, and mitigate burnout [27,29,30,36,42,50]. Empirical findings underscore the importance of aligning AI technology systems with existing workflows and preserving trust and relational care [41,44]. Interpretively, these results highlight AI technology as both a facilitator of efficiency and a disruptor of traditional care

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models, requiring intentional leadership to ensure adoption aligns with nursing values and professional autonomy. AI technology, leveraged by nurse leaders, also presents an opportunity to change systems that impact nurses, transforming the work environment into one that benefits both nurses and patient care. Substantive opportunities to leverage AI technology are appropriately guided by informed nurse leaders who involve staff in decisions related to AI technology. Li et al [39] specifically found that leaders who intentionally facilitate work environment strategies can mitigate burnout and improve job satisfaction during AI integration. Conversely, the potential risks of failing to engage with AI technology may result in missed opportunities to enhance nursing practice, patient care delivery, and the work environment. Taken together, these findings demonstrate that the adoption of AI technology reshapes the work environment and demands leadership presence in guiding organizational change.

Research Gaps, Global Perspectives, and the Canadian Context

The findings of this scoping review suggest that effective nursing leadership plays a crucial role in integrating AI technology within health care systems. The inclusion of recent empirical work expanded global perspectives from Egypt, Sweden, and Korea, enriching applied knowledge of actionable leadership strategies, readiness assessments, and program evaluations [40-43,47]. The updated dataset reinforces the prominent role of nurse executives as change agents, ethics stewards, and education champions [41-44,46,49-51], yet findings reveal persistent variability in AI technology literacy and readiness, highlighting a continuous need for strategic training and system-level support.

As AI technology continues to instigate change in health care delivery, advancements are rapidly shifting nursing practice, and the requisite expertise of nurse leaders is outpacing research.

The lack of scientific inquiry at the intersection of nursing leadership and AI technology is evident in the profound scarcity of empirical research currently available. Of the 14 articles from the primary search, only 3 were empirical studies, all conducted outside of North America [37-39]. The paucity of empirical inquiry highlights a global gap, marked by a notable absence of a Canadian presence. Although the secondary search added 5 empirical studies [40-44] within a 12-month period, a significant increase when compared to the previous decade, Canadian representation in empirical research remains absent, despite evidence that Canadian nurse leaders are already engaging with AI technology in practice [4]. This gap highlights the urgency for targeted funding, infrastructure, and academic partnerships to support Canadian nurse scientists and leaders in AI technology research [52]. The sharp increase in publications during the secondary search period also signals growing global attention and a time-sensitive opportunity for nursing leadership to claim space in AI development.

A Canadian presence within the AI technology and nursing leadership research space is crucial to match the nuanced landscape of our health system and diverse patient needs [52]. The remaining articles included for review (ie, commentaries and editorials authored in the USA) reflect the intense interest of nurse leaders as the arena continues to change shape under the influence of AI technology. As nursing leadership demands expand with AI technology, creating a new leadership practice dimension, nurse leaders need not only to shift to adapt but also take a definitive role in shaping how AI technology influences practice [27,28,30,32-34].

Together, these articles highlight the multifaceted nature of nursing leadership in the era of AI technology, emphasizing the profession's dual role as both caregivers and architects of transformation. The findings affirm that intentional leadership development, ethical discernment, and education grounded in the realities of nursing work are essential to guiding this integration in ways that honor both technological advancements and the core values of the profession, which may have a profound impact on our profession moving forward.

Limitations

This review has limitations that need to be described. First, while every attempt was made to include articles relevant to the topic, because of the specificity of the inclusion criteria, only 14 articles that met the eligibility criteria were identified in the initial search, with a further 12 added through the secondary extended timeline search. In addition, despite a broad search strategy to ensure a wide capture of relevant information reflective of the scoping review process, limitations based on the inclusion and exclusion criteria may have limited the findings. These limitations include the language of publication being restricted to the English language and the exclusion of dissertations and book chapters due to the capacity of the inquiry team. Although the publication date range for the initial search was set at 10 years, this restriction likely did not limit the results, as the relevant articles matching the inclusion criteria were published from 2018 onward. Interestingly, when the publication date range was extended by 1 year for the secondary search, the number of included articles from a 1-year period, 12 articles, almost matches the 14 originally included from the previous 10-year period. This significant increase in included articles, especially empirical studies, which were noted to be only three in the previous decade, reveals the increase in research and interest in this subject matter.

Despite a broadened data set, limitations remain. Language was restricted to English due to resource constraints, potentially excluding relevant non-English articles. The review included theoretical and commentary-based articles, which, while valuable, may lack empirical validation. The diversity of AI applications and leadership roles made the standardization of synthesis challenging. Nonetheless, the expansion from 14 to 26 articles improved representativeness and thematic saturation.

Conclusions

This scoping review provided insights into the contemporary perspectives on AI technology and nursing leadership, resulting in the identification of a significant research gap and a lack of scientific inquiry in this emergent area of leadership practice, which, with the secondary search, reveals promising signs of advancement in empirical research. The demand for leadership discussion and development is an essential area for advancing the profession, as it enables the maintenance of parallel expertise

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with the growth of this leadership dimension [31,33,34,36]. Furthermore, this investigation into nursing leadership and AI technology revealed a unique opportunity for nurse leaders to promote health equity in care delivery and professional equity for nursing itself, with the potential to alleviate oppressive practices that have hindered the actualization of the profession [28,34].

Future research should prioritize inclusive, empirical explorations that elevate diverse leadership voices and deepen understanding of AI technology's transformative role in nursing leadership practice, with particular attention to the work environment. Future research should use diverse methodologies, including longitudinal and mixed methods designs, to examine how nurse leaders engage with AI technology across varying contexts. Comparative and interprofessional studies, as well as inquiry focused on rural, Indigenous, and underserved populations, are needed to inform both leadership practice and policy frameworks.

Positioning nurses as AI technology directors presents an opportunity for the nursing profession to influence and define its own future, rather than being influenced by external forces.

Douglas and Gray [31] emphasize the need for tailored AI technology education approaches to support nurses in thriving in practice. Specific nurse leadership education for practicing nurse leaders should be developed in tandem by nurse scientists and leaders to promote and support nurse leaders as change agents in the integration of AI technology into practice. Taken collectively, it is clear that the nursing profession needs to become fully engaged in the rapidly evolving landscape of AI technology [30,36,37].

Acknowledgments

This scoping review partially fulfills the requirements of the PhD program in nursing at Western University. The primary researcher acknowledges with gratitude funding support from Western University 2022/2023/2024/2025/2026, including competitive funding: Joseph and Vera Byrne 125th Anniversary Alumni Graduate Scholarship in Nursing 2022 awarded by Western University, the Dorothy Wylie Awards 2022 & 2025 from the Nursing Leadership Network of Ontario, the Dorothy Wylie Awards 2022 & 2025 from the Registered Nurses Foundation of Ontario, Ontario Graduate Scholarships 2024 - 2025 & 2025 - 2026 from the Ontario Ministry of Colleges and Universities, the Canadian Nurses Foundation 2025 - 2026, and the Irene E. Nordwich Foundation PhD award 2025, as well as bursary support from the Royal Canadian Legion, Ontario Command, District D, Zone 3, Branch #10 -Todmorden 2022/2023/2024/2025 and the Registered Nurses Association of Ontario 2022/2023/2024/2025.

Data Availability

All data generated or analyzed during this study are included in this published paper (and its supplementary information files).

Conflicts of Interest

None declared.

Multimedia Appendix 1
Literature review detailed search string syntax.
[PDF File, 51 KB - nursing_v8i1e80085_app1.pdf]

Multimedia Appendix 2
Literature review search strategy results.
[PDF File, 115 KB - nursing_v8i1e80085_app2.pdf]

Multimedia Appendix 3
Overview of findings.
[PDF File, 136 KB - nursing_v8i1e80085_app3.pdf]

Checklist 1
Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist.
[PDF File, 133 KB - nursing_v8i1e80085_app4.pdf]

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Abbreviations

AI: artificial intelligence

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JBI: Joanna Briggs Institute
PCC: population, concept, and context
PRISMA-ScR : Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews

Edited by E Borycki; submitted 08.07.25; peer-reviewed by U Khan, X Liang; revised version received 10.10.25; accepted 13.10.25; published 14.11.25.

Please cite as:
Burford JS, Booth RG, McIntyre A
Exploring the Intersection of Nursing Leadership and Artificial Intelligence: Scoping Review
JMIR Nursing 2025;8:e80085
URL: https://nursing.jmir.org/2025/1/e80085
doi:10.2196/80085

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Opportunities, Challenges, and Future Directions for the Integration of Automation in Nursing Practice: Discursive Study

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Abstract

Background: Global health care systems are under increasing strain due to aging populations, workforce shortages, and rising patient complexity. In response, automation technologies are being explored as a means to optimize nursing workflows, reduce burdens, and improve patient outcomes. However, the integration of such technologies raises complex ethical, legal, and professional considerations that remain insufficiently addressed in current literature.

Objective: This study aims to critically examine the integration of automation into nursing practice through a discursive analysis. Specifically, it seeks to (1) identify nursing tasks most amenable to automation; (2) evaluate the benefits and drawbacks of automating these tasks; (3) explore ethical and legal implications; (4) propose strategies for ethical and equitable integration; and (5) outline future directions for research, practice, and policy.

Methods: An integrative review and conceptual analysis were conducted, grounded in sociotechnical systems theory and the ethics of care. A structured search across PubMed, CINAHL, Scopus, Web of Science, and JMIR Publications identified 73 peer-reviewed papers published between 2019 and 2025. Thematic synthesis was performed to identify key domains relevant to automation in nursing.

Results: Five major categories of automatable nursing tasks were identified: administrative documentation, medication management, patient monitoring, infection control, and mobility support. Automation in these areas was associated with improved efficiency, enhanced patient safety, and reduced physical and cognitive workload for nurses. Nevertheless, challenges such as deskilling, dehumanization of care, inequitable access, and unclear legal accountability were prominent. The study proposes the Integration of Automation Technologies in Nursing Practice Conceptual Framework.

Conclusions: The ethical integration of automation into nursing practice requires more than technological readiness; it demands policy development, targeted education, and inclusive governance. When guided by professional values and human-centered design, automation can complement nursing practice and improve care delivery. Future research should prioritize longitudinal impact assessments, legal clarity, and equitable infrastructure investment to support sustainable adoption.

(JMIR Nursing 2025;8:e72674) doi:10.2196/72674

KEYWORDS

nursing automation; artificial intelligence; nursing ethics; healthcare technology; patient safety; digital health; sociotechnical systems

Introduction

Background

Health care systems worldwide face escalating demands due to aging populations, increased prevalence of chronic disease, and workforce shortages [1]. The evolving health care landscape, characterized by increasing patient complexity, health care worker shortages, and escalating health care costs, necessitates innovative approaches to optimize patient care delivery [2]. Nursing, a cornerstone of patient care, is particularly affected. Automation has emerged as a promising solution to streamline tasks, reduce errors, and enhance job satisfaction [3]. One such approach involves the automation of routine and repetitive tasks within nursing practice. However, understanding which tasks are automatable and the consequences of such automation

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remains underexplored. In recent years, the integration of automation technologies into health care has generated significant discourse across academic, professional, and policy-making domains [4,5]. Within the nursing profession, the adoption of automation has been hailed as a means to alleviate the workforce burden, enhance efficiency, and improve patient outcomes [6].

While technology has infiltrated various sectors, its integration within nursing has been a subject of ongoing debate and exploration. Nevertheless, the integration of these technologies presents both opportunities and challenges, warranting a nuanced examination of their implications for nursing practice. Current literature highlights the potential of automation to streamline repetitive, time-intensive tasks such as medication dispensing, patient monitoring, and administrative documentation, thereby freeing up nurses to focus on higher-level cognitive functions such as patient assessment, critical thinking, and emotional support [7].

Despite these advances, critical gaps remain in understanding the ethical, practical, and sociocultural dimensions of automating certain tasks in nursing. For instance, while some studies have emphasized the potential for task automation to reduce burnout and improve job satisfaction, others have raised concerns about deskilling, reduced human interaction, and inequities in access to technological resources [8]. The literature also reveals significant gaps in our understanding regarding patient safety, ethical considerations, job displacement, and the potential for dehumanization of care [9,10]. Existing studies primarily focus on specific technologies such as robotics or telemedicine, with limited comprehensive frameworks for evaluating the broader implications of automation within the nursing profession [7,11].

The significance of this research lies in its potential to address these gaps by providing a comprehensive exploration of the integration of automation in nursing practice, along with its associated benefits and inherent challenges. In doing so, this study seeks to inform evidence-based strategies for integrating automation into nursing workflows in a manner that aligns with professional values and enhances health care delivery. Specifically, this discursive paper aims to answer the following questions: (1) What tasks in nursing practice are most amenable to automation? (2) What are the perceived benefits and drawbacks of automating these tasks? (3) What are the ethical considerations and legal implications of automating nursing tasks? (4) How can automation be integrated ethically and equitably to maximize its positive impact while mitigating potential risks? and (5) What are the future directions for the development and integration of automated technologies in nursing?

The rationale behind this research stems from the growing demand for health care services amid an aging population, nursing shortages, and escalating care complexities. Automation, if implemented thoughtfully, holds promise as a transformative solution to these systemic challenges [12,13]. By addressing the identified research questions, this study aims to advance scholarly understanding of how automation can be leveraged in nursing practice to achieve both operational efficiency and high-quality care. Moreover, the findings have the potential to contribute to policy development, workforce planning, and the design of technology that supports, rather than supplants, the role of nurses. Ultimately, this research seeks to provide actionable insights that bridge the gap between technological innovation and the enduring humanistic ethos of nursing, ensuring that automation serves as a tool for empowerment rather than displacement. To enhance clarity and reader engagement, this paper includes visual aids, such as a table summarizing automatable nursing tasks, benefits, and ethical considerations, as well as conceptual figures presenting the integration of automation within nursing workflows.

Thesis Statement

While automation holds promise for improving nursing efficiency and patient outcomes, this paper argues that its integration must be critically navigated to preserve ethical standards, professional integrity, and the relational core of nursing care. Through discursive analysis, the paper proposes frameworks to ensure that technological innovation supports, rather than displaces, the humanistic foundations of nursing.

Methods

Study Design

This discursive paper used an integrative review combined with conceptual analysis to explore the integration of automation into nursing practice. Consistent with discursive inquiry methodologies, the approach emphasized critical reflection, synthesis, and argumentation rather than empirical measurement. The study aimed to develop a theoretically informed understanding of how automation shapes nursing roles, ethics, and care delivery. Methodological rigor was ensured through a systematic literature search strategy, thematic categorization, and the application of established theoretical frameworks that guided the analysis.

Theoretical Framework

The conceptual analysis was grounded in sociotechnical systems theory and ethics of care principles. Sociotechnical theory [14] recognizes the interdependence between social (human) and technical (automation) elements in complex systems, while the ethics of care foregrounds the relational, moral dimensions central to nursing practice [15]. These frameworks informed the identification of core concepts and the interpretation of findings, ensuring alignment with nursing's humanistic values.

Literature Search Strategy

A comprehensive literature search was conducted across PubMed, CINAHL, Scopus, Web of Science, and JMIR Publications to identify relevant peer-reviewed papers published between April 2019 and March 2025. The search strategy used Boolean operators and a combination of controlled vocabulary (eg, Medical Subject Headings terms) and keywords to capture a wide range of relevant literature. The key search terms included "automation in nursing," "artificial intelligence in health care," "robotics in nursing," "automated decision support," and "nursing informatics." This approach ensured a comprehensive retrieval of studies addressing both practical implementations and theoretical frameworks related to

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automation in nursing. To maintain breadth and depth in the analysis, the search included both empirical studies and theoretical or discursive works.

Inclusion and Exclusion Criteria

Studies were included in the analysis if they focused explicitly on the application, impact, or perception of automation technologies within nursing practice. In addition, eligible studies addressed ethical, legal, operational, or sociocultural dimensions of automation, providing a comprehensive view of its implications in clinical contexts. Only studies that were peer-reviewed and published in English were considered to ensure quality and accessibility.

Conversely, studies were excluded if they focused solely on disciplines outside of nursing without clear relevance to the profession. Papers that lacked sufficient methodological detail or a solid theoretical foundation were also omitted, as were opinion pieces that did not present substantive evidence or analysis.

Following the initial database search, which yielded 136 papers, a total of 73 studies met the inclusion criteria after a rigorous process of title and abstract screening, followed by full-text review.

Data Extraction and Analytic Process

Key information was extracted using a standardized thematic framework aligned with the study's overarching objectives. The analysis focused on five primary domains: types of automatable nursing tasks, perceived benefits and drawbacks, ethical and legal implications, strategies for ethical and equitable integration, and future research directions. These thematic categories were selected to reflect the conceptual structure of the study and guide a comprehensive synthesis of the literature.

An iterative process of inductive and deductive thematic analysis was used. The process began with open coding of the selected literature, which produced a broad set of descriptive codes. This initial coding allowed for the organic emergence of themes directly from the data. The resulting codes were then organized into thematic categories that were both informed by the study's research objectives and theoretically anchored in sociotechnical systems theory and the ethics of care framework.

To ensure thematic coherence and analytic saturation, each emerging theme was critically appraised based on its recurrence across sources, its relevance to theoretical constructs, and its explanatory power about the study's aims. Although the literature supported a wide range of potential themes, final theme selection was guided by their alignment with the 5-core research aims and their frequency and conceptual significance across the dataset. This rigorous and reflective synthesis enabled the condensation of a complex, multidisciplinary literature base into 5 analytically robust and practically relevant thematic domains.

Results

Overview

The analysis yielded 5 core thematic domains representing key areas in which automation is transforming nursing practice. These domains include (1) types of automatable nursing tasks, (2) perceived benefits and drawbacks of automation in nursing, (3) ethical and legal implications, (4) strategies for ethical and equitable integration, and (5) future directions and research gaps.

Types of Automatable Nursing Tasks

The integration of automation technologies into nursing practice offers transformative opportunities across multiple domains of patient care and operational workflows [16]. A synthesis of the current literature reveals five primary categories of nursing tasks that are highly amenable to automation: administrative and documentation duties, medication administration and management, patient monitoring and data collection, infection control and environmental management, and patient assistance and mobility support. Automation in these areas promises to alleviate workload, enhance patient safety, and optimize health care delivery, provided that it is implemented thoughtfully.

One major area of opportunity is the automation of routine administrative tasks, which constitute a significant portion of nurses' daily workload [6]. Technologies such as electronic health records (EHRs) streamline data entry, retrieval, and sharing, facilitating faster documentation and information exchange [17]. Automated scheduling systems optimize shift planning by balancing staff availability with patient needs [18], while voice-to-text transcription tools reduce the time nurses spend on manual charting [19]. By automating administrative responsibilities, health care organizations can free up nurses to focus on direct patient care, thereby improving both job satisfaction and care quality. For instance, at the Mayo Clinic, the integration of speech recognition tools reduced nursing documentation time by 40%, enhancing direct patient interaction [20]. Similarly, Fraser Health Authority reported a 91% accuracy in scheduling after adopting artificial intelligence (AI)-based workforce planning software [21].

Equally critical is the automation of medication administration and management, where precision and reliability are paramount. Automated dispensing cabinets, such as Pyxis (Pyxis Corporation) and Omnicell (Omnicell, Inc), enhance medication security, reduce errors, and provide real-time inventory tracking [22]. Smart infusion pumps equipped with dose error reduction systems proactively alert clinicians to potential dosing mistakes based on preprogrammed limits [23]. A 2022 multihospital study at the Mayo Clinic observed a 16% reduction in medication errors following the implementation of smart infusion pumps with integrated dose error reduction systems [24]. Robotics further augments this domain by automating medication preparation and bedside delivery; for instance, TUG robots at Dartmouth Hitchcock Medical Center autonomously navigate clinical environments to deliver medications securely, reducing medication delivery times and improving workflow efficiency [25]. Integrating these technologies with EHRs

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ensures seamless prescription tracking and communication, collectively minimizing the risk of adverse drug events.

Building on these innovations, automation has significantly advanced patient monitoring and data collection. Continuous glucose monitors and telemetry devices allow for real-time tracking of vital signs, enabling early detection of physiological deterioration [26]. Wearable biometric sensors support remote monitoring of chronic conditions, leading to reductions in hospital readmissions [27]. Johns Hopkins University demonstrated the efficacy of wearable biosensors and predictive analytics for sepsis detection, resulting in an 18.2% decrease in sepsis-related mortality [28]. The wearable health patch used for chronic obstructive pulmonary disease monitoring enabled continuous, remote physiological data collection, supporting early detection and lowering hospital readmission rates [29]. Internet of Things–integrated monitoring systems facilitate continuous data capture and analysis, reducing manual errors and enhancing the accuracy of clinical decision-making [30].

In the realm of infection control and environmental management, automation serves as a critical ally in minimizing health care–associated infections. Technologies such as UV-C disinfection robots and hydrogen peroxide vapor systems have been shown to substantially reduce bacterial contamination in clinical environments [31]. At an academic hospital in Austria, UV-C disinfection robots led to a 96.9% reduction in bacterial surface contamination, contributing to lower infection rates [32]. Automated hand hygiene monitoring systems, using radio-frequency identification and video analytics, enhance compliance among health care workers [33]. Radio-frequency identification–enabled hand hygiene compliance systems at Toronto General Hospital boosted adherence by 38%, demonstrating the potential of automated surveillance to reinforce institutional infection control protocols. In addition, AI-driven surveillance platforms improve early outbreak detection by analyzing EHR data for unusual infection patterns [34]. Robotic waste management systems and smart bins further reduce contamination risks by optimizing hazardous material handling and disposal processes [35].

Finally, the automation of patient assistance and mobility support addresses both patient safety and the physical demands placed on nurses. Robotic lifts and transfer devices assist with repositioning and mobility tasks, mitigating the risk of musculoskeletal injuries among staff [35]. A scoping review reported reductions in musculoskeletal injuries following the implementation of robotic exoskeletons, alongside improved patient rehabilitation outcomes [36]. Smart beds equipped with pressure sensors and automated repositioning features not only improve patient comfort but also help prevent pressure ulcers [37]. In long-term care settings, smart beds with pressure-sensing and repositioning features have reduced the incidence of pressure ulcers, improving patient comfort while reducing physical demands on nursing staff. Robotic exoskeletons support patients with mobility impairments during rehabilitation, promoting independence while reducing nurse burden [38].

In summary, the types of nursing tasks most amenable to automation are those characterized by routine, repetitive, or high-risk activities in which technology can reliably enhance efficiency, safety, and care outcomes. Administrative workflows, medication management, patient monitoring, infection control, and mobility assistance each present a compelling case for automation, backed by a growing body of empirical evidence. By strategically adopting these technologies, health care systems can optimize nursing workflows while safeguarding the humanistic core of the nursing profession. A balanced, evidence-based integration of automation, therefore, holds the potential to transform nursing practice while preserving its essential values (Table 1).

Table . Summary of automation domains, associated technologies, benefits, and ethical implications in nursing practice.

Domain	Example technologies	Benefits	Ethical or legal considerations
Administrative tasks and documentation	Scheduling tools, automated check-in kiosks, voice-to-text systems, and smart charting software	Reduced documentation burden, improved workflow, and enhanced data accuracy	Privacy concerns, documentation integrity, and risk of deskilling
Medication management	Automated dispensing cabinets, barcode scanning, and smart infusion pumps	Reduced medication errors, improved safety, and time efficiency	Overreliance on automation and liability in medication errors
Patient monitoring	Wearable sensors and AI-driven[a] predictive analytics dashboards	Early detection of deterioration and fewer ICU[b] admissions	Algorithmic bias, data accuracy, and alarm fatigue
Infection control	UV disinfection robots and automated hand hygiene monitoring systems	Reduced hospital-acquired infections and improved compliance	Accountability for failure and surveillance ethics
Patient mobilization	Robotic lifts and exoskeletons	Fewer musculoskeletal injuries and safer patient transfers	Informed consent and device malfunction

[a]AI: artificial intelligence.

[b]ICU: intensive care unit.

Benefits and Drawbacks of Automation in Nursing

While automation introduces significant advantages—such as reduced workload, enhanced safety, and streamlined workflows—it also presents critical challenges that must be thoughtfully managed to avoid unintended consequences. Several benefits discussed earlier, including improved efficiency in documentation, medication accuracy, and real-time monitoring, are being realized in frontline care. However, to maintain coherence with the overarching themes of this paper,

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it is equally essential to examine the nuanced drawbacks and how these are being addressed in practice.

A primary concern is the dehumanization of care, particularly when routine interactions are delegated to machines [10]. For example, while robotic medication carts can enhance efficiency, studies show that patients sometimes perceive these interactions as impersonal, reducing their sense of emotional support and trust [39]. This aligns with the broader ethical theme of preserving relational care in the face of technological delegation.

Another key drawback is the risk of deskilling. As automation assumes responsibility for routine tasks, such as documentation via voice-to-text or algorithm-driven triage, there is concern that nurses may lose proficiency in essential clinical and cognitive skills over time [40]. This risk is particularly salient among early-career nurses, who may rely more heavily on automated systems [41]. To counteract this, some institutions have introduced hybrid training models that pair manual and automated workflows, reinforcing foundational competencies while promoting digital fluency [42].

Equitable access is also a pressing issue. Rural or under-resourced facilities may lack the infrastructure to adopt sophisticated automation technologies, exacerbating health care disparities [43]. For instance, while smart beds and robotic lifts are transforming mobility assistance in urban hospitals, facilities in remote regions continue to rely on manual methods. Policy makers and health care systems must prioritize equitable technology distribution and workforce support to prevent systemic gaps.

Real-life implementations further illustrate how health care settings are navigating this balance. At Mount Sinai Hospital, the integration of predictive analytics for early sepsis detection has reduced ICU admissions by 23%. However, the hospital also instituted a “human-in-the-loop” protocol requiring nurse verification of all algorithm-based alerts, ensuring that clinical judgment is not bypassed [44]. Similarly, at Tallahassee Memorial HealthCare, robotic exoskeletons have been adopted to assist in patient mobility but are always deployed alongside staff to preserve patient-nurse interaction and ensure safety [45].

Ultimately, the integration of automation in nursing must be guided by deliberate strategies that align technological efficiency with professional integrity and ethical care. Continuous evaluation, inclusive co-design, and hybrid implementation models represent practical approaches to achieving a sustainable balance between automation’s benefits and its potential drawbacks.

Ethical and Legal Implications

Overview

The integration of automation into nursing practice presents both significant promise and profound ethical and legal challenges. The current ethical and legal landscape in this domain is fragmented, characterized by evolving policies, emerging frameworks, and limited case law specific to nursing [16,46]. While foundational principles such as patient autonomy, data privacy, and informed consent are well established within health care ethics, their application to AI-driven or automated nursing tasks remains underdeveloped in both policy and practice [47,48].

Ethical Landscape: Established and Emerging Areas

On the ethical front, principles such as autonomy, beneficence, nonmaleficence, and justice remain cornerstones. However, their operationalization within automated systems often lacks clarity [49]. For example, while nurses are ethically obliged to respect patient autonomy, the use of algorithmic decision support tools can inadvertently standardize care in ways that diminish individualized, contextualized decision-making [50]. Similarly, concerns about algorithmic bias, such as underrepresentation of minority populations in training datasets, pose equity challenges that current ethical frameworks only partially address [51,52].

Practical initiatives addressing these concerns are beginning to emerge. At institutions such as Johns Hopkins and Kaiser Permanente, AI toolkits are being codeveloped with nurses to evaluate fairness and transparency during pilot phases, embedding ethical scrutiny into design and deployment processes [53]. These models exemplify how ethics can be embedded at the system level rather than imposed retroactively.

Legal Landscape: Gaps and Opportunities

Legally, the terrain is less defined. While privacy regulations such as the Health Insurance Portability and Accountability Act (United States) and the General Data Protection Regulation (European Union) provide a baseline for data protection, there is little consensus on liability in cases where automated systems contribute to patient harm [54,55]. Questions remain about whether responsibility lies with nurses, software developers, or health care institutions when AI malfunctions lead to adverse outcomes. Although regulatory bodies such as the US Food and Drug Administration (FDA) have begun classifying and approving AI-driven clinical tools [56,57], these often focus on static algorithms and offer limited guidance for dynamic, learning systems that evolve postdeployment.

In contrast, the European Union’s AI Act represents a forward-looking model by categorizing health care AI as “high-risk” and mandating transparency, human oversight, and postmarket surveillance [58]. However, practical implementation remains at an early stage, and nursing-specific legal guidance is still lacking.

From Concept to Practice: Grounding Ethical-Legal Integration

While previous discussions often remain at a conceptual level, actionable pathways are necessary to ensure that automation supports nursing values rather than undermining them. A balanced approach integrating ethical guidelines and legal safeguards must be grounded in concrete practices such as mandatory ethical impact assessments before implementation of automation tools, focusing on issues such as bias, accessibility, and implications for patient-nurse interaction; clear role delineation and documentation protocols that define when nurses may override AI outputs and how such decisions should be recorded, thereby preserving clinical judgment and legal clarity; ethics and legal literacy programs, integrated into

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continuing professional development, to equip nurses with the knowledge to navigate emerging automation technologies responsibly; pilot testing with human-in-the-loop models, such as requiring nurse validation before automated triage decisions are enacted, already in use at several US trauma centers, to ensure accountability and foster trust.

In conclusion, while the ethical and legal frameworks governing automation in nursing are still maturing, incremental steps toward embedding these considerations into technology design, policy development, and clinical education are both feasible and necessary. Grounding these principles in practical strategies can help ensure that automation is not only safe and effective but also aligned with the core values of nursing care.

Strategies for Ethical and Equitable Integration

As automation increasingly permeates health care systems, its integration into nursing practice must be approached with deliberate, ethical, and equity-focused strategies. The goal is not merely to introduce technology for operational efficiency, but to align automation with the core values of the nursing profession—compassion, advocacy, and patient-centered care—while also addressing the risk of exacerbating existing health disparities and workforce inequalities.

Ethical Principles in Automation Integration

Foundational ethical principles of autonomy, beneficence, nonmaleficence, and justice must underpin the deployment of automation technologies in nursing practice [59]. Studies underscore the potential of automation to enhance nursing efficiency, accuracy, and safety, particularly in routine, repetitive, and data-intensive tasks such as medication administration, documentation, and vital signs monitoring. However, automation must not compromise the nurse-patient relationship or marginalize vulnerable populations.

Autonomy is particularly relevant where AI-driven decision support tools are deployed; nurses must retain clinical judgment and the ability to override automated recommendations when they conflict with contextual patient needs [60]. Similarly, beneficence and nonmaleficence demand that technologies demonstrably improve patient outcomes and do not introduce new harms, whether physical, emotional, or relational [61]. Justice, in turn, mandates equitable access to the benefits of automation across diverse patient populations and care settings [62].

Addressing Equity in Technological Design and Deployment

Current research emphasizes that digital health innovations often reflect and reinforce systemic inequities when implemented without inclusive design. Therefore, strategies for equitable implementation should begin at the design stage. Inclusive co-design approaches, such as engaging nurses from diverse backgrounds, patients, and other stakeholders, can help ensure that automated systems are culturally sensitive, linguistically appropriate, and attuned to the unique needs and contexts of underrepresented populations. Moreover, rural and resource-limited settings must be considered in automation planning. Without equitable infrastructure investments, such areas risk being left behind in the digital transformation of care, further widening health outcome gaps.

Workforce Implications and Professional Integrity

Ethical implementation also requires thoughtful consideration of the nursing workforce. Automation should be framed not as a replacement, but as a tool that augments nursing capabilities. Evidence suggests that when automation is introduced transparently and with robust change management strategies, it can reduce cognitive burden and allow nurses to focus on complex, relational aspects of care [3,8]. However, there is also evidence of skepticism and resistance when automation is perceived as a threat to job security or professional identity.

To address these concerns, health care organizations must invest in continuous professional development, ensuring that nurses are not only technologically competent but also empowered to contribute to implementation decisions [63,64]. This participatory approach respects nurses' experiential knowledge and fosters a culture of trust, critical for successful technology adoption.

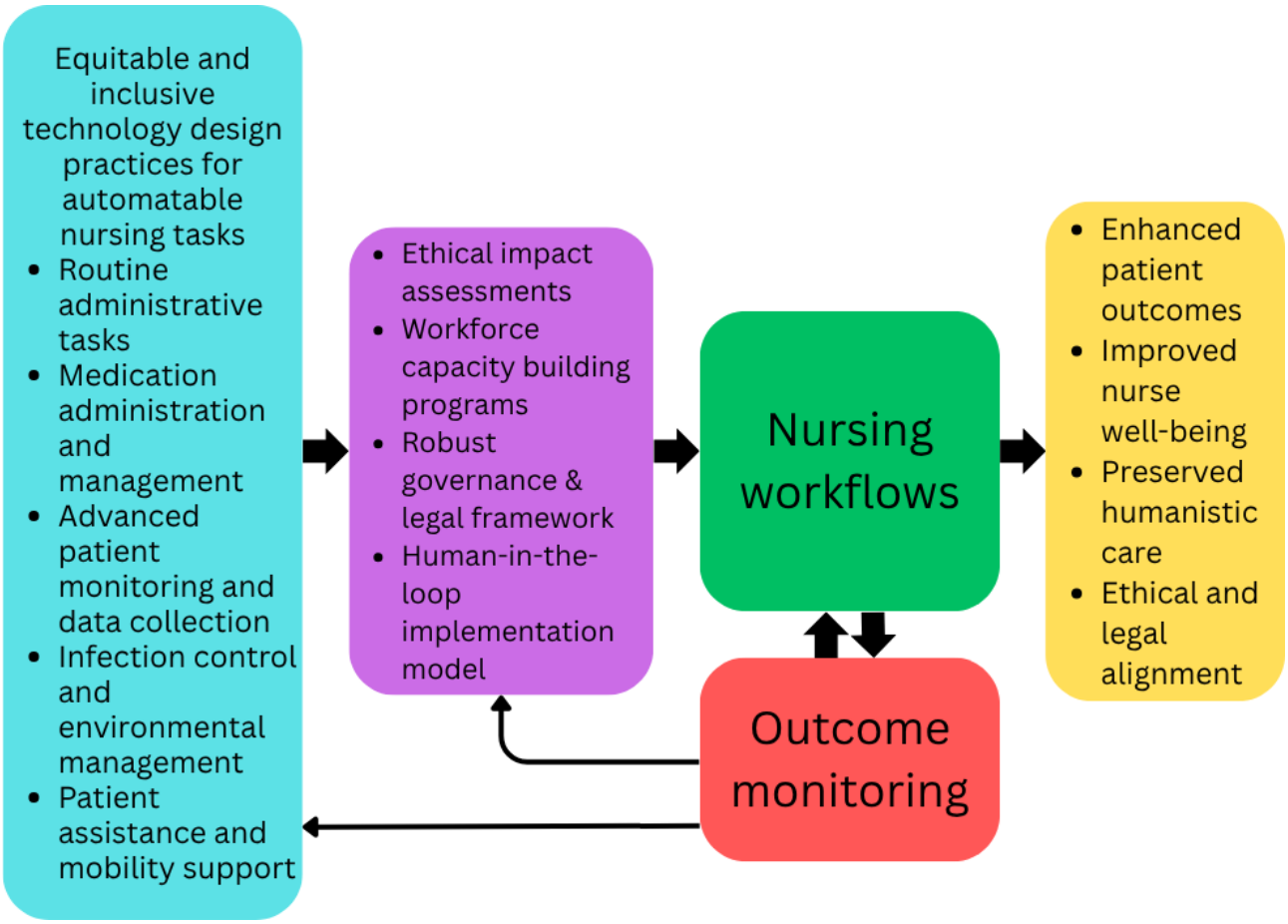
Governance, Accountability, and Legal Considerations

Effective governance mechanisms are essential to oversee the ethical use of automation in nursing [55,65]. This includes establishing clear lines of accountability, particularly in scenarios involving clinical decision support systems or autonomous robotics. The absence of well-defined legal and regulatory frameworks poses challenges in attributing responsibility for errors or adverse outcomes arising from automated actions.

Professional bodies and regulatory agencies must collaborate to develop standards that protect both patients and practitioners, ensuring that automation enhances rather than undermines professional accountability [55,66]. Policies must also address data privacy, algorithmic transparency, and bias mitigation in AI systems used in nursing care. The Integration of Automation Technologies in Nursing Practice Conceptual Framework illustrates the integration of automation technologies into nursing practice in Figure 1.

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Figure 1. The Integration of Automation Technologies in Nursing Practice Conceptual Framework illustrates the integration of automation technologies into nursing practice by linking equitable and inclusive technology design for automatable tasks with nursing workflows, guided by ethical governance and human-centered implementation. It positions ethical impact assessments, workforce development, and legal frameworks as mediating structures that ensure automation supports nursing workflows without compromising care quality. Outcome monitoring feeds back into both design and governance, creating a continuous improvement loop. This framework aligns with the study's research questions by mapping how ethical, technical, and organizational factors interact to optimize nurse well-being, preserve humanistic care, and enhance patient outcomes.



Future Directions and Research Gaps

To ensure the ethical, effective, and equitable integration of automation into nursing practice, future work must align with the core thematic domains identified in this study. The following narrative outlines tailored research, practice, and policy directions under each theme to guide meaningful advancement in the field.

Automatable Nursing Tasks: Refinement and Validation

Future research should focus on identifying context-specific opportunities for automation using mixed methods that assess task suitability across different care environments, such as long-term and acute care settings. On the practical front, pilot studies can evaluate automation's effectiveness in emerging domains, such as discharge planning or clinical triage, while simultaneously measuring impacts on workflow and patient experience. From a policy perspective, the development of standardized evaluation frameworks will be critical to support regulatory bodies and institutions in making informed, evidence-based decisions aligned with nursing priorities.

Benefits and Drawbacks: Longitudinal Impact Assessment

Research in this area should include long-term studies that assess automation's influence on nurse burnout, job satisfaction, and patient outcomes, while also addressing potential unintended consequences such as deskilling or the depersonalization of care. In clinical practice, the use of human-centered metrics—such as patient-nurse trust and perceived empathy—alongside traditional indicators can provide a more holistic understanding of automation's value. Policy efforts should mandate outcome monitoring and the incorporation of fail-safe mechanisms, including human-in-the-loop design and regular reassessment protocols to ensure that automation remains accountable to patient and nurse well-being.

Ethical and Legal Implications: Translating Principles Into Practice

Future research should aim to operationalize abstract ethical concepts, such as autonomy, beneficence, and justice, by transforming them into measurable safeguards embedded within automated systems. In practice, the implementation of ethical impact assessments before technology adoption should be normalized, with nurse involvement in co-design and governance structures that enhance transparency and

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accountability. On the policy front, legal frameworks must evolve to address liability concerns associated with automation. National regulations should adopt and localize global standards, such as the EU AI Act, to establish clear legal guidance tailored to specific nursing contexts.

Implementation Strategies: Inclusive and Adaptive Models

Research should explore best practices in co-design, involving not only nurses but also patients and underrepresented groups, to improve the cultural fit, usability, and safety of automation tools. In the clinical realm, hybrid implementation models—which combine automation with manual oversight—should be tested and refined for efficacy, equity, and resilience across diverse care settings. Policy measures should support resource allocation strategies that enable adoption in rural and under-resourced institutions, thereby mitigating the risk of deepening the digital divide in nursing care delivery.

Education, Workforce, and Policy Alignment: Capacity Building

Research should evaluate how digital literacy, AI ethics, and interdisciplinary competencies are taught in nursing education, with attention to gaps in confidence and skill development. From an educational standpoint, nursing curricula must be updated to integrate informatics, AI governance, and collaborative learning, ensuring that nurses are well-prepared to lead in increasingly tech-integrated environments. At the policy level, regulatory and licensing bodies should establish and enforce core competencies for nurses working with automation. These efforts should be supported by the development of credentialing pathways and continuing education mandates that promote ongoing capacity building.

By aligning future directions with the themes explored in this paper, the nursing profession can ensure that automation evolves in ways that are ethically responsible, clinically effective, and socially equitable. Through focused efforts across research, practice, and policy domains, nursing can shape the integration of automation as a tool for improving care—rather than diminishing it.

Discussion

Implications for Nursing Practice

The integration of automation into nursing practice represents a transformative shift in health care delivery. It offers significant potential to enhance efficiency, optimize patient outcomes, and support workforce sustainability. However, realizing these benefits requires deliberate, evidence-based strategies for practice adaptation, professional development, and system redesign. Several actionable implications emerge from the synthesis of current literature and analysis.

Integration of Digital Literacy in Nursing Curricula

To adequately prepare future nurses for a technologically enhanced health care environment, nursing education must evolve to incorporate comprehensive digital literacy components. Digital literacy should extend beyond basic computer skills to encompass competencies in health informatics, AI ethics, algorithmic decision-making, cybersecurity, and data privacy principles [67].

Specifically, nursing curricula should embed mandatory courses on health information technology and AI in health care, covering subjects such as the operation of clinical decision support systems, the risks associated with algorithmic bias, and the principles of data stewardship [68,69]. In addition, simulation-based training should be used, allowing students to interact with AI-driven tools—such as predictive analytics dashboards and automated medication dispensers—to promote critical thinking around technology-supported clinical decision-making [70,71]. Furthermore, interprofessional education modules should be introduced, where nursing students collaborate with informaticians, engineers, and ethicists to solve clinical scenarios involving automation, fostering both technical fluency and collaborative problem-solving skills [72,73]. These curricular innovations can ensure that newly qualified nurses possess the digital fluency required to safely, ethically, and effectively engage with automated systems in clinical settings.

Competency Framework for Human-AI Collaboration

The successful integration of automation in nursing practice requires the development of a structured competency framework for human-AI collaboration. Building on emerging models in medical informatics and AI governance, this framework should define key competencies for nurses in several critical areas.

Nurses must develop the ability to critically evaluate AI outputs, including assessing the validity, reliability, and clinical relevance of AI-generated recommendations [74,75]. Ethical and legal reasoning is also essential; nurses should be well-versed in the ethical frameworks and regulatory guidelines that govern the use of automated technologies in clinical care [55,76]. Moreover, nurses should be trained in clinical judgment augmentation, synthesizing AI insights with holistic patient assessments to inform decisions, rather than relying on technology to dictate care [77,78]. Another vital area is advocacy and patient education, where nurses must be equipped to advocate for patients when automation introduces risk or confusion, and to educate patients about the role of technology in their care [55,79]. Finally, nurses should be able to navigate health care systems and report incidents, demonstrating awareness of automation-related failures and the protocols for escalating such issues within institutional frameworks [3].

These competencies can be operationalized by health care institutions and professional organizations through the creation of credentialing pathways, the provision of continuing education programs, and the use of competency-based assessments to ensure readiness for AI-integrated practice.

Concrete Applications: Automation Improving Outcomes and Reducing Workload

Real-world examples from clinical settings underscore the potential of automation to enhance both outcomes and workload management in nursing.

One such example is the early detection of patient deterioration through AI-driven predictive analytics. These systems have been shown to reduce unplanned ICU admissions by 25% by

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providing real-time alerts to nurses regarding changes in patient status. This enables timely escalation of care and improves patient safety [16].

In the area of medication management, the use of automated dispensing cabinets has led to a 30% reduction in medication errors, along with decreased narcotic diversion rates and minimized time spent on medication rounds. These efficiencies allow nurses to devote more time to direct patient care and patient education [80].

In addition, robotic assistance in patient mobilization—such as robotic exoskeletons and smart lift devices—has significantly lowered the incidence of musculoskeletal injuries among nurses by reducing physical strain during patient transfers. This not only protects the well-being of nursing staff but also improves patient safety through safer and more efficient mobilization practices [45].

Collectively, these examples demonstrate that when thoughtfully implemented, automation can serve as a powerful tool to support clinical efficiency, nurse well-being, and patient-centered outcomes.

Conclusion

The integration of automation into nursing practice represents a paradigm shift with the potential to transform health care delivery by enhancing operational efficiency, reducing cognitive and physical burden, and improving patient outcomes. This paper has identified five key domains of automatable nursing tasks: administrative documentation, medication management, patient monitoring, infection control, and mobility assistance, each demonstrating substantial promise for streamlining workflows and enabling nurses to focus on relational, analytical, and human-centered care.

However, automation is not a neutral intervention; its implementation raises complex ethical, legal, and sociotechnical challenges that, if unaddressed, may compromise the foundational values of nursing. The findings emphasize that the humanistic core of nursing—embodied in empathy, critical judgment, and person-centered engagement—must remain central as automation becomes increasingly embedded in clinical settings. Multimedia Appendix 1 depicts a graphical abstract summarizing these findings.

To guide the practical and ethical implementation of automation in nursing, we offer the following prioritized, actionable recommendations for stakeholders, including policy makers, educators, health care leaders, and technology developers. First, it is important to establish robust governance and legal frameworks. This involves developing comprehensive regulatory policies that delineate liability, ensure algorithmic transparency, and safeguard data privacy. National nursing boards and health authorities should collaborate with legal experts and technologists to create adaptive, profession-specific guidelines that anticipate the evolving capabilities of AI and automation systems. Second, stakeholders should implement workforce capacity-building programs by integrating digital health literacy, ethics of automation, and informatics competencies into nursing education and continuing professional development. Institutions should adopt a tiered training model that equips nurses at all levels with the critical skills to engage with, interpret, and, when necessary, override automated systems in clinical contexts. Third, it is essential to advance equitable and inclusive design practices. Automation technologies should be developed through participatory co-design involving frontline nurses, patients from diverse backgrounds, and underserved communities. Policy makers must prioritize infrastructure investment in rural and low-resource settings to mitigate the digital divide and promote equitable access to innovation. Fourth, human-in-the-loop implementation models should be adopted. This means deploying automation in ways that preserve and augment clinical judgment rather than replace it. This includes embedding nurse validation protocols in AI decision-making pathways, promoting hybrid workflows, and conducting ongoing assessments of automation's impact on empathy, job satisfaction, and patient trust. Finally, there is a need to mandate ethical impact assessments and outcome monitoring. Before widespread deployment, automation tools should undergo rigorous ethical evaluation to assess potential harms, biases, and unintended consequences. Postimplementation, health care systems must continuously monitor both technical performance and relational outcomes, such as patient-nurse communication quality and perceived quality of care.

Taken together, these recommendations provide a roadmap for aligning technological advancement with the ethical imperatives and professional identity of nursing. As the health care sector moves toward increasing reliance on intelligent systems, the nursing profession must proactively shape the discourse and deployment of automation to ensure it serves as a tool for empowerment, equity, and compassionate care.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Graphical abstract.
[PNG File, 1199 KB - nursing_v8i1e72674_app1.png]

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Abbreviations

AI: artificial intelligence
EHR: electronic health record
FDA: US Food and Drug Administration

Edited by E Borycki; submitted 14.02.25; peer-reviewed by A Nashwan, CY Chen; revised version received 23.06.25; accepted 28.06.25; published 14.08.25.

Please cite as:
Pepito JA, Acaso NJ, Merioles R, Ismael J
Opportunities, Challenges, and Future Directions for the Integration of Automation in Nursing Practice: Discursive Study
JMIR Nursing 2025;8:e72674
URL: https://nursing.jmir.org/2025/1/e72674
doi:10.2196/72674

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Using Large Language Models to Assess Burnout Among Health Care Workers in the Context of COVID-19 Vaccine Decisions and Health Beliefs: Retrospective Cohort Study

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Abstract

Background: Burnout among health care workers affects their well-being and decision-making, influencing patient and public health outcomes. Health care workers' health beliefs and COVID-19 vaccine decisions may affect the risks of burnout. Therefore, understanding the interplay between these crucial factors is essential for identifying at-risk staff, providing targeted support, and addressing workplace challenges to prevent further escalation of burnout-related issues.

Objective: This study examines how burnout is impacted by health beliefs and COVID-19 vaccine decisions among health care workers. Building on our previously developed Health Belief Model (HBM) classifier based on the HBM framework, which explains how individual perceptions of health risks and benefits influence behavior, we focused on key HBM constructs, including the perceived severity of COVID-19, perceived barriers to vaccination, and their relationship to burnout. We aim to leverage natural language processing techniques to automatically identify theoretically grounded burnout symptoms from comments authored by nurses in a large-scale, national survey and assess their associations with vaccine hesitancy and health beliefs.

Methods: We analyzed 1944 open-ended comments written by 1501 vaccine-hesitant nurses, using data from the Nurses' Health Study surveys. We fine-tuned LLaMA 3, an open-source large language model with few-shot prompts and enhanced performance with structured annotation guidance and reasoning-aware inference. Comments were classified into burnout dimensions—Emotional Exhaustion, Depersonalization, and Inefficacy—based on the Maslach Burnout Inventory framework.

Results: The model achieved a high weighted accuracy of 92% and an F_1-score of 91% for Depersonalization. Emotional Exhaustion was identified in 52% (1003/1944) of comments, correlating strongly with perceived severity (189/323, 59%) and barriers to vaccination (281/650, 43%). Demographic analyses revealed significant variations in burnout prevalence, with older age groups reporting greater burnout.

Conclusions: This study highlights the relationship between burnout and vaccine decision-making among health care workers, uncovering areas for further exploration. By exploring the complex interplay between psychological strain and vaccine hesitancy, this study sets the stage for developing transformative interventions and policies that could redefine workforce resilience and public health strategies.

(JMIR Nursing 2025;8:e73672) doi:10.2196/73672

KEYWORDS

burnout; health care workers; nurses; COVID-19; health beliefs model; Maslach Burnout Inventory; text classification; LLMs; prompt engineering; LLaMA; fine-tuning; large language models

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Introduction

Background

The COVID-19 pandemic has profoundly impacted health care workers, intensifying professional burnout and shaping vaccine-related decisions that are critical to public health outcomes [1]. Health care workers faced unprecedented challenges: extreme fatigue, overwhelming stress, and profound grief while managing increased workloads, critical staffing shortages, and limited access to protective equipment [2]. Burnout, defined by the World Health Organization as a syndrome resulting from unmanaged, chronic workplace stress [3], manifests through mental and physical exhaustion, feelings of detachment or cynicism toward one's job, and a diminished sense of personal accomplishment. These compounding pressures not only affected their well-being but also influenced their perceptions and decisions regarding COVID-19 vaccination, reflecting broader concerns about institutional credibility and policy-driven decisions [4].

Vaccination of health care workers serves a dual purpose: protecting this highly exposed group and preventing iatrogenic spread within health care settings. As one of society's most trusted professions, health care workers' attitudes toward vaccination significantly influence public perception and behavior [5]. However, efforts to promote COVID-19 vaccination through community engagement and trust-building initiatives often fell short in addressing health care workers' fundamental concerns about vaccine mandates, personal autonomy, perceived coercion of incentives, misinformation, and accessibility [6].

Despite substantial research on burnout and vaccine hesitancy, few studies have explored how these factors interact to shape decision-making among health care workers. This gap is especially pronounced in research involving nurses—a population that makes up the backbone of health care systems and has faced disproportionate levels of burnout during the COVID-19 pandemic. Recent studies highlight rising emotional exhaustion and diminished professional fulfillment among nurses, driven by excessive job demands and inadequate institutional support [7,8].

Two theoretical frameworks inform our understanding of the relationship between burnout and vaccine decisions. First, the Total Worker Health Model provides a holistic perspective on how occupational stress, including burnout, influences both personal health decisions and overall job performance [9]. This model evaluates multiple levels of contextual factors, worker characteristics, and organizational elements to assess their impact on both organizational outcomes and worker well-being. Second, the Health Belief Model (HBM) examines how individual perceptions influence health behaviors, including vaccination decisions, through key factors such as perceived susceptibility to disease, perceived severity, perceived benefits of action, and perceived barriers to action [10]. For health care workers experiencing burnout, these constructs may interact in complex ways, reshaping their decision-making processes and potentially exacerbating vaccine hesitancy [11].

Understanding how burnout intersects with vaccine-related health beliefs is critical, yet much of the existing literature relies on structured survey tools that fail to capture the complexity of health care workers' lived experiences. Free-text narratives provide richer insights into emotional and cognitive processes but pose analytical challenges at scale. To address this, this study applies large language models (LLMs), which excel at interpreting nuanced, unstructured textual data. Unlike traditional machine learning models—which require extensive feature engineering and often miss deeper linguistic or conceptual structures—LLMs can process entire sentences or paragraphs as coherent units, capturing context, tone, and latent psychological meaning [12]. Their capacity to generalize across varied linguistic expressions makes them particularly well suited to analyzing complex constructs such as burnout and vaccine hesitancy in narrative form.

Related Works

A growing body of research has documented the psychological toll of the COVID-19 pandemic on health care workers, particularly those on the front lines with burnout and vaccine hesitancy emerging as key concerns [13,14]. Burnout—widespread among nurses during the pandemic—has been linked to emotional exhaustion, reduced engagement, and diminished adherence to public health responsibilities [15-17].

Researchers have used a variety of conceptual models to study these effects. Among these, the Maslach Burnout Inventory (MBI) provides a widely recognized framework for measuring and understanding burnout through three key dimensions: Emotional Exhaustion, Depersonalization, and Inefficacy [18]. Previous research has demonstrated that burnout emerged as the most prevalent mental health issue among health care workers during the COVID-19 pandemic, affecting nearly half of the workforce globally and heightening emotional exhaustion, distrust in systems, and impaired decision-making regarding public health measures [19,20].

Galanis et al [21] found that COVID-19-related burnout reduced health care workers' willingness to be vaccinated, with psychological resilience partially mitigating this effect. Similarly, Limbu et al [22] conducted a systematic review applying the HBM and concluded that perceived barriers, susceptibility, and severity were strong predictors of vaccine hesitancy among health care professionals.

Luna et al [23] applied latent profile analysis to identify distinct burnout patterns in health care workers, linking them to work-related variables such as shift type and job satisfaction, and calling for more personalized burnout interventions. More recently, Nagle et al [24] conducted a scoping review of conceptual burnout models and emphasized the need for integrative, theory-driven tools capable of capturing both individual and systemic drivers of burnout—particularly those that move beyond the limitations of existing instruments like the MBI. Notably, all these studies relied on structured survey instruments and predefined scales rather than open-ended narrative data or language-based classification, which our approach aims to complement.

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Despite these advancements, few studies have brought together burnout theory, health behavior models, and LLM-driven text analysis to examine vaccine hesitancy among health care workers. This study addresses that gap by analyzing narrative data from nurses through the dual lenses of MBI and HBM, using LLMs to extract theoretically grounded, fine-grained burnout symptoms from large-scale free-text comments to reveal how burnout and belief structures jointly influence vaccine decisions. The following research questions guided the investigation.

The Main Research Question is: how does burnout correlate with COVID-19 vaccine decisions among health care workers during the pandemic, and how do these correlations vary across demographic factors?

To address this, we break down the main research question into four subquestions:

1. How effective are LLMs in automatically identifying burnout symptoms among health care workers, based on the MBI framework, within the context of the COVID-19 pandemic?
2. What is the relationship between specific MBI burnout dimensions (Emotional Exhaustion, Depersonalization, and Inefficacy) and HBM constructs (barriers, severity, and susceptibility) among vaccine-hesitant (VH) health care workers during the COVID-19 pandemic, and which burnout dimensions are most strongly associated with each HBM construct?
3. How do demographic factors (eg, age, education, and region) influence the relationship between burnout dimensions and vaccine hesitancy?
4. What are the most common themes of the comments in the intersection of burnout dimensions and the HBM?

Methods

Ethical Considerations

The study was approved as Protocol 2020P001020 of the Institutional Review Board of Brigham and Women's Hospital in Boston, Massachusetts, which allowed voluntary survey completion to represent participant consent.

Data Source, Study Design, and Study Participants

This study used data from our previous investigation of COVID-19 vaccine hesitancy among participants in the Nurses' Health Study II and Nurses' Health Study 3, conducted in Winter 2021 [25]. These large-scale, longitudinal cohorts include health care professionals who provided responses on their COVID-19 vaccination intentions and related beliefs. In the prior study, we identified VH individuals based on their responses to the survey question, "Do you plan to receive a COVID-19 vaccine?" Participants who answered "no" or "unsure" (excluding those already vaccinated, intending to get vaccinated, or with missing data) were classified as VH [26]. Of the 4242 participants who provided at least one open-ended comment in the survey (categorized under "vaccine" or "other"), 1501 were classified as VH and included in this analysis. We also considered the personal protective equipment–related comments of these VH participants because these comments are more likely to be work-related and might be a good source for finding work burnout. In total, we analyzed 1,944 open-ended comments provided by VH participants. The vast majority of survey participants (1380/1944,71%) were not actively working at the time of vaccination, while (n=564/1944, 29%) were actively practicing nurses. This cohort, therefore, represents both actively and formerly practicing nurses, highlighting unique perspectives from both groups regarding their vaccination decisions.

In the prior study, these comments were categorized according to constructs of the HBM using supervised learning: perceived barriers, perceived severity, perceived susceptibility, and a category for non-HBM-related comments. This classification enabled us to analyze the underlying health beliefs associated with vaccine hesitancy. This study builds upon this framework, linking these HBM categories with burnout dimensions based on the MBI to explore the intersection of psychological factors and health beliefs in vaccine hesitancy.

For a detailed description of the data collection process and the HBM categorization methodology, refer to our previous work [26].

Model Selection and Classification Optimization Strategy

We selected LLaMA 3 8B for its open-source accessibility, balanced performance, and ability to run locally, essential for ensuring full control over sensitive health care narratives. The 8B variant offers a practical trade-off between language understanding and computational efficiency, making it suitable for fine-tuning on modest hardware. Its support for Low-Rank Adaptation, a parameter-efficient fine-tuning method, further reduces resource demands by updating only a small subset of model weights [27].

We fine-tuned LLaMA 3 8B on 340 labeled comments, including both original and augmented examples from a manually annotated subset of the dataset. The model was trained using the AdamW 8-bit optimizer, with a linear learning rate scheduler, gradient checkpointing, and mixed-precision (FP16) training. Training was conducted with a small batch size and capped at 60 steps to fit within resource constraints.

To further enhance model understanding of burnout categories, we used the Annotation Guidelines–based Knowledge Augmentation (AGKA) approach developed by Liu et al [28]. AGKA systematically enriches prompts with task-relevant information from annotation guidelines. It has three key components: (1) label definition knowledge, where detailed explanations for each class (eg, Emotional Exhaustion, Depersonalization, and Inefficacy) are retrieved from the annotation guidelines; (2) task instruction formatting, where prompts are carefully structured to include task claims and output expectations; and (3) representative few-shot examples, which demonstrate how to apply the label definitions in context. This design mimics the logic human annotators follow, reading label definitions and using representative cases for guidance. Details of the AGKA prompts are provided in Multimedia Appendix 1.

To improve reliability during inference, we implemented the Reasoning-Aware Self-Consistency (RASC) framework [29].

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RASC performs iterative classification on each comment and collects multiple model outputs. When a consistent majority is reached (eg, 70% of outputs align), the system returns that label; otherwise, it continues sampling up to a maximum number of iterations before returning "Undecided." This approach helps stabilize predictions, particularly for ambiguous or borderline inputs.

Model Evaluation

In evaluating the model's performance, we followed a 3-step process. First, we applied the RASC framework, which helped prioritize high-confidence outputs. Then, we measured the model's performance using metrics of weighted accuracy and F_1-score across the burnout dimensions: Emotional Exhaustion, Depersonalization, and Inefficacy. Finally, we conducted an error analysis to identify recurring misclassification patterns, particularly those involving ambiguous language or overlapping burnout symptoms.

This evaluation framework not only allowed us to assess classification quality but also demonstrated how LLMs can support scalable, interpretable analysis of psychological constructs in free-text narratives. By embedding our approach within the MBI framework and refining it with RASC and AGKA techniques, we provide a replicable methodology for investigating burnout and vaccine hesitancy in health care settings, one that bridges computational and behavioral science in a practical, privacy-preserving way.

Thematic Analysis

To explore overarching themes at the intersection of burnout and health beliefs, we conducted a one-shot LLM-assisted thematic analysis. Using a prompt-based approach, we provided the base LLaMA 3 model with a single example and instructed it to generate a concise, central theme (limited to 7 words) for each participant's comment. This method enabled efficient and consistent interpretation of open-ended responses without additional fine-tuning. We then qualitatively reviewed and grouped the model-generated themes to identify recurring patterns related to the intersection of burnout experience and psychological strain.

Results

Effectiveness of LLMs in Identifying Burnout Dimension

To evaluate the effectiveness of LLaMA 3 in identifying burnout dimensions based on the MBI framework, we assessed classification accuracy for Emotional Exhaustion, Depersonalization, and Inefficacy using a separate set of 150 unseen labeled comments (50 per dimension). Leveraging the RASC framework with AGKA, the model achieved weighted accuracy ranging from 82% to 92% and F_1-scores from 78% to 91%. The highest weighted accuracy of 92% and an average F_1-score of 91% was achieved for classifying Depersonalization. Emotional Exhaustion and Inefficacy showed slightly lower accuracies of 84% and 82%, respectively. Our classification revealed that Emotional Exhaustion accounted for 52% of the comments, followed by Depersonalization at 25%, and Inefficacy at 11%. This distribution underscores the prominence of Emotional Exhaustion and reflects its strong representation in the dataset.

To evaluate the effectiveness of LLaMA 3 in identifying burnout dimensions based on the MBI framework, we assessed classification performance for Emotional Exhaustion, Depersonalization, and Inefficacy using a separate set of 150 unseen labeled comments (50 per dimension). Leveraging the RASC framework with AGKA, the model achieved weighted accuracy ranging from 82% to 92% and F_1 -scores from 78% to 91%. The highest weighted accuracy of 92% and an F_1 -score of 0.91 were achieved for classifying Depersonalization, which also had a precision of 0.95 and recall of 0.88. Emotional exhaustion showed slightly lower performance, with a precision of 0.81, recall of 0.88, F_1 -score of 0.85, and accuracy of 0.84. Inefficacy had the highest precision (0.99) but a lower recall (0.64), resulting in an F_1 -score of 0.78 and accuracy of 0.82.

Analysis of Burnout and HBM Construct Intersections

We analyzed the association between specific burnout dimensions and previously categorized HBM constructs: perceived barriers to getting a vaccination, severity of COVID-19, and susceptibility to COVID-19. These associations are represented in Table 1, which illustrates the distribution of burnout dimensions across HBM constructs. Emotional Exhaustion correlated strongly with perceived severity (59%). Additionally, 43% of comments referenced barriers, highlighting both logistical and psychological obstacles to vaccination. Depersonalization was most closely linked to the perceived severity of the disease (27%) and perceived susceptibility to the disease (23%). A smaller proportion of those with depersonalization (17%) referenced perceived barriers, indicating a weaker link to barriers to obtaining the vaccine. Inefficacy showed weaker associations overall, with only 14% of comments reflecting the perceived severity of COVID-19, a total of 8% referenced perceived susceptibility to the disease, and 7% mentioned perceived barriers to getting vaccinated.

Table . Distribution of HBM[a] constructs across burnout dimensions[b].

Burnout dimension	Perceived barriers (%)	Perceived severity (%)	Perceived susceptibility (%)	Non-HBM (%)
Emotional exhaustion	43	59	52	56
Depersonalization	17	27	23	32
Inefficacy	7	14	8	15

[a]HBM: Health Belief Model.

[b]Emotional exhaustion shows the highest associations with perceived severity (59%) and non-HBM (56%), while depersonalization and inefficacy show lower percentages across all constructs.

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Demographic Analysis

Further analysis of burnout dimensions by demographic factors revealed significant variations. To examine trends across age groups, we categorized participants into four bins and further assessed the impact of active versus inactive status. As shown in Table 2, Emotional Exhaustion remained consistently high across all groups (≥50%), with the highest prevalence among active nurses younger than 65 years (55%). Interestingly, inactive nurses older than 65 years of age reported similar levels (50%), suggesting that work status may not strongly influence this dimension.

Table . The prevalence of burnout dimensions among active and inactive nurses, stratified by age group[a].

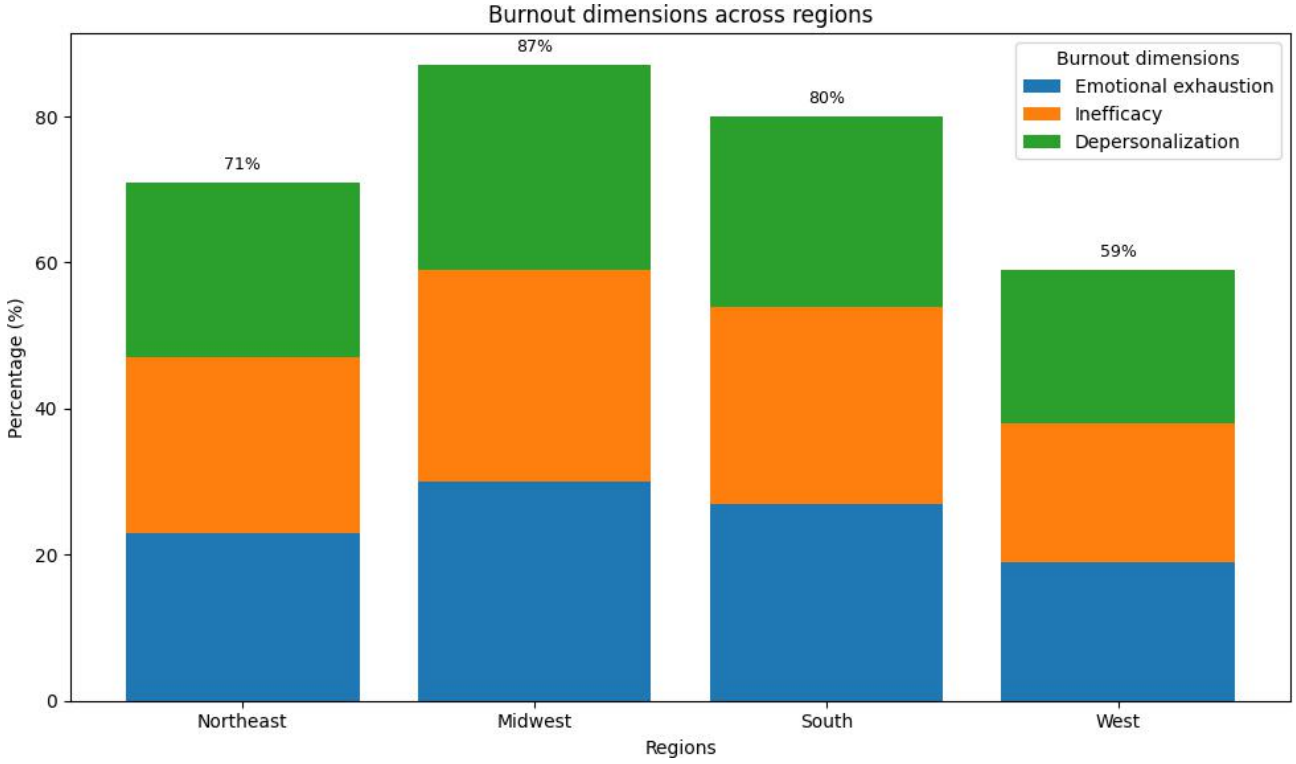
Group and burnout dimension	Age (<65 years), n (%)	Age (>65 years), n (%)
Active		
Emotional exhaustion	255 (55)	50 (50)
Depersonalization	136 (29)	21 (21)
Inefficacy	74 (16)	6 (6)
Inactive		
Emotional exhaustion	241 (51)	457 (50)
Depersonalization	112 (24)	211 (23)
Inefficacy	52 (11)	89 (10)

[a]Emotional Exhaustion remains high across all groups, while Depersonalization and Inefficacy show notable differences, with active nurses younger than 65 years of age reporting the highest levels.

In contrast, Depersonalization and Inefficacy showed more variation. Active nurses, particularly those younger than 65 years, exhibited significantly higher rates of both compared to their inactive counterparts (29% vs 24% for Depersonalization; 16% vs 11% for Inefficacy). Chi-square tests confirmed statistically significant differences across burnout dimensions (P<.001), particularly for Depersonalization and Inefficacy across age and activity levels. These findings highlight the distinct stressors faced by active nurses and underscore the need for targeted interventions.

Regional differences in burnout prevalence were also observed (Figure 1). The Midwest reported the highest total burnout percentage (87%), with Emotional Exhaustion, Inefficacy, and Depersonalization contributing 30%, 29%, and 28%, respectively. The South followed with a total burnout percentage of 80%, while the Northeast region reported a similar pattern at 71%. The West exhibited a lower total burnout percentage of 59%.

Figure 1. Burnout dimensions across regions. Midwest shows the highest burnout (87%), followed by south (80%) and west (71%).



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Key Themes at the Intersection of Burnout and HBM Constructs

To address subquestion 4, our thematic analysis identified overlapping concerns at the intersection of burnout dimensions and HBM constructs. Health and safety concerns, including vaccine side effects, efficacy, and misinformation, were dominant among comments highlighting perceived barriers to vaccination. Emotional and psychological strain, characterized by stress, loss, and work-life challenges, further underscored the mental toll of burnout in shaping vaccine hesitancy. In some cases, participants cited low perceived risk due to high COVID-19 recovery rates, which reduced the urgency for vaccination.

Broader themes reflected distrust toward government and political systems, frustrations with systemic obstacles, and the pandemic's impact on social and family dynamics. Faith and resilience were also significant factors, with many participants relying on spiritual beliefs and community support to navigate vaccine-related concerns. These themes illustrate the complex interplay between burnout dimensions and health beliefs, shaping health care workers' vaccine decisions.

Error Analysis

We conducted both quantitative and qualitative error analysis, focusing on predicted versus true labels, classification confidence, and label-specific performance metrics such as precision, recall, and F_1-score.

Initial results revealed key challenges, with multiclass classification achieving only 55% accuracy. Misclassified outputs showed ambiguity and overlapping language, particularly between Emotional Exhaustion and Depersonalization, which frequently co-occurred and shared similar linguistic cues.

For example, comments such as "Changing expectations & policies at work are frustrating causing burnout. Lack of free speech/generally one-way group think causes burnout feeling. Everyone is tired of the isolation and changes to our social lives" could be classified as either Emotional Exhaustion or Depersonalization, depending on interpretation. Phrases like "frustration causing burnout" and "everyone is tired of the isolation" suggest fatigue and feeling emotionally overwhelmed, which align with Emotional Exhaustion. On the other hand, mentions of "lack of free speech" and "one-way group think" could reflect feelings of disconnection or detachment from the work environment, or an insensitive attitude toward colleagues and tasks, aligning more with Depersonalization.

Similarly, the comment "I was working as an R.N. in the pandemic and eventually developed severe anxiety, panic attacks, and depression and am currently on a leave of absence from work for these reasons" strongly reflects Emotional Exhaustion, characterized by emotional and psychological depletion. However, the mention of a leave of absence might also suggest withdrawal, potentially overlapping with Depersonalization and contributing to misclassification.

Depersonalization, in particular, showed high precision but low recall. This discrepancy likely stems from the smaller proportion of comments classified under Depersonalization, leading to more cautious predictions for this dimension and reduced sensitivity to identifying all relevant instances.

Discussion

Overview

This study examined the role of burnout and health beliefs in shaping COVID-19 vaccine decisions among health care workers, offering novel insights through the integration of LLM-based text analysis. By leveraging LLaMA 3 for categorizing burnout dimensions and analyzing their intersection with HBM constructs, the findings align with and extend prior research on the psychological and behavioral factors influencing vaccine hesitancy.

Key Findings and Comparisons

The predominance of Emotional Exhaustion (52% of comments) and its strong correlation with perceived severity (59%) and barriers (43%) underscores the critical role of psychological strain in vaccine hesitancy. These results are consistent with previous studies that link high levels of emotional distress among health care workers with increased concerns about vaccine safety and efficacy [30-33]. Depersonalization, which showed associations with perceived severity (27%) and susceptibility (23%), highlights the psychological detachment experienced by some health care workers, reflecting findings by Zhang et al [34], who identified significant links between burnout dimensions such as depersonalization and factors influencing job satisfaction and turnover intentions among nurses in high-stress settings. In contrast, inefficacy, while less prevalent, aligns with research indicating that feelings of low personal accomplishment may undermine self-efficacy and motivation, thereby dampening proactive health behaviors [35].

Our findings indicate widespread emotional exhaustion across all groups, with at least 50% of both active and inactive nurses reporting high burnout. While we expected active nurses to experience greater burnout due to workplace stress during COVID-19, inactive nurses older than 65 years of age exhibited similar levels, suggesting additional contributing factors. Notably, most inactive nurses in this study were retired, and some reported caregiving responsibilities for spouses, older parents, or grandchildren during pandemic-related closures. These stressors, along with the broader emotional toll of the pandemic, may explain their high burnout levels. Given that data collection occurred early in the pandemic and before mandatory vaccination, we cannot conclude that burnout led to early retirement. However, for those nearing retirement (55-65 years of age), pandemic-related stress may have influenced workforce decisions. The consistently high emotional exhaustion across groups underscores the long-term psychological burden of health care work, warranting further research into postretirement burnout and its lasting effects.

The interplay between burnout dimensions and vaccine hesitancy highlights significant psychological and contextual barriers to vaccination among health care workers. These findings align with prior research, which demonstrates that emotional exhaustion and distrust in systemic structures exacerbate vaccine

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hesitancy during crises [36,37]. Addressing such multifaceted concerns requires holistic approaches that consider not only health beliefs but also the broader sociopolitical and personal challenges faced by health care workers.

The application of LLaMA 3 with the RASC framework demonstrated robust performance in classifying burnout dimensions, achieving high accuracy and F_1-scores, particularly for Emotional Exhaustion and Inefficacy. These findings underscore the potential of leveraging domain-specific knowledge and few-shot learning strategies for complex classification tasks, aligning with prior research emphasizing the role of targeted annotation and reasoning-based approaches to improve natural language processing model outcomes [28,29]. Future studies could explore fine-tuning strategies to address challenges with overlapping burnout dimensions.

Policy Implications and Interventions

The findings of this study also have significant implications for policy makers. Systemic interventions are needed to address organizational stressors contributing to burnout, including manageable working hours, adequate staffing ratios, and improved access to mental health resources tailored to health care workers. Transparent communication and inclusive decision-making processes are essential to rebuilding trust in health care systems and alleviating systemic distrust that influences vaccine hesitancy.

Policy makers should also support the development of monitoring frameworks that use real-time data to identify at-risk health care workers. Machine learning–driven tools, such as those leveraging LLMs, could enhance early detection of burnout symptoms through employee feedback systems. Finally, interventions must be culturally sensitive and address the diverse needs of underrepresented health care worker populations. These systemic approaches, informed by this study, could improve workforce well-being and public health outcomes by addressing burnout and vaccine hesitancy at their root causes.

Limitations and Future Directions

While this study provides valuable insights, several limitations warrant attention. The reliance on self-reported comments may introduce reporting bias, as participants may underreport or selectively emphasize certain factors influencing their vaccine hesitancy. Additionally, the study's dataset, derived from the Nurses' Health Study cohorts, includes only female registered nurses, with the majority identifying as White. This demographic homogeneity limits the generalizability of the findings to other health care professions, genders, and ethnic groups. Furthermore, challenges remain in distinguishing overlapping burnout dimensions which require further refinement in annotation guidelines and modeling strategies.

Conclusions

Future research should explore the longitudinal effects of burnout on vaccine-related behaviors and incorporate diverse health care worker populations. Efforts should also focus on identifying additional burnout factors not included in the MBI. Additionally, designing a preventive framework or tool to monitor and follow up with health care workers for early detection of burnout symptoms could transform interventions. Such tools, integrating real-time machine learning algorithms, could provide tailored interventions to address burnout symptoms before escalation. Expanding the application of LLMs to include multitask learning and fine-tuning with larger annotated datasets may enhance the understanding of complex psychological constructs and their implications for vaccine decisions.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Annotation Guidelines-based Knowledge Augmentation (AGKA prompts) with emotional exhaustion prompt.
[DOCX File, 17 KB - nursing_v8i1e73672_app1.docx]

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Abbreviations

AGKA: Annotation Guidelines–based Knowledge Augmentation
HBM: Health Belief Model
LLM: large language model
MBI: Maslach Burnout Inventory
RASC: Reasoning-Aware Self-Consistency
VH: vaccine hesitant

Edited by E Borycki; submitted 09.03.25; peer-reviewed by M Assadi, RS Gomaa Mahmoud; revised version received 04.05.25; accepted 07.05.25; published 04.07.25.

Please cite as:
Omranian S, He L, Talsma A, Scoglio AAJ, McRoy S, Rich-Edwards JW
Using Large Language Models to Assess Burnout Among Health Care Workers in the Context of COVID-19 Vaccine Decisions and Health Beliefs: Retrospective Cohort Study
JMIR Nursing 2025;8:e73672
URL: https://nursing.jmir.org/2025/1/e73672
doi:10.2196/73672

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Advancing Clinical Chatbot Validation Using AI-Powered Evaluation With a New 3-Bot Evaluation System: Instrument Validation Study

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Abstract

Background: The health care sector faces a projected shortfall of 10 million workers by 2030. Artificial intelligence (AI) automation in areas such as patient education and initial therapy screening presents a strategic response to mitigate this shortage and reallocate medical staff to higher-priority tasks. However, current methods of evaluating early-stage health care AI chatbots are highly limited due to safety concerns and the amount of time and effort that goes into evaluating them.

Objective: This study introduces a novel 3-bot method for efficiently testing and validating early-stage AI health care provider chatbots. To extensively test AI provider chatbots without involving real patients or researchers, various AI patient bots and an evaluator bot were developed.

Methods: Provider bots interacted with AI patient bots embodying frustrated, anxious, or depressed personas. An evaluator bot reviewed interaction transcripts based on specific criteria. Human experts then reviewed each interaction transcript, and the evaluator bot's results were compared to human evaluation results to ensure accuracy.

Results: The patient-education bot's evaluations by the AI evaluator and the human evaluator were nearly identical, with minimal variance, limiting the opportunity for further analysis. The screening bot's evaluations also yielded similar results between the AI evaluator and human evaluator. Statistical analysis confirmed the reliability and accuracy of the AI evaluations.

Conclusions: The innovative evaluation method ensures a safe, adaptable, and effective means to test and refine early versions of health care provider chatbots without risking patient safety or investing excessive researcher time and effort. Our patient-education evaluator bots could have benefitted from larger evaluation criteria, as we had extremely similar results from the AI and human evaluators, which could have arisen because of the small number of evaluation criteria. We were limited in the amount of prompting we could input into each bot due to the practical consideration that response time increases with larger and larger prompts. In the future, using techniques such as retrieval augmented generation will allow the system to receive more information and become more specific and accurate in evaluating the chatbots. This evaluation method will allow for rapid testing and validation of health care chatbots to automate basic medical tasks, freeing providers to address more complex tasks.

(JMIR Nursing 2025;8:e63058) doi:10.2196/63058

KEYWORDS

artificial intelligence; patient education; therapy; computer-assisted; computer; understandable; accurate; understandability; automation; chatbots; bots; conversational agents; emotions; emotional; depression; depressive; anxiety; anxious; nervous; nervousness; empathy; empathetic; communication; interactions; frustrated; frustration; relationships

Introduction

Faced with a projected shortfall of 10 million health care workers by 2030 [1], the health care sector urgently requires innovative solutions to sustain patient care and education. Artificial intelligence (AI) automation in low- to mid-level tasks like patient education and initial therapy screening emerges as a strategic response to mitigate this shortage, reallocating medical staff to higher-priority tasks [2,3].

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The advent of advanced multimodal large language models (LLMs) such as GPT-4 introduces a paradigm shift, promising scalable, cost-effective chatbot solutions, which are particularly helpful for tasks that require the provider to interact with the patient [4]. GPT-4 and similar models offer a more dynamic, conversational approach, tailoring information to individual patient needs with minimal logistical or financial overhead for health care institutions. This technological evolution promises not only to fill the imminent workforce gap but also to enhance the quality and accessibility of health care services, leveraging AI's capacity for on-demand, personalized patient support [4-7]. It has been reported that LLMs have the cognitive capacity to role-play the character as portrayed in the dialogue prompt [8]. Shao et al [9] showed that GPT-3.5 can be used to score the believability of LLM role-playing. Finally, Yang et al [10] pointed to the high potential that medical chatbots have in clinical settings, while Gilbert et al [11] warned of the need to extensively test health care chatbots.

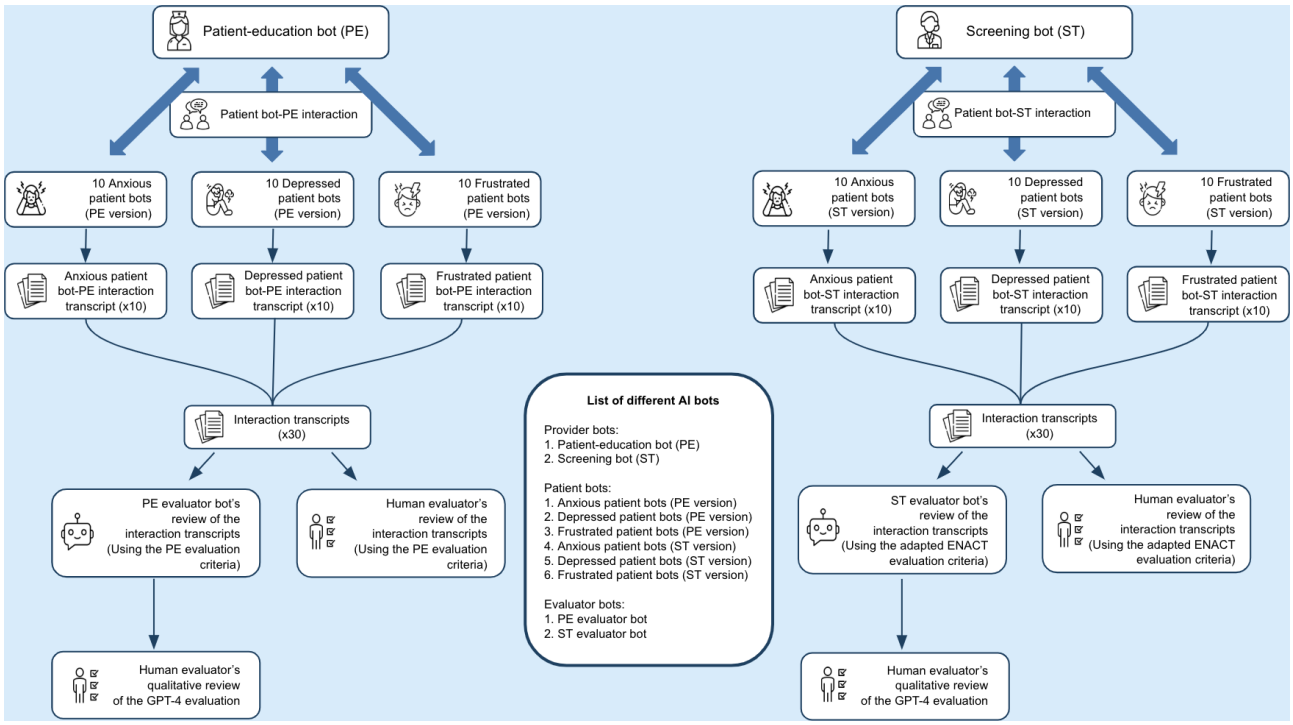
However, current methods of creating and evaluating early-stage health care bots face steep development costs due to the high level of human involvement in each phase of the development process. In this study, we present a novel, bot-driven method of developing, testing, and evaluating automated health care chatbots. At the center of this strategy is the use of the LLM as an "evaluator agent" to iteratively review and provide feedback on the dialog between the health care bot being evaluated and a set of "digitally simulated patients" also role-played by the LLM. This approach provides a fully automated system that will not only reduce the amount of time and effort required to develop the chatbots but also provide a feasible way to continuously monitor the performances of health care chatbots in different clinical settings.

Methods

Study Design

This study introduces a novel bot-driven method to evaluate the abilities of LLMs in health care tasks. In this approach, LLMs were configured to perform as a patient-education bot, a pretherapy screening bot, patient bots, and evaluator bots. The patient bots simulated distinct emotional personas—depressed, anxious, and frustrated—to test the adaptability and competency of the provider bots. The evaluator bots assessed the interactions based on predefined criteria. Results from the AI evaluations were cross-referenced with human expert reviews for accuracy and reliability (Figure 1).

Figure 1. Interaction and evaluation methodology for the patient-education bot and the initial screening bot. Includes a list of all the different bots used. AI: artificial intelligence; ENACT: Enhancing Assessment of Common Therapeutic Factors.



Setup

To demonstrate the system, 2 AI provider bots were developed using GPT-4 in collaboration with an experienced oncology nurse and a licensed cognitive behavior counselor. One provider bot emulated a patient-education nurse, delivering medical information with clarity and empathy. The second bot acted as a mental health therapist, modeled on acceptance and commitment therapy and mindfulness practices, to provide nonpharmacological mental health support.

AI patient bots, also developed using GPT-4, were programmed to represent 40-year-old male patients with lung cancer with 1 of 3 emotional personas: depressed, anxious, and frustrated. In total, 30 patient bots (10 per persona) were created, with each provider bot engaging in 30 interactions. The patient bots' responses were unique due to GPT-4's stochastic generation processes, even with consistent prompts.

Evaluator bots were created for each provider bot to assess their performance based on predefined criteria, offering scores and qualitative feedback. These AI-generated evaluations were

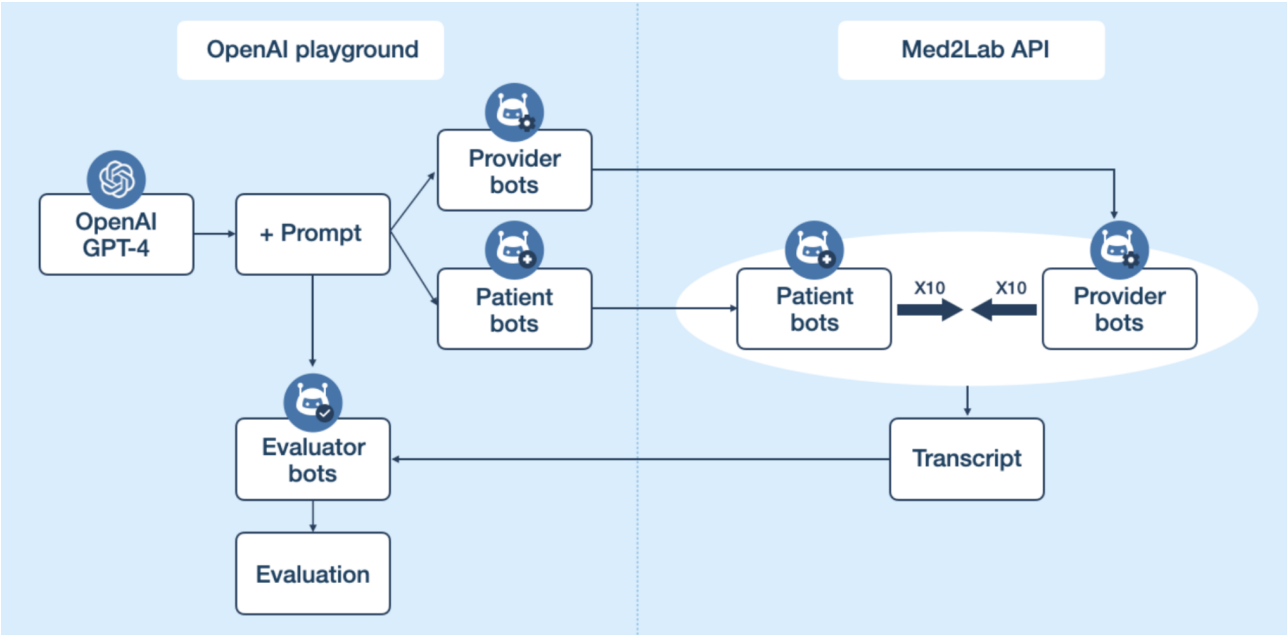
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subsequently reviewed by human experts in relevant fields to ensure validity.

Once the evaluator bots reviewed each provider-patient transcript, human experts in each field reviewed the transcripts, scored the interaction using the same criteria as the GPT-4 bots, commented on the provider's overall performance, and then reviewed the evaluator bot's assessment.

The patient-education bot was reviewed by the same pediatric hematology-oncology nurse who helped create the patient-education approach, while the pretherapy screening bot was reviewed by a PhD in IT psychology as well as by the cognitive behavior counselor (Figure 2).

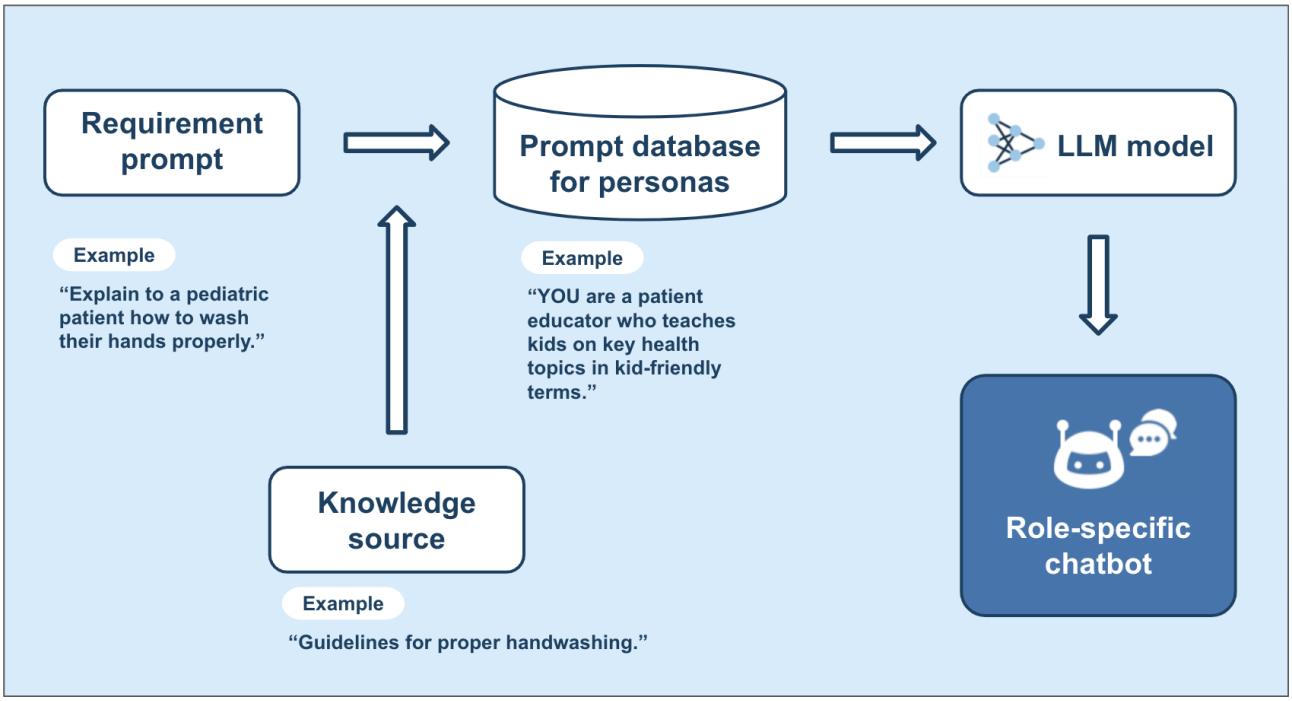
Figure 2. Outline of the bot-bot interactions and evaluations. API: application programming interface.



Prompting

To ensure that the bots adhered strictly to their designated roles while mitigating unwanted behaviors, explicit, role-specific instructions were incorporated into their prompts. This design approach balanced general AI capabilities with task-specific requirements, ensuring consistent and contextually appropriate responses (Figure 3).

Figure 3. Chatbot architecture. LLM: large language model.



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Patient-Education Bot Prompting

The patient-education bot was designed to emulate the role of a "patient-education nurse" tasked with educating patients with cancer about medical vocabulary, procedures, and treatment options. The bot was prompted with detailed instructions, emphasizing clarity, empathic expressions in communication, and a patient-centered approach. The following guidelines were incorporated into its prompt: (1) adopt a teaching role tailored to patients with limited medical knowledge; (2) provide accurate, comprehensive explanations of medical terms and procedures in simple, relatable language; (3) exhibit empathy and warmth while refraining from making medical recommendations outside the scope of a patient-education nurse; and (4) ensure consistency in tone and responsiveness to patient questions while maintaining a clear boundary of professional role.

Screening Bot Prompting

The screening bot was designed to act as a "therapist" specializing in supporting patients with cancer dealing with fear, anxiety, depression, or other stress-related conditions. The prompt emphasized its role in fostering emotional well-being and therapeutic rapport. Key instructions included (1) respond as a therapist practicing nonjudgmental support, inspired by principles from acceptance and commitment therapy and mindfulness practices; (2) reduce patient stress by validating emotions, exploring coping mechanisms, and encouraging hope for change; (3) avoid clinical diagnostic language or prescribing treatments, focusing instead on promoting self-reflection and stress management strategies; and (4) engage the patient through open-ended questions and supportive dialogue, tailored to the specific emotional state of the patient persona.

Patient Bot Prompting

The patient bots were modeled to represent 3 distinct emotional personas—anxious, depressed, and frustrated—and were designed to simulate real-life patient interactions. Each patient bot was assigned the role of a 40-year-old male patient with lung cancer undergoing treatment. Detailed persona-specific instructions were included to guide their interactions:

- Persona-specific emotional states:
  - Anxious persona: Expresses uncertainty and seeks detailed explanations.
  - Depressed persona: Exhibits low engagement and responds with shorter, less optimistic answers.
  - Frustrated persona: Displays irritability and impatience in responses.
- Respond consistently with the designated persona's characteristics throughout the dialogue.
- Do not use or understand high-level medical terms unless explicitly explained by the provider bot.
- For the patient-education bot interactions:
  - Frame responses as questions about unclear cancer-related terms, procedures, or treatments.
- For the screening bot interactions:
  - Actively participate in therapy sessions, responding to the therapist bot's efforts to reduce stress while maintaining the persona's emotional tone.

Evaluator Bot Prompting

Evaluator bots were designed to act as "supervisors," assessing the interactions between a provider and a patient. They evaluated transcripts based on a scoring scale (1=poor and 3=excellent) tailored to the respective provider bot's role.

For the patient-education bot, the following five criteria (maximum score: 15) were used: (1) medical information accuracy, (2) clarity and simplicity of explanations, (3) expressions of empathy and warmth, (4) explanation of purpose or importance of procedures, and (5) adherence to professional role boundaries.

For the screening bot, fourteen criteria (adapted from the Enhancing Assessment of Common Therapeutic Factors tool [12]; maximum score: 42) were used: (1) verbal communication: open-ended questions, summarization, and clarification; (2) relationship building; (3) exploration and normalization of emotions; (4) expressions of empathy and warmth; (5) assessment of functioning and life evaluation; (6) exploration of social support; (7) incorporation of coping mechanisms; (8) evaluation of recent life events; (9) assessment of mental health; (10) collaborative goal-setting; (11) promotion of realistic hope for change; (12) use of simple, jargon-free language; (13) problem-solving steps and processes; and (14) integration of feedback.

Criteria unsuitable for chatbot interactions, such as nonverbal communication, were excluded with detailed reasons listed in Table 1.

Table . List of Enhancing Assessment of Common Therapeutic Factors (ENACT) factors removed with the reason for their removal.

ENACT factor	Reason for removal
Nonverbal communication and active listening	Therapist is a chatbot and therefore cannot display body language.
Therapist self-disclosure	Therapist is a chatbot and therefore has no real experiences to disclose.
Alcohol or drug and physical problems	Patient has cancer; therefore, physical, alcohol, or drug issues would need to go through their oncologist.
Involvement of family members or caregivers	Patient and therapist are chatbots; therefore, all sessions are assumed to be individual and one-on-one with no family involvement.
Confidentiality promotion	Therapist and patients are chatbots, so all conversations are assumed to be confidential and private.
Assessment of harm to self, harm to others, developing a collaborative response plan	For this study, patient chatbots were assumed not to have violent or suicidal tendencies.

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Provider-Patient Interactions

Each provider bot engaged in 30 unique conversations, distributed evenly across 3 patient personas: anxious, depressed, and frustrated (10 conversations per persona). Conversations were facilitated through an application programming interface designed to streamline the flow of interactions. Each conversation consisted of 20 interactions, defined as 10 turns exchanged between the provider bot and the patient bot.

To simulate concise and realistic clinical exchanges, both provider and patient bots were programmed with the following parameters: a temperature setting of 0.7 (to ensure balanced creativity and consistency), Top P: 1, frequency penalty: 0, and presence penalty: 0. The token limit was removed to avoid interruptions, and each conversation was capped at 10 conversational turns to maintain brevity and clinical relevance. The resulting transcripts from these conversations were reviewed by evaluator bots using predefined criteria and subsequently cross-validated by human experts to ensure the reliability and validity of the evaluations.

Provider Bot Validation

A 2-step validation process was conducted. First, evaluator bots assessed the provider bots based on predefined criteria, generating scores and qualitative feedback. These results were then reviewed by human experts, a pediatric oncology nurse for the patient-education bot and a cognitive behavior counselor and PhD in IT psychology for the screening bot, using the same criteria used by the evaluator bots to ensure consistency and reliability.

Evaluator Bot Validation

Evaluator bots graded each interaction transcript based on predefined criteria, producing quantitative scores and qualitative comments. Human experts then reviewed the same transcripts, blind to the evaluator bot's results, and provided their own scores for comparison. The experts then reviewed the bots' evaluations to ensure that a consistent and reliable evaluation was carried out by the evaluator bot.

Statistical Analysis

Descriptive analyses were performed to evaluate interaction characteristics, including word count and sentiment trends. Cronbach α analysis was used to assess the reliability of evaluation criteria across evaluators. Differences in responses between GPT evaluators and human experts were analyzed using the Kruskal-Wallis test. ANOVA was used to identify significant variations in provider bot responses to different patient personas. All analyses were conducted using SPSS (version 24.0; IBM Corp).

Ethical Considerations

We did not have any human participants or animal subjects and therefore did not need to go before an ethics board.

Results

Evaluation of the Patient-Education Bots by AI and Human Evaluators

The patient-education bot, evaluated by both AI and human evaluators, exhibited remarkably consistent performance across interactions with patient bots displaying frustrated, depressed, and anxious personas. The patient-education bot consistently provided accurate medical information, as validated by an experienced oncology nurse, and delivered clear explanations that were fully understood by patient bots, with no instances of confusion reported. Specifically, the AI evaluator assigned perfect or near-perfect mean scores of 15 (SD 0.00), 14.9 (SD 0.31), and 15 (SD 0.00), respectively, while the human evaluator echoed these assessments with similarly high mean scores of 14.9 (SD 0.31), 14.9 (SD 0.31), and 15 (SD 0.00), respectively. The AI evaluator described the patient-education bot to have "... demonstrated excellent skills in providing education and support to the patient. The information provided was accurate, comprehensive, and clearly articulated, catering to the patient's understanding. The nurse exhibited great empathy and warmth throughout the interactions, which significantly contributed to patient comfort, trust, and engagement. The nurse did not overstep their boundaries by making specific medical recommendations, respecting the role of the patient's treatment team. Overall, the nurse demonstrated exceptional patient-education skills."

A singular point of contention arose from the AI evaluator's interpretation of the patient-education bot potentially recommending treatments beyond its scope. The AI evaluator stated that the nurse could benefit from "being cautious and mindful to avoid being perceived as providing personalized treatment suggestions." This was later clarified as a misunderstanding, attributing the issue to the AI evaluator's scoring framework rather than the patient-education bot's performance.

The patient-education bot was described by the human evaluator to be "correct" and "well-organized and explained," but the bot's "[constant expression] of empathy" was reported to "[feel] a bit mechanical." It was noted that this bot would "likely be helpful, as it can repeatedly explain medical concepts on behalf of medical staff members who do not always have enough time for explanations."

Evaluation of the Screening Bot by AI and Human Evaluators

The average AI evaluator bot's scores for the pretherapy screening bot when interacting with the frustrated, depressed, and anxious patient bots, respectively, were 40.1 (SD 1.28), 40.3 (SD 1.05), and 40.7 (SD 1.15), of a total possible score of 42. Across all 3 patient bots, the lowest scoring criterion was the evaluation of realistic hope for change, which had an average score of 2.53 out of 3 (SD 0.51). Human expert evaluators corroborated the AI evaluation results. The average human evaluator scores of the screening bot when interacting with the frustrated, depressed, and anxious patient bots, respectively, were 37.5 (SD 0.84), 37.6 (SD 0.96), and 36.9 (SD 2.60) for

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the first reviewer and 36.8 (SD 1.31), 36.9 (SD 1.10), and 36.2 (SD 2.09) for the second reviewer.

The AI evaluator, under the impression it was assessing a human, reported that the pretherapy screening bot excelled in maintaining effective communication, building a warm relationship, and demonstrating empathy. The evaluator bot identified several strengths of the screening bot, stating that it "... provides a warm and empathetic attitude and responds likewise to the patient's negative reactions and feelings and leads the conversation naturally." The most common areas for improvement mentioned in the final comments were "exploration of prior successful coping strategies and providing more explicit encouragement for feedback."

Human evaluators similarly concluded that the pretherapy screening bot excelled in "... [communicating] clearly," building a "warm and empathetic" relationship, and "[leading] the conversation naturally." The screening bot reportedly could improve upon "exploring prior coping strategies and patient history a little more deeply" and was occasionally reported to be too informational or talkative. It was reported to "[pass] to the next topic too quickly (possibly due to its large list of duties—which the therapist was prompted to do)." Overall, the human reviewers suggested that "the bot is useful for initial consultations—the AI fluently checks for components of the initial step of counseling." Furthermore, it was noted that "a more detailed score standard is required for the evaluator bot's prompt."

Statistical Analysis Result

Patient-Education Bot

For the patient-education bot, the evaluation scores from both AI and human evaluators were remarkably consistent, showing minimal variance. This uniformity limited the opportunity for further analysis, as the lack of significant differences between evaluator scores precluded more detailed statistical comparisons.

Screening Bot

The Kaiser-Meyer-Olkin and Bartlett sphericity test results indicate that the Kaiser-Meyer-Olkin value of 0.714 suggests that the sample is suitable for factor analysis, and the significance probability of Bartlett sphericity test is less than .001, indicating that the correlation between variables is significant. The results of the communality analysis show that all variables have a communality of 1, indicating that all variables explain the extracted factors well. The 5 extracted factors explain 66.327% of the total variance of the variables.

Significant findings from the ANOVA analysis indicate notable variations in group responses across several key evaluation criteria for the screening bot. This variability suggests that specific factors or treatments have a meaningful impact on participant responses, reflecting their efficacy or relevance in different contexts. Verbal communication (open-ended questions, summarization, and clarification) demonstrated a highly significant difference between groups (P<.001), suggesting that the approach to verbal communication significantly affects the responses. Assessment of functioning and life evaluation exhibited one of the highest significances (P<.001), pointing to the critical role this factor plays in differentiating responses among groups. Exploration of the patient's social support network also showed a highly significant difference (P<.001), indicating a strong effect of social support exploration on participant responses. Assessment of mental health highlighted the most substantial difference between group means (P<.001), underscoring the importance of mental health assessment in eliciting varied responses. Evaluation of recent events in the patient's life and evaluation of realistic hope for change both showed significant differences between groups (P<.001 for the former and P<.001 for the latter), suggesting these areas notably influence responses.

Other significant areas include relationship building and exploration, interpretation, and normalization of emotions, with P values of .004 and .002, respectively, indicating noticeable effects on the responses, albeit less pronounced compared to the areas mentioned earlier. Nonsignificant findings were observed in the expression of empathy, warmth, and genuineness and collaborative goal-setting and managing patient's expectations, with P values of .36 and .28, respectively. These results suggest that variations in group responses to these criteria might not be significantly influenced by the tested factors, potentially due to inherent similarities in the implementation or perception of these aspects.

The use of easy-to-understand vocabulary and integration of feedback, giving advice, and recommendations showed moderate significant differences (P=.04 and P=.02, respectively), indicating that these areas have a discernible but varied impact on participant responses.

The detailed ANOVA analysis underscores the nuanced impact of different therapeutic communication and evaluation strategies on participant responses. It highlights the areas where specific approaches significantly influence outcomes, offering insights into the effectiveness of various therapeutic and communicative techniques.

The ANOVA results highlight the variability in how different groups responded to the questions. Significant P values (P<.05) indicate that the groups do not share the same mean response to a question, suggesting that the factor or treatment being tested influences the responses. The strength of this effect varies among the questions, as evidenced by the range of F values and P values.

Discussion

Principal Findings

Overall, the insights gained from this research suggest that AI health care chatbots can be developed, tested, and validated within a relatively short time frame using the 3-bot system. The results of the 3-bot evaluation system suggest that this method can prove valuable for extensive testing of early-stage health care chatbots. The patient bots are able to mimic patient dialogue and provide a platform for the provider bots to output their responses, while the evaluator bot is able to comb through the interaction transcripts and flag any potentially inappropriate responses, greatly reducing the amount of work for researchers. Furthermore, this 3-bot system is highly customizable and can

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be adapted to fit the needs and cultural norms required by the developers. It is also highly scalable, as the basic requirements to perform the 3-bot evaluations are a computer system and access to an LLM. Performing more iterations of an evaluation only requires a marginal amount of researcher effort, and performing multiple, different evaluations can be accomplished simultaneously, given the computer system has enough processing power.

This study introduces a novel AI-powered health care chatbot validation system featuring 3 types of AI bots—provider, patient, and evaluator. This 3-bot AI system represents a novel methodology not previously explored in existing literature, extending beyond the importance of validation discussed by Bohr and Memarzadeh [2] in AI's rise in health care, which did not delve into the conversational capabilities between different AI systems in clinical simulations. To our knowledge, our method of testing and evaluating the performance of AI health care provider bots by having them interact with other patient bots and then reviewing the transcripts with an evaluator AI bot has never been reported before.

In our study, we created 2 health care provider bots as examples to demonstrate our system, a patient-education bot and a mental health screening bot. The provider bots were intricately designed to replicate the roles traditionally held by human health care providers, addressing the urgent need for scalable and effective patient care solutions highlighted by Patel et al [13]. These bots are intended to support the health care workforce, which, according to the World Health Organization, is expected to face a significant shortfall [14]. By automating routine tasks, these AI systems could alleviate some of the burdens placed on human staff, allowing them to focus on more complex and sensitive care activities. Already, several health care chatbots are in development, including those designed to answer patient questions and provide mental health therapy [14,15].

However, provider chatbots such as these still require extensive testing, traditionally done by enrolling patients as subjects, which negatively affects the speed and resource cost of developing these tools while running the risk of exposing the patients to unvalidated AI. Therefore, we created 3 types of AI patient bots with personas as examples to test our provider bots. In designing the patient bots, we drew inspiration from Fortin et al [16], who emphasize the importance of personalized and empathetic care in treatment outcomes. In previous studies, various digital patient bots were reported in medical education. In our study, the patient bots were imbued with diverse emotional and psychological states to test the adaptability and responsiveness of the provider bots in a controlled, yet realistic environment, simulating real-life patient interactions.

Comparison to Prior Work

These current methods require great human input during the iterative testing and evaluation phases, which requires researchers and developers to invest significant time and effort. In contrast, using the 3-bot validation method removes the need for separate human responders and human evaluators, greatly streamlining the initial testing and evaluation process and focusing work efforts on areas of the evaluated bot that require improvement.

Until now, bot-bot interactions were manually reviewed by human experts, which greatly slows the validation process. Current methods of evaluating health care chatbots include a human reviewer reviewing the health care chatbot's performance against a grading standard as seen in Lechien et al [17] and Goodman et al [18], a human reviewer grading the health care chatbot's performance against another pre-established chatbot as seen in Aljamaan et al [19], or a mix of the methods, as seen in Huang et al [20].

In this study, we created 2 AI evaluator bots to demonstrate the feasibility of using them as first-line evaluators in addition to human experts. The role of the evaluator bots was crucial in objectively assessing the quality of interactions between provider and patient bots, ensuring adherence to predefined criteria. This evaluation process mirrors the necessity of validation for AI systems before clinical application as emphasized by Kretzschmar et al [21]. By comparing the evaluations conducted by AI evaluator bots with assessments from human experts, we ensured the feasibility of our system, further grounding the study in rigorous scientific methodology. To date, AI bots have been used to review text messages and academic manuscripts, but this is the first study to review dialogue between 2 bots for the purposes of evaluation.

Limitations and Future Directions

While promising, this study has limitations that warrant consideration. First, the evaluation criteria used were relatively limited in scope, which may not have captured subtle differences in performance between AI and human evaluators. Future research should incorporate more comprehensive and granular criteria to enable more nuanced evaluations. Retrieval-augmented generation could further enhance the evaluator bots by enabling them to cross-verify provider bot responses against dynamic, vetted information sources, thereby increasing the accuracy and reliability of evaluations.

Second, the patient bots were prompted using relatively concise instructions due to the practical constraints of maintaining response speed. This may have limited the complexity and variability of their responses, potentially underrepresenting the breadth of emotions and behaviors seen in real-world patients. Future studies should explore more elaborate prompting strategies or advanced techniques like retrieval-augmented generation to overcome this limitation.

Third, the study used prioritized examples of clinically relevant patient personas (anxious, depressed, and frustrated), chosen for their significance in addressing common and challenging scenarios in clinical practice. While these personas are a high priority for an initial evaluation, they do not fully represent the diversity of patient interactions.

Finally, biases inherent in LLMs may have influenced the results, despite efforts to standardize demographic inputs across all patient bots. Nonessential demographic details were excluded to minimize biases related to race, political affiliation, sexual orientation, or socioeconomic status. Nonetheless, future research should explore the use of specialized LLMs with controlled training datasets to further mitigate such biases.

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Conclusions

We underscore the successful development and implementation of a novel 3-bot evaluation system. This system, consisting of provider bots, patient bots, and evaluator bots, represents a pioneering approach to testing and validating AI functionalities without the need for real patient interactions. Our findings offer a practical solution and set a benchmark for future AI-driven health care services, providing a direction for subsequent research and development efforts.

Acknowledgments

This research was supported by a grant from the Korea Health Technology R&D Project from the Korea Health Industry Development Institute, funded by the Ministry of Health & Welfare, Republic of Korea (grant HI23C038700), as well as through the resources of Med2Lab, Inc. The authors would like to express their sincere gratitude to all the individuals who contributed to the successful completion of this study. The authors would like to thank Binh Nguyen and Ha Huynh for setting up the application programming interface and providing large language model–related advice, Eunju Cho for helping set up the patient-education nurse evaluation criteria and for evaluating the patient-education nurse, Yoojin Seo for setting up the screening therapist approach and for evaluating the screening therapist, and Jungyi Ma for evaluating the screening therapist.

Conflicts of Interest

BT and KE have disclosed a financial relationship with Med2Lab Inc., which includes board membership, employment, and equity or stock ownership. They confirm that they had no involvement or influence in the design of the methodology or the results of this study. All other authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Abbreviations

AI: artificial intelligence
LLM: large language model

Edited by E Borycki, K Cato; submitted 09.06.24; peer-reviewed by D Chrimes, E Bai, M Chatzimina; revised version received 21.12.24; accepted 02.01.25; published 27.02.25.

Please cite as:
Choo S, Yoo S, Endo K, Truong B, Son MH
Advancing Clinical Chatbot Validation Using AI-Powered Evaluation With a New 3-Bot Evaluation System: Instrument Validation Study
JMIR Nursing 2025;8:e63058
URL: https://nursing.jmir.org/2025/1/e63058
doi:10.2196/63058

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Impact of AI Literacy on Well-Being Among Nursing Students—Mediating Roles of Empowerment and Anxiety: Cross-Sectional Study

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Abstract

Background: The integration of artificial intelligence (AI) in health care is changing nursing practice, and it calls for the acquisition of AI literacy by students, which includes knowledge, skills, and attitudes. An understanding of the effect of AI literacy on the well-being and empowerment of students is crucial in guiding effective educational strategies.

Objective: This study aims to investigate the impact of AI literacy on well-being, with psychological empowerment and anxiety serving as mediating variables. Using partial least squares structural equation modeling (PLS-SEM), this study examines gender differences within these relationships.

Methods: A cross-sectional design was used, and data were gathered from 497 nursing students from Imam Abdulrahman Bin Faisal University, Saudi Arabia, via a structured online questionnaire assessing AI literacy, psychological empowerment, anxiety, and well-being. PLS-SEM was used to evaluate both the measurement and structural models, encompassing mediation and multigroup analyses based on gender.

Results: The constructs demonstrated substantial reliability and validity, and the model's fit was deemed satisfactory. Well-being was moderately accounted for (R^2=0.41), whereas empowerment and anxiety exhibited lower levels of explained variance. All hypotheses were supported, indicating that AI literacy positively influenced empowerment and negatively affected both anxiety and well-being. Furthermore, empowerment was found to negatively impact both anxiety and well-being. The mediation effects were significant, and no gender differences were observed.

Conclusions: The study demonstrates that AI literacy significantly influences psychological empowerment, anxiety, and overall well-being through both direct and indirect pathways. The findings elucidate the intricate relationships among these variables and provide evidence for the applicability of the model across genders. This underscores the critical importance of promoting AI literacy and empowerment as a means to improve well-being outcomes.

(JMIR Nursing 2025;8:e79789) doi:10.2196/79789

KEYWORDS

artificial intelligence; anxiety; sex factors; well-being; structural equation modeling

Introduction

Background

The rapid integration of artificial intelligence (AI) into health care is transforming both clinical practice and nursing education. As future frontline health care providers, nursing students are increasingly exposed to AI technologies that promise to enhance clinical decision-making, operational efficiency, and patient outcomes [1,2]. However, this advancement also introduces educational and psychological challenges, including the need for sufficient AI literacy, psychological empowerment, and strategies to manage emotional responses to AI integration.

Understanding how AI literacy influences psychological empowerment, anxiety, and overall well-being is essential for equipping nursing students with the competencies required in evolving health care environments [3,4]. AI literacy—defined as the knowledge, skills, and ethical understanding necessary to effectively use AI tools—is key to enabling students to engage with these technologies confidently [5,6]. Psychological empowerment, reflecting a sense of control, competence, and meaning in one's role, may mediate the relationship between AI literacy and psychological outcomes [7].

In this study, anxiety refers to general anxiety symptoms, measured using the Generalized Anxiety Disorder 7-item (GAD-7) scale, rather than AI-specific or job-related anxiety.

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Although not directly tied to AI, general anxiety captures broader emotional distress, which may be influenced by students' perceptions and experiences with AI [8]. Conversely, AI-related anxiety, defined as apprehension or fear specifically related to the use or implications of AI, has also been shown to negatively affect academic performance and mental health [9,10].

Given these dynamics, exploring the interplay among AI literacy, psychological empowerment, and general anxiety is critical for developing targeted educational and psychological interventions to support nursing students' resilience and well-being in the era of AI.

Literature Review

AI literacy in nursing education encompasses ethical awareness, technical knowledge, and practical skills in working with AI-driven health care technology [3,5]. The literature suggests that the readiness of nursing students in accepting AI is a function of their attitude toward technology, perceived digital literacy, and ethics [4,11]. Limited access to AI resources and knowledge gaps remain significant barriers to full integration, stemming from students' confidence and intention to apply AI tools in practice [5,12].

Psychological empowerment is essential to enhance motivation and engagement in technology adoption. Zhang et al [7] demonstrated that perceived affordances of AI applications significantly support psychological empowerment, which leads to the adoption of AI-based medical consultations. In nursing practice, AI literacy empowerment can reduce feelings of helplessness and enhance self-efficacy, allowing for more effective learning and clinical performance [11].

Despite the potential benefits, AI adoption can evoke anxiety, characterized by uncertainty and fear about job security, capability, and moral concerns [3,10]. AI anxiety was found to be linked to poorer mental health status, increased stress, and opposition to using AI technologies [9]. In nursing students, this anxiety can undermine academic performance and decision-making, underscoring the need for targeted psychological interventions [13,14].

Readiness for AI is positively correlated with students' well-being, as adequate preparation reduces uncertainty and improves resilience [13,15]. AI literacy with psychological empowerment enables nursing students to use AI for academic success and mental health benefits, such as burnout decrease and self-management enhancement [16,17].

This study is guided by the Job Demands-Resources (JD-R) model and Psychological Empowerment theory. The JD-R model clarifies that job demands, including AI complexity and ethical concerns, lead to strain and anxiety, whereas resources, including AI literacy and empowerment, reduce stress and increase well-being [11]. Psychological empowerment theory concentrates on 4 cognitions—meaning, competence, self-determination, and impact—which are enhanced by AI literacy and influence affective responses to technology [7]. Together, these models explain how AI literacy is a resource that enhances empowerment, reduces AI anxiety, and ultimately improves well-being in nursing students.

The significance of this study is in addressing crucial gaps in the knowledge of the psychological impact of AI adoption in nursing education. By examining the interplay among AI literacy, psychological empowerment, anxiety, and well-being, this study will provide nursing educators and policymakers with insights into effective strategies to enhance AI readiness while safeguarding students' mental health. Empowerment and AI literacy can reduce anxiety, improve academic performance, and ready future nurses to apply AI technologies in patient care with confidence. Additionally, results can guide the development of AI-driven personalized interventions, such as mental health services and ethics education, to guarantee a skilled and resilient nursing workforce for the digital age [3,16,18].

Research Objectives

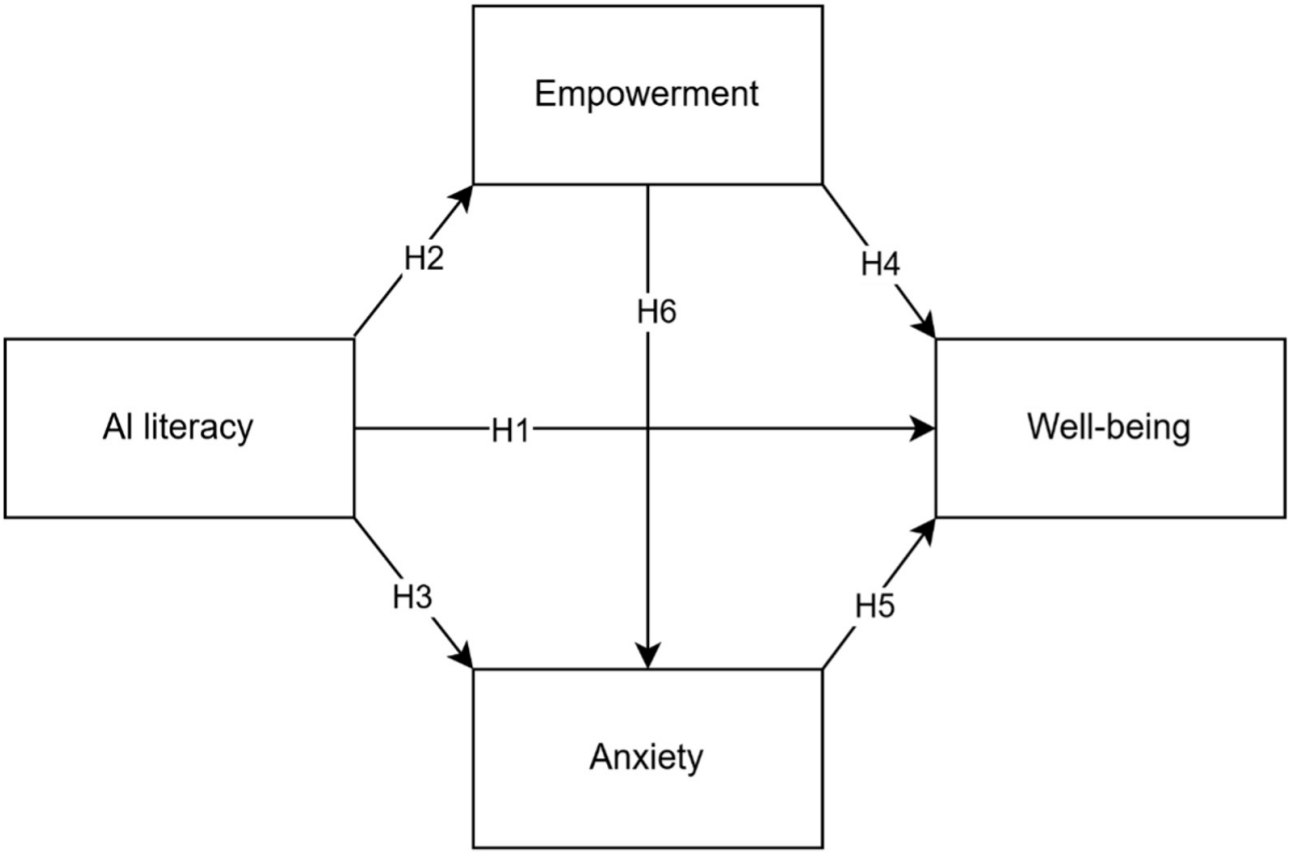
This study seeks to explore how literacy in AI influences well-being, considering psychological empowerment and anxiety as mediating factors. Using partial least squares structural equation modeling (PLS-SEM), this study also examines potential gender differences within these relationships.

Hypotheses

The conceptual framework and study hypotheses are summarized in Figure 1.

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Figure 1. Conceptual framework and hypotheses.



Our study hypotheses are as follows:

- **H1:** AI literacy directly affects well-being.
- **H2:** AI literacy directly affects empowerment.
- **H3:** AI literacy directly affects anxiety.
- **H4:** Empowerment directly affects well-being.
- **H5:** Anxiety directly affects well-being.
- **H6:** Empowerment directly affects anxiety.

Methods

Site and Setting

This study took place among nursing students at Imam Abdulrahman Bin Faisal University in the Eastern Province of Saudi Arabia from January to April 2025.

Sampling Size and Technique

This study concentrated on students enrolled in the College of Nursing, encompassing nursing students from the first to the fifth year, as well as those participating in their internship year. Data collection was conducted using a convenience sampling method. The sample size was determined using the Raosoft calculator [19] based on a total population of 1200 nursing students, a 95% confidence level, and a 5% margin of error. A sample of 292 nursing students was established as being representative of the population.

Variables and Tools

This study evaluated 4 critical variables—AI literacy, psychological empowerment, anxiety, and well-being—each assessed using validated measurement instruments as detailed in the subsequent sections.

AI literacy was assessed using the Artificial Intelligence Literacy Scale (AILS) [20], which evaluates participants' comprehension, skills, and attitudes regarding AI technologies. The scale encompasses 12 items related to AI concepts, applications, and ethical considerations. Responses were measured on a Likert-type scale, ranging from 1=strongly disagree to 5=strongly agree. Elevated scores denote a higher level of AI literacy. The Arabic version of the AILS successfully replicated the original four-factor structure and exhibited excellent internal consistency, as evidenced by a Cronbach α of 0.92 [21].

Psychological empowerment was assessed using the Psychological Empowerment Scale developed by Spreitzer [22], which comprises 12 items that evaluate 4 dimensions: meaning (the significance of work goals), competence (self-efficacy), self-determination (autonomy in the workplace), and impact (influence over outcomes) [22]. Participants responded to each item on a 5-point Likert scale, ranging from 1=strongly disagree to 5=strongly agree. Higher scores indicate a greater level of psychological empowerment. The scale demonstrated acceptable reliability within the current sample (Cronbach α=0.72) [22].

Anxiety symptoms were evaluated using the GAD-7 scale [23], a widely recognized 7-item self-report instrument designed for the screening and assessment of anxiety severity. Respondents are asked to indicate the frequency of symptoms experienced over the preceding 2 weeks, with ratings ranging from 0 (not at all) to 3 (nearly every day). Total scores can vary from 0 to 21, with higher scores signifying more severe anxiety symptoms.

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The GAD-7 demonstrated acceptable reliability, with a Cronbach α of 0.76 [23].

Well-being was assessed using the World Health Organization-Five Well-Being Index (WHO-5) [24], a concise 5-item questionnaire designed to evaluate subjective psychological well-being over the preceding 2 weeks. Each item is rated on a 6-point scale ranging from 0=at no time to 5=all of the time, with higher total scores indicative of improved well-being. The WHO-5 exhibited robust reliability and validity across 3 countries (Spain, Chile, and Norway), with Cronbach α values ranging from 0.81 to 0.90 [25].

All questionnaires were administered via an online platform using a structured format to ensure standardized data collection. Composite scores for each variable were calculated by summing or averaging item responses in accordance with the respective scoring manuals. These scores provided the foundation for subsequent statistical analyses.

Ethical Considerations

The study received ethical approval from the Institutional Review Board (IRB) of Imam Abdulrahman Bin Faisal University (approval number IRB-2025-04-0240). Before recruiting undergraduate nursing students, the IRB conducted a thorough review of all study procedures and survey instruments. Participants were given an information sheet and verbal instructions outlining the voluntary nature of their participation, including their right to withdraw at any time without affecting their academic standing or rights. Efforts were made to ensure participants fully understood the study, including its potential risks and benefits. They were encouraged to ask questions before providing informed consent. Confidentiality and privacy measures were implemented in accordance with ethical guidelines. The information sheet also included details about the research's purpose, significance, and potential benefits of participation.

Data Analysis

Data were analyzed using SmartPLS (version 3.0; SmartPLS GmbH). PLS-SEM was selected over covariance-based structural equation modeling due to the primary objective of this study, which emphasized prediction and theory development rather than stringent theory confirmation [26]. Furthermore, PLS-SEM is particularly advantageous for examining complex models that encompass multiple constructs and mediation effects, and it exhibits greater robustness when the data do not fully adhere to the assumptions of multivariate normality and when operating with moderate sample sizes.

The analysis was conducted in 2 distinct stages. Initially, the measurement model was assessed through the examination of factor loadings, composite reliability, average variance extracted (AVE), and discriminant validity, using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio [26,27]. Multicollinearity was evaluated using variance inflation factor (VIF) values. Subsequently, the structural model was analyzed to elucidate the direct and indirect relationships among AI literacy, psychological empowerment, anxiety, and well-being. Bootstrapping with 5000 resamples (P<.05) was executed to determine the significance of the paths. R^2 and Q^2 values were reported to assess the explanatory and predictive capabilities of the model, respectively. Furthermore, partial least squares-multigroup analysis (PLS-MGA) was performed to investigate potential gender differences.

Results

The findings from the assessment of construct validity and reliability reveal that all 4 constructs—AI literacy, anxiety, empowerment, and well-being—exhibited robust internal consistency, with Cronbach α and composite reliability values surpassing the recommended threshold of 0.70. Convergent validity was further substantiated, as all constructs recorded AVE values exceeding 0.50. While the majority of item loadings were deemed acceptable (greater than 0.70), one item within the empowerment construct (item 11 [Psychological Empowerment]=.57) demonstrated weak loading and may warrant consideration for removal. Additionally, multicollinearity was not identified as a concern, given that all VIF values remained below 5. Collectively, the measurement model evidenced strong reliability and validity (Table 1).

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Table . Construct validity and reliability.

Construct and items		Loading	Cronbach α	rho_A	Composite reliability	AVE[a]	VIF[b]
AI[c]		—[d]	0.79	0.80	0.86	0.55	—
	AI4	.76					1.66
	AI6	.75					1.61
	AI7	.68					1.39
	AI8	.73					1.53
	AI9	.77					1.60
Anxiety		—	0.91	0.91	0.93	0.65	—
	GAD1	.79					2.23
	GAD2	.85					2.80
	GAD3	.86					3.08
	GAD4	.82					2.23
	GAD5	.77					2.06
	GAD6	.77					1.98
	GAD7	.79					2.12
Empowerment		—	0.91	0.92	0.92	0.50	—
	PE1	.69					1.83
	PE10	.67					2.24
	PE11	.57					1.55
	PE12	.75					1.99
	PE2	.65					2.15
	PE3	.70					1.96
	PE4	.65					2.02
	PE5	.68					2.03
	PE6	.77					2.20
	PE7	.80					2.77
	PE8	.75					2.22
	PE9	.76					2.08
Well-being		—	0.86	0.87	0.90	0.65	—
	WHO1	.81					2.01
	WHO2	.82					2.13
	WHO3	.86					2.47
	WHO4	.82					2.15
	WHO5	.70					1.48

[a]AVE: average variance extracted.

[b]VIF: variance inflation factor.

[c]AI: artificial intelligence.

[d]Not applicable.

The findings presented in Tables 2 and 3 provide empirical support for the presence of acceptable discriminant validity. The square roots of the AVE values, represented as the diagonal elements, exceed the interconstruct correlations indicated by the values below the diagonal, thereby fulfilling the Fornell-Larcker criterion. Furthermore, all HTMT values, displayed above the diagonal, remain below the conservative threshold of 0.85, further corroborating the discriminant validity of the constructs. These results, in conjunction with the demonstrated internal consistency and convergent validity of the measures, suggest that each construct—AI literacy, anxiety, empowerment, and well-being—is empirically distinct from

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the others, indicating a lack of overlap among these variables. This distinctiveness ensures that the relationships estimated in the structural model are both reliable and interpretable, thereby supporting the robustness of subsequent path analyses. Additionally, these findings align with prior research examining teacher-related constructs in the domains of technology adoption and psychological empowerment.

Table . Fornell-Larcker criterion discriminant validity. The italicized text is the square root of the average variance extracted.

Constructs	AI[a]	Anxiety	Empowerment	Well-being
AI	*0.739*			
Anxiety	–0.163	*0.807*		
Empowerment	0.344	–0.235	*0.707*	
Well-being	–0.238	0.586	–0.375	*0.805*

[a]AI: artificial intelligence.

Table . Heterotrait-Monotrait (HTMT) ratio of correlations discrimination validity of the measurement model.

Constructs	AI[a]	Anxiety	Empowerment
Anxiety	0.191		
Empowerment	0.393	0.244	
Wellbeing	0.290	0.658	0.415

[a]AI: artificial intelligence.

The model fit indices presented in Table 4 indicate a satisfactory fit for the model. The standardized root-mean-square residual is 0.061, which is below the recommended threshold of 0.08, thereby suggesting a good fit. Additionally, both the d_ULS and d_G values are acceptable. The normed fit index was 0.825, which exceeds the minimum acceptable threshold of 0.80. Furthermore, the equivalence of the values for saturated and estimated models reinforces the robustness of the model. Collectively, these fit indices confirm that the structural model is well-specified.

Table . Model fit.

Models	SRMR[a]	d_ULS	d_G	Chi-square	NFI[b]
Saturated model	0.061	1.626	0.468	1343.696	0.825
Estimated model	0.061	1.626	0.468	1343.696	0.825

[a]SRMR: standardized root-mean-square residual.

[b]NFI: normed fit index.

The R^2 and Q^2 values reveal varying levels of explanatory power across the constructs examined. Well-being exhibits a moderate level of explained variance (R^2=0.409), indicating that the model accounts for approximately 41% of the variance in well-being. Conversely, empowerment presents a weak yet acceptable R^2 value of 0.118, while anxiety demonstrates a low R^2 of 0.063, reflecting its limited explanatory power. The Q^2 values for all constructs are positive, thereby affirming the predictive relevance of the model, with well-being once again demonstrating the strongest predictive relevance (Q^2=.261). Overall, the model is most effective in predicting well-being (Table 5).

Table . R^2 and Q^2 values.

Constructs	R^2	Q^2
Anxiety	0.063	0.040
Empowerment	0.118	0.056
Well-being	0.409	0.261

All hypothesized paths demonstrated statistical significance (P<.05), thereby providing support for hypotheses H1 through H6. AI literacy was found to have a positive predictive relationship with empowerment (β=.344) and a negative predictive relationship with both anxiety (β=−.094) and well-being (β=−.075), although the effect on well-being was relatively minor. Empowerment exhibited a negative influence on anxiety (β=−.203) and, unexpectedly, also revealed a negative effect on well-being (β=−.227), which may necessitate further exploration. Additionally, anxiety was positively correlated with well-being (β=.521), a finding that appears conceptually

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incongruent and may indicate a potential issue with scale coding (Table 6).

Table . The path coefficient and hypothesis testing.

Hypothesis	Path	β	SD	Nonparametric *t*	*P* values
H1	AI[a] → well-being	–.075	0.038	1.976	.048
H2	AI → empowerment	.344	0.042	8.115	<.001
H3	AI → anxiety	–.094	0.048	1.969	.049
H4	Empowerment → well-being	–.227	0.042	5.37	<.001
H5	Anxiety → well-being	.521	0.036	14.39	<.001
H6	Empowerment → anxiety	–.203	0.048	4.274	<.001

[a]AI: artificial intelligence.

The results of the path analysis indicate that all direct, indirect, and total effects are statistically significant ($P<.05$). AI literacy exhibited a significant total negative effect on well-being (β=−.238), comprising both direct (β=−.075) and indirect (β=−.163) effects. Likewise, AI demonstrated a significant negative total effect on anxiety (β=−.163), which was partially mediated by empowerment. Empowerment also revealed a significant negative total effect on well-being (β=−.333), prominently featuring a robust indirect effect through anxiety. Furthermore, anxiety was identified as a strong direct positive predictor of well-being (β=.521), although this relationship may be influenced by scale coding issues. Collectively, these findings underscore the significance of both direct and mediated pathways in shaping well-being (Table 7).

Table . Path analysis: direct, indirect, and total effects.

Hypothesis	Path	Direct effect		Indirect effect		Total effect	
		β	*P* values	β	*P* values	β	*P* values
H1	AI → well-being	–.075	.048	–.163	<.001	–.238	<.001
H2	AI → empowerment	.344	<.001	—[a]	—	.344	<.001
H3	AI → anxiety	–.094	.049	–.070	<.001	–.163	<.001
H4	Empowerment → well-being	–.227	<.001	–.106	<.001	–.333	<.001
H5	Anxiety → well-being	.521	<.001	—	—	.521	<.001
H6	Empowerment → anxiety	–.203	<.001	—	—	–.203	<.001

[a]Not applicable.

PLS-MGA results showed no significant gender differences across all paths, with *P* values ranging from .47 to .86, indicating consistent model relationships between males and females.

Discussion

Principal Findings

This study investigated the influence of AI literacy on well-being, with a focus on psychological empowerment and anxiety as mediating variables, while also examining potential gender differences using PLS-SEM. The results indicated that the model accounted for a moderate proportion of the variance in well-being (R^2=0.41), whereas the explained variance in empowerment and anxiety was comparatively lower. In alignment with the proposed hypotheses, AI literacy demonstrated a positive correlation with empowerment and a negative association with both anxiety and well-being. Furthermore, empowerment was found to exert a negative impact on anxiety and well-being. The significant mediating effects underscore the intricate pathways through which AI literacy influences well-being. Notably, no significant gender differences were identified, suggesting that these relationships are consistent across both male and female participants.

The results of this study confirm the hypotheses raised and prove the intricate relationship among AI literacy, psychological empowerment, anxiety, and well-being. First, AI literacy was found to positively affect well-being, which is in accordance with evidence by Dai et al [15], which emphasized that students better prepared for the AI era experience higher well-being. Similarly, Shahzad et al [13] noted that students who use AI to facilitate their academic and psychological requirements feel more life satisfaction as well as mental well-being. However, Varol [28] explained that heightened AI anxiety—specifically among students who are unsure of their AI skills—will detract

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from well-being, a sign that AI literacy may not be sufficient to safeguard mental health. The result of this study is rational based on the fact that ability begets confidence and significance, and knowledge deficits will fuel anxiety.

In this study, AI literacy also contributed substantially positively to psychological empowerment. This is amply evidenced by Arboh et al [11], who established that employees who knew more about AI perceived themselves as more independent and competent in the workplace. Additionally, Zhang et al [7] also claimed that recognizing how AI tools can support medical consultations improves a sense of effectiveness among health care providers. An extensive literature search results in no opposing evidence emerging for this result, reinforcing the theory that AI knowledge transforms uncertainty into agency. This indicates that empowerment and literacy are translated when one can connect knowledge to a useful application.

Regarding anxiety, in this study, higher AI literacy was associated with lower levels of anxiety among nursing students. This finding corroborates those of Albikawi et al [29], who found that nursing students who were comfortable with AI-mental health–driven tools and technologies had fewer symptoms of anxiety [29]. Similarly, Varol [28] also described how AI self-efficacy served to buffer against anxiety in learning situations. Yet, Salimi et al [9] stated that AI literacy is associated with heightened anxiety if the learning is unstructured, representing that how literacy is fostered matters. Therefore, this finding implies that the benefits of AI literacy are not only dependent on content but on the manner and the context under which it is being taught.

This study also proves a direct correlation between well-being and psychological empowerment. Long and Lin [17] also reported the same trends, where students empowered by AI-assisted learning material indicated improvements in mental health. Arboh et al [11] also proved that when AI devices enhanced people's sense of control and confidence, well-being improved significantly. No reports contradicted this, highlighting empowerment's robust role as a well-being driver.

Another significant finding was the inverse correlation between well-being and anxiety. This is in line with the work of Nashwan et al [18], who chronicled how unaddressed anxiety could destabilize the psychological well-being and clinical performance of nurses. These observations verify anxiety as one of the key barriers to well-being, which must be addressed in any plan for integrating AI.

Empowerment also reduced levels of anxiety in this study. This finding is supported by Zhang et al [7] and Arboh et al [11], both of whom found that empowered users reported being safer and less stressed in AI situations. Psychological confidence generated by empowerment appears to be an effective antidote to fear and uncertainty, so it is a significant mediating factor in the generation of mental well-being.

The mediation effects that were uncovered in this study confirm the premise of empowerment and anxiety as central mechanisms by which AI literacy affects well-being. The same conclusion was drawn by Migdadi et al [3], who proved that emotional outcomes of AI use are heavily reliant on inner psychological states, and Albikawi et al [29], who emphasized the psychological benefits of well-structured AI exposure. These findings suggest that fostering empowerment and minimizing anxiety are essential components of any AI literacy program aimed at fostering general well-being.

Contrary to expectations, no significant gender variations were found for any of the pathways investigated. This concurs with results from Asio and Sardina [30], who found that AI self-efficacy by anxiety interaction was not moderated by gender. Our results point toward the potential for training programs on AI literacy to be designed such that male and female learners are treated equally without significant content differentiation.

The finding that AI literacy was negatively correlated with Saudi nursing students' well-being may indicate a new form of psychological tension arising from increased awareness of AI's impact on the health care profession. Although AI literacy is essential for future nurses, greater understanding may also heighten anxiety, uncertainty, and perceived threats to job security and professional identity. Rony et al [31] reported that nursing students feared being replaced by AI technologies, feeling that their work could become redundant or undervalued. Similarly, Varol [28] found that students with higher AI awareness experienced greater anxiety—particularly when self-efficacy was low—suggesting that increased knowledge without corresponding confidence may contribute to psychological distress. Additionally, Naureen et al [32] noted that despite recognizing the benefits of AI, students expressed significant concerns about ethical issues, loss of autonomy in decision-making, and inadequate training, all of which can result in emotional overload. AlAli [33] further emphasized that in the absence of institutional academic support, increased exposure to AI-related content may lead to more questions than answers, potentially causing cognitive overload. In the Saudi context, Al-Olaimat et al [34] observed that students' emotional readiness for AI integration remains moderate; thus, greater AI literacy is not necessarily accompanied by emotional preparedness or organizational reassurance. Overall, these findings suggest that AI literacy, when not paired with emotional support and structured curriculum integration, may inadvertently compromise well-being by amplifying fear rather than fostering empowerment.

Implications for Education and Future Research

Our findings suggest that the inclusion of AI literacy in nursing education can enhance psychological empowerment and reduce anxiety, thus ensuring student well-being. The positive link with empowerment and negative correlation with anxiety and well-being imply that nursing programs should emphasize AI-focused training alongside confidence-building and digital competency skills development in practice environments. Lack of gender difference indicates interventions can be universally applied across different student groups.

Follow-up studies then need to examine these relationships in the long term to ascertain causality and measure the effect of AI literacy on students over time. Extending investigations to samples from various institutions, locations, and disciplines, and including covariates like prior exposure to AI and access

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to technology, will validate and simplify educational interventions that lead to well-being through AI competence.

Limitations

This study has several limitations. Its cross-sectional design limits the ability to draw causal inferences, and the use of a convenience sample from a single nursing college in Saudi Arabia restricts the generalizability of the findings. Data were self-reported, which introduces potential recall and selection biases. While the GAD-7 demonstrated strong psychometric properties within this sample, it may not fully capture the unique societal and psychological concerns associated with AI-specific anxiety. Additionally, factors such as prior AI exposure, digital literacy, and access to technology were not assessed, though they may influence both AI literacy and perceptions.

Future research should consider the development and validation of a dedicated scale to measure AI-related anxiety in health care education contexts. Such a tool would allow for a more precise understanding of the psychological impact of AI on students and guide targeted interventions to support emotional preparedness alongside technological competence.

Conclusion

This study investigated the impact of AI literacy on well-being, with psychological empowerment and anxiety serving as mediating variables. The findings reveal that AI literacy significantly affects psychological empowerment, anxiety, and overall well-being through both direct and indirect pathways. These results highlight the complex interrelationships among the variables and support the model's applicability across genders. The study underscores the vital role of promoting AI literacy and psychological empowerment as strategies to enhance well-being outcomes.

Data Availability

The data are available from the corresponding author upon request.

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence
AILS: Artificial Intelligence Literacy Scale
AVE: average variance extracted

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GAD-7: Generalized Anxiety Disorder 7-item
HTMT: Heterotrait-Monotrait
IRB: Institutional Review Board
JD-R: Job Demands-Resources
PLS-MGA: partial least squares-multigroup analysis
PLS-SEM: partial least squares structural equation modeling
VIF: variance inflation factor
WHO-5: World Health Organization-Five Well-Being Index

Edited by T Risling; submitted 28.06.25; peer-reviewed by TT Wijaya, YQ Ouyang; revised version received 22.10.25; accepted 15.11.25; published 22.12.25.

Please cite as:
Alshowkan A, Shdaifat E
Impact of AI Literacy on Well-Being Among Nursing Students—Mediating Roles of Empowerment and Anxiety: Cross-Sectional Study
JMIR Nursing 2025;8:e79789
URL: https://nursing.jmir.org/2025/1/e79789
doi:10.2196/79789

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Review

Examining the Role of AI in Changing the Role of Nurses in Patient Care: Systematic Review

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Abstract

Background: This review investigates the relationship between artificial intelligence (AI) use and the role of nurses in patient care. AI exists in health care for clinical decision support, disease management, patient engagement, and operational improvement and will continue to grow in popularity, especially in the nursing field.

Objective: We aim to examine whether AI integration into nursing practice may have led to a change in the role of nurses in patient care.

Methods: To compile pertinent data on AI and nursing and their relationship, we conducted a thorough systematic review literature analysis using secondary data sources, including academic literature from the Scopus database, industry reports, and government publications. A total of 401 resources were reviewed, and 53 sources were ultimately included in the paper, comprising 50 peer-reviewed journal articles, 1 conference proceeding, and 2 reports. To categorize and find patterns in the data, we used thematic analysis to categorize the systematic literature review findings into 3 primary themes and 9 secondary themes. To demonstrate whether a role change existed or was forecasted to exist, case studies of AI applications and examples were also relied on.

Results: The research shows that all health care practitioners will be impacted by the revolutionary technology known as AI. Nurses should be at the forefront of this technology and be empowered throughout the implementation process of any of its tools that may accelerate innovation, improve decision-making, automate and speed up processes, and save overall costs in nursing practice.

Conclusions: This study adds to the existing body of knowledge about the applications of AI in nursing and its consequences in changing the role of nurses in patient care. To further investigate the connection between AI and the role of nurses in patient care, future studies can use quantitative techniques based on recruiting nurses who have been involved in AI tool deployment—whether from a design aspect or operational use—and gathering empirical data for that purpose.

(JMIR Nursing 2025;8:e63335) doi:10.2196/63335

KEYWORDS

artificial intelligence; AI; nursing practice; technology; health care; PRISMA

Introduction

Background

The science and engineering field of artificial intelligence (AI) is concerned with the theory and application of creating systems that display the traits we identify with intelligence in human behavior [1]. The years 2000 to 2015 saw an upward trend in the growth of AI. With dramatic revolutions influenced by both ideas and methodologies, the progress of AI has promoted the development of human civilization in our day and age. However, due to its interdisciplinary nature and rapid expansion, AI is a

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discipline that is challenging to fully comprehend and is getting more and more flexible from the standpoint of reference behavior [2].

The previous decade was defined by AI, and the upcoming one will most likely also be defined by it. Systems that exhibit intelligent behavior by analyzing their surroundings and acting with some autonomy to accomplish predetermined goals are referred to as AI systems. Greater accuracy is needed to have relevant and fruitful discussions on AI because it encompasses so many different methodologies and circumstances. Arguments regarding straightforward "expert systems" that serve advising functions, for instance, must be separated from those about sophisticated data-driven algorithms that make conclusions about specific persons automatically. Similarly, it is crucial to distinguish between arguments regarding hypothetical future advancements that may never materialize and those regarding actual AI that already has an impact on society today including the nursing practice [3].

Numerous ideas, including computing, developing software, and transmitting data, are built on AI. Machine learning (ML), deep learning, natural language processing (NLP), voice recognition, robots, and biometric identification are examples of technologies that use AI. AI is used in a wide range of industries, including the health care, industrial, and automotive sectors as well as corporate organizations. AI also provides several benefits that help it become increasingly popular across numerous industries. AI-powered machines are accurate and efficient, can do many tasks at once, and their work costs less than a human's. However, there are other issues with AI that make it difficult to use. Technology, security, and data issues are common with AI, and if users do not comprehend the system, mishaps may occur. The expanded use of AI has changed several industries by improving organizational effectiveness and enabling data security [4].

AI in nursing is revolutionizing the field by enhancing patient care, improving efficiency, and reducing the workload on nurses. AI-powered tools and applications enable real-time monitoring of patient's vital signs, predicting potential health deteriorations, and providing alerts for immediate intervention. AI algorithms can analyze large volumes of patient data to assist in accurate diagnosis and personalized care plans [5]. Moreover, AI chatbots and virtual assistants support administrative tasks, such as scheduling and documentation, allowing nurses to focus more on direct patient care [6]. By automating routine tasks and providing decision support, AI empowers nurses to deliver higher quality care with greater precision and efficiency [7].

Research Rationale and Aim

The rationale behind this research is to investigate how the increasing use of AI in health care affects the role of nurses in patient care. As AI technologies become more integrated into health care systems, understanding their impact on nursing practice is crucial. AI's applications, ranging from clinical decision support to operational improvements, promise to transform various aspects of health care, including nursing. By examining whether AI has led to changes in the nursing role or is likely to do so, this research aims to provide insights into how these technologies influence nursing responsibilities and practices. The aim of this review is to explore the evolution of AI as a technology through its various developmental phases. In this systematic literature review, we examine the different applications and deployments of AI in the nursing field. The primary research question addressed is "How will AI transform the role of nurses in patient care?"

Research Significance

The review offers important perspectives on how AI is transforming the roles and duties of nurses in patient care. This understanding is essential for adapting nursing education, training, and practice to align with evolving technological advancements. By identifying how AI impacts nursing roles, the research can guide the effective implementation of AI tools in health care settings. It highlights the importance of involving nurses in the development and deployment of AI technologies to ensure that these tools enhance rather than disrupt nursing practice. The findings can inform health care policies and training programs by emphasizing the need for ongoing professional development and support for nurses as they integrate AI into their workflows. This ensures that nurses are prepared to leverage AI effectively while maintaining high standards of patient care. The study contributes to the existing body of knowledge on AI in health care and sets the stage for future research. It opens avenues for quantitative studies and empirical data collection to further explore the relationship between AI and nursing roles, providing a foundation for evidence-based practice and decision-making. Overall, this research is important for its potential to enhance the understanding of AI's impact on nursing practice, guide effective technology integration, and shape the future of nursing education and policy.

Methods

Overview

A well-defined review protocol (Textbox 1) was established at the outset of the research to guarantee that the review process is transparent, reproducible, methodical, and provides a clear roadmap for conducting and reporting the review.

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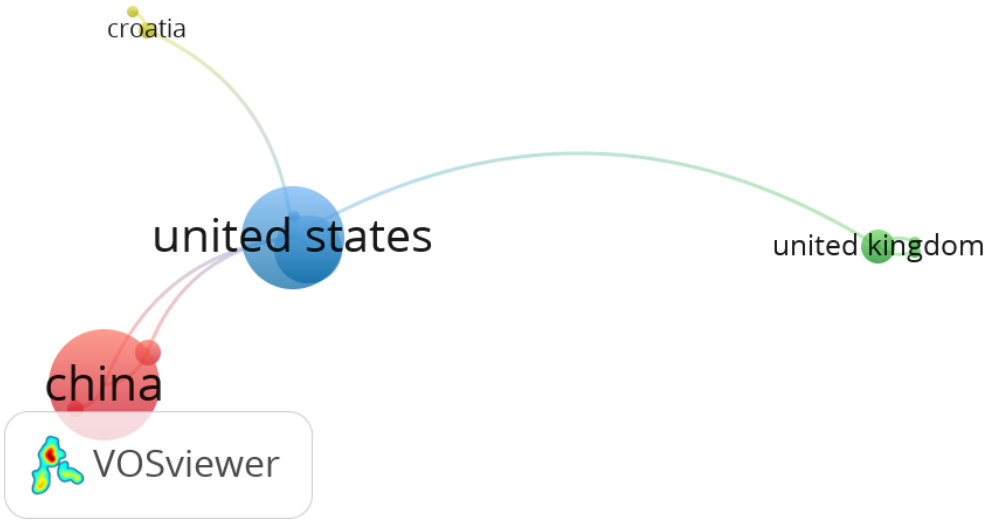
Textbox 1. Systematic literature review protocol.

- Title: confirm a clear, descriptive title for our systematic review.
- Background: explain the rationale behind this research, why it is needed, and its significance. In addition, define the main research aim and research question of the systematic literature review.
- Eligibility criteria: define what was included and excluded from the review inclusive of the search time frame.
- Information sources: list the database searched for academic sources and the gray literature used.
- Search strategy: detail the search terms used and justification of their use.
- Study selection: describe the process for screening that involved reviewers and selecting studies.
- Data extraction and analysis: define the data extraction process and the outcome of data analysis.

This paper presents the findings of a thorough analysis and critical assessment of the pertinent literature using systematic database-searching approaches. The critical assessment in this systematic literature review involves evaluating study quality, relevance, biases, findings synthesis, and implications. This systematic review draws information from credible industry sources as well as published, peer-reviewed English language papers. To comprehend the development of this idea, we consulted trustworthy industry publications known as "gray paper" and the Scopus database covering the last 33 years (ie, 1991-2024). A total of 53 sources comprised of 50 peer-reviewed academic articles, 1 conference proceeding, and 2 reports were included in the research.

After completing a bibliographic analysis, a suitable keyword search strategy was chosen, such as "AI applications in nursing," and the search was restricted to the previously specified time frame. On the basis of the outputs of the Scopus database, which have been used in this study to build the various bibliometric maps, bibliometric networks were created using the VOSviewer program (Centre for Science and Technology Studies). After exporting the sophisticated Scopus-based search results to the VOSviewer program, a network visualization was created, as shown in Figure 1, to show how the authors in this area are related to each other through publications on this subject.

Figure 1. Most countries with research subject "artificial intelligence applications in nursing"—network visualization.



In the network visualization illustrated in Figure 1, the United States, followed by China and the United Kingdom, has been publishing journals about AI applications in the field of nursing, demonstrated by the weight of those countries' representation. Furthermore, the links between those circles indicate that the relatedness of the journals in terms of cocitation links also illustrates that other countries' journal publications relied on the US publications. A VOSviewer mapping was then done using "AI applications in nursing" as the keyword.

This has prompted the expansion of the search keywords; Table 1 represents a series of search strings focusing on various aspects of AI and its applications, particularly in nursing and related technologies. Alongside, the rationale for each search string is provided along with the number of academic journals found for each. Each search string is designed to capture specific facets of AI to ensure a comprehensive and inclusive exploration of relevant literature. By using these specific search strings, the research ensures a thorough and targeted review of the literature across different aspects and applications of AI, with a special focus on health care and nursing.

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Table 1. Search string in the Scopus database (N=2870).

Search string	Justification	Results, n (%)
"AI" AND "technology" AND "in" AND "nursing"	This broad search term is used to gather general information and foundational literature on AI[a], which will provide a broad understanding and context for more specific searches.	164 (5.71)
"Artificial" AND "Intelligence" AND "applications" AND "in" AND "nursing"	This phrase search ensures that both terms are explicitly present, helping to find more specific and relevant documents that discuss AI in a detailed manner.	226 (7.87)
"AI" AND "use" AND "in" AND "nursing"	This search string targets the literature that explores the application and impact of AI technologies specifically within the field of nursing, ensuring relevance to health care.	162 (5.64)
"Nursing" AND "AI" AND "applications"	By including these terms, the search focuses on technological advancements and their practical uses in the nursing profession, broadening the scope beyond just AI.	105 (3.65)
"Evolution" AND "of" AND "Artificial" AND "Intelligence" AND "Approaches" AND "in" AND "nursing"	This search string aims to find the literature on the historical development and various methodologies within AI, providing context and background on how AI approaches have changed over time.	6 (0.20)
"Symbolic" AND "AI" AND "Approach"	Symbolic AI is a specific paradigm within AI research. This search will help identify works focused on this particular approach, which is crucial for understanding different AI methodologies.	620 (21.60)
"Data-Driven" AND "AI" AND "Approach" AND "in" AND "nursing"	Data-driven AI approaches, including ML[b] and neural networks, are fundamental to modern AI. This search focuses on the literature that discusses these data-centric methodologies.	2 (0.06)
"Artificial" AND "General" AND "Intelligence" AND "Approach" AND "in" AND "nursing"	AGI[c] represents a more advanced and comprehensive form of AI. This search will help identify research on AGI, exploring its potential and challenges.	10 (0.34)
"Artificial" AND "Intelligence" AND "application" AND "in" AND "nursing"	This search string is designed to find specific case studies and examples of how AI is being applied in nursing, providing practical insights and real-world applications.	230 (8.01)
"Rothman" AND "Index" AND "Use" AND "for" AND "Patient" AND "Acuity" AND "and" AND "Risk"	The Rothman Index is a specific tool used in health care. This search targets the literature on its use and effectiveness in assessing patient acuity and risk, relevant for AI applications in patient monitoring.	1 (0.03)
"Social" AND "robots" AND "use" AND "in" AND "nursing"	Social or companion robots are an emerging area within AI and robotics. This search aims to find the literature on their use, particularly in providing care and support in health care settings.	104 (3.62)
"TeleRobots"	Telerobots are used for remote operations, which can be highly relevant in health care for tasks such as remote surgery or patient care. This search focuses on this specific technology.	105 (3.65)
"Natural" AND "Language" AND "Processing" AND "in" AND "nursing"	NLP[d] is a key area within AI, crucial for developing systems that can understand and process the human language. This search targets the literature on NLP, which has substantial applications in health care communication and data analysis.	256 (8.91)
"Robotic" AND "Process" AND "Automation" AND "in" AND "nursing"	RPA[e] is a form of business process automation technology based on AI. This search string is aimed at finding the literature on how RPA can be applied in health care operations and administration.	13 (0.45)
"Machine" AND "Learning" AND "use" AND "in" AND "nursing"	ML is a core component of AI. This search aims to gather comprehensive literature on ML techniques and their applications across various domains, including health care.	208 (7.24)
"nurse" AND "role" AND "transformation"	AI is driving significant changes in health care by automating tasks, supporting decision-making, and transforming traditional nursing functions. The focus on "role" and "transformation" highlights how nurses' responsibilities are evolving due to AI integration, requiring new skills and altering patient care practices. These keywords enable a targeted exploration of the evolving landscape of nursing in the context of AI-driven health care.	658 (22.92)

[a]AI: artificial intelligence.

[b]ML: machine learning.

[c]AGI: artificial general intelligence.

[d]NLP: natural language processing.

[e]RPA: robotic process automation.

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Data Collection and Analysis

Academic Search

The inclusion and exclusion criteria are presented in Textbox 2.

Textbox 2. Inclusion and exclusion criteria.

Inclusion criteria

- Empirical studies, conference proceedings, and reports
- Papers with clear research questions and objectives on the application of artificial intelligence in the field of nursing
- Time period: from 1991 to 2024 (ie, 33 years)
- Papers published in the English language

Exclusion criteria

- Conceptual papers, editorials, academic book sections, and literature reviews
- Industrial sectors other than health care
- Publications before 1991
- Other languages

Data Selection

Overview

Information from all the 401 references was compiled in a soft copy folder. These references were independently reviewed by the main author, who selected the final list of papers to be analyzed. The first author examined the articles' topics and content and used our criteria for inclusion and exclusion of material to eliminate papers whose research questions were not fully aligned with the scope of this review. The second author upheld the main author's decision to exclude the resource from the study. The inclusion criteria are the characteristics that must exist to be included in this study, while the exclusion criteria are those characteristics that disqualify a data source from inclusion in the paper, which leads to the identification of 50 relevant journals published between 1991 and 2024.

Gray Literature Search

With regard to searching supplementary sources, it was imperative to expand the search radius to include official newspapers and reliable industry sources because the topic of this study is a prominent issue in industry trends. These sources capture the expert opinions of subject matter experts and produce additional information from trustworthy sources such as the European Parliamentary Research Service and National Bureau of Economic Research. Pertinent supplemental sources were found as a result, and the study report examined them all.

The critical assessment of the included studies was conducted through a self-rating process by 2 authors. Each author independently reviewed and appraised the quality of the studies based on predefined criteria relevant to the study designs, including risk of bias, methodology, and relevance to the research question. The 2 authors then compared their ratings, and any discrepancies were discussed and resolved through a consensus. This self-rating approach was used to streamline the evaluation process while ensuring consistency in the appraisal.

Furthermore, Table 2 provides a summary of the selected data in the systematic review literature by type.

Table 2. Systematic review analysis summary by type.

Reference type	Values, n (%)
Journal article	50 (94)
Conference proceeding	1 (2)
Report	2 (7)

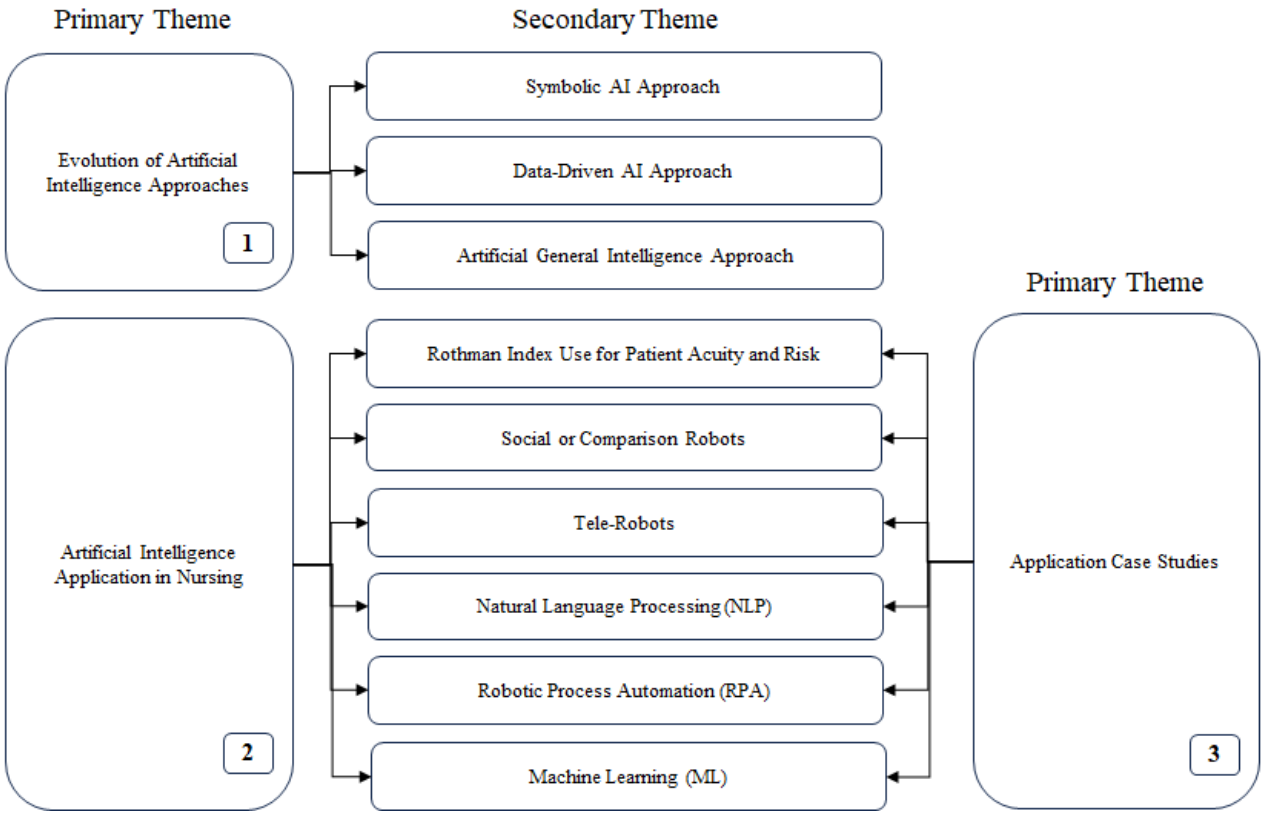
Thematic Analysis

The study made use of secondary data sources; these resources offer details on the numerous ways AI is being used in nursing and how this is changing the role of nurses. The collected material was examined using a thematic analysis approach. The information gathered from the literature study was carefully reviewed by 2 independent reviewers and categorized in accordance with the primary themes and supporting themes that surfaced. Common patterns, trends, and important discoveries must be found to comprehend the connection between the findings. The primary themes that were identified from the literature are mapped in Figure 2.

This methodology was consistently applied throughout the paper and the results produced will be discussed in the subsequent section.

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Figure 2. Primary and secondary themes in the systematic literature review. AI: artificial intelligence.



A thematic analysis was conducted explicitly designed to assess the impact of AI on the role of nurses. The use of the keyword "nurse role transformation" triggered an extensive review of the relevant literature, where we systematically screened for statements or data points related to the interaction between nurses and AI-based technologies. For example, we examined whether articles explicitly discussed shifts in task allocation, automation of routine functions, or changes in decision-making responsibilities. Furthermore, we used a matrix systematization process where each identified AI technology was mapped against the roles and responsibilities traditionally held by nurses, as well as any newly emerging roles due to the technology's integration. This allowed us to systematically capture how AI is transforming the scope of nursing practice, such as by enabling nurses to focus more on patient-centered care while AI systems manage data analysis or administrative tasks.

In the Results section, we expanded on this by introducing a subtheme explicitly titled "roles of nurses and role transformation." This subtheme synthesized case studies and literature findings that demonstrated specific examples of role shifts, such as how AI-assisted diagnostic tools are enabling nurses to participate more actively in clinical decision-making or how AI-driven administrative systems reduce the clerical burden on nurses. These shifts were categorized into functional changes (such as delegation of monitoring tasks to AI systems) and strategic changes (such as enhanced involvement in decision-making processes due to AI's real-time data processing capabilities).

This systematic approach clarifies the origin of our conclusions, making it explicit that role transformation insights were derived from both the literature and our thematic analysis, supported by the matrix framework developed during the study.

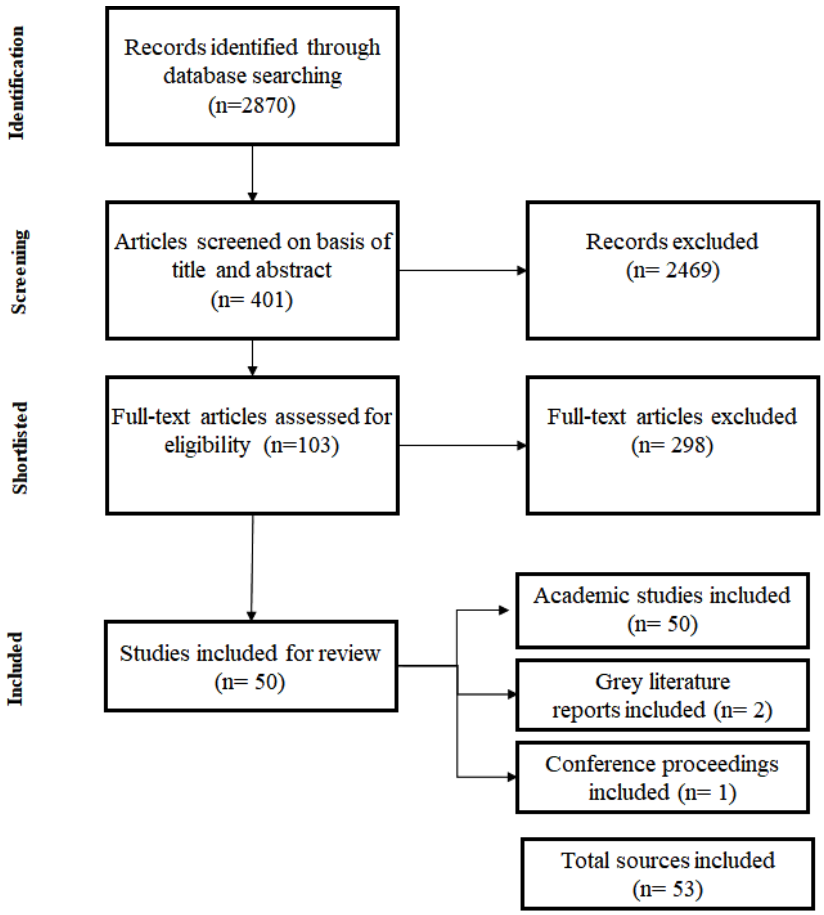
Results

Results of Data Collection

The outcome of the journal searches yielded 2870 results, out of which 401 sources were shortlisted to be analyzed further, as demonstrated in Figure 3 and elaborated further in the subsequent section.

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Figure 3. The systematic article selection process for this review.



Evolution of AI Approaches

Wave 1: Symbolic AI Approach

Expert systems and symbolic AI are 2 terms used to describe the initial wave of early AI approaches. In this case, human specialists develop exact rule-based processes, or "algorithms," that a computer may use to decide how to respond intelligently to a particular circumstance. A variation of this strategy called fuzzy logic allows for varying degrees of confidence in a scenario, which is helpful for capturing intuitive knowledge and enabling the algorithm to make wise judgments in the presence of numerous, uncertain, and interconnected factors. In contexts with rigorous rules and variables that are clear-cut and measurable, which do not vary significantly over time, symbolic AI performs well. These techniques may seem old, yet they are still used today [3].

Wave 2: Data-Driven AI Approach

The second wave of AI consists of more modern, "data-driven" methodologies that have advanced quickly over the past 2 decades and are primarily to blame for the present rebirth of AI. These do away with the first wave AI's reliance on human specialists by automating the learning of algorithms. Artificial neural networks (ANNs) are modeled after how the brain functions. The translation of inputs into signals that are then sent across a network of synthetic neurons to produce outputs that are seen as reactions to the inputs. ANNs can handle increasingly complicated issues by adding additional neurons and layers. An ANN with several layers is simply referred to as deep learning. ML is the process of changing a network so that its outputs are seen as useful or intelligent answers to its inputs. By using evolutionary concepts to produce slow improvements in huge populations of ANNs or by making gradual changes to individual ANNs, ML algorithms may automate this learning process [3].

Wave 3: Artificial General Intelligence Approach

The third wave of AI is a hypothetical term for potential future waves of AI. First and second wave approaches are referred to as "weak" or "narrow" AI in that they can act intelligently in just certain contexts and issue domains, whereas "strong" or "general" AI refers to algorithms that can act intelligently across a variety of contexts and problem domains. With existing technology, such artificial general intelligence is not feasible and would need paradigm-shifting development. Advanced evolutionary techniques, quantum computing, and brain emulation are a few possible strategies that have been considered. Although self-explanatory and contextual AI may have modest goals compared to other futuristic AI types, their potential influence and implementation challenges should not be understated [3].

AI Applications in Nursing

There is still much to learn about the innovative and intricate challenges surrounding AI. For health care businesses to best serve patients and physicians, AI must be fully used [8]. In subsequent sections, we have discussed examples of AI applications in nursing.

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Rothman Index Use for Patient Acuity and Risk

The level of acuity and risk of a patient are both reflected by the Rothman Index. The electronic medical record (EMR) data connected to 26 variables, including 11 graphically represented nurse evaluation measures, are used to determine scores. The introduction of the Rothman Index was accompanied by doubts regarding its accuracy and dependability in delivering results that could be put into practice. At first, there was not enough peer-reviewed research on the technology to persuade nurses and other professionals that the outcomes would improve patient care. The capacity of nurses to affect patient care is crucial, as evidenced by a recent study indicating that the Rothman Index's performance is positively impacted by nurses' evaluation data [9].

Social or Companion Robots

Social robots are made to react to human interactions in a way that makes them human. Sophia (Hanson Robotics) is an illustration of a social robot designed as a companion for older adults that shows the possibility of technological developments to enhance how robots operate. Robots are being developed by researchers all across the world to enhance therapeutic telemedicine applications, reduce suicide rates, and more. The role of nurses in providing care will evolve as robots learn to carry out nursing tasks such as ambulation support, vital sign assessment, drug administration, and infectious disease procedures. According to research, nonnursing chores and activities take up between 8% and 16% of nursing time. With robot assistance, nurses will be able to reclaim this time and devote it to patients more. Does this imply that nursing is doomed to extinction? Absolutely not; in fact, the exact reverse is happening. Robots created and used for patient care and older adults' assistance are being developed by nurses. Nurses can receive assistance from the robots at the bedside or in the community [9].

Telerobots

Telerobots can support health care professionals who are at "high risk for infection due to routine patient contact, handling of contaminated materials, and challenges associated with safely removing protective gear." Furthermore, telepresence robots support nurse-led treatments for the promotion of healthy lifestyles and the management of chronic illnesses by combining an initial in-home visit to launch the health care program with subsequent remote telehealth visits made at the patient's home. Data are gathered on participant health outcomes as well as the robot intervention's usefulness and pleasure [9].

NLP Approaches

A language is a system of rules or a collection of symbols that are integrated and used to express ideas or disseminate information. NLP serves users who lack the time to learn new languages or become proficient in their current ones because not all users have a strong background in machine-specific language. In actuality, NLP is a branch of linguistics and AI whose goal is to enable computers to comprehend assertions and words spoken in human languages. It was developed to make the user's job easier and to fulfill their desire to speak to a computer in natural language. It can be divided into 2 categories: natural language generation and natural language understanding, which progresses the task of understanding and producing the text [10]. In nursing, NLP assists in nursing practice and decision-making. Using NLP, it is possible to analyze nursing records, spot patterns and trends in patient care, and gain knowledge that will enable nurses to give patients more individualized and effective treatment [11].

Robotic Process Automation

Robotic process automation (RPA) is a method that uses robotics as a set of techniques for the operation and use of automata (ie, robots) in the execution of multiple tasks in place of humans as the standard, method, or system. RPA results in the automatic execution of administrative, scientific, or industrial tasks. RPA tools are a set of methods intended to enhance productivity by automating and minimizing the number of repetitive jobs. The inclusion of AI algorithms and techniques to the use of RPA enhances the accuracy of the execution of automated procedures [12].

ML Algorithms

The study of algorithms and statistical models that computer systems use to carry out a particular task without being explicitly taught is known as ML. There are several daily-use programs that incorporate learning algorithms. One of the reasons a web-based search engine like Google works so well every time it is used to search the internet is because of a learning algorithm that has mastered the art of ranking websites. These algorithms are used for several different tasks, including data mining, image processing, and predictive analytics. The major benefit of ML is that once an algorithm understands how to use data, it can carry out its task autonomously [13].

The study of ML considers how to automatically generate reliable predictions from complicated data. It is strongly tied to contemporary statistics, and in fact, statisticians have contributed many of the most brilliant concepts in ML (eg, the lasso, trees, and forests). However, the ML community has been more focused on the single objective of maximizing predictive performance, in contrast to statisticians who have frequently concentrated on model inference—that is, knowing the parameters of their models (eg, testing on individual coefficients in a regression). "Out-of-sample" tests, which assess how well a model trained on 1 dataset would predict fresh data and serve as the benchmark for the whole ML discipline [14].

Application Case Studies

Overview

Relevant case studies and examples from the literature were used to highlight the involvement of nurses in the identified AI applications or tool deployments and to assess whether there is a change or anticipated elimination to the role of nurses in patient care. These case studies focused on certain types of AI applications that are tied to certain activities carried out by nurses as part of their core patient care role. The following examples were selected due to their applicability, importance, and contribution to the comprehension of the study's subject.

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Rothman Index Use

The Specialized Workforce for Acute Transport (SWAT) team of nurses trained in critical care, advanced cardiovascular life support, and trauma care at Yale New Haven Hospital is a real-world example of using the Rothman Index technique. When signs point to a patient's condition deteriorating, they immediately receive alerts on their mobile phones. The SWAT team looks through the EMR, evaluates the patient as needed, and works together with clinical nurses and other medical personnel on pertinent areas of treatment. SWAT nurses identify as "a second pair of eyes" in their own description. The index's information came from widely available nursing literature. Given that the index is updated in real time from the EMR, timely submission of nurse assessment data is essential for the computation and value of the index score [9].

Social or Companion Robots

Sophia is an illustration of a social robot designed as a companion for older adults that shows the possibility of technological developments to enhance how robots operate. Sophia had a refurbishment in 2018 that included movement features, and she is currently the first robot to be granted citizenship in a nation (ie, Saudi Arabia) [9]. The next generation of social robots with cutting-edge AI is the LOVOT robot. The social robot LOVOT was well received by most patients with dementia. LOVOT exhibited beneficial impacts, improved communication, and promoted social engagement. Although LOVOT had no appreciable benefits on social well-being, it provided individuals with a break from daily living. Following their interactions with LOVOT, some residents experienced emotional overstimulation. The social robot was embraced by medical specialists and nurses, who saw LOVOT as a new tool for working with patients with dementia as a supporting tool and not as a replacement of the care provider's role [15].

A major factor in concentrating on the older adults is AI. It can, for instance, strengthen the bonds between older adults and their relatives or care teams. Furthermore, an AI chatbot can converse with the older adult without any difficulties and may remind them of important dates, such as medication intake and medical exams. Many of the AI smartphone apps available now have the ability to screen wellness data in a less intrusive manner, including daily activity, food, and, shockingly, older adults lifestyle choices. In certain situations, it could be helpful to anticipate and, thus, prevent any potential hypertension or irregular heart rate. In essence, robotic "pets" are also helping to improve patient attention while also assisting in the battle against emotions of loneliness. One such model, called Tombot, is a small, dog-like device designed to relieve anxiety in patients with dementia. Its head movements, appearance, and swinging tail are remarkably similar to those of the genuine dog, giving owners the impression that they have their own pet to truly concentrate on. The care of the older adults is one of the problems that low-income nations are experiencing. The global shift of older populations has worsened the shortage of trained people in the older adults health care context. Given that the number of older people worldwide is predicted to almost treble in the next 3 decades, there may be a greater need for older adult care [16].

Telepresence Robots

Health care professionals who are at "high risk for infections due to routine patient contact, handling of contaminated materials, and challenges associated with safely removing protective gear" are the focus of Tele-Robotic Intelligent Nursing Assistant, a remote-controlled robot, at Duke University Pratt School of Engineering and School of Nursing. Noting that Tele-Robotic Intelligent Nursing Assistant is 20 times slower than a nurse, it presently completes around 60% of the preset nursing tasks in the nursing simulation laboratory where it is being evaluated. Results from individuals getting telehealth coaching from home reveal that patients and clinicians alike find satisfaction in the mix of live face-to-face interventions and robotic telehealth visits. Designing meaningful treatments that can take use of new technology requires the nurse to have a key part in the development and execution of telehealth robots [9].

Inpatient rooms at the nonprofit, tertiary, 958-bed Cedars-Sinai Hospital in Los Angeles, California, are equipped with Alexa robots created by Amazon to serve as virtual nurse aides. To support patients with their daily routines, Alexa fulfills the monotonous activities performed by nurses. She also assists in answering medical queries and reminds patients to take their pills on time [17].

NLP Use

The most commonly used AI functions in studies of AI-related nursing activities were profiling and prediction, followed by assessment and evaluation. Virtual reality teaching interventions and learning successes were beneficial to nurses because they provided a safe learning environment with the possibility of multiple tries, overcoming challenges, the ability to consolidate knowledge, and professional efficacy [18]. Furthermore, the use of chatbots improves student learning compared to traditional teaching techniques [19], acting as supporting tools to nursing educators rather than eliminating the entirety of their role.

NLP is used by triage nurses to register and categorize patients based on their speech. When conducting triage activities, RMIS-AI is quicker than using the manual input approach, which decreases the time it takes to register patients and classify them. To address the existing level of subpar sensitivity and accuracy provided by nurses, technological augmentation is necessary [20].

Primary care nurses are faced with increasing demands from patients who have wounds from a variety of sources. Both nurses and patients can benefit from a chatbot that provides information properly verified on the basis of evidence. By providing instructions on the suggested wound dressing techniques for each type of wound, BOTCURATIVO, a chatbot, seeks to assist nonspecialists in the management of wounds. A reasonable degree of content validity was attained by the script that was created and implemented into the chatbot prototype. The chatbot's usability was seen as being good, which increased the device's credibility. Noting that regardless of their specialty, the nurse will always undertake wound management tasks [21].

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Most people lack the medical knowledge necessary to investigate or understand the severity of their conditions or symptoms. In this regard, NLP is essential to health care. These chatbots gather health information from patients, analyze it, and recommend actions to patients based on more pertinent knowledge of their physical conditions. Health care chatbots similar to NOVA—a virtual nursing assistant driven by AI—are helpful in the medical field because they help patients and point them in the direction of the right resources. When consumers or patients look up answers to inquiries they have about their health on the internet, chatbots are more helpful. A user of this program may text requests for health care and may receive pertinent health advice in return. A chatbot can provide medical information, including illness symptoms and treatment options. Patients receive professional guidance in real time, and their personal and medical data are kept in a database for future research. The number of AI-powered health care apps has significantly increased recently. Consequently, there are shorter wait times in offices, which saves money and energy. Patients may be helping in their own place and at their own speed while learning medical knowledge. User input is received by the system via text or speech data. The system interprets the input data. The virtual nursing help system may be accessed by the user who can also send an inquiry to it. The output that the system produces is a list of user symptoms and suggested diagnoses. In the area of virtual nursing help, the suggested system serves as the user's personal assistant. The created bots are useful for keeping track of patient information. The technology can also help numerous people at once [22].

In MobiGuide, the role of nurses in creating, providing, and assessing eHealth-based services was examined with an emphasis on atrial fibrillation home monitoring. To obtain suggestions, warnings, and reminders about drugs and measures that they should conduct, patients were given smartphones and electrocardiogram sensors. This mobile decision support system was regularly updated by a backend system. Health care professionals are supplied patient data so they may view it and take appropriate action. With their participation in the design of the caregiver interface, responsibility for the enrollment phase (ie, including patient training), daily data checks, triage of patient concerns, and patient interviews about their experiences with the system, nurses play a key role in such settings [23].

The Smart Wearable Physiological Signal Measurement Integration System is used in home care, nursing homes, and other health care settings to continuously monitor their patients' vital signs, which enables nurses to see early warning indicators of deterioration and take quick action to stop unfavorable outcomes. When a patient exits a specified area or when vital signs suggest an emergency, the system may notify the care providers, improving patient safety in nursing homes and home care settings [24].

The development of indoor positioning technology has made it feasible to track the movement of mobile medical equipment within a hospital ward, including patient monitors and electrocardiography devices. Nurses can quickly detect and locate a gadget with the help of an item tracking system, particularly while they are getting ready for a medical procedure or shift change. Given that nurses typically have a heavy workload, it would be ideal to give them access to a well-liked mobile app with an intuitive search interface that they can use on a regular basis. To help with this, DBOS, a dialogue-based object query system, offers voice and text inquiry services to nurses while mimicking a genuine discussion with users through the chatbot interface of the Line messaging app [25].

The accurate assessment of pain in the neonatal intensive care units is essential due to the high prevalence of painful experiences. Video-based assessment of neonatal pain could be reliably used, as confirmed by the high intrarater and interrater reliability between direct observation and the video-based assessment, as well as the AI method-based performance evaluation, even with various disturbances in real-world neonatal intensive care units. Video-based assessment is viable for neonatal pain assessment in a clinical setting, and the extent of neonatal pain can be evaluated remotely in real time, which can better identify and treat it and thus improve the neonatal pain condition. Video-Based Neonatal Pain Assessment can reduce the stressful surroundings of a clinical setting, the contextual noise, and other elements that could shift the focus of the trainees from the rating. There has been an increasing interest in using ML methods for understanding human behavioral responses to pain based on the analysis of facial expressions, crying sounds, and body movement. Several automated methods have been introduced to automatically assess infants' pain based on behavioral or physiological pain indicators analysis. Using AI-based neonatal pain assessment, the nursing staff can also use these recordings to judge the pain level by observing the painful procedure video in the nurse station and taking timely intervention measures, which could greatly reduce the bedside observation time and improve work efficiency [26].

Robotic Process Automation

Patients with diabetes mellitus face a 15% to 25% lifetime risk of developing diabetic foot ulcers (DFUs). Monitoring and assessing DFUs for complications and healing progress is essential, and this was traditionally performed using manual measurements. A past study compared conventional measurement methods with an AI-powered mobile application for wound imaging, the CARES4WOUNDS (C4W) system [27]. The length and breadth of the wound were the major characteristics measured. C4W measures had good intra- and interrater reliability compared to standard wound measuring. The C4W was a helpful tool for keeping track of DFU wound healing, yet it did not eliminate the role of wound care nurses.

Machine Learning

In 1 in 8 to 10 cases where primary care physicians and nurse practitioners used AI, they made better diagnoses, suggesting the potential for raising the standard of dermatologic treatment. The diagnoses showed improvements of 10% and 12% for primary care physicians and nurse practitioners, respectively, indicating a significant positive impact [28].

For long-term patient care, Vitalerter has developed a program that combines advanced biosensors and deep learning to provide contactless and continuous vital sign monitoring, as well as cloud-based early warning protection services. Some of the standout features of these systems are accurate body movement

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analysis, continuous heart and respiratory rate monitoring, and contactless detection of patients moving out of bed. In the event of an adverse event, the system will automatically sound an alarm to remind nurses to take immediate action and lower the risk of falls, pressure sores, and septicemia [29].

Converting pediatric nursing diagnoses into a digital format and adding them to a case base to evaluate how well the prototype handled these cases allowed for case comparison, retrieval, adaptation, and indexing. Therefore, this study offers a computational tool for the health sector that makes use of case-based reasoning, an AI method. While case-based reasoning is merely another paradigm for problem solving, what sets it apart from other AI approaches is how it differs from them. Rather than relying just on a general understanding of the issue or creating connections between problem descriptions and conclusions, this paradigm can use specific information from past experiences or real problem situations. It is acknowledged that using nursing care systematization necessitates that nurses develop a variety of abilities and adhere to theoretical support to enhance decision-making. Decisions should then be discussed with the patient whenever feasible. The application of these records or technology in various clinical health situations, in which observations about the care needs of patients accompany the decision-making process about the care provided, assists in the subsequent evaluation of the outcomes that are obtained with professional intervention. In this way, it is known that the nursing care systematization collaborates to provide safe, logical, and effective nursing care. Organizing the administration of nursing care and assisting nurses in making decisions is also predicated on ensuring patient safety at various care levels [30].

Table 3 summarizes the thematic analysis and links the respective case studies outlined in this research paper.

On the basis of the themes outlined from the literature review, 81% (13/16) of the AI applications within the nursing fields are in the proof-of-concept phase, with 19% (3/16) of those deployed demonstrating a positive impact on the nursing role within the patient's journey with the United States leading the way in such research and developments. Furthermore, applications that would enhance or streamline the nurses' role seem to be focused on the treatment stage, followed by 25% on posttreatment care (ie, recovery). Noting that the applications cover various aspects of the nursing activities from diagnosis, treatment, wound management, education, and training to triaging.

Multimedia Appendix 1 [1-53] provides a clear summary of our systematic review by analyzing 37 sources in terms of key findings, methodology, sample size, potential biases, and validity. This is to ensure the robustness and reliability of the conclusions drawn from the systematic review.

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Table 3. Outcome of the thematic analysis.

AI[a] application in nursing and country	Name	Nursing involvement	Status
Rothman Index			
United States (Yale New Haven Hospital)	Rothman Index	Treatment	Operationally deployed
Social or companion robots			
Saudi Arabia	LOVOT	Posttreatment care (ie, recovery)	Operationally deployed
United States	Tombot	Posttreatment care (ie, recovery)	POC[b]
Telepresence robots			
United States (Duke University Pratt School of Engineering and School of Nursing)	TRINA[c]	Treatment	POC
United States (Cedars-Sinai Hospital)	Alexa	Treatment	Operationally deployed
NLP[d]			
United States	RMIS-AI	Triage	POC
United States	BOTCURATIVO	Nurse education and training	POC
United States	NOVA-a virtual nursing assistant	Diagnosis	POC
United States	MobiGuide	Posttreatment care (ie, recovery)	POC
United States	Smart Wearable Physiological Signal Measurement Integration System	Posttreatment care (ie, recovery)	POC
United States	DBOS[e], a dialogue-based object query system	Treatment	POC
United States	VB-AI[f] NPA	Treatment	POC
RPA[g]			
Singapore	CARES4WOUNDS system, Tetsuyu	Wound management	POC
Machine learning			
United States	Artificial intelligence aid	Diagnosis	POC
United States	Vitalerter vital sign monitoring	Treatment	POC
United States	CBR[h]	Treatment	POC

[a]AI: artificial intelligence.
[b]POC: proof of concept.
[c]TRINA: Tele-Robotic Intelligent Nursing Assistant.
[d]NLP: natural language processing.
[e]DBOS: dialogue-based object query system.
[f]VB-AI: video-based artificial intelligence.
[g]RPA: robotic process automation.
[h]CBR: case-based reasoning.

Roles of Nurses and Role Transformation

The integration of AI technologies into health care has significantly transformed the roles of nurses, shifting their focus from routine tasks to more advanced and patient-centered care [6]. AI systems automate many traditional nursing responsibilities, such as monitoring patient vitals, data entry, and medication management, allowing nurses to prioritize clinical decision-making, patient education, and emotional support. This role transformation not only enhances the efficiency of health care delivery but also enables nurses to engage more deeply in patient care by using AI as a collaborative tool [31]. AI-driven systems support clinical decision-making, triaging, and diagnostic processes, leading to improved patient outcomes and job satisfaction among nurses [32]. Table 4 provides an overview of how AI can transform nursing roles across various functions.

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Table 4. Traditional nurse role versus artificial intelligence (AI)–driven role transformation.

Traditional nurse role	AI-driven role transformation	Example of AI technology involved	Impact on patient care	Academic reference
Monitoring patient vital signs	AI takes over continuous monitoring, alerting nurses only when intervention is needed	AI-based monitoring systems (eg, wearable sensors and IoT[a] devices)	Frees up nurses' time for more personalized, hands-on patient care and reduces error risk through automation	Ross et al [37]
Data entry and record keeping	AI automates data entry, streamlining the EHR[b] updating process	AI-enabled EHR systems with NLP[c]	Reduces administrative burden, allowing nurses to focus on direct patient care	Zou and Schiebinger [33]
Routine diagnostic procedures	Nurses assist in AI-driven diagnostics, focusing more on patient interaction and explaining results	AI diagnostic tools (eg, image analysis for radiology and pathology)	Enhances the role of nurses as educators, helping patients understand diagnoses and treatments	Ng et al [38]
Medication administration	AI systems manage medication scheduling, and dosing, with nurses overseeing AI-generated plans	Automated dispensing systems and AI-driven dose calculators	Reduces medication errors and ensures timely administration, allowing nurses to focus on patient observation	Shang [39]
Patient triage and assessment	AI aids in triaging by prioritizing patients based on real-time data, allowing nurses to focus on high-priority cases	AI-powered triage systems (eg, in emergency departments)	Increases efficiency in patient care and enhances the accuracy of triage decisions	Govindaraj et al [40]
Clinical decision support	Nurses collaborate with AI systems that provide real-time decision support based on predictive analytics and historical data	AI-based decision support systems (eg, IBM Watson and AI in ICU[d] for risk prediction)	Empowers nurses to contribute more significantly to clinical decision-making and patient care planning	El-Kareh and Sittig [41]
Health education and counseling	AI tools provide nurses with real-time personalized health data to tailor patient education more effectively	AI-driven patient education platforms (eg, AI chatbots and personalized health apps)	Enhances the nurse's ability to deliver personalized health education and counseling based on real-time insights	Li et al [42]
Supervision of junior staff	Nurses oversee AI-driven workflows and ensure that AI-generated protocols are followed, focusing more on clinical mentorship	AI systems for task delegation and workflow automation	Enhances leadership roles, allowing nurses to take on a supervisory role and focus on mentorship and training	Rony et al [43]
Wound care and management	AI tools help nurses monitor wound healing through image analysis and predictive algorithms	AI-based wound care imaging systems (eg, predictive models for healing times)	Improves the accuracy of wound assessment, reduces manual checks, and improves patient outcomes	Rippon et al [44]
Patient discharge planning	AI assists in generating discharge plans, predicting postdischarge risks, and automating referrals to follow-up care systems	AI-driven discharge planning tools	Optimizes discharge planning and postdischarge care, reducing the likelihood of readmissions	Jack et al [45]
Emotional support and communication	AI systems can handle administrative tasks, enabling nurses to spend more time on patient emotional support and communication	AI-powered administrative assistants (eg, scheduling systems, automated communication)	Allows nurses to prioritize emotional support and patient communication over routine tasks	Robert [9]

[a]IoT: Internet of Things.

[b]EHR: electronic health record.

[c]NLP: natural language processing.

[d]ICU: intensive care unit.

Recent studies support these findings, showing that AI systems can help optimize workflows, reduce administrative burdens, and allow nurses to contribute more meaningfully to clinical care. Health care AI tools, such as predictive analytics and automated documentation systems, have been shown to improve patient outcomes while minimizing the risk of human error in routine tasks [33,34]. Moreover, AI-based decision support tools in critical care environments enable nurses to make informed decisions quickly, positively impacting patient care quality [35]. These advancements are particularly evident in the transformation of nursing roles, as evidenced in a thematic analysis of health care AI implementations [36].

Critical Assessment of the Literature

The literature collectively covers a broad spectrum of AI applications, ranging from technical reviews and policy

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implications to specific domains such as health care and nursing. The mix of older foundational papers and recent studies provides both historical context and insights into current advancements. Practical and policy-oriented papers enhance the literature by addressing real-world applications and implications of AI. However, some biases were identified, particularly in policy reports like the one by Boucher [3], which reflect institutional viewpoints. The focus on health care and nursing in several papers could skew the overall perspective toward these fields. In addition, journals with lower impact factors might have less rigorous peer review processes, potentially affecting research quality.

The synthesis of findings indicates a strong direction toward integrating AI in various fields, particularly health care and nursing. There is a clear emphasis on the transformative potential of AI, along with discussions on challenges and ethical considerations. Comparative studies and reviews highlight the advantages and limitations of different AI approaches, suggesting the need for context-specific solutions. The quality and diversity of the studies imply that AI is a rapidly evolving field with significant interdisciplinary impacts. Practical guides and policy reports emphasize the need for continuous education and ethical considerations in AI deployment. The focus on health care underscores AI's potential to improve patient outcomes, though it also highlights the importance of rigorous evaluation and context-specific applications.

In conclusion to this section, the systematic literature review provides a comprehensive overview of AI, balancing theoretical foundations, recent advancements, practical applications, and policy implications. While some sources may carry biases or lack depth in certain areas, the collective insights offer valuable guidance for understanding AI's multifaceted impact as outlined in Multimedia Appendix 2 [1-53].

AI in Nursing From a Theory and Management Perspective

Numerous theoretical and managerial contexts have debated the use of AI in health systems in general and in tasks associated with the nurses' role in particular. As an overarching theoretical viewpoint, nurses will continue to provide direct patient care due to nuances in human behavior. The ability to incorporate new tools and technology will be required of nurses. As technology is being incorporated into nursing programs' curricula, the nursing profession is evolving. Thus, from a management viewpoint, nurses will continue to integrate the data produced by AI tools. They will need to have the skills to incorporate AI findings into evidence-based practice while combining that knowledge with nursing expertise [9].

Despite limitations in identifying numerous pieces of the literature that address the impact of deploying AI, given that many tools and techniques are in project or testing stages, our research contributes to current discussions on contextualized research.

Through this systematic literature review, we attempted to establish a foundation to identify the existing studies from the context emic perspective. By encouraging the research community to focus on "optimal allocation of effort between exploitation and exploration," looking at theoretical contributions from the periphery will progress management and organization science [46]. We encourage academics to perform empirical studies for the benefit of advancing literature in this arena. From a practical perspective, physicians, nurses, ML scientists, and hospital and clinical executive administrators when designing their clinical pathways could use this research when designing their treatment plans [47]. Furthermore, academics in the field of medicine, nursing, paramedics, hospital executive administration, patient access, and information technology will benefit from this systematic review as it allows them to build on the existing relevant literature.

Discussion

Principal Findings

The evolution of AI in nursing has transitioned from early symbolic AI, using rule-based algorithms and fuzzy logic, to modern data-driven approaches such as ML and ANNs and is now exploring hypothetical future waves such as artificial general intelligence. AI applications in nursing include the Rothman Index for patient acuity and risk assessment, social robots such as Sophia and LOVOT for older adults' companionship, telerobots for remote patient interaction, and NLP for enhancing decision-making and patient communication. RPA and ML are used to automate repetitive tasks and improve diagnostic accuracy, while AI-powered tools such as chatbot assistants and wearable monitoring systems assist in patient care and safety. Case studies demonstrate AI's role in supporting, rather than replacing, nursing functions, enhancing efficiency, and allowing nurses to focus more on direct patient care. The success or failure of the medical AI solution will depend on how closely system architects collaborate with real-world nurses in health care fields, as they are needed to work closely together to assess and evaluate which technologies will be prioritized for development [17].

Inadequate evaluation, careless supervision, a lack of fundamental nursing knowledge, a lack of service awareness, and unlawful activity by nursing personnel are all contributing factors to poor nursing care. Inadequate evaluation forces nursing staff members to advance their own skills, be able to analyze certain nursing conditions, and act quickly to take timely, scientifically sound action. Poor nursing is also largely caused by a lack of thorough inspection by nursing staff. Individuals who make nursing errors because of inadequate nursing knowledge should enhance their own skills and training. Ultimately, the nursing profession is a service sector. The essential spirit of service is required when treating patients. It is imperative that corresponding services are rendered completely in compliance with industry standards, and any illicit activities are forbidden. To address this, the use of AI alone will not mitigate those issues; instead, the health care facility's relevant departments must develop a mechanism to penalize slack investigation and prevent the recurrence of such unfavorable circumstances [48].

Methodological Approach Limitations

The limitations of our systematic literature review methodological approach include potential publication bias;

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additionally, the quality and relevance of included studies can vary, impacting the overall reliability of the findings. The search strategy may also be limited by the databases and sources selected, potentially missing relevant literature elsewhere. Furthermore, the exclusion of non–English language studies might introduce language bias. Finally, the subjective nature of data extraction and thematic analysis can lead to inconsistencies and affect the validity of the conclusions.

Future Directions and Recommendations

Due to research that is still in the early stages of development and the considerable variation in AI types and situations, AI used in health care and nursing care is still a developing practice with minimal evidence. AI in nursing becomes a crucial component of health care delivery in general and nursing practice in particular. There is still a great deal of room for advancement with these systems in terms of ensuring not only the professional autonomy of nurses but also better access to sources of health information to maximize their use in multitasking, to cover the greatest number of factors that may affect the patient, environment, clinical practice, and various medical services. Additional research is required to determine how previous research findings using AI-based systems with virtual reality or simulated scenarios can be applied to real-world clinical nursing practice or to examine how these AI-based support systems may enhance patient safety and help nurses in specific clinical settings [28]. A blueprint of nurse involvement in the deployment of AI-based systems and applications can act as a guiding reference and is an area that is worth further research and exploration.

AI has become a game-changing technology that is transforming several industries, the health care industry most notably. It is essential for diagnosing uncommon genetic diseases, streamlining patient care in mental health clinics, supporting clinical judgment, and revolutionizing pathological research. However, the growing use of AI in health care also raises difficult moral, practical, and legal questions, especially in light of the General Data Protection Regulation framework in Europe. The significance of understanding data owner rights and developing moral guidelines for AI use in medical applications, particularly nursing, is another area for future research. Comprehending the ethical discussion around AI helps health care and nursing professionals create moral AI procedures for practice and assists in navigating the complex landscape of AI-driven health care regulations, ethical issues, and data protection [49]. AI presents several risks, particularly in the context of deep reinforcement learning–based mobile robot assistants. Ensuring safety in environments where humans and robots interact is crucial, especially when autonomous mobility robots rely on deep reinforcement learning for navigation and decision-making. This is particularly important in health care settings, where hospital patients using these AI-driven mobility assistants may face potential hazards that require careful evaluation and mitigation [50]. Therefore, there is an opportunity to further research the risks associated with the use of AI in nursing.

Conclusions

To fully benefit from AI technology, nurses will need to develop their ability to collaborate with data scientists. Although computer science and nursing are two separate fields, knowledge and skill transfer between the two is crucial as technology develops so that nurses may learn to interpret the data. In the future, nurses will play the role of coaches who will assist people in managing their health and achieving better results. The provision of touch and building connections with patients are the foundations of the nursing profession and their role in patient care, and they will never be fully replaced by AI tools or robots, especially when collecting medical information, such as heart monitoring, urinalysis, and range-of-motion analysis [9].

As emerging AI technologies take over some of the jobs that nurses already do, nursing will be impacted. Although technology will alter the way nurses spend their time providing patient care, nurses will still be required. The nurse will acquire new ways of thinking about and processing information; they will become information integrators, health coaches, and providers of human care, assisted by AI technologies rather than being replaced by them [9]. Current research and implementations demonstrate the effectiveness and promise of AI in nursing practice. However, they do not eliminate the need for field supervision and emotional support from humans [51]. Therefore, and to answer the research question, “Will AI change the role of nurses in patient care?” based on the outcome of this literature review, the answer is “yes” with a varying extent depending on the AI tool in use by the nursing professionals.

Interest in incorporating AI into nursing practice will not go away, although its technological potential is not well understood. It is highly recommended that academic institutions and professional associations implement suitable educational and training initiatives. It is imperative that nurses enhance their comprehension of fundamental AI and its integration into nursing practice [52].

Acknowledgments

The work in this study was supported, in part, by the Open Access Program from the American University of Sharjah, United Arab Emirates.

Data Availability

All data generated or analyzed during this study are included in this published article and its supplementary information files.

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Authors' Contributions

IAK was responsible for writing and analyzing the study. MN reviewed the content for accuracy and clarity.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Systematic review analysis.
[XLSX File (Microsoft Excel File), 15 KB - nursing_v8i1e63335_app1.xlsx]

Multimedia Appendix 2
Critical assessment of the literature.
[XLSX File (Microsoft Excel File), 15 KB - nursing_v8i1e63335_app2.xlsx]

Multimedia Appendix 3
PRISMA Checklist.
[PDF File (Adobe PDF File), 287 KB - nursing_v8i1e63335_app3.pdf]

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Abbreviations

AI: artificial intelligence
ANN: artificial neural network
C4W: CARES4WOUNDS
DFU: diabetic foot ulcer
EMR: electronic medical record
ML: machine learning
NLP: natural language processing
RPA: robotic process automation
SWAT: Specialized Workforce for Acute Transport

Edited by E Borycki, K Cato; submitted 17.06.24; peer-reviewed by K Seibert; comments to author 04.08.24; revised version received 07.08.24; accepted 09.09.24; published 19.02.25.

Please cite as:
Al Khatib I, Ndiaye M
Examining the Role of AI in Changing the Role of Nurses in Patient Care: Systematic Review
JMIR Nursing 2025;8:e63335
URL: https://nursing.jmir.org/2025/1/e63335
doi:10.2196/63335
PMID:39970436

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Impact of Attached File Formats on the Performance of ChatGPT-4 on the Japanese National Nursing Examination: Evaluation Study

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Abstract

Abstract: This research letter discusses the impact of different file formats on ChatGPT-4's performance on the Japanese National Nursing Examination, highlighting the need for standardized reporting protocols to enhance the integration of artificial intelligence in nursing education and practice.

(JMIR Nursing 2025;8:e67197) doi:10.2196/67197

KEYWORDS

nursing examination; machine learning; ML; artificial intelligence; AI; large language models; ChatGPT; generative AI

Introduction

Numerous generative artificial intelligences (AIs), exemplified by all versions of ChatGPT [1] and Llama [2], have been developed using large language models and evaluated in health care, particularly in nursing education [3,4], successfully passing national nursing examinations in several countries [5,6]. Generative AIs are evolving to handle multimodal information, including text and images [1]. However, previous evaluations have not assessed the impact of file formats [5,6].

Prompts, particularly long ones, can affect response accuracy owing to potential context loss or exceeded token limits [7-9]. In this study, we hypothesized that the file format attached to prompts could affect the results of nursing research that uses generative AI and aimed to evaluate its impact on ChatGPT-4's performance on the Japanese National Nursing Examination. The findings of this study would be useful for improving the quality of reports on future nursing research that uses generative AI.

Methods

Ethics Approval

This study did not require ethical approval or informed consent, as the data analyzed were obtained from a published database from the Ministry of Health, Labour and Welfare.

Generative AI Model

We used the original, unmodified GPT-4 (gpt-4‐1106-preview, accessed March 2024) without additional training, tuning, or data. ChatGPT, launched by OpenAI in 2022, with GPT-4 released in March 2023, is currently widely used.

Input Data

The dataset included all 50 basic knowledge questions from the 2023 Japanese National Nursing Examination, along with 190 general questions. The passing standard for these basic knowledge questions was approximately 80%. ChatGPT-3.5 has consistently failed to meet this standard [4], leading us to consider whether performance might vary based on file format. Questions were prepared in TEXT (.txt), DOCX (.docx), PDF (.pdf), and IMAGE (.jpg) formats and in a format that directly described all questions in the prompt (PROMPT-ONLY format). Although other formats, including CSV, JSON, XML, and Markdown, could be used to present questions and choices, we excluded them to maintain consistency and focus on more common formats.

Prompt Engineering

The prompts for each file format are summarized in Textbox 1.

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Textbox 1. Prompts provided to ChatGPT-4. The files (mentioned at the end of the prompt for TXT, DOCX, PDF, and JPG formats) were made viewable via OpenAI's application programming interface (API) function: ASSISTANT (type = retrieval).

<Prompt for PROMPT-ONLY format>

You are an expert in the field of nursing. Answer the given questions briefly and numerically. {Question number}. {Question}. Options: (1) {Option 1}, (2) {Option 2}, (3) {Option 3}, (4) {Option 4}

> ***Example:*** *1. Which vessel sends blood from the fetus to the placenta in the fetal circulation? Options: (1) Common carotid artery, (2) Pulmonary artery, (3) Umbilical artery, and (4) Umbilical vein.*

<Prompt for TXT, DOCX, PDF, and JPG formats>

You are an expert in the field of nursing. Answer briefly and numerically all questions given by the file.

Data Analyses

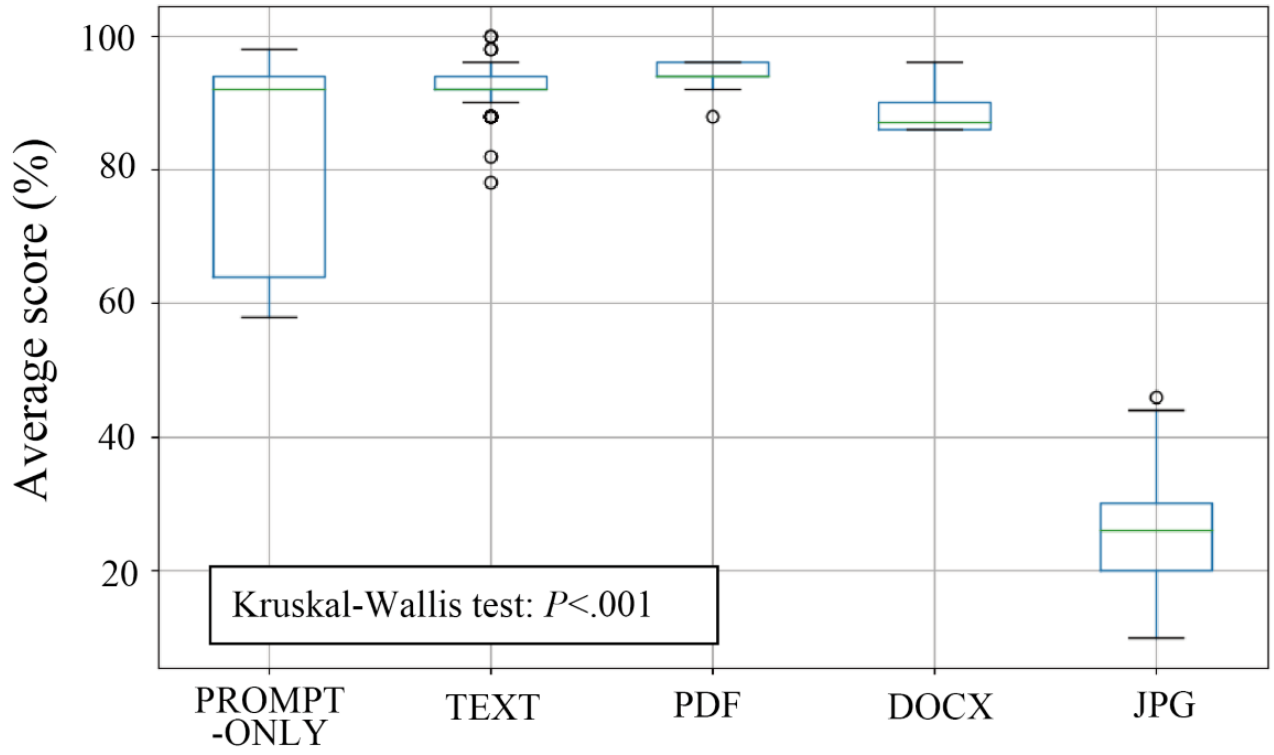
Prompts for all formats were processed for 100 iterations each; the median and IQR of the percentage of correct answers were calculated. Differences among the percentages of correct answers by the attached file format were compared using the Kruskal-Wallis test and Dann-Bonferroni test. Statistical analyses were performed using Python (version 3.11.4) with the *pandas* (version 1.5.3) and *matplotlib* (version 3.7.1) libraries.

Results

The median percentages of correct answers were 92% (IQR 64% - 94%), 92% (IQR 92% - 94%), 94% (IQR 94% - 96%), 87% (IQR 86% - 90%), and 26% (IQR 20% - 30%) for PROMPT-ONLY, TEXT, PDF, DOCX, and JPG formats, respectively. The differences between the attached formats were statistically significant in all pairs (P<.01) except for the PROMPT-ONLY versus TEXT and PROMPT-ONLY versus DOCX pairs (Figure 1).

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Figure 1. Performance evaluation of ChatGPT-4 on the Japanese National Nursing Examination by the attached file format. Outliers, shown as dots, are values below Q1 – 1.5 or above Q3 + 1.5 in the IQR.



Median (IQR)	92% (64%-94%)	92% (92%-94%)	94% (94%-96%)	87% (86%-90%)	26% (20%-30%)
Dann-Bonferroni test	PROMPT -ONLY	*P*>.99	*P*<.001	*P*=.58	*P*<.001
	TEXT		*P*=.003	*P*<.001	*P*<.001
	PDF			*P*<.001	*P*<.001
	DOCX				*P*<.001

Discussion

ChatGPT-4's performance on the Japanese National Nursing Examination varied significantly across file formats. The best performance was observed with PROMPT-ONLY, TEXT, and PDF formats (median scores >92%), followed by DOCX (87%), and the worst performance was with JPG (26%). The PROMPT-ONLY format exhibited a larger IQR and more variability than TEXT, PDF, and DOCX formats. JPG's poor performance highlights a significant limitation of generative AI, which excels at processing digital text but struggles with interpreting text from images. This "visual comprehension" gap has critical implications for AI applications involving nondigital text sources. The variability in PROMPT-ONLY performance may reflect reduced accuracy with longer prompts [7,8].

Therefore, to prepare for a future where generative AI is integrated into nursing practice and education [10], it is crucial to understand the interaction between humans and generative AI, including the impact of input file formats. Additionally, it is essential to report the following aspects in a standardized manner:

- Name and version of the generative AI model
- Presence of additional training, tuning, or knowledge transfer
- Prompt design and attached file formats
- Response generation parameters, including the number of iterations, temperature settings, and maximum token count
- Execution environment (if applicable)

However, as we only examined ChatGPT-4's performance on the Japanese National Nursing Examination and the impact of major file formats, investigations on other formats and AI models are warranted. Particularly, evaluating the performance of AI that specializes in image processing and image formats other than JPG and expanding the evaluations to include national nursing examinations in other countries and clinical questions in practice will be important in future research.

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Acknowledgments

This study was supported by the Japan Society for the Promotion of Science (JSPS KAKENHI 22K17549). The funder played no role in the study design, data collection, analysis, interpretation, or writing of the report. We would like to thank Editage for the English-language editing. During the preparation of this work, the authors used DeepL and ChatGPT to improve the language and readability. The article was completely structured by author-oriented content; these artificial intelligence (AI) tools were only used to correct English expressions and check for grammar. Therefore, these AIs did not affect the results or interpretations. After using these tools, the authors reviewed and edited the content as necessary and take full responsibility for the content of the published article.

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence

Edited by E Borycki; submitted 15.10.24; peer-reviewed by G Sun, PH Liao, ST Arasteh; revised version received 23.12.24; accepted 26.12.24; published 22.01.25.

Please cite as:
Taira K, Itaya T, Yada S, Hiyama K, Hanada A
Impact of Attached File Formats on the Performance of ChatGPT-4 on the Japanese National Nursing Examination: Evaluation Study
JMIR Nursing 2025;8:e67197
URL: https://nursing.jmir.org/2025/1/e67197
doi:10.2196/67197

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