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Acceptance of Digital Technology Among Nursing Staff in Geriatric Long-Term Care: Systematic Review

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Abstract

Background: Digital technologies are increasingly being introduced into the health care system and in settings such as hospitals and geriatric long-term care (LTC) facilities, offering potential benefits such as improved care quality, reduced workload, or enhanced documentation processes. However, the success of these technologies also depends on the acceptance by the primary users, that is, the nursing staff.

Objective: This review synthesizes empirical studies that have explored the acceptance of digital technologies by nursing staff in geriatric LTC settings, building upon the foundational work by Yu et al (2009). The goal is to identify influencing factors, assess the extent of existing evidence, and highlight research gaps in this care setting.

Methods: A systematic literature review was conducted following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines. The SPIDER (sample, phenomenon of interest, design, evaluation, research type) framework was used for eligibility criteria. Databases searched included PubMed, ACM Digital Library, Web of Science, and the Health Administration Database ProQuest. Studies were included if they empirically examined the acceptance of digital technologies by nursing staff in geriatric LTC settings. Two reviewers independently screened the studies, extracted data, and assessed methodological quality using the CASP (Critical Appraisal Skills Programme) checklist.

Results: A total of 3 studies met the criteria, highlighting a gap in research on this topic. The studies applied cross-sectional quantitative designs and highlighted critical determinants of technology acceptance, including perceived usefulness, ease of use, digital competence, and organizational support. The studies involved a total of 1019 participants from Germany, Australia, and the Netherlands. Barriers included lack of user involvement, lack of training, poor system design, and demographic differences in digital affinity.

Conclusions: This review shows that the acceptance of digital technologies by nursing staff in geriatric LTC settings is shaped by a constellation of individual factors, such as digital competence and perceived relevance of technology, as well as organizational factors such as access to training and involvement of staff in the implementation process. Despite these insights, the limited number of empirical studies highlights a research gap in this care setting. To ensure sustainable digital transformation in geriatric LTC, future research should prioritize rigorous and participatory approaches, using longitudinal, intervention-based, or multilevel study designs.

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KEYWORDS

digitalization; elderly care; health information technology; geriatric nurse; long-term care; LTC; nursing; organizational innovation; systematic review; technology acceptance

Introduction

Overview

"A promising approach to understanding social dynamics lies in conceiving our society as a globalized knowledge society undergoing a comprehensive and multifaceted digital transformation" [1]. The adoption of digital technologies in health care and nursing care reflects the complex digital transformation taking place across society [2]. Digital technologies are already having an immense impact on how nursing care is delivered [3-10]. In elderly care settings, particularly in geriatric long-term care (LTC) facilities, digital technologies such as electronic health records, assistive robotic systems, telehealth apps, assistive sensory systems, information and communication technologies, or artificial intelligence monitoring platforms [4,9,11] offer important opportunities to address current and future challenges [12-15]. These include workforce shortages, improving working conditions, or increasing the attractiveness of the nursing profession. The demographic shift associated with an aging population [16] is also one of the major challenges in this context. In Germany, the number of individuals in need of LTC rose to over 5.7 million people by December 2023 [17], with projections indicating a further increase in this number. In Germany, several programs were initiated for supporting the digital pathway [18,19]. The Bavarian State Chancellery decided in a cabinet meeting on March 19, 2024, to promote digitalization in health care and nursing. The goal is to further improve medical and nursing care for the population [20]. On the other hand, not only is the demand for LTC places increasing, but also the need for nursing staff in general is growing [21].

The real-world implementation of digital innovations in the health care system, especially elderly care, remains inconsistent and is frequently challenging [7,22-25]. One of the most significant challenges is the level of acceptance among nursing staff [26-29]. As the primary users of these technologies and new systems, nursing staff play a crucial role in determining whether such tools will be adopted and integrated into everyday work [15-19]. While research in acute and primary care has increasingly examined digital transformation through staff training, workflow redesign, and implementation frameworks, geriatric LTC remains comparatively underexplored. In acute care settings, digital competence programs and structured IT implementation strategies are often supported by institutional infrastructure [30,31]. Theoretical models such as the technology acceptance model (TAM) [32] or TAM2 [33] highlight that perceived usefulness and perceived ease of use are key predictors of user acceptance [34]. However, practical experience shows that digital transformation, especially in the field of care, often falters at the stage of user engagement, particularly when it fails to consider organizational, cultural, ethical, and educational conditions [2,5,10,35-38]. In geriatric LTC, where staff is more involved in basic care of older adults, these challenges become even more important [14,39-41]. A simple example of how digital technology in geriatric LTC could avoid high risks and time waste of the nursing staff is the occurrence of discrepancies between medication plans sent via fax by general practitioners and the actual administration records in nursing homes. Paper-based updates made during medical visits are sometimes not transferred into the official documentation, creating dangerous information gaps and avoidable risks for residents. This example illustrates how outdated communication practices and the lack of integrated digital infrastructures can compromise care quality and safety. It further highlights the importance of user-accepted digital solutions in daily nursing work and a scientifically grounded framework for implementation in LTC. Geriatric LTC facilities often face limited access to training resources and less technical and managerial support for digital adoption. Consequently, empirical evidence on how nursing staff in LTC acquire digital skills, engage in technology implementation, and perceive organizational support remains scarce. This gap underscores the need for research specifically focusing on acceptance factors, training needs, and contextual barriers unique to geriatric LTC, rather than extrapolating findings from hospital-based studies. Despite the critical role of nursing staff in implementing digital innovations, scientific evidence addressing their perspectives, needs, and acceptance in LTC contexts remains very low [25,42].

Objective

Despite considerable political interest and investments in digital transformation, the success of such efforts in the care setting hinges on a crucial factor that remains underexplored, at least in the geriatric LTC, which is the acceptance of digital technologies by nursing staff. Their perspective is not only relevant but essential to the sustainable implementation of digital solutions in care. The primary objective of this systematic review is to synthesize existing empirical research that investigates the acceptance of digital technologies among nursing staff in geriatric LTC settings, building upon the work of Yu et al [39], which was one of the first studies with focus on acceptance factors among nursing staff in LTC, published in 2009. By identifying the most relevant influencing factors, the review contributes to a better understanding of the conditions under which circumstances digital innovations can be effectively and successfully implemented in geriatric LTC environments, with particular attention to the acceptance factors of the nursing staff in this setting.

Methods

Study Design

This systematic review was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines (Checklist 1) [43]. For the development of the eligibility criteria, the SPIDER (sample, phenomenon of interest, design, evaluation, research type) framework [44] was applied to ensure a structured and targeted selection of studies.

Eligibility Criteria

The eligibility criteria and methodological steps were defined a priori; however, no protocol was registered for this review. The inclusion and exclusion criteria were defined in alignment with the SPIDER components (Table 1), focusing for instance on studies involving nursing personnel in LTC (sample); their acceptance of digital technologies (phenomenon of interest); and empirical research designs with quantitative, qualitative, and mixed methods approaches (design and research type). This focus reflects the review's aim to identify scientific evidence on how acceptance shapes digital adoption among LTC nursing staff. The studies had to be peer-reviewed and published in English or German. Exclusion criteria comprised studies conducted only in hospital, outpatient, or home care environments, as well as research focusing on other professional groups without separately analyzing the nursing staff perspective. Although qualitative and mixed methods studies were eligible according to the SPIDER framework, no such studies met all inclusion criteria (ie, focus on nursing staff in geriatric LTC and explicit assessment of technology acceptance). As a result, all included studies employed cross-sectional quantitative designs. This limitation is discussed in the *Results* and *Discussion* sections, but the inclusion parameters were retained to ensure methodological consistency and comparability across studies.

Table . Inclusion and exclusion criteria—SPIDER (sample, phenomenon of interest, design, evaluation, research type) components.

SPIDER components	Inclusion criteria	Exclusion criteria
S=Sample	• Nursing staff employed in long-term care facilities (nursing homes, elderly care)	• Studies focusing in general on non-nursing staff (eg, administrators, managers) • Studies involving participants who are not working in long-term care facilities • Studies with samples not clearly defined as nursing staff in geriatric long-term care
PI =Phenomenon of interest	• Acceptance, adoption, barriers, experiences related to digital innovations in care settings, including technologies like electronic health records, telehealth services, assistive robotics, digital documentation, sensory, ICT[a], IoT[b], AI[c]-driven decision support systems	• Studies focusing only on nondigitalized operations in long-term care • Studies exclusively addressing competencies and education without looking at technology acceptance • Studies not involving digital technologies
D=Design	• Intervention studies, observational or cross-sectional surveys, studies employing qualitative, mixed methods designs	• Nonresearch
E=Evaluation	• Outcomes related to staff attitudes, perceptions, barriers, willingness to use, fears, and facilitators to adoption, satisfaction, perceived usefulness of digital technologies in long-term care	• Studies not reporting on outcomes related to staff digital technology acceptance • Studies focusing solely on managerial or administrative evaluations without staff input. • Studies focusing only on nursing staff from hospitals or private home care settings
R=Research type	• Qualitative, quantitative, or mixed methods research focusing on the care employees regarding digital innovation adoption • Peer-reviewed journal articles published between January 1, 2010, and December 31, 2024 in English or German	• Conference papers, reviews, editorials, letters to the editor, and studies not published in peer-reviewed journals • Publications not in English or German • Studies published outside the specified date range before January 1, 2010 (except for Yu et al [39])

[a]ICT: information and communication technology.

[b]IoT: internet of things.

[c]AI: artificial intelligence.

Search Strategy

The search strategy employed an inclusive keyword combination, which was discussed and refined beforehand. Boolean operators were used to capture the intersection of acceptance, digitalization, technology, nursing, and geriatric LTC. The primary search string used was as follows: (“acceptance” AND (“digital technology” OR “digital” OR “technological” OR “artificial” OR “robotic” OR “digitalization” OR “artificial intelligence” OR “IoT” OR “robot” OR “virtual reality” OR “socially assistive robots” OR “digital tools” OR “telehealth” OR “Internet of Things” OR “EHR”)) AND (“nursing homes” OR “elderly” OR “geriatric” OR “inpatient home” OR “care facility” OR “nursing facilities” OR “nursing home” OR “aged care” OR “care home” OR “long-term care” OR “senior living center” OR “LTC”). Exact search strings for each database are documented in Multimedia Appendix 1.

The literature search was conducted across PubMed, Web of Science, ProQuest, and the ACM Digital Library. These databases were selected to ensure broad interdisciplinary coverage of nursing, health care, and technology-related research. Gray literature was not searched systematically. However, 1 relevant report identified through manual search [45] was used to provide contextual information for the discussion and was not part of the primary evidence base.

Although specialized databases, such as CINAHL, were not included due to missing license at University of Applied Sciences Neu-Ulm, the chosen databases offer considerable overlap. This limitation and the potential risk of missed studies are acknowledged in the *Discussion* section. To enhance comprehensiveness, the database search was supplemented by citation tracking and manual searches. Searches were limited to the period from January 1, 2010, to December 31, 2024. As noted previously, 1 of the included studies [39] falls outside the formal inclusion window set; however, it was retained based on discussions among all internal reviewers involved and due to the fact that this study represents the first known empirical study with the focus on the acceptance of digital technology among nursing staff in LTC settings. The identification process is illustrated in the PRISMA 2020 flow diagram, in the *Results* section.

The systematic search was conducted on April 14, 2025, following an initial exploratory search for an overview of the existing literature on October 25, 2024 (Multimedia Appendix 2). The primary researcher (JI) led the systematic review process, including database search, screening, and data extraction. The second reviewer (RH) independently screened the publications and also evaluated them for eligibility. Any discrepancies or critical assessments concerning study relevance, methodological quality, or thematic clarity were discussed in regular virtual meetings with senior reviewers (WS) and (DH). To manage the studies, the open-source software Zotero, version 7.0.11 (64-bit) was used as the reference software.

Study Selection

Study selection was conducted in 2 phases. The first phase was the selection via title and reading the abstract. In the second phase, the full texts of potentially eligible studies were reviewed in detail. Studies that met the inclusion criteria and passed quality checks were included in the synthesis. Excluded studies and reasons for exclusion are presented in Multimedia Appendix 3.

Due to the limited number of eligible studies, a formal sensitivity analysis was not possible. However, the impact of study quality on synthesis outcomes was qualitatively assessed during reviewer discussions.

Data items from included studies were extracted with the following variables using an Excel form:

- Study identification: authors, title, year of publication, country
- Study design: methodological approach
- Participants: number, role (nursing staff, management)
- Aim of study: nature of the digital technology studied
- Key findings: outcome measures, determinants, and facilitators affecting acceptance

Quality Assessment

Methodological quality was assessed using the Critical Appraisal Skills Programme (CASP) [46], applying item-level judgments (“Yes,” “Can’t tell,” “No”). The overall confidence rating was categorized as “low,” “moderate,” or “high,” with no studies falling into the “high” category. Each study was independently assessed by 2 reviewers across all checklist domains, including study aims, design, recruitment strategy, data collection, analysis, and potential bias. Discrepancies between the reviewers were resolved through consensus. To further strengthen methodological rigor and confirm the reliability of the CASP-based evaluations, the AXIS (Appraisal tool for Cross-Sectional Studies) [47] checklist for cross-sectional studies was additionally applied as a supplementary framework (Multimedia Appendix 4).

Synthesis Approach

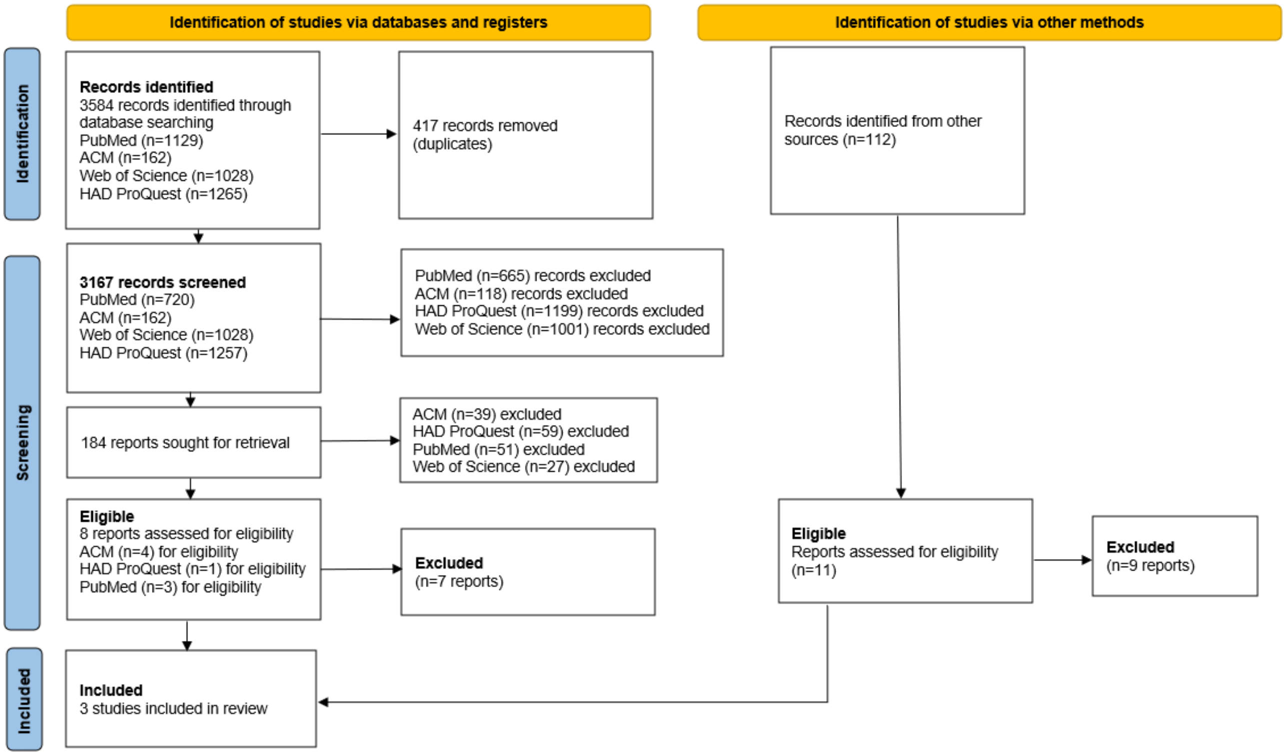
With regard to the synthesis approach, due to the heterogeneity of the included studies (technologies, outcome measures, countries), a narrative synthesis approach was applied keeping in mind the principles of thematic content analysis [48]. Data were coded inductively to identify recurring themes related to determinants and facilitators of digital technology acceptance. These themes were subsequently compared and mapped to ensure conceptual coherence across studies [49]. As this review analyzed previously published studies, no ethical approval was required.

Results

Study Selection

The outcome of the literature search initially yielded 3584 records from the databases and an additional 112 studies from citation tracking and manual searching as demonstrated in Figure 1.

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 flow diagram—identification of studies.



After the removal of duplicates, the screening of the studies, and the application of eligibility criteria, 3 studies were included in the final analysis [12,26,39]. The included studies reported quantitative findings using the following measures:

- Likert-scale derived scores: these were used in all studies to assess acceptance variables (eg, attitudes, fears, perceived usefulness).
- Regression coefficients: these were reported in Barisch-Fritz et al [12] and Yu et al [39] to identify predictors of acceptance (eg, age, gender, professional group).
- Descriptive statistics: frequencies, means, and standard deviations were commonly used to present the results.

For this study, qualitative studies were eligible; however, none were identified for the final selection. Although limited in number, these studies offer initial insights into key acceptance factors and provide a basis for further investigation. These studies were conducted in Germany, the Netherlands, and Australia. Together, they involved 1019 participants, most of whom were direct care workers in nursing homes or LTC facilities. Across all studies, 867 were nursing staff, 99 were nursing home managers, and 53 were other staff members in LTC facilities (eg, clerks). The technologies under investigation ranged from electronic documentation systems to assistive robotic devices and digital communication platforms.

Risk of Bias

The risk of bias was assessed using the CASP checklist for cross-sectional studies (Table 2). Individual checklist items were evaluated qualitatively to appraise methodological rigor, and each cell in Table 2 represents the reviewer's consensus.

Table . Critical Appraisal Skills Programme (CASP) evaluation.

CASP	Barisch-Fritz et al (2023) [12]	de Veer et al (2011) [26]	Yu et al (2009) [39]
1. Did the study address a clearly focused issue?	Yes	Yes	Yes
2. Did the authors use an appropriate method to answer their question?	Yes	Yes	Yes
3. Were the subjects recruited in an acceptable way?	Yes	Yes	Cannot tell
4. Were the measures accurately measured to reduce bias?	Cannot tell	No	Yes
5. Were the data collected in a way that addressed the research issue?	Yes	Yes	Yes
6. Did the study have enough participants to minimize the play of chance?	Cannot tell	Yes	Cannot tell
7. How are the results presented and what is the main result?	Yes	Yes	Yes
8. Was the data analysis sufficiently rigorous?	Yes	Yes	Yes
9. Is there a clear statement of findings?	Yes	Yes	Yes
10. Can the results be applied to the local population?	Cannot tell	Yes	Cannot tell
11. Is the research valuable?	Cannot tell	Yes	Yes

While the CASP checklist provided a structured approach to appraising methodological quality, we also considered the AXIS critical appraisal tool, and it confirmed the initial CASP-based judgments.

Two studies [12,39] were rated as having moderate risk of bias. The study by Barisch-Fritz et al [12] addressed a clearly focused issue using validated instruments. Although the sample was good, it was not randomly selected, introducing potential self-selection bias. The study by Yu et al [39] also had a moderate risk of bias. It demonstrated strong internal validity through the use of validated TAM2-based instruments and a clearly defined research aim. However, some limitations remain; for instance, the convenience sampling reduced the strength of the recruitment process. Also, the relatively small sample size limits generalizability. These facts increase the potential for selection and sampling bias. The study by de Veer et al [26] demonstrated low risk of bias, supported by transparent reporting and robust measurement design. Nevertheless, the study lacked detailed information on how bias was addressed through measurement design.

Study Characteristics

The key findings and characteristics of the included studies are summarized in Table 3. Across the 3 studies, several patterns emerged regarding the implementation and acceptance of technology in nursing and LTC settings. In the study by de Veer et al [26], approximately half of the nursing staff had encountered new technologies within the past 3 years and generally perceived these introductions positively. However, actual use was hindered by technology-related factors, such as ease of use, patient relevance, and potential risks. Respondents emphasized the need for structured innovation strategies and organizational support. Similarly, Yu et al [39] in Australia confirmed the validity of a modified TAM2 model for LTC facilities, identifying perceived usefulness, ease of use, professional image, and computer skills as primary determinants of the intention to adopt health IT applications. The German nationwide survey by Barisch-Fritz et al [12] extended these findings, showing that acceptance and technology affinity depend on education, professional role, and sociodemographic characteristics. Lower acceptance was observed among older employees.

Table . Included studies: key findings.

Authors	Title	Year of publication	Research method	Country	Aim of study	Which technology?	Participants included	Key findings
de Veer et al [26]	Successful implementation of new technologies in nursing care: a questionnaire survey of nurse-users	2011	Questionnaire survey	The Netherlands	To gain a better understanding of determinants influencing the success of the introduction of new technologies as perceived by nursing staff	• New technologies introduced in the past three years • Electronic information systems • Distant care technology • Medical devices	• 685 nursing staff	• Half of the respondents were confronted with the introduction of new technology in the past 3 years • Half of them rated the introduction of the technology as positive • Factors impeding actual use were related to the technology itself: ie, malfunctioning, ease of use, relevance for patients, risk to patients • Nursing staff stressed the importance of an adequate innovation strategy

Authors	Title	Year of publication	Research method	Country	Aim of study	Which technology?	Participants included	Key findings
Yu et al [39]	Health IT acceptance factors in LTC[a] facilities: a cross-sectional survey	2009	Self-administered questionnaire	Australia	To examine the factors determining the acceptance of health IT applications by caregivers in LTC facilities	• Health IT applications (software, documentation)	• 134 questionnaires • Nurses (n=105) • LTC clerks (n=11) • Nursing managers (n=18)	• Approved the validity of a modified TAM2[b] in LTC facilities • Factors influencing caregivers' intention to use IT technology were perceived usefulness, perceived ease of use, image, and computer skills
Barisch-Fritz et al [12]	Are nursing home employees ready for the technical evolution? German-wide survey on the status quo of affinity for technology and technology interaction	2023	Online survey	Germany	Examine affinity for technology and technology interaction and related sociodemographic confounders, as well as detect possible requirements and boundary conditions relevant for the development and implementation of assistive technologies among nursing home employees	• Technology, assistive technologies (eg, networked systems, assistive humanoid or social robots, mobile applications)	• 200 nursing home employees • Nursing and therapy operation (n=77) • Nursing home manager (n=81) • Others in LTC (n=42)	

Authors	Title	Year of publication	Research method	Country	Aim of study	Which technology?	Participants included	Key findings

								• Positive consequences depended on education and professional group and the affinity for technology varied across age and gender
								  • Lower acceptance with increasing age
								  • Lower acceptance for females
								  • Lower acceptance among nursing home managers

[a]LTC: long-term care.

[b]TAM2: technology acceptance model.

Despite differences in geographic context and methodological design, the studies share some overlapping findings regarding common factors that influence the acceptance. Perceived usefulness and perceived ease of use [26,39] consistently emerged as important determinants of acceptance. In addition, digital competence, defined as the ability to interact confidently with digital tools, was positively associated with willingness to use technology, particularly among younger staff members [12].

Organizational support, including leadership endorsement, training opportunities, and the involvement of staff in decision-making processes, also acted as a strong facilitator [26].

These cross-cutting themes are summarized in Table 4, which illustrates the main factors affecting the acceptance across studies.

Table . Factors affecting acceptance.

Authors	Title	Year of publication	Strengths	Weaknesses	Practical relevance	Factors affecting acceptance
de Veer et al [26]	Successful implementation of new technologies in nursing care: a questionnaire survey of nurse-users	2011	Strategic depth, very practical, multisectoral representativeness	• Little quantitative analysis • Mainly qualitative; not 100% LTC-specific[a]	Very high: helpful for implementation planning, LTC sector, and hospital	• Involvement of nursing staff during development and implementation affects acceptance. • Organizational support, such as leadership endorsement, communication, and available training does increase adoption. • Perceived relevance of the technology for patient care enhances likelihood of use.
Yu et al [39]	Health IT acceptance factors in LTC facilities: a cross-sectional survey	2009	Theoretically grounded, structural modeling, clear implications	• Limited representativeness, convenience sample, preimplementation data	Moderate to high: theoretical insights; limited practical transferability relevant for IT strategies in the LTC context	• Perceived usefulness is the strongest predictor of care staff intention to use digital technologies. • Digital competence correlates positively with willingness to use technology, particularly among younger staff. • Negative perceptions through IT use (image factor) reduce acceptance. Ease of use significantly influences both perceived usefulness and intention to adopt technology. • Perceived relevance of the technology for patient care enhances likelihood of use.

Authors	Title	Year of publication	Strengths	Weaknesses	Practical relevance	Factors affecting acceptance
Barisch-Fritz et al [12]	Are nursing home employees ready for the technical evolution? German-wide survey on the status quo of affinity for technology and technology interaction	2023	Good sample, valid measurement instruments, differentiated results	• Confounder control • Nonrandom sampling, response bias likely	High: directly applicable to nursing homes	• Digital competence correlates positively with willingness to use technology, particularly among younger staff. • Technology affinity varies strongly across age, gender, and professional role. • Organizational support, such as leadership endorsement, communication, and available training does increase adoption. • Ethical concerns can limit technology acceptance.

[a]LTC: long-term care.

All 3 studies contributed important evidence regarding factors influencing acceptance, organizational support, training availability, perceived usefulness, and digital competence. To account for heterogeneity across technologies and study designs, the extracted data were grouped thematically into 3 analytical levels: individual, organizational, and technological (Table 5).

This comparative thematic structure enabled a coherent synthesis across diverse contexts. Perceived usefulness, digital competence, organizational readiness, and usability emerged consistently across studies, supporting central constructs of the TAM.

Table . Thematic synthesis of factors affecting acceptance.

Level	Technology type	Emerging themes	Example evidence	Studies contributing
Individual	Electronic information and documentation systems; telecare software	Digital literacy, perceived usefulness, professional image, computer self-efficacy	Staff with higher digital competence and positive attitudes toward electronic documentation and telecare reported higher acceptance. Perceived usefulness and ease of use predicted intention to adopt these systems.	Barisch-Fritz et al (2023) [12] ; Yu et al (2009) [39]
Organizational	EHR[a] systems; digital readiness tools	Training, managerial support, workload, innovation climate	Organizational readiness, management involvement, and access to training facilitated technology use, while workload and lack of structured implementation strategies reduced uptake.	de Veer et al (2011) [26]; Barisch-Fritz et al (2023) [12]
Technological	Assistive technologies; robots; health IT software	Usability, reliability, system relevance, perceived ethical and professional implications	Usability and reliability were decisive for acceptance across all technologies, whereas assistive and robotic technologies introduced concerns regarding trust, ethics, and role identity.	de Veer et al (2011) [26]; Yu et al (2009) [39]; Barisch-Fritz et al (2023) [12]

[a]EHR: electronic health record.

Discussion

Interpretation of Findings

The synthesis of the 3 studies revealed that the acceptance of digital technologies in geriatric LTC depended on a combination of individual and organizational factors. Consistent with TAM and its extensions, usefulness and ease of use were the most robust predictors across the studies.

Beyond individual and organizational determinants, contextual factors, such as organizational culture, leadership style, and national policy frameworks, also influence digital readiness in LTC. Environments with a long-standing emphasis on innovation and participatory care culture may facilitate staff involvement in digital implementation, whereas strict data-protection orientation and reliance on paper-based processes may hinder the change. National eHealth infrastructures, such as Germany's Telematics Infrastructure and reimbursement policies, can affect incentives for adoption. Recognizing these dimensions is essential, as technological acceptance should not be understood in isolation from broader policy and organizational environments [50].

Previous reviews have also highlighted the importance of user attitudes and digital competencies for successful implementation [51-53]. Staff who feel confident in their ability to use digital tools are more willing to adopt them. This is particularly relevant given the generational differences observed in digital affinity. Younger staff members tend to have higher levels of acceptance, while older staff may require more training and support.

Organizational conditions further contribute to acceptance. Early staff involvement in the selection, testing, and implementation of new technologies, combined with training and transparent communication, fosters adoption.

A valuable complement to the peer-reviewed evidence is the BGW report "Pflege 4.0" [45], which constitutes gray literature but offers important contextual insights. Drawing on a mixed methods dataset of 576 professional caregivers in Germany—140 of whom were from geriatric LTC facilities—the report explored both actual technology use and perceived barriers to adoption. Using various 5-point Likert scales (ranging from "does not apply" to "fully applies"; from "not familiar at all" to "very familiar"), the survey identified key concerns, such as fear of job loss, data protection concerns, lack of technical skills, and low participation in implementation processes. While the professional composition of respondents was not fully specified, the findings add practical relevance by highlighting workplace-level perceptions that mirror those reported in the peer-reviewed studies.

Limitations of Evidence

The limited number (n=3) of eligible studies and their predominantly cross-sectional nature restrict the ability to draw clear conclusions, even though they identify relevant influencing factors. Additionally, the studies differ in the types of technologies investigated, outcome measures used, representation of demographic groups, and regional contexts. This heterogeneity complicates direct comparisons, and it further limits the generalizability of the findings. For instance, Yu et al [39] conducted a preimplementation survey based on TAM2 in an Australian LTC context, focusing on intention to use the technology. On the other hand, de Veer et al [26] investigated actual technology implementation across multiple health care sectors in the Netherlands, including nursing homes, but not exclusively. Barisch-Fritz et al [12] explored technology affinity in German nursing homes, but their heterogeneous sample included managers and other staff in LTC facilities with a relatively small response rate. This fact raises concerns regarding representativeness. These limitations hinder generalizability.

Although comprehensive efforts were made to include all relevant research, the review was limited to publications in English or German, and no protocol was registered in advance. In addition, the CINAHL database was not searched due to a missing institutional license. As CINAHL is a relevant source, other studies may not have been captured.

Implications

Given the limited number of studies and their methodological heterogeneity, the implications hereby should be interpreted with caution. Nevertheless, the evidence indicates that the successful implementation of digital technologies in geriatric LTC relies on strategies that are aligned to the needs, competencies, and experiences of nursing staff. Policies should prioritize ongoing digital training programs based on the different groups of users. Furthermore, implementation efforts should involve staff from the earliest planning stages, ensuring that their expertise informs both system design and rollout. Organizational support and transparent communication regarding the objectives, benefits, and limitations of new systems are essential to build trust and reduce uncertainty among nursing staff. Ethical concerns must be addressed proactively, particularly in relation to surveillance technologies and the preservation of interpersonal care dynamics. In terms of research, there is definitely a need for more robust, rigorous, and longitudinal studies to enhance external validity and provide a more comprehensive understanding of technology acceptance among nursing staff in geriatric LTC.

Conclusion

This systematic review demonstrates that the acceptance of digital technologies by nursing staff in geriatric LTC settings is shaped by a constellation of individual and organizational factors. Three key determinants emerged consistently across all studies.

First, digital competence significantly influences willingness to adopt new technologies. Nursing staff with higher digital affinity, especially younger staff members, show greater readiness to engage with digital tools in the workplace. This highlights the need for training programs that target all age and experience groups.

Second, perceived relevance of technologies to daily care practice affects acceptance. Nursing staff are more likely to accept innovations that support main aspects of nursing home care, such as documentation efficiency, communication, or safety.

Third, organizational support, including communication, managerial encouragement, access to training, and staff participation in the implementation processes of digital technologies, plays a crucial role.

In light of the structural and demographic relevance of geriatric LTC, future research should be directed toward building a strong evidence base on technology acceptance. This review offers several testable hypotheses derived from the synthesized evidence. Future studies should empirically examine how early involvement of nursing staff in the development and implementation of digital technologies affects subsequent acceptance and sustained use. It can be hypothesized that organizational support mechanisms, including leadership endorsement, effective communication, and targeted digital training, strengthen the relationship between perceived usefulness and intention to use. Likewise, digital competence may mediate the relationship between training and technology adoption, while factors such as technology affinity, age, and professional role may moderate these effects. Furthermore, perceived relevance for patient care likely increases acceptance by reinforcing the perceived usefulness of digital tools, whereas ethical concerns or a negative professional image of IT use may inhibit adoption. Testing these mechanisms through longitudinal, intervention-based, or multilevel study designs could provide stronger causal evidence for the transformation strategies in geriatric LTC.

Acknowledgments

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Authors' Contributions

JI, WS, and DH participated in the design of the study. JI conducted the search. JI and RH were responsible for the screening of the results. JI, WS, and DH reviewed, evaluated critically, and edited the manuscript. All authors read and approved the final version of the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Search strings for the databases searched.
[PNG File, 213 KB - nursing_v9i1e82223_app1.png]

Multimedia Appendix 2
Overview search in PubMed conducted on October 25, 2025, to explore the topic prior to the systematic search.
[PNG File, 196 KB - nursing_v9i1e82223_app2.png]

Multimedia Appendix 3
Excluded publications after eligibility assessment according to the exclusion criteria.
[XLSX File, 15 KB - nursing_v9i1e82223_app3.xlsx]

Multimedia Appendix 4
AXIS (Appraisal tool for Cross-Sectional Studies) quality assessment of included studies.
[XLSX File, 12 KB - nursing_v9i1e82223_app4.xlsx]

Checklist 1
PRISMA 2020 checklist.
[PDF File, 190 KB - nursing_v9i1e82223_app5.pdf]

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Abbreviations

AXIS: Appraisal tool for Cross-Sectional Studies
CASP: Critical Appraisal Skills Programme
LTC : long-term care
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SPIDER: sample, phenomenon of interest, design, evaluation, research type
TAM: technology acceptance model

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Developing a Best Practice Guideline for Clinical Practice in a Digital Health Environment: Systematic Reviews Based on the Grading of Recommendations, Assessment, Development, and Evaluation Approach

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Abstract

Background: Digital health refers to the field of knowledge and practice associated with the development and use of digital technologies to improve clinical practice and health outcomes. Knowledge of digital health technology is becoming essential for all nurses and health providers.

Objective: This study aims to present the results of the systematic reviews that were used to inform the recommendations in a best practice guideline (BPG) following the GRADE (Grading of Recommendations, Assessment, Development, and Evaluation) approach. Reviews focused on digital health education for nurses and health providers, peer champion models, and the use of predictive analytics in digital health environments.

Methods: The BPG team, in collaboration with a panel of 17 experts, conducted 5 systematic reviews to address 5 recommendation questions. Systematic searches looked for relevant studies published in English from January 2017 to July 2022 from 10 databases. The GRADE approach was used to synthesize and evaluate the quality of evidence, ensuring the guideline aligned with international reporting standards.

Results: A total of 18 articles across 4 systematic reviews met the inclusion criteria. From these reviews, 4 corresponding recommendations were drafted for nurses and health providers. The strength of the recommendations was determined through discussion and consensus by the expert panel using the GRADE approach. Among all, 1 systematic review resulted in no recommendation due to insufficient evidence.

Conclusions: The BPG on digital health provides 4 evidence-based recommendations for nurses and health providers on how to incorporate digital health technologies into clinical practice. This BPG is intended to be used across all health care settings.

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KEYWORDS

digital health; nursing; electronic health; health informatics; clinical guidelines

Introduction

Over the last decade, there has been an increased uptake of digital health technologies across global health care systems [1]. Digital health is a broad term that refers to the field of knowledge and practice associated with the development and use of digital technologies to improve health [2]. Digital health technologies refer to tools, systems, or devices that can generate, create, store, or process data, enabled through microprocesses that are programmed to perform specific functions [3]. Specifically in health care settings (or digital health environments), digital health technologies may encompass eHealth, mHealth, health informatics, artificial intelligence (AI), machine learning, big data, robotics, and advanced computing sciences [2]. A digital health environment refers to any setting where health providers, informatics professionals, administrators, managers, and persons or families receiving care work in supportive teams to leverage digital tools, technologies, and services to optimize care delivery and empower and activate people to manage their health and wellness [4]. Nurses and health providers use a variety of digital health technologies in practice, including electronic health records, clinical decision support systems (CDSSs) that use predictive analytics, robotics, mobile apps, virtual care platforms, wearable devices, remote monitoring systems, smart home technologies, and others [4]. As nursing practice continues to evolve across all settings and sectors to incorporate these technologies, ongoing education is essential for nurses and health providers to deliver comprehensive clinical care [4,5].

Digital health technologies are advancing at a rapid pace; however, challenges remain in supporting nurses and health providers in using these technologies safely and effectively [6]. Educators and health systems leaders must work to evolve the understanding of novel nurse-patient interactions involving digital health technologies, alongside other core nursing topics [5]. Through further education and training, nurses will have a greater understanding of how both new and existing digital health technologies may impact clinical processes and communication patterns between patients, caregivers, and the interprofessional team [7]. Furthermore, nurses in clinical practice will require initial and ongoing professional development opportunities to aid in the use of digital health technologies [8,9]. Effective training will enable nurses to use these technologies both safely and effectively. Many of the good practice statements, recommendations, and resources within this best practice guideline (BPG) provide guidance on education for nurses and health providers to address this growing need.

The Registered Nurses' Association of Ontario (RNAO) published a new BPG entitled *Clinical Practice in a Digital Health Environment* in March 2024 [4]. The BPG was developed with an expert panel, which included 17 digital health experts representing diverse backgrounds including nursing, education, research, allied health, and people with lived experience. The purpose of the BPG is to provide evidence-based recommendations that foster nurses' ability to maintain, advance, and strengthen professional practice in the context of a digital health environment [4]. The guideline is intended for all nurses (registered nurses, nurse practitioners, and registered practical nurses), nursing students, as well as members of the interprofessional health care team, educators, administrators, executives, policymakers, researchers, and people with lived experience. Within the context of this BPG, people with lived experience refer to patients and family within health systems wherein digital health is used.

The aim of this paper is to describe the BPG development process and the results from 4 systematic reviews that were used to inform the recommendations in the BPG, following the GRADE (Grading of Recommendations, Assessment, Development, and Evaluation) approach [10]. Additionally, this paper will reflect on the health equity considerations, research gaps, and limitations noted during guideline development, related to the integration of digital health technologies in clinical practice.

Methods

Development Approach

RNAO's BPG development team used the GRADE approach to develop this guideline, which is in line with international reporting standards [10]. GRADE is a transparent and structured process to evaluate the certainty of a body of evidence from systematic reviews in order to develop sound, evidence-based recommendations in guidelines [10]. The systematic reviews were conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [11] (Checklist 1). The following section will describe how the purpose and scope of the guideline were determined, the 5 systematic reviews that were conducted, and the resulting 4 recommendations that were drafted following completion of the systematic reviews.

Scoping the Best Practice Guideline

To determine the purpose and scope of this BPG, the guideline development team conducted an environmental scan on existing clinical guidelines on this topic and appraised those guidelines. Two guideline development methodologists (GDMs) determined inclusion or exclusion criteria and searched an established list of websites for guidelines and other relevant content (eg, quality standards) published between January 2016 and March 2021 (Multimedia Appendix 1). Expert panel members were also asked to suggest additional guidelines for review. Guidelines were reviewed for content, applicability to health provider scope of practice, accessibility, and quality. Each GDM individually evaluated guideline quality using the Appraisal of Guidelines for Research and Evaluation II instrument [12]. Through this process, it was determined that no guidelines had been developed addressing evidence-based recommendations in this unique and growing area, especially as it relates to nurses and clinical practice.

The team also completed a preliminary literature review to examine available evidence on digital health for nurses, including how digital health technologies are being integrated into the nursing process; how digital health technologies are facilitators and/or barriers for nurses when maintaining and advancing professional practice; and what outcomes are used to measure the impact of using digital health technologies in nursing practice. Two databases were searched for literature (CINAHL and MEDLINE) between January 2016 and May 2021. Screening for eligibility was conducted independently by 2 GDMs with conflicts resolved through consensus. Data extraction was completed for the included studies on a customized Microsoft Excel sheet developed by the GDMs. Elements of data extraction (such as study setting, intervention, and outcomes) were determined by the GDMs. An analysis of themes across the studies was synthesized, and the themes, interventions, and outcomes were later presented to the expert panel.

GDMs also conducted 22 key informant interviews and 2 discussion groups with diverse experts in the field. Key informants included people with lived experience, direct care health and social service providers, and researchers selected based on their knowledge and expertise related to the BPG topic. Snowball sampling was also used to recruit key informants. See Textbox 1 for a description of the questions asked during the interviews. For the discussion groups, 3 sessions were convened with a total of 18 nursing students, clinical informatics nurses, and frontline nurses to understand the needs of nurses within digital health environments. GDMs used inductive qualitative content analysis to analyze data collected from key informant interviews and discussion groups, and this information was also presented to the expert panel.

Textbox 1. Key informant interview questions.

- How can digital health technologies impact the quality of care a person receives?
- How can digital health technologies promote or hinder the therapeutic nurse-client relationship?
- In what ways can a digital health environment enhance or hinder patient care delivery for underserved populations?
- What skills or competencies do nurses require in order to maintain professional practice in a digital health environment?
- What skills and competencies do nurse leaders require in order to support the interface between nursing clinical practice and digital health technology?
- What challenges do nurses face when working in a digital health environment?
- What challenges or struggles do you face in your current practice related to the use or implementation of digital health technologies?
- What challenges do nurses face when trying to engage in the design, development, and evaluation of digital health environments?
- What policies or practices can help nurses maintain professional practice in a digital health environment?
- What outcomes should we explore in the literature to measure the impact of using digital health technologies in clinical nursing practice?
- What should the scope of this guideline be?
- What should this best practice guideline (BPG) address in order to be most useful in practice for nurses and people receiving care?
- Are there any last thoughts on what is important for us to consider when starting the development of this BPG?

Identifying Priority Recommendation Questions and Outcomes

The BPG development team assembled a panel of 17 experts, including 2 cochairs, from nursing practice, research, education, and policy, as well as other members of the interprofessional team, and people with lived experience representing a range of sectors and practice areas. The BPG was supported by 2 cochairs with relevant clinical and research experience, one of whom was a doctorate-prepared registered nurse, and the other cochair led the pan-Canadian Electronic Health Record Clinical Engagement Strategy for 6 years at Canada Health Infoway. The expert panel also included representatives from different geographical areas, including rural, suburban, and urban. From July to December 2021, 4 panel meetings were held to determine the BPG's purpose, scope, and research questions that informed the systematic reviews. During the first orientation meeting, the expert panel was introduced to RNAO's BPG program, the systematic review process, and the GRADE approach. Additional electronic materials were also sent to the panel to familiarize them with the BPG development process and the GRADE approach. Declarations of conflicts of interest that might be construed as constituting a perceived and/or actual conflict were made by all members of the expert panel prior to their participation in guideline development work, and on an ongoing basis.

During the initial phase of the guideline development process, the expert panel prioritized 4 research questions and corresponding outcomes deemed most important to this topic. An amendment to the PROSPERO registration was made following these initial meetings, once the panel determined through email correspondence that a fifth research question should be added. Textbox 2 displays the final recommendation questions and outcomes that informed focused research questions for the systematic reviews.

Textbox 2. Recommendation questions and outcomes in the clinical practice in a digital health environment best practice guideline.

Recommendation question 1: Should practical (eg, hands-on) professional development education focused on the use of digital health technologies within an organization be recommended or not for all nurses?

Outcomes: nurse competence (with using technology), nurse acceptance of technology, nurse-sensitive outcomes (eg, falls, pressure injuries, and pain), nurse involvement in the technology life cycle, nurse confidence (with using technology), and nurse-person therapeutic relationship.

Recommendation question 2: Should education about relational care and interpersonal communication skills be recommended or not for nurses practicing in virtual care settings and in-person digital health environments?

Outcomes: person or caregiver or family experience or satisfaction, nurse competence (with using technology), nurse confidence (with using technology), nurse-person therapeutic relationship, and person or caregiver or family involvement and engagement in care.

Recommendation question 3: Should the implementation of interdisciplinary peer champion models in health service organizations be recommended or not to facilitate education for health providers on the use of digital health technologies?

Outcomes: health provider competence (with using technology), health provider adoption of technology, health provider confidence (with using technology), health provider sensitive outcomes (eg, pressure injuries and pain), and sustainability of education (ie, knowledge and skills retention).

Recommendation question 4: Should the use of predictive analytics software or systems (eg, command centers and risk assessment software tools) for nurses providing care in all practice settings be recommended or not to inform clinical decision-making and improve clinical outcomes?

Outcomes: proactive or anticipatory care, critical incidents, failure to rescue, consistent application of evidence-based practice, and nurse-sensitive outcomes (eg, falls, pressure injuries, and pain).

Recommendation question 5: Should a distributive model (vs no distributive model or any other type of change management model) be recommended to integrate digital health competencies into the professional practice roles and responsibilities of nurses at all levels within an organization?

Outcomes: nurse competence (with using technology), nurse engagement (with using, developing, acquiring, and participating in education about the technology), nurse confidence (with using technology), person or caregiver or family experience or satisfaction, and nurses being able to define what their role is.

Systematic Retrieval of the Evidence

The systematic reviews for the guideline were registered with PROSPERO in 2022 (CRD42022321580). Upon consultation with the expert panel, 4 amendments were made to the original PROSPERO registered protocol. These included: (1) adding an additional database to search (IEEE Xplore) in April 2022, (2) adding an additional systematic review question (December 2022), (3) conducting indirect evidence searches (January 2023), and (4) publishing the final version of the guideline online (May 2024). All other systematic review methods followed the protocol outlined in the original PROSPERO registration.

Five separate systematic review search strategies were developed and run by an external health sciences librarian from the University Health Network after consulting with 2 GDMs (CB and LH). The systematic searches included peer-reviewed studies of any study design (eg, quantitative, qualitative, mixed methods, and systematic reviews) published in English from January 2017 to July 2022. The following databases were searched: MEDLINE, MEDLINE Epub Ahead of Print and In-Process, Embase, Emcare Nursing, Cochrane Central Register of Controlled Trials, Cochrane Database of Systematic Reviews, APA PsychInfo, CINAHL, and IEEE Xplore. Expert panel members were also asked to review their personal libraries for key studies not found through the above search strategies. For more details and the full search strategy used for each systematic review, please refer to Multimedia Appendix 2.

After conducting the initial searches, it was decided to look for further indirect evidence to support each question. Direct evidence comes from research that directly compares the interventions of interest when applied to the populations of interest and measures outcomes important to patients [13]. Evidence can be indirect if the population differs, the intervention differs, or outcomes differ from those of original interest [13]. The health science librarian conducted additional indirect evidence searches from January 2023 to March 2023 for systematic reviews published in English. The BPG team recognizes that direct evidence allows for more confidence in the results; however, in the absence of direct evidence, GRADE notes that indirect evidence can be used and downgraded accordingly [10,13]. The broader populations and interventions searched were considered sufficiently direct by the expert panel and in line with the original methodology. To ensure the most up-to-date evidence was included in the BPG, an update search was also conducted in English between January 2023 to January 2024 for recommendation questions 1 to 4. However, an update search for question 5 was not completed since a recommendation was not drafted for this area. For the full search strategies, see Multimedia Appendix 2.

Eligibility Criteria

All search results from the librarian were uploaded into DistillerSR software (DistillerSR Inc). All steps of the systematic review process were completed by 2 GDMs (CB and LH for the initial search and CB and LB for the update search). Two GDMs independently completed title and abstract screening using standardized screening guides developed by the GDMs. Screening guides were reviewed by senior members of the RNAO team prior to use. Studies included at this stage had the full text reviewed independently by both GDMs. Final inclusion was deemed appropriate if studies answered the research question, included prioritized outcomes, were published in English, and were accessible for retrieval. See Textbox 3 for inclusion and exclusion criteria, and Multimedia Appendix 2 for further details. Disagreements were settled by consensus. For the initial systematic search, any study design was eligible to be included. For the updated indirect systematic searches, study designs were limited to systematic reviews and meta-analyses.

Textbox 3. Inclusion and exclusion criteria.

Inclusion criteria:

- A primary focus on the interventions of interest and the prioritized outcomes per research question
- A focus on digital health technologies
- Applicable to nurses or health providers providing care in all practice settings (including registered nurses, registered practical nurses, nursing students, and nurse practitioners)
- Applicable to all health or social service organizations, or academic institutions
- Published after January 2017
- Published in English
- Accessible for retrieval
- Conducted in any geographic region
- Peer-reviewed literature
- Any study design (eg, quantitative, qualitative, mixed methods, and systematic reviews), but when conducting the indirect searches, only systematic reviews and meta-analyses were included.

Exclusion criteria:

- Topic NOT related to the interventions or prioritized outcomes per research question
- Dissertations, commentaries, narratives, discussion papers, case studies, expert reports, consensus documents, and studies with no specific methodology
- Studies not published in English
- Unpublished literature (eg, gray literature)
- Studies published prior to 2017

Data Extraction and Quality Appraisal

Data extraction was completed on the included studies for each research question. The included studies were divided between GDMs and each reviewer independently extracted details from their assigned studies using standardized Excel sheets that were developed by the RNAO team (Multimedia Appendix 3). Each Excel sheet had a designated outcome for which study details were recorded. Details such as the setting, intervention and control description, the outcome and how it was measured, and study results were recorded by 1 GDM. Any harms (such as adverse effects), information on values, preferences, and health equity were also recorded. The second GDM independently reviewed the extracted data for accuracy. Quality appraisal of each article was completed independently by each GDM. The Cochrane Risk of Bias 2.0 tool [14] was used to appraise randomized controlled trials (RCTs), the risk of bias in nonrandomized studies—of interventions (ROBINS-I) tool [15] was used to appraise nonrandomized studies, and the risk of bias in systematic reviews (ROBIS) tool [16] was used to appraise systematic reviews. If a systematic review received a low risk of bias score using the ROBIS tool, and the review's authors completed a risk of bias assessment within the paper, those assessments were also considered when conducting the GRADE consensus. After quality appraisal was completed by both GDMs, GRADE consensus was completed to assess the certainty of evidence for each outcome for each research question. GRADE uses five categories to rate the certainty of evidence as high, moderate, low, and very low by examining (1) risk of bias, (2) inconsistency, (3) imprecision, (4) indirectness, and (5) publication bias [10]. After the 5 categories had been graded, a certainty of evidence was determined for each of the 4 drafted recommendations corresponding to the research questions.

Drafting Recommendations in the BPG

As per the GRADE methodology, the GDMs created an evidence profile (EP) and evidence to decision (EtD) framework for each recommendation [4,10]. The EP outlined details regarding the certainty of evidence across outcomes and the GRADE domains (Multimedia Appendices 4-7). The EtD frameworks provided a narrative summary of the evidence for draft recommendations, described the certainty of evidence, and provided details around values and preferences regarding the intervention, as well as health equity considerations found in the systematic reviews. Expert panel members were provided with the EPs and EtD frameworks to review prior to 3 (virtual) half-day meetings to determine the direction (ie, a recommendation for or against an intervention) and the strength (ie, strong or conditional) of the BPG's recommendations. A conditional recommendation is one for which the desirable effects probably outweigh the undesirable effects, and there is a need to consider more carefully than usual the individual's circumstances, values, and preferences [10]. If there was insufficient direct or indirect evidence to develop a recommendation, the expert panel also had the option not to proceed with a recommendation. The expert panel determined that current evidence was insufficient to assess the certainty of effects of a distributive model (recommendation question 5) compared to other types of change management models to integrate digital health competencies into the professional practice roles and responsibilities of nurses within an organization; thus, no recommendation was made.

The recommendations and draft BPG also underwent several rounds of internal and external review prior to publication [17]. External reviewers for RNAO BPGs are identified through a public call issued on the RNAO website [17]. For this BPG, the written external review process was completed between September 14, 2023, and October 23, 2023. External reviewers with diverse perspectives, such as nurses and health providers, administrators, researchers, educators, nursing students, and people with lived experience, provided direct feedback.

Results

Summary of Results

For PRISMA flow diagrams, see Figures 1-5. Two reviewers screened over 22,500 articles for the 5 original research questions. After screening, the 2 GDMs reviewed 253 full-text articles for relevance to the research questions and outcomes, and 18 articles met the requirements to inform the recommendations. It was determined through consultation with the expert panel that question 5 did not have enough evidence to support the recommendation, so a recommendation was not developed. Thus, 4 recommendations were drafted (one per each of the corresponding systematic reviews), and the strength of the recommendations was determined through discussion and consensus by the expert panel, based on the available evidence (Table 1).

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for recommendation question 1: "Should practical (eg, hands-on) professional development education be focused on the use of digital health technologies within an organization be recommended or not for all nurses?" Adapted from Page MJ et al [11].

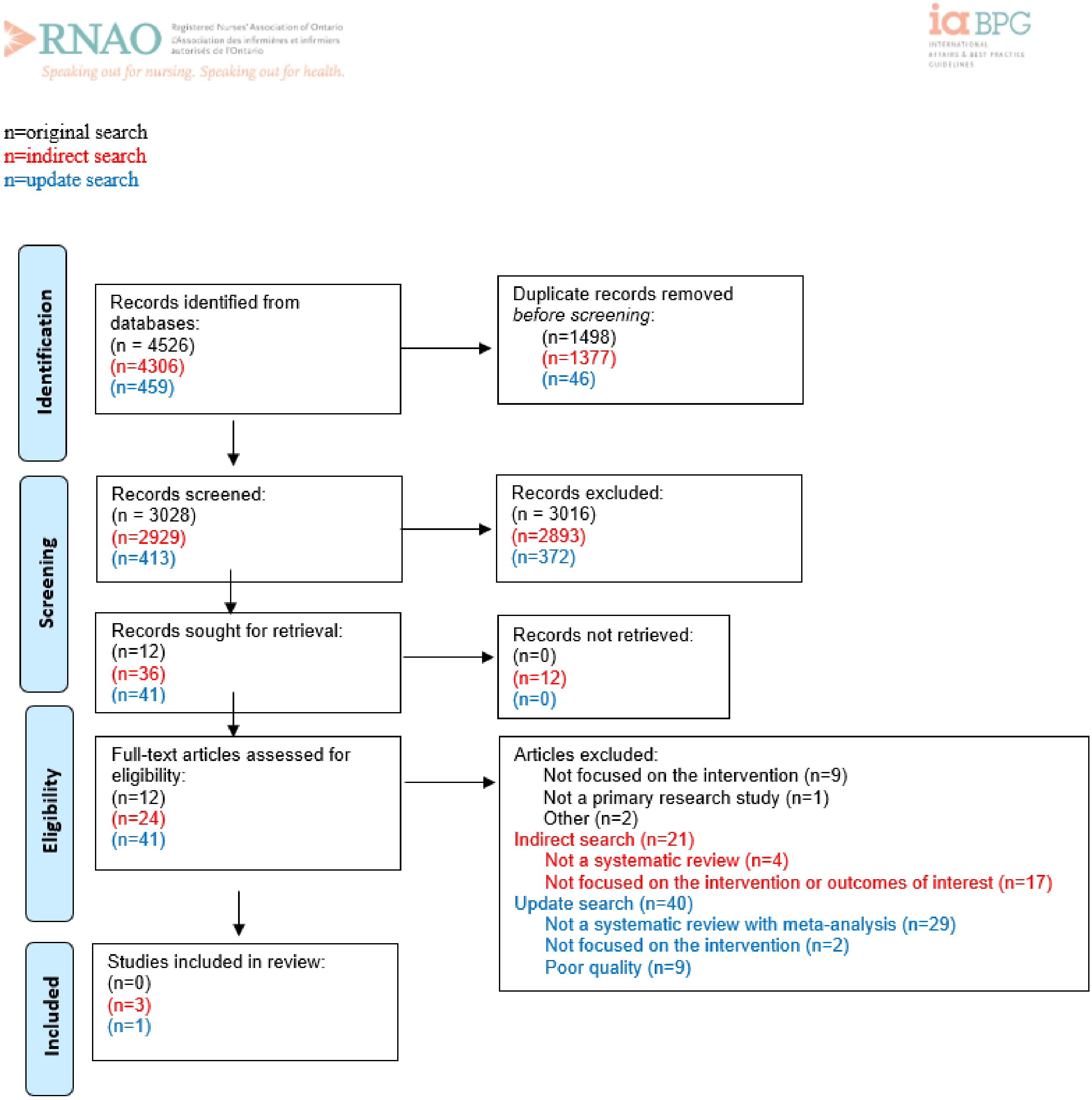

Figure 2. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for recommendation question 2: “Should education about relational care and interpersonal communication skills be recommended or not for nurses practicing in virtual care settings and in-person digital health environments?” Adapted from Page MJ et al [11].

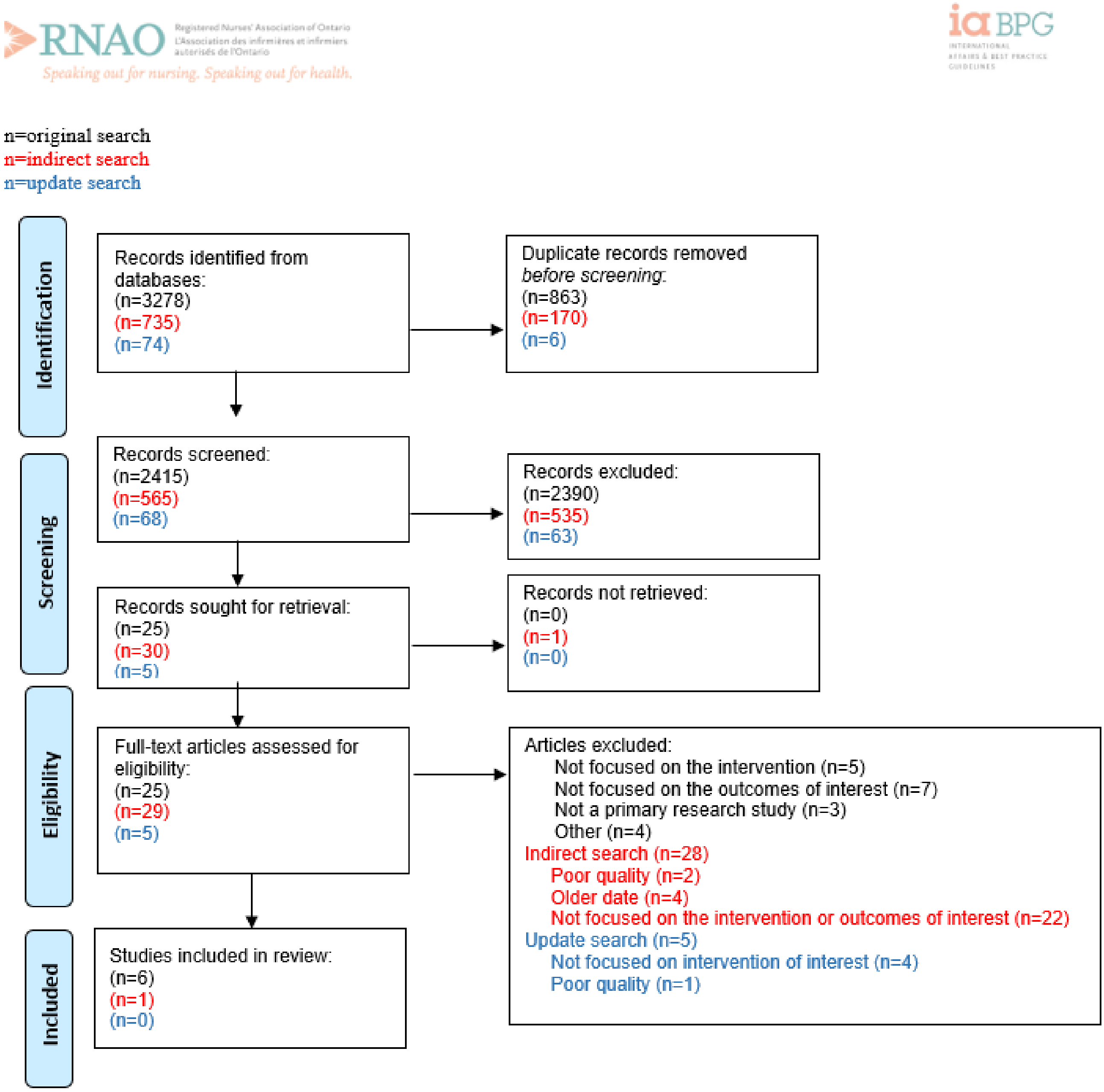

Figure 3. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for recommendation question 3: “Should the implementation of interdisciplinary peer champion models in health service organizations be recommended or not to facilitate education for health providers on the use of digital health technologies?” Adapted from Page MJ et al [11].

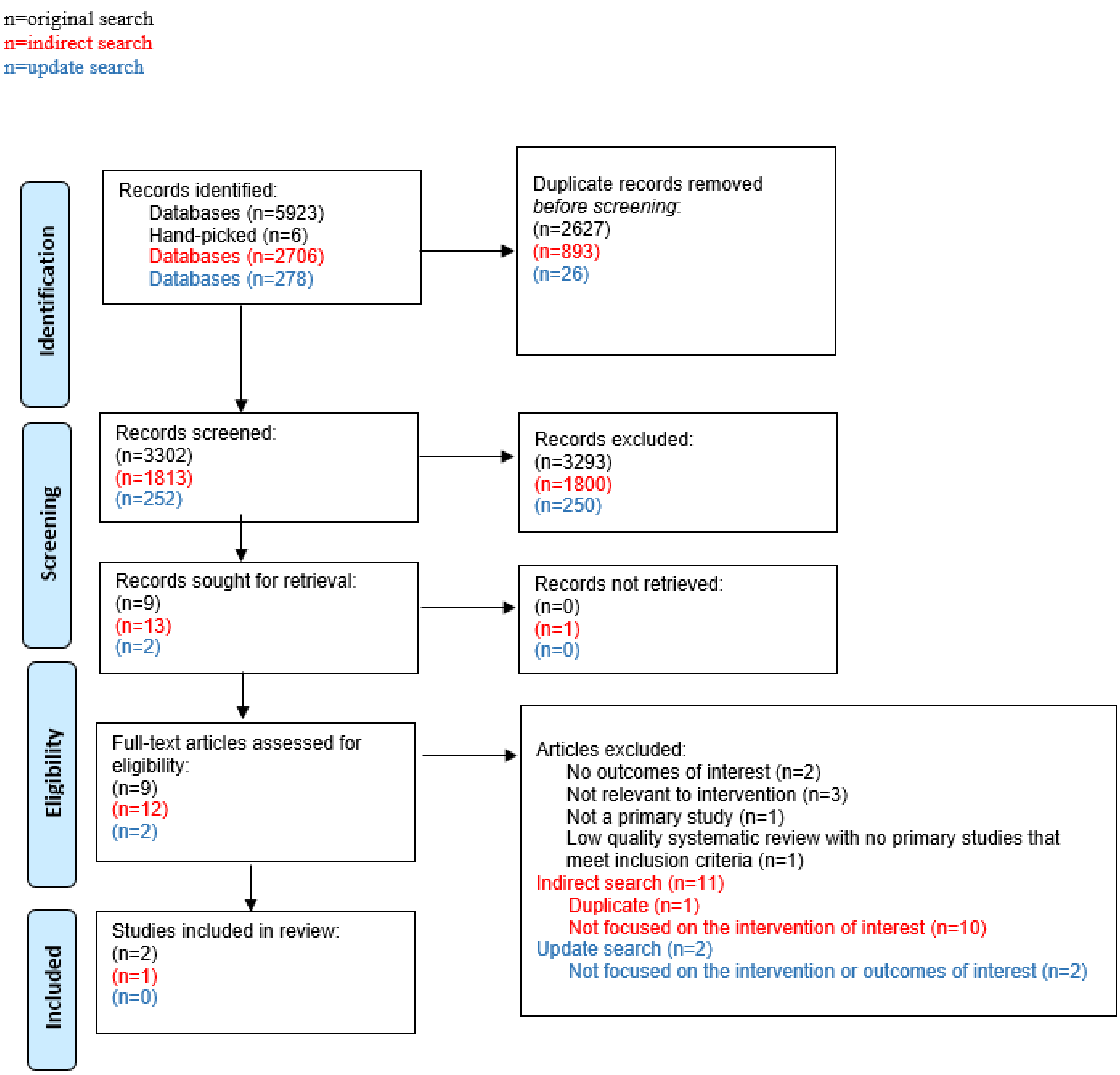

Figure 4. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for recommendation question 4: "Should the use of predictive analytics software or systems (eg, command centers and risk assessment software tools) for nurses providing care in all practice settings be recommended or not to inform clinical decision-making and improve clinical outcomes?" Adapted from Page MJ et al [11].

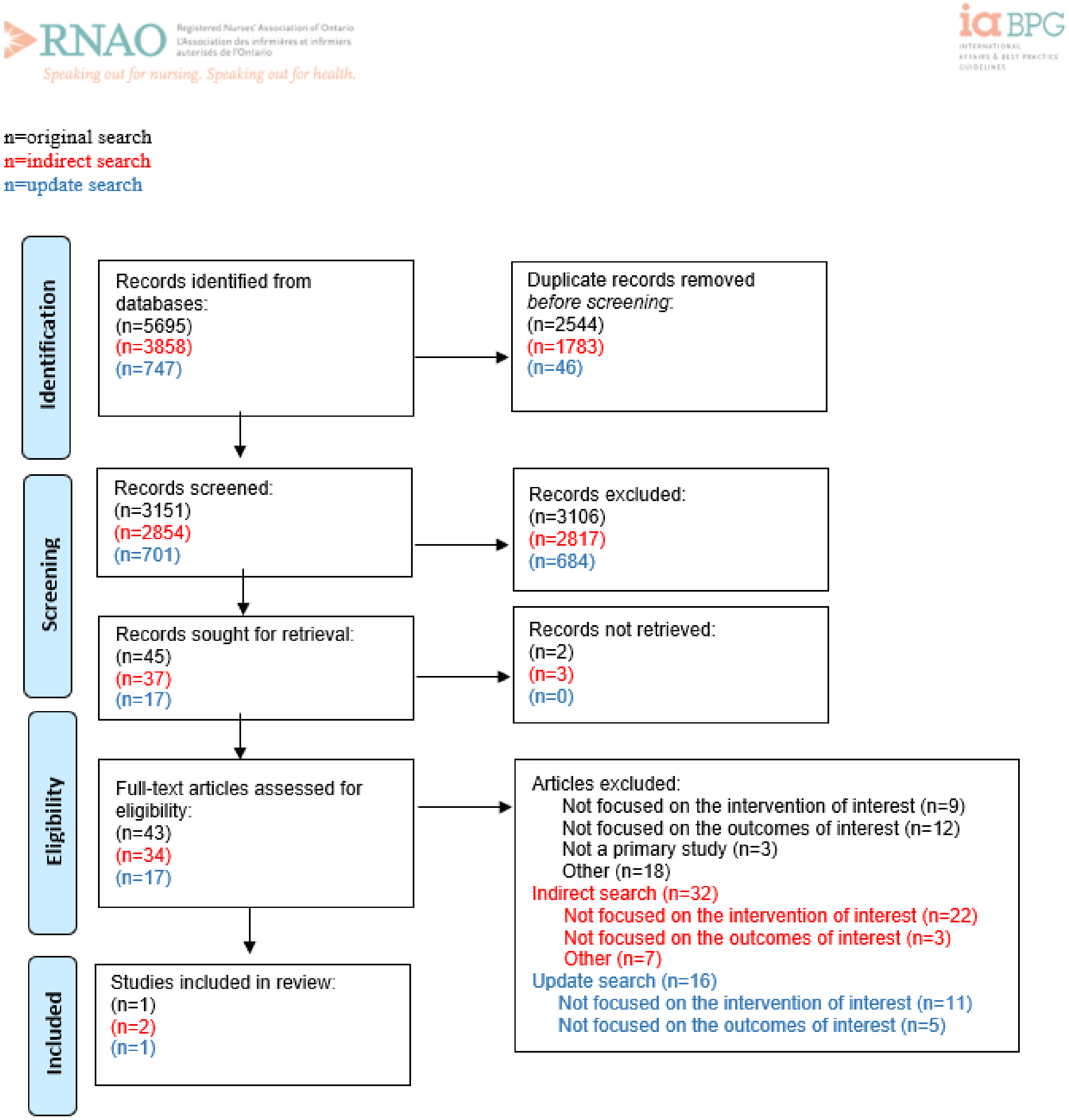

Figure 5. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for recommendation question 5: “Should a distributive model (vs no distributive model or any other type of change management model) be recommended to integrate digital health competencies into the professional practice roles and responsibilities of nurses at all levels within an organization?” Adapted from Page MJ et al [11].

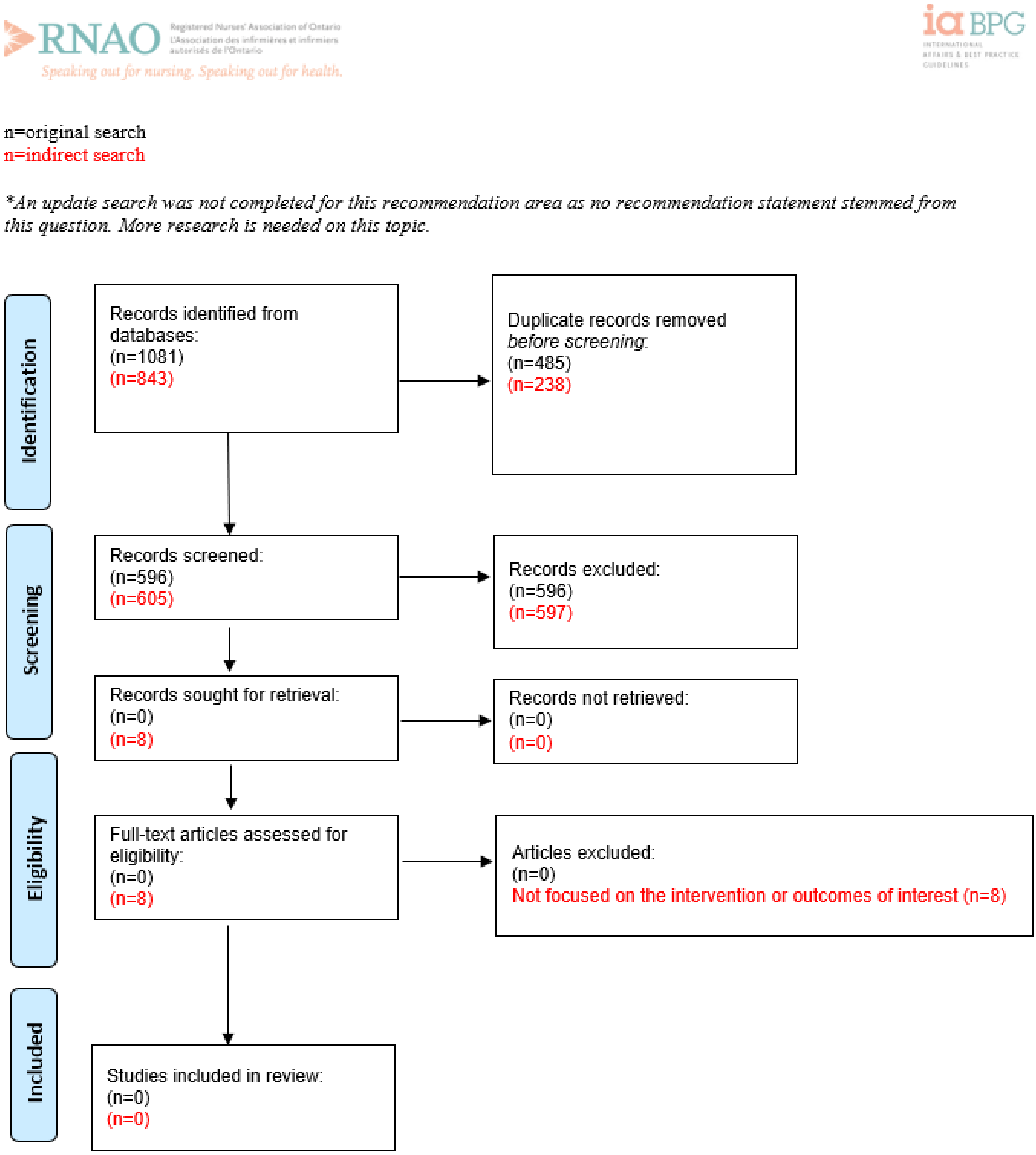

Table . Summary of recommendations in the best practice guideline.

Recommendation	Strength of recommendation
Recommendation 1.0: the expert panel suggests that health service and academic organizations provide ongoing education to nurses and health providers that includes hands-on training for the use of digital health technologies.	Conditional
Recommendation 2.0: the expert panel suggests that health service and academic organizations provide ongoing education to nurses and health providers that focuses on interpersonal communication skills when using digital health technologies.	Conditional
Recommendation 3.0: the expert panel suggests that health service organizations implement interdisciplinary peer champion models to facilitate education for nurses and health providers on the use of digital health technologies.	Conditional
Recommendation 4.0: the expert panel suggests that health service organizations implement CDSS[a] or early warning systems that use artificial intelligence–driven predictive analytics to support nurses' and health providers' clinical decision-making.	Conditional

[a]CDSS: clinical decision support system.

Recommendation 1.0: The Expert Panel Suggests That Health-Service and Academic Organizations Provide Ongoing Education to Nurses and Health Providers That Includes Hands-on Training for the Use of Digital Health Technologies

Practical or hands-on education refers to deliberate practice, hands-on training, or simulation training (ie, more than just viewing e-learning modules) [4]. The intervention of interest examined whether practical or hands-on education for professional development was more effective than standard education (ie, no-hands-on education component) when training nurses and health providers on the use of digital health technologies [4]. Four meta-analyses informed this recommendation [18-21]. The 4 meta-analyses were assessed for risk of bias using the ROBIS tool, and each one had a low risk of bias [18-21]. Studies included in the meta-analyses were assessed by the authors of the meta-analyses, and they used the Cochrane risk-of-bias 2.0 tool for RCTs, the ROBINS-I tool for nonrandomized studies, and the National Institute for Health and Care Excellence quality appraisal checklist [18-21]. Nine studies within the meta-analyses had a critical risk of bias, 18 studies had high risk of bias, 4 studies had unclear risk of bias, and 1 study had low risk of bias [18-21]. There were concerns noted around allocation concealment, blinding, incomplete outcome data, missing outcome data, selection of the reported results, confounding, allocation concealment, and selection of participants [18-21].

Examples of practical or hands-on professional development education discussed in the studies included nurses practicing using electronic health records while being supervised in a computer lab, and hands-on training for using virtual care platforms [18-21]. For more details on the study designs, the risk of bias assessments, how the interventions were delivered, and outcome measures, refer to the GRADE EP found in Multimedia Appendix 4.

The results of the systematic review suggest that hands-on education for nurses and health providers may improve nurses' competence and confidence, and the nurse-person therapeutic relationship (while the technology is used with the person receiving care). The expert panel determined that the overall evidence was of very low certainty due to the risk of bias in the primary studies, indirectness in the outcomes, inconsistency in the results, and imprecision due to small sample sizes [4]. Based on this certainty of evidence, the panel determined the strength of the recommendation to be conditional.

Recommendation 2.0: The Expert Panel Suggests That Health-Service and Academic Organizations Provide Ongoing Education to Nurses and Health Providers That Focuses on Interpersonal Communication Skills When Using Digital Health Technologies

Interpersonal communication describes the communication between a nurse or health provider and a person receiving care. It includes both verbal and nonverbal communication, as well as leading and listening skills that enable a person to interact positively with others in an effective manner [4,22]. The types of education varied across the studies and included didactic and simulation-based education (eg, simulated patients) to improve medical students' interpersonal communication during consultations; training on incorporating computers or electronic health records into nurse-patient encounters; and education on telehealth communication strategies (eg, phone and video consults) [23-29]. Most studies examined focused on medical students [23-27,29], and 1 study focused on nursing students [28].

Seven studies informed this recommendation, including 1 systematic review, 5 additional nonrandomized studies, and 1 mixed methods study [23-29]. The review was assessed using the ROBIS tool and had a low risk of bias [23]. Studies included in the review were assessed by the review authors in accordance with the Cochrane Handbook for Systematic Reviews of Interventions; none were deemed as having a high risk of bias overall [23]. Nonrandomized studies and the mixed-methods study were assessed using the ROBINS-I tool, and there was a critical risk of bias related to confounding variables, deviations from the intended interventions, missing data, measurement of outcomes, and selection of the reported results [24-29].

The 7 studies illustrated that there may be benefits when health service and academic organizations provide nurses and other health providers with education about the importance of interpersonal communication when using digital health technologies [4,23-29]. Benefits may include improved person, caregiver, or family experience or satisfaction with care, and increased competence and confidence among nurses; however, the overall certainty of the evidence using the GRADE methodology was very low, due to risk of bias in the seven studies, few participants, and inconsistency in results [4]. Based on these factors, the expert panel determined the strength of the recommendation to be conditional. For more details on the study designs, risk of bias assessments, how the interventions were delivered, and outcome measures, refer to the GRADE EP in Multimedia Appendix 5.

Recommendation 3.0: The Expert Panel Suggests That Health Service Organizations Implement Interdisciplinary Peer Champion Models to Facilitate Education for Nurses and Health Providers on the Use of Digital Health Technologies

Interdisciplinary peer champions refer to super-users or champions that are nurses or other members of the interdisciplinary health care team with expertise and additional training in digital health [4]. These individuals function as a resource for other staff, helping to answer questions and teach staff about new technology during implementation. Peer champions can also help identify gaps in the technology or its implementation in practice. This recommendation examined the effects of organizations implementing peer champion models to facilitate education for staff about digital health technologies.

One systematic review of 6 RCTs and 2 nonrandomized single-arm studies informed this recommendation [30-32]. The review was assessed using the ROBIS tool and had a low risk of bias [30]. Studies included in the review were assessed by the review authors using the Cochrane risk-of-bias tool for RCTs; 5 studies had a high risk of bias and 1 study had an unclear risk of bias [30]. The nonrandomized studies were assessed using the ROBINS-I tool, and there was a critical risk of bias related to confounding variables, missing data, measurement of the outcomes, and selection of the reported results [31,32].

The use of peer champions in health service organizations may increase health providers' adoption of technology and health provider competence [4]. The overall certainty of evidence was low due to a serious risk of bias in the individual studies and a low number of participants [4]. Based on the available evidence, the expert panel determined the recommendation to be conditional. For more details on the study designs, risk of bias assessments, how the interventions were delivered, and outcome measures, refer to the GRADE EP in Multimedia Appendix 6.

Recommendation 4.0: The Expert Panel Suggests That Health Service Organizations Implement Clinical Decision Support Systems or Early Warning Systems That Use AI-Driven Predictive Analytics to Support Nurses' and Health Providers' Clinical Decision-Making

CDSS or early warning systems refer to software found in risk assessment software tools, early warning systems, command centers, and other software systems that use AI machine learning algorithms to interpret data independently [4]. The recommendation question examined whether adding these systems benefits clinical decision-making for nurses and other health providers.

One systematic review of RCTs, 1 nonrandomized single-arm study, and 2 systematic reviews of nonrandomized studies informed this recommendation [33-36]. Included reviews were assessed using the ROBIS tool and had a low risk of bias [33,35,36]. Studies included in 1 review were assessed by the review authors using the Critical Appraisal Skills Programme checklist for RCTs; 2 studies had a low risk of bias and 1 study had a high risk of bias [33]. Concerns were noted around the lack of details describing the methods, and the lack of blinding [33]. Studies included in another review were assessed by the review authors using the Prediction model Risk Of Bias Assessment Tool; all 10 studies had high or unclear risk of bias [36]. The nonrandomized study was assessed using the ROBINS-I tool and had a critical risk of bias due to lack of control for confounding variables, deviations from the intended intervention, and selection of the reported results [34]. Studies in the final review were assessed by the review authors using the ROBINS-I tool; all 5 included studies had a critical risk of bias [35]. Concerns were noted around confounding, selection of participants, missing data, measurement of outcomes, and selection in reported results [35].

There may be benefits when implementing CDSS or early warning systems that use AI-driven predictive analytics to inform nurses' clinical decision-making, such as improved proactive or anticipatory care, decreased failure to rescue, consistent application of evidence-based practice, and improved nurse-sensitive outcomes [4]. The overall certainty of evidence was low due to risk of bias and few participants [4]. As evidence is still emerging on this topic and the results were mixed, the expert panel determined the strength of the recommendation to be conditional. For more detail on the study designs, risk of bias assessments, how the interventions were delivered, and outcome measures, refer to the GRADE EP in Multimedia Appendix 7.

Discussion

Digital Health Considerations

In 2019, the World Health Organization released a global strategy on digital health acknowledging the vital role digital health plays in planning and providing health services [2]. As digital health technologies become increasingly integrated into health care, nurses need leadership and guidance to safely and effectively use technology in practice. RNAO's BPG provides evidence-based recommendations to foster nurses' ability to maintain, advance, and strengthen professional practice in the context of a digital health environment [4]. The guideline's recommendations focus on (1) hands-on education related to the use of digital health technologies, (2) education about interpersonal communication skills when using digital health technologies, (3) using interdisciplinary peer-champion models to provide education about digital health technologies, and (4) implementing CDSS that uses AI to support but not replace clinical decision-making. While not discussed in this article, additional good practice statements are also provided in the guideline [4].

While digital health has the potential to enhance the quality of care and address key health system challenges, the importance of considering the digital determinants of health, including digital literacy and the digital divide, to ensure equitable delivery of care must be considered. Digital literacy refers to a person's ability to effectively interact with digital technology, using skills required to find, understand, appraise, and apply health information specifically from electronic sources [37]. The digital divide refers to the gap between those who have access to digital technologies, including the internet, accessible health websites and portals, versus those who do not [38]. The World Health Organization's global strategy on digital health notes that digital technologies are to be adaptable to different countries and contexts to help address key health system challenges, while incorporating equity, diversity, and inclusion principles [2]. Unfortunately, the use of certain digital health technologies such as CDSS that use AI may be difficult to implement in less affluent health care systems due to the digital divide [39]. The effectiveness of implementing CDSS that use AI to detect changes in a patient's condition is also dependent on having staff who respond appropriately to these digital tools as well as nursing leadership to continuously oversee the refinement of CDSS and algorithms as needed. As outlined by Richardson et al [40] in their framework for digital health equity, there are several domains of equity including biological, behavioral, physical/built environment, sociocultural environment, and the health care system. The framework can help support the work of digital health technology developers to think about and incorporate principles of digital health equity from the very beginning of the technology development process [4,40]. The framework is also important for end-users, researchers, and health systems leaders, as digital health transformation requires health leaders at all levels to understand how the digital determinants impact health equity [4,40].

In addition to considering the digital determinants of health, when discussing the use of digital health technology with a person receiving care and/or their family, nurses must consider: their preferences and goals; capability and motivation for using technology; how the technology fits into their current care routines; and any costs associated with using the technology [4,41]. Digital health technologies have the potential to enhance a person's experience of the care they receive [5]; however, nurses must consider a person's values and preferences for using technology and ensure that using the technology does not negatively impact or compromise the nurse-patient therapeutic relationship [2,5].

Implementation and Evaluation Considerations

Evidence-based guidelines are effective when there are tools and strategies in place to facilitate their implementation into practice [12]. RNAO uses an integrated approach to ensure that guidelines are both trustworthy and applicable in real-world settings [17]. This BPG includes several tools to support its implementation, including implementation tips, supporting resources, appendices related to the recommendations, and good practice statements. The BPG also directs readers to RNAO's Leading Change Toolkit, which can be used to guide change initiatives, including the implementation of BPGs [42]. RNAO has a network of best practice champions who are the change agents that aid in the implementation of the guidelines, and Best Practice Spotlight Organizations® (BPSO®) internationally from over 13 different countries that partner with RNAO to systematically implement and evaluate RNAO's BPGs [17].

Finally, a monitoring and evaluation table outlines structure, process, and outcome indicators that health service organizations can use to monitor the impact of BPG implementation. Ongoing evaluation is crucial to support the uptake and impact of BPGs on person, organizational, and health systems outcomes [17]. RNAO houses 2 data systems to support BPSOs to monitor and evaluate BPGs: MyBPSO and Nursing Quality Indicators for Reporting and Evaluation® [17]. These 2 data systems are used by BPSOs to report evaluation and monitoring data. As of November 2025, implementation of this BPG has begun in BPSOs, and 1 large Canadian community hospital BPSO has demonstrated 99% (555/562) of nursing staff were compliant with orientation to technologies. Evaluation has also indicated that 84% (474/562) of nurses at this hospital reported comfort with hospital-based technologies to deliver care, and 30% (20,188/72,342) of patients enrolled in a digital patient portal over an 18-month period. Evaluation and monitoring of outcomes is ongoing, and it is anticipated that in the coming years, more BPSOs will implement this valuable BPG.

Future Research Considerations

The expert panel noted that although rigorous RCTs are needed, more exploration including qualitative research is also needed in the area of digital health as it pertains to nursing and clinical practice. For example, studies that examine the efficacy, accuracy, and generalizability of AI-driven predictive analytics, and qualitative studies exploring how nurses and health providers adapt their communication skills in digital health environments. National and international research institutes focused specifically on advancing digital health technologies and integrating digital health practices into clinical care for nurses and health providers would also be beneficial.

Limitations

A few limitations were noted by the expert panel and GDMs during the development of the BPG. First, research in digital health that is specific to nurses and clinical practice is an emerging area. As research is yet to be well established, most evidence for the prioritized research questions was of low or very low certainty; thus, all the recommendations contained in the BPG were deemed conditional. There were few well-designed RCTs, and many of the nonrandomized studies had a high risk of bias, small sample sizes, and inconsistent results. In addition, due to the paucity of research evidence focused on nurses and digital health, the expert panel considered indirect evidence. According to the GRADE methodology, directness is assessed based on the relevance to the target population, intervention, and outcomes of interest [10]. Although GRADE methods allow for the use of indirect evidence, the reliance on indirect evidence due to insufficient direct evidence is a limitation in this BPG, recognizing that indirect evidence may introduce potential biases or uncertainties. The absence of research and use of indirect evidence is noted in the BPG as research gaps, stressing areas for further exploration.

Despite these limitations, expert panel members and additional external reviewers noted the need for guidance on this topic and the importance of publishing this guideline. Conditional recommendations are not to be seen as less important or less trustworthy; they simply imply that there is a need to consider more carefully than usual the individual person or family's circumstances, preferences, and values [10]. When implementing conditional recommendations, health providers need to allocate more time to shared decision-making and comprehensively explain the potential benefits and harms to people and their families [10]. It is becoming increasingly common for clinical guidelines to only include conditional recommendations, as guideline panels and developers recognize the importance of thinking holistically [43,44]. As evidenced by the COVID-19 pandemic, guideline developers also must balance the need for guidance with rapidly evolving research topics [43]. In this BPG specifically, conditional recommendations allow for guidance on an emerging topic (clinical practice in a digital health environment) while recognizing the need for nurses and health providers to consider the implications within their own health care context. Additionally, it has been argued that the implementation of all recommendations, including strong recommendations, depends on social and relational processes governing decision-making for individuals [43]. With this argument in mind, end users of all guidelines should think about contextual implications and the values and preferences of patients when implementing both strong and conditional recommendations.

A final limitation is that the authors only included studies published in English from 2017 onwards. They did not search for gray literature or search reference lists of included studies for further evidence due to timelines and feasibility. Therefore, it is possible that some additional studies were missed.

Conclusions

Digital health within the context of the clinical environment is an emerging topic. This BPG provides 4 evidence-based recommendations, along with good practice statements, implementation and evaluation, and monitoring resources. At the time of BPG development, no guidelines had been developed addressing evidence-based recommendations in this unique and growing area, especially as it relates to nurses and health providers. It is anticipated that this BPG can support nurses, other health providers, and health and academic organizations to make informed decisions about education and care related to digital health that can ultimately improve provider, patient, and system outcomes.

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Data Availability

All data generated or analyzed during this review are included in this published article and its supplementary multimedia appendices. This information is also publicly available on the BPG website [4].

Authors' Contributions

Conceptualization: LB, LH, NN, CB, MC, JY

Formal analysis: LB, CB, LH
Funding acquisition: NN, JY
Project administration: LH, NN, CB
Supervision: MC, JY
Writing – original draft: LB, CB, LH, NN
Writing – review & editing: LB, LH, NN, CB, MC, JY

Conflicts of Interest

None declared.

Multimedia Appendix 1
Guideline Search Strategy.
[PDF File, 201 KB - nursing_v9i1e74942_app1.pdf]

Multimedia Appendix 2
Systematic Review Search Strategies.
[PDF File, 4325 KB - nursing_v9i1e74942_app2.pdf]

Multimedia Appendix 3
Sample Data Extraction Tables.
[XLSX File, 30 KB - nursing_v9i1e74942_app3.xlsx]

Multimedia Appendix 4
Recommendation 1 Evidence Profile.
[PDF File, 246 KB - nursing_v9i1e74942_app4.pdf]

Multimedia Appendix 5
Recommendation 2 Evidence Profile.
[PDF File, 333 KB - nursing_v9i1e74942_app5.pdf]

Multimedia Appendix 6
Recommendation 3 Evidence Profile.
[PDF File, 259 KB - nursing_v9i1e74942_app6.pdf]

Multimedia Appendix 7
Recommendation 4 Evidence Profile.
[PDF File, 310 KB - nursing_v9i1e74942_app7.pdf]

Checklist 1
PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.
[PDF File, 193 KB - nursing_v9i1e74942_app8.pdf]

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Abbreviations

AI: artificial intelligence
BPG: best practice guideline
BPSO: Best Practice Spotlight Organization
CDSS: clinical decision support system
EP: evidence profile
EtD: evidence to decision
GDM: guideline development methodologist
GRADE: Grading of Recommendations, Assessment, Development, and Evaluation
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROSPERO: International Prospective Register of Systematic Reviews
RCT: randomized controlled trial
RNAO: Registered Nurses' Association of Ontario
ROBINS-I: risk of bias in nonrandomized studies—of interventions
ROBIS: risk of bias in systematic reviews

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The Effects of Adequate Rest on Nurse Job Satisfaction, Burnout Prevention, and Physical Health in Medical and Emergency Units at a Hospital in Western Jamaica: Qualitative Study

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Abstract

Background: The demanding work environment of nurses in medical and emergency units often results in high stress, job dissatisfaction, and burnout. Adequate rest is crucial for maintaining nurses' physical health, mental clarity, and emotional resilience, yet it is often overlooked in these high-pressure settings. This qualitative study explores the perceptions of nurses at a hospital in Western Jamaica regarding the quality and duration of rest they receive and its impact on their professional, mental, physical, and personal well-being. The hospital was selected due to the unique challenges health care workers face in Jamaica, including limited resources, high patient loads, and frequent staff shortages, which may exacerbate rest-related issues.

Objective: This study aimed to explore the perceptions of registered nurses working in the emergency and medical units of the hospital in Western Jamaica regarding their rest experience and its implications for burnout, job satisfaction, and overall health.

Methods: The study used a constructivist epistemological lens and used purposive sampling to select 12 registered nurses. The principal researcher conducted in-depth interviews with each participant via Zoom, using a semistructured guide. Interviews lasted 25 to 45 minutes, were audio-recorded, and attended only by participants and the researcher. Thematic analysis was used to transcribe, code, and analyze the data, culminating in the development of a thematic map of findings.

Results: The findings indicated that nurses face significant challenges in obtaining adequate rest due to staff shortages, heavy workloads, irregular shifts, and limited management support. A total of three primary themes emerged: (1) noncompliance with rest policies, (2) resource limitations, and (3) management issues, each influencing job satisfaction, burnout, and overall health. Within noncompliance, nurses highlighted suboptimal nurse-to-patient ratios, absenteeism, and inadequate break time. For example, ratios as high as "30 to 2" or "60 to 3" were cited, affecting nurses' ability to take breaks. Resource constraints included inadequate staffing, insufficient staff replacement, and the absence of suitable rest areas. Management concerns included weak policy enforcement, inadequate policy awareness, and limited support for rest breaks. These challenges collectively contributed to poor sleep quality, increased stress, and diminished job satisfaction.

Conclusions: The study highlights the need for systemic improvements to address nurse rest and well-being, including increased staffing, structured policies on break enforcement, and enhanced management engagement. While the study is specific to the hospital in Western Jamaica, the findings may have broader implications for health care systems in similarly resource-constrained settings in the Caribbean and other low- and middle-income regions.

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KEYWORDS

emergency nursing; Jamaica; job satisfaction; nurse burnout; nurse-patient ratio; nurse well-being; qualitative research; rest; staffing shortages

Introduction

Registered nurses (RNs) are among the most vital resources globally, a reality that was illuminated during the COVID-19 pandemic [1]. The pandemic not only highlighted the essential role that nurses play in maintaining health care systems but also brought global attention to the immense pressures they face [1]. As reported by the British Broadcasting Corporation, nurses were at the frontline, often working extended hours under extreme conditions, which magnified the importance of addressing issues such as adequate rest, burnout, and job satisfaction [2,3]. This growing global realization of the system relevance of the nursing profession continues to shape discussions on health care reforms and support for the nursing workforce.

While nurses are vital in delivering health care and patient care, there has been less focus on their health promotion. The demanding nature of nursing in medical and emergency units puts professionals at high risk for stress and burnout [3,4]. The World Health Organization defines burnout as emotional exhaustion from chronic workplace stress, leading to fatigue and decreased performance [5,6]. Reports of burnout among RNs are prevalent, particularly in high-pressure environments like the US health care system [7]. However, there is a noticeable gap in the literature regarding the role of rest in preventing burnout among nurses, particularly in Caribbean or low-resource contexts. Most existing research focuses on high-income countries, leaving a lack of context-specific understanding in regions such as Jamaica.

RNs are expected to provide high-quality care while managing intense workloads and irregular hours, underscoring the need for effective strategies to enhance nurse well-being and job satisfaction [7]. Job satisfaction reflects a positive emotional response to one’s role and work environment [6,8,9]. Among these strategies, ensuring adequate rest is a crucial yet often overlooked component, essential for physical recovery and maintaining mental clarity and emotional resilience [10,11].

Despite being an upper-middle-income country, Jamaica faces a low nurse-to-patient ratio that negatively affects the rest quality and job satisfaction of RNs [12]. In contrast, socio-economically similar countries like Cuba and the Dominican Republic have much higher ratios [12,13]. Given the significant role of rest in job satisfaction, burnout prevention, and overall health, there is a lack of comprehensive research on its effects in Jamaican health care settings. This study aims to fill this gap by examining the perceptions of nurses at the hospital regarding the quality and duration of their rest and its impact on their well-being. This study focuses specifically on the medical and emergency units due to their particularly high levels of stress and burnout, as well as practical access considerations. These wards also represent high-acuity environments where the effects of inadequate rest are likely to be most pronounced. In fact, burnout rates on these wards are notably higher, ranging from 25% to 55% [14,15].

Through an in-depth analysis of how rest influences nurse satisfaction and burnout, this research seeks to generate evidence that can drive meaningful improvements in health care work environments. By focusing on the specific context of Western Jamaica, an underresearched region facing high patient loads and limited staffing, this study offers context-specific insights into the impact of rest on nurse well-being and performance. Its findings aim to support the development of evidence-based policies and institutional practices that prioritize staff recovery, reduce burnout, and ultimately improve patient outcomes. Beyond contributing to academic understanding, this research aspires to influence workforce planning and retention strategies, offering actionable recommendations to help build a more resilient, efficient, and sustainable health care system in Jamaica.

Methods

Setting

The hospital, established in 1964, is a key facility in western Jamaica. As a type B hospital, it provides 5 basic specialties: general surgery, internal medicine, obstetrics and gynecology, orthopedics, and pediatrics, ensuring comprehensive care for its diverse population. Although its capacity is 190 patients, it currently houses up to 300, leading to significant overcrowding and challenges for the health care system and medical staff [16].

This was a qualitative study that used purposive sampling to identify research participants, grounded in a constructivist epistemological approach. This perspective recognized the coconstruction of knowledge between the researcher and participants, aligning with the study’s aim to explore the subjective experiences of nurses [17].

The principal researcher acknowledged their potential influence on the research process, particularly given prior acquaintance with 2 participants. Efforts were made to remain self-aware and neutral during interviews and analysis, to minimize bias and enhance the credibility of the findings.

Participant Recruitment

Permission was obtained from the Director of Nursing Services at the hospital on April 8, 2024, after discussing the research’s objectives, methodology, and potential impacts. A formal written request outlining the research aims, methodology, ethical considerations, and data management was submitted on April 11, 2024. Following approval, a signed permission letter was issued. The hospital administration assisted in ethically disseminating recruitment emails to 15 potential participants (see Table 1 for inclusion/exclusion criteria). While all 15 acknowledged receipt, only 12 participated: 1 did not sign the consent form, and 2 failed to respond after signing.

Table . Inclusion and exclusion criteria.

Criteria	Inclusion	Exclusion
Employment	Registered nurses currently employed in the medical or emergency units at the hospital.	Nurses who do not work in the medical or emergency units at the hospital.
Clinical experience	Minimum of 1 year of clinical experience in their respective units.	Nurses with <1 year of clinical experience in their respective units.
Educational qualification	Possession of a Bachelor of Science degree in Nursing or a higher-level nursing qualification.	Nurses who do not possess a Bachelor of Science degree in Nursing or a higher-level nursing qualification.
Willingness to participate	Willingness to participate in qualitative interviews discussing their experiences and perceptions related to rest, job satisfaction, burnout, and physical health.	Nurses who are unwilling to participate in qualitative interviews discussing their experiences and perceptions related to rest, job satisfaction, burnout, and physical health.
Availability	Availability to participate in a 45- to 60-minute interview session, either in person or virtually.	Nurses who are not available to participate in a 45- to 60-minute interview session, either in person or virtually.
Language proficiency	Ability to understand and communicate in English effectively, as the interviews will be conducted in English.	Nurses who are unable to understand or communicate effectively in English, as the interviews will be conducted in English.
Male nurses	Male nurses who meet the above criteria are included, ensuring a diverse representation within the study.	Male nurses who do not meet the above criteria are excluded to maintain consistency in the participant pool and ensure a focused analysis.

Data Collection and Analysis

An interview guide was developed with open-ended questions exploring nurses' practices in managing rest, perceptions of rest's impact on satisfaction and burnout, and the role of hospital policies in promoting well-being. It also included recommendations for improving rest in the medical and emergency units at the hospital (see Multimedia Appendix 1).

Prior to the interview, participants were emailed the participant information sheet and subsequently the consent form and were asked to sign them via DocuSign. Interviews, averaging 45 minutes, were all conducted via Zoom using a semistructured guide with only the participants and the principal researcher present. Each session was audio recorded for accuracy, with no photos or videos taken. Data from interviews were transcribed, coded, and analyzed thematically following the 6-step framework of Braun and Clarke [18], which involved familiarization with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and writing up. An inductive approach was used, allowing themes to emerge from the data without being driven by preexisting theories or frameworks [18].

The trustworthiness of the data was reinforced through transparency in the research process and ongoing critical reflection. While one researcher led the initial coding, all authors reviewed the coding framework and contributed to the interpretation of findings. This collaborative process helped ensure consistency, reliability, and analytical depth, supported by clear documentation maintained throughout. Feedback from all authors further shaped the development of the analysis and structure of the paper, enhancing its overall rigor and quality.

Ethical Considerations

The research was conducted in adherence to ethical guidelines outlined by the Declaration of Helsinki and followed institutional protocols to ensure quality, integrity, and ethical responsibility [19]. The methodology was rigorously designed to ensure reliability, validity, and participant protection, following best practices for qualitative research [20].

Ethical approval was granted by the Research Governance and Integrity Team at Imperial College London (ethics application ID 7069331).

Data management was robust, with clear documentation and secure storage. Paper forms were scanned into the primary author's OneDrive space and then securely shredded. The data were securely stored. Any sensitive data archived were encrypted and access was restricted to authorized personnel only. Risks were managed by transparent communication, voluntary participation, and anonymization of data. To anonymize the data, personal identifiers such as names were removed and replaced with pseudonyms. Unique codes were assigned to each participant, and any identifying information was stored separately from the research data to maintain confidentiality.

All participants received a Participant Information Sheet prior to recruitment and provided written informed consent electronically before taking part in the study. Participation was voluntary, and participants were informed of their right to withdraw at any time without consequence. No financial or material compensation was provided for participation.

Results

Participant Characteristics

Twelve RNs participated in the study (see Table 2). The mean age of the participants was 28 (SD 2.2; range 25 - 33) years. All nurses held a Bachelor of Science in Nursing degree, with 1 nurse also possessing a critical care certificate.

Participants had a mean of 3.6 (SD 1.8; range 1.2 - 6) years of experience working at the hospital. The sample was evenly distributed across clinical units, with 50% (6/12) of participants assigned to the Accident and Emergency (A&E) unit and 50% (6/12) to the Medical unit.

Table . Demographic and professional characteristics of nurses at the hospital: female participant 1 - 11, male participant 12; numbers indicate the chronological order of interviews.

Pseudonyms	Age (y)	Educational background	Experience at hospital (y)	Current unit	Sex
Female Participant 1	29	BSN[a]	5	A&E[b]	Female
Female Participant 2	28	BSN	4.5	Medical	Female
Female Participant 3	33	BSN	5.5	Medical	Female
Female Participant 4	28	BSN	5	Medical	Female
Female Participant 5	30	BSN	3	Medical	Female
Female Participant 6	29	BSN	5	A&E	Female
Female Participant 7	27	BSN	1.5	A&E	Female
Female Participant 8	25	BSN	1.2	Medical	Female
Female Participant 9	29	BSN+critical care certificate	6	A&E	Female
Female Participant 10	27	BSN	3	A&E	Female
Female Participant 11	28	BSN	1	Medical	Female
Male Participant 12	32	BSN	2	A&E	Male

[a]BSN: Bachelor of Science in Nursing.

[b]A&E: Accident and Emergency unit.

Themes

Overview

Three key themes emerged from the interviews, on factors influencing rest quality and its impact on job satisfaction, burnout, and physical well-being. These themes were as follows: (1) noncompliance with rest policies, with subthemes of high nurse-patient ratios, high absenteeism, and rest duration; (2) resources, including limited human resources and the absence of rest facilities; and (3) management, focusing on policy improvement and implementation, as well as nonadherence to duties (see Multimedia Appendix 2 for coding table).

Noncompliance With Rest Policies

Overview

Noncompliance with rest policies among nurses in public hospitals is a persistent and multifaceted issue that has serious implications for staff well-being and patient care. Although formal guidelines are in place to ensure that nurses receive adequate breaks during their shifts, various systemic challenges make it difficult to adhere to these policies. Three critical subthemes emerged in relation to this problem: high nurse-patient ratios, high absenteeism, and inadequate rest duration.

High Nurse-Patient Ratios

The issue of noncompliance with rest policies among nurses is exacerbated by unsustainable nurse-patient ratios, making it nearly impossible for nurses to take their designated 1-hour breaks. Participants reported ratios as high as “sometimes 30 to 2, 35 to 2, 60 to 3, it varies” (Male Participant 12: A&E), highlighting the overwhelming workload they face. It is also common for a single RN to manage a unit with only an enrolled assistant nurse, meaning that while the RN receives assistance, they are still solely responsible for the entire unit, including supervising the enrolled assistant nurse. The consensus was clear; without addressing these staffing imbalances, compliance with rest policies will remain a significant challenge.

High Absenteeism

High absenteeism among nurses is a significant consequence of noncompliance with rest policies, as many nurses report having various medical illnesses, feeling overwhelmed, and burnt out, leading them to take frequent sick days. One participant noted, “the call-in rate is very high because when you realize that you are burnt out and tired you’ll find that persons are not coming in” (Female Participant 1: Medical). Another participant echoed this sentiment, stating, “I will wake up in the morning and say, OK, yes, I’m going to make it to work today… I just find that I am tired, not just physically tired, but emotionally tired” (Female Participant 2: Medical). This chronic fatigue often results in nurses prioritizing their health over work obligations. The pervasive culture of exhaustion and the lack of adequate rest contribute to a cycle of absenteeism that further strains the already limited nursing staff, ultimately impacting patient care and overall hospital operations.

Rest Duration

Rest duration remains a significant issue among nurses in public hospitals in Jamaica. Although the policies mandate a 1-hour break during 8-hour day shifts and 2 hours for night shifts, these rest periods are rarely observed in practice. One participant verbalized, "You're supposed to get one hour in the day shift and two hours in the night, but we don't get that" (Female Participant 6: A&E). Participants highlighted that despite these official guidelines, the reality of high patient complexity and understaffing often makes it impossible to take the full allotted break or even time to eat. Many nurses expressed frustration with the gap between policy and practice, noting that the workload and staffing shortages leave little time for adequate rest. This chronic lack of rest not only exacerbates fatigue, medical illnesses, and burnout but also negatively impacts patient care [21,22].

Resources

Overview

The availability and quality of resources, particularly human resources and physical infrastructure, play a critical role in shaping nurses' ability to rest during their shifts. Inadequate resources contribute significantly to poor rest quality, increased burnout, and decreased job satisfaction. Two key subthemes emerged under this category: limited human resources and the absence of adequate rest facilities.

Limited Resources (Including Human Resources)

The theme of resources, particularly limited human resources, emerged as one of the main factors influencing rest quality and, consequently, job satisfaction, burnout, and physical well-being among nurses. Participants consistently expressed concerns about inadequate staffing levels, which directly impact their ability to take necessary breaks. Among all, 1 nurse articulated the challenge succinctly when asked if management does not actively hire new staff, stating, "If you go there now and say, oh, we need staff, they're going to say based on the quota that they have… but be reminded they have opened a lot of different areas and the population has expanded" (Female Participant 9: A&E). The overwhelming workloads resulting from these staffing shortages leave little room for rest. The lack of adequate resources not only hinders compliance with rest policies but also exacerbates feelings of burnout, as nurses struggle to manage their responsibilities without sufficient support.

Absence of Adequate Rest Facilities

The lack of adequate rest facilities at the hospital severely affects nurses' ability to recuperate during shifts. All participants expressed dissatisfaction with the current designated rest areas, citing issues such as overcrowding, noise from nearby units, and the combination of a bed and lunch area with a microwave in the same space, posing safety and health risks. While some nurses resorted to resting in their cars, others had no choice but to endure the suboptimal conditions. This shows that without proper rest facilities, nurses struggle to fully recover during their shifts, which in turn affects their physical well-being and their ability to provide quality patient care.

Management

Overview

The role of hospital management, particularly nursing leadership, is central to ensuring that rest policies are effectively implemented and that nurses are supported in their demanding roles. However, participants highlighted ongoing management-related challenges that undermine nurse well-being and disrupt the delivery of quality care. Two key subthemes emerged: the need for policy improvement and implementation, and nonadherence to managerial duties.

Policy Improvement and Implementation

Participants expressed a clear need for more effective policies that not only address staffing levels but also prioritize the well-being of nursing staff. Among all, 1 participant noted, "I think we need more policies to actually not just cater for the staffing of the hospital… but also to cater to the nurses" (Female Participant 1: Medical). Despite the existence of policies that outline break times, the implementation of these policies is often lacking. As one nurse stated, "the policy exists… however, there's no implementation of the actual policy" (Female Participant 7: A&E). This sentiment was echoed by another participant who remarked, "I don't think there is a collaborative effort among the hospital, administration, and nurses in promoting nurse well-being through proper rest practices" (Female Participant 3: Medical). The need for management to actively engage in policy enforcement and to create a supportive environment for nurses is paramount, as inadequate rest not only affects nurse satisfaction but also compromises patient care and safety.

Nonadherence to Duties

The issue of nursing managers not adhering to their duties at the hospital has been a significant concern among the interviewees. Participants expressed frustration over the lack of support from nursing managers, particularly during critical times when the unit is short-staffed. One participant noted, "the sisters are supposed to come there and assist and ensure that the unit is running to full capacity… but you find that when you fall into an emergency situation… they either tell you that they are short-staffed or they tell you did you call this ward for this" (Female Participant 4: Medical). This lack of responsiveness leaves nurses feeling overwhelmed and unsupported, as they are often left to manage high patient loads and intense emergency situations without adequate assistance. Another participant highlighted that "most of their tasks, they leave it for the nurses to do while they basically do nothing" (Female Participant 9: A&E), indicating a perceived neglect of managerial responsibilities on the units. The absence of proactive engagement from nursing managers not only exacerbates the challenges faced by nurses but also compromises patient care and safety, as the staff is unable to effectively manage their duties under such conditions.

Differences Based on Gender, Unit Type, and Experience Level

To further contextualize these findings, differences based on gender, unit type, and experience level were also observed among participants, offering deeper insight into how individual and situational factors shape nurses' experiences with rest policy compliance.

Gender Differences

The male nurse often highlighted issues related to workload and understaffing with a strong focus on managerial support and policy enforcement. For example, the male participant in the A&E unit emphasized frustration with the lack of implementation of break policies. Female nurses frequently discussed challenges around balancing work demands with personal responsibilities, such as family care, which impacted their ability to rest adequately during shifts. They also noted more about the emotional toll and burnout symptoms.

Unit Differences (A&E vs Medical)

Nurses working in A&E units reported higher stress levels due to patient complexity and unpredictability of cases. They described fewer opportunities for breaks and greater difficulty taking rest because they were often the only RN on the unit during shifts. Nurses in the Medical units acknowledged the challenges of patient care but reported slightly more opportunities for breaks compared to A&E. However, they also noted the workload increased significantly during night shifts.

Experience and Role

More experienced nurses, working 3 years or more, tended to express frustration with systemic issues such as staffing policies and managerial accountability. Less experienced nurses, working less than 3 years, were more likely to discuss immediate physical fatigue and emotional exhaustion, focusing on day-to-day survival rather than broader systemic changes.

Discussion

Summary of Major Findings

This study examined the role of adequate rest in nurse satisfaction, burnout prevention, and physical well-being in medical and emergency units. It uncovered systemic challenges that hinder nurses from obtaining sufficient rest. High patient-to-nurse ratios, staffing shortages, and lack of managerial support were identified as key contributors to fatigue and burnout. Nurses' personal responsibilities, such as caregiving at home, also affected their ability to prioritize rest. These findings show how both institutional and personal factors compromise nurses' well-being and, in turn, patient care.

Interpretation of Demographic Differences

Demographic differences reflect social, cultural, and professional dynamics shaping nurses' experiences. Female nurses often balance work and caregiving roles, heightening stress and burnout risk [23]. A&E nurses reported higher fatigue levels than those in Medical units, due to the unpredictable nature of emergency care. Experienced nurses highlighted systemic issues, while newer nurses focused on the immediate physical and emotional toll, reflecting their frontline pressures [24].

Interpretation of Findings

The study reaffirms the link between rest and well-being. Nurses with more rest reported better physical and mental health, supporting global research on this topic [25]. Challenges at this hospital, such as high workloads and weak managerial support, mirror trends in other resource-limited settings [26]. For example, a Namibian study also found burnout tied to understaffing and lack of rest infrastructure [27]. Nurses at the hospital in Western Jamaica frequently reported physical exhaustion and long-term health concerns, echoing global findings on rest-related health risks, including musculoskeletal pain and emotional exhaustion, key components of burnout [7,25,28].

Relation to Wider Context and Integration With Existing Literature

Jamaica faces a severe brain drain, with 80% of skilled workers emigrating, including health care professionals [29]. Ranking second globally on the brain drain index [30], Jamaica's workforce shortages worsen burnout. Similar trends are noted in Guyana and Trinidad and Tobago [31]. Cultural and economic pressures often lead nurses to work extended hours without adequate compensation or rest. In contrast, high-income countries enforce stricter work hour regulations. At Spanish Town Hospital in Southeast-Central Jamaica, the nurse-patient ratio is 1:10, far above ratios in wealthier nations, contributing to burnout and absenteeism [32-34]. The Maslach Burnout Inventory indicated "very high" burnout among nurses, especially in emotional exhaustion [22,35]. The International Council of Nurses [36] highlights the negative outcomes that occur from high-income countries attempting to address their nursing shortages through "inequitable international recruitment." Through recruiting via migration, it leaves nursing workforces in low- and middle-income countries without adequate care, masks the underlying issues leading to high turnover, and costs low- and middle-income countries lost training expenses after public investment in education.

Nurses struggle to maintain work-life balance in these settings. Overcrowding and understaffing lead to long hours and little time for self-care [37,22]. The State of the World's Nursing Report 2025 [38] illustrated that only 55% of countries had regulations on working hours and conditions, whereas the remaining 45% had partial or no regulations. Care packages for mental well-being of nurses were implemented in 42% of countries, whereas 64% only implemented partial or no care packages. A study in Iceland showed higher satisfaction among nurses working standard hours versus those on overtime [39]. However, extended shifts remain necessary at this hospital in Western Jamaica, negatively affecting health and morale. These findings call for urgent action to support nurses and improve patient care through systemic reform. This is supported by the International Council of Nurses 2025 report [36], which states that solutions such as "ensuring adequate staffing and a balanced skill mix and workforce capacity aligned with patients demands" need to be implemented.

Strengths and Limitations

This study's strength lies in its qualitative design, which captured rich personal narratives often missed in quantitative research [17]. Familiarity between the researcher and some participants may have encouraged openness. However, it may also have introduced bias. The lead researcher's nursing background may have shaped interpretations. Additionally, excluding non-English-speaking nurses, such as Cuban staff [1], limited the diversity of views. With only 12 participants from 2 units, generalizability is limited. Self-reported data also carry risks of under- or over-reporting.

Future Work

Future studies should explore strategies for staff recruitment and retention to reduce burnout. Research is needed on how managerial practices affect rest and well-being. Peer support systems and cultural change around rest and self-care should be evaluated. Post-COVID recovery efforts should prioritize mental health support and enforceable rest policies [40].

Policy and Intervention Recommendations

The hospital should address high nurse-to-patient ratios by increasing staff, ensuring breaks without compromising care. California's Nurse-to-Patient Ratios Law (1:2 in intensive care units; 1:4 in medical-surgical) reduced burnout and improved outcomes [4]. Structured break policies and cross-unit support systems are vital. UK hospitals implementing scheduled breaks reported reduced stress and higher job satisfaction [41]. Australia's cross-unit model ensures continuity of care and relieves pressure during breaks [39,42,43].

Hospital leadership should prioritize nurse well-being. Programs in Australia train managers to promote self-care and regular breaks, leading to greater satisfaction and lower turnover [44]. At Cleveland Clinic in the United States, managerial training on rest and mental health improved morale and retention [45,46]. Wellness programs like Johns Hopkins' Resilience in Stressful Events provide peer support and counseling, significantly reducing burnout and emotional exhaustion among nurses [47].

Conclusion

This study underscores the role of adequate rest in preventing burnout and enhancing job satisfaction among nurses in medical and emergency units. The findings reveal that systemic barriers, such as high workloads, inadequate staffing, and chaotic work environments, significantly hinder nurses' ability to achieve sufficient rest. Nurses in the emergency unit, in particular, face higher stress levels due to the demanding nature of their work, which worsens fatigue and burnout. The lack of localized studies focusing on the physical and mental well-being of Jamaican nurses, particularly in high-pressure emergency units, creates a significant academic gap.

Addressing these issues can enhance the global understanding of burnout in various contexts while providing region-specific strategies to improve nurse retention, job satisfaction, and overall health care quality in Jamaica. A multifaceted approach is required to tackle these challenges, incorporating policy changes, management training, and the creation of supportive work environments. By prioritizing the well-being of nurses through adequate rest, health care institutions can not only improve nurse satisfaction but also ensure better patient care outcomes.

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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: CS (lead)
Data curation: CS
Formal analysis: CS
Funding acquisition: NC, KKM
Investigation: CS
Methodology: CS
Project administration: CS
Supervision: NC, KKM

Validation: CS
Writing – original draft: CS (lead)
Writing – review & editing: NC (supporting), KKM (supporting)

Conflicts of Interest

None declared.

Multimedia Appendix 1
Interview guide.
[DOCX File, 12 KB - nursing_v9i1e84106_app1.docx]

Multimedia Appendix 2
Coding table: from quotes to theme.
[DOCX File, 12 KB - nursing_v9i1e84106_app2.docx]

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Abbreviations

A&E: Accident and Emergency
RN: registered nurse

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The Relational Playbook Nurse Leadership Development Program Using the Whistle Systems Employee Recognition Platform: Feasibility Mixed Methods Study

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Abstract

Background: Leadership development programs in health care often fail due to their lack of adaptability to the schedules of busy clinicians. This study addressed the need for scalable, flexible programs tailored to nurse leaders.

Objective: This study evaluated the acceptability, appropriateness, and feasibility of the Relational Playbook, an evidence-based leadership development program developed in the Veterans Health Administration delivered through the Whistle Systems employee recognition web application and mobile app.

Methods: A 1-year, single-team pilot was deployed using descriptive survey data and qualitative interview analysis. The Relational Playbook's educational content and interventions were hosted on the Whistle platform, which integrates behavioral science and gamification strategies. Content was delivered weekly via app-based nudge notifications and email. Engagement metrics included activity completion rates. User experience data were collected through weekly reflection surveys (with Likert-scale responses and open-text options); monthly check-ins; and a postimplementation acceptability, appropriateness, and feasibility survey and interview. Descriptive statistics summarized engagement levels and trends, and qualitative data were analyzed using content analysis to identify recurring concepts. Quantitative and qualitative data were analyzed sequentially for comprehensive insights.

Results: The section chief and 4 practicing cardiology nurse practitioners from a large academic medical center participated. The nurse practitioner section chief deemed the Whistle platform an acceptable, appropriate, and feasible technology for delivering the Relational Playbook content. They valued the weekly nudges, microlearning content, and flexibility of the web application and mobile app. The Relational Playbook content supported their personal growth and fostered positive shifts in attitudes toward work.

Conclusions: Delivering leadership development content through the Whistle platform is an acceptable approach to support the growth and well-being of busy nurse leaders. The small sample and absence of a comparison group limit generalizability.

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KEYWORDS

leadership; nursing; mobile app; development; workforce

Introduction

The well-being of nurse leaders and the nursing workforce is an urgent concern worsened by the COVID-19 pandemic, increasing patient complexity, evolving hospital systems, and high workloads [1]. Nurse leaders play a pivotal role in improving nurse well-being, patient care, and clinical outcomes by managing frontline clinical staff [2]. However, leadership is a challenging role that requires skills to foster interdisciplinary teamwork, continuous learning, and high reliability. Most nurse leadership training occurs through face-to-face didactic education or on-the-job training that falls short of true leadership development [3]. Digital leadership programs are available; however, most lack scientific rigor and impact evaluation [4].

With many nurse leaders nearing retirement, developing the next generation is essential to sustaining the profession and ensuring high-quality care [5].

The Relational Playbook is an innovative leadership development program grounded in adult learning principles, including experiential learning [6] and situated learning theories [7]. The Relational Playbook is designed to equip frontline clinical leaders with the skills to foster a culture of learning and high reliability within clinical teams. The Relational Playbook integrates evidence-based concepts and practices from positive psychology, team science, servant leadership, the Veterans Health Administration (VHA) Whole Health model, and clinical team training [8-10]. The Relational Playbook's key innovation lies in bringing these principles together into a single, cohesive program tailored specifically for frontline health care leaders. These principles are presented in an e-book with five chapters on (1) creating a positive culture, (2) teamwork, (3) leading teams, (4) creating joy in work, and (5) communication and high reliability. The Relational Playbook contains brief asynchronous learning modules, 11 kick-off interventions, and 39 additional evidence-based interventions. Table 1 provides more details on the Relational Playbook chapters, their resource topics, and their kick-off interventions. Frontline leaders complete weekly self-directed education and then select and implement specific Relational Playbook interventions into existing meetings or trainings. Each chapter builds on the previous one and results in the development of supportive learning environments.

Table . Relational Playbook chapters, modules, and kick-off interventions.

Relational Playbook chapter	Resource topics	Kick-off interventions
Chapter 1: Creating a Positive Culture	• Positive culture • Assessing team well-being • Appreciative inquiry	• ”Three Good Things” practice [11] • Appreciative inquiry questions [12]
Chapter 2: Teamwork	• Building a team • Relationships at work • Difficult relationships at work • Hiring for high-performing teams	• “Walk in My Shoes” exercise [13] • Ice breaker questions [13]
Chapter 3: Leading Teams	• Wellness-centered leadership • Servant leadership • Essential leadership skills	• “Stop, Start, Continue” method [13] • “Situation-Behavior-Impact” feedback [14]
Chapter 4: Creating Joy in Work	• Burnout • Joy and happiness • Gratitude	• Understanding what matters [15] • “Was It Worth It?” method [16] • Gratitude huddle [17]
Chapter 5: Communication and High Reliability	• Effective communication • High-reliability practices	• Start-of-day huddles [18] • Debriefs [18]

Pilot research with the Relational Playbook has suggested improvements in employee engagement and retention while reducing burnout and turnover, which are critical workforce challenges [8]. The Relational Playbook aligns with multiple priority areas in health care, including the shift toward learning health systems to improve patient safety. In 2022, the Relational Playbook was registered as an invention with the VHA Technology Transfer Program (VHA ID 2022-474) to foster partnerships with external digital technology innovators and leverage emerging technology to expand and scale the program.

The Relational Playbook team collaborated with Whistle Systems, a company specializing in digital programs and trainings to sustain employee behavior change and improve workplace culture. Leveraging a mobile-first design, the Whistle platform integrates evidence-based strategies such as microlearning, gamification, and strategic nudges to optimize user engagement and adherence [19]. The platform delivers real-time feedback through notifications, on-demand resources, and a user-centric interface to enhance accessibility. Whistle has shown measurable success in improving employee engagement and reducing turnover across sectors, including aviation, finance, and construction [20]. The partnership aimed to adapt Relational Playbook content to the Whistle platform and assess whether this innovative technology is an acceptable, appropriate, and feasible tool for delivering the Relational Playbook to nurse leaders.

Methods

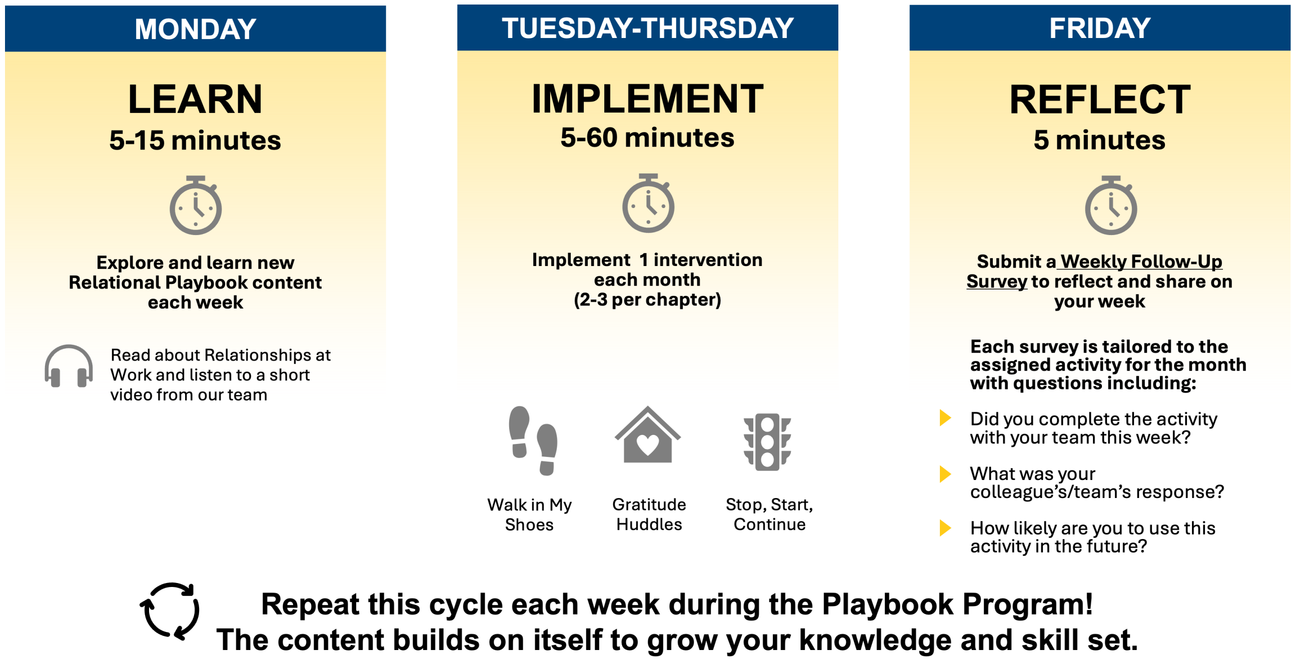
Overview

We conducted a 1-year, single-team feasibility study of the Relational Playbook delivered on the Whistle platform within a real-world clinical setting using descriptive survey data and qualitative interview analysis. A cardiology nurse practitioner (NP) team (n=5) at a large academic medical center volunteered to pilot the Relational Playbook on Whistle driven by an interest in leadership development training to improve team dynamics. The NP section chief was the primary participant, and their team members were invited to engage with the platform to enhance team understanding and participation. To maintain participant confidentiality, detailed demographic information was not reported. The inclusion criterion was a formal supervisory role in the department. Participation was voluntary and considered part of the employees' work.

The Relational Playbook and Whistle team established a cooperative research and development agreement enabling collaboration between the VHA and private companies. The first author adapted the Relational Playbook content for delivery on the Whistle platform with input from the Relational Playbook developers (HMG and BC) and Whistle engineers. The educational content was reformatted into a microlearning flash card model incorporating short text, colored images, videos, and kick-off interventions (Multimedia Appendix 1). The Whistle-enabled Relational Playbook used multiple behavioral science mechanisms, including celebratory feedback (confetti) to trigger dopaminergic reward responses, progress indicators (completion bars) to leverage the goal gradient effect, microlearning modules to reduce cognitive load and enhance perceived task simplicity, and strategic nudges to serve as action triggers and mitigate decision inertia. The Whistle web platform hosted the content, with accessible iPhone and Android mobile apps.

The Relational Playbook on Whistle begins with participants completing the 13-item Learning Environment Assessment Tool (Multimedia Appendix 2), an abbreviated version of the validated 64-item Learning Environment Survey [10,21]. The Learning Environment Assessment Tool evaluates key aspects of supportive learning environments through statements such as “The cardiology team demonstrates trust and mutual respect with each other,” “The cardiology team is comfortable asking for help and feedback from others,” and “The cardiology team can control their own practice and regularly participate in decisions about their work.” Each item is rated on a 3-point scale (1=“rarely,” 2=“sometimes,” and 3=“almost always”). Responses are automatically summed in Qualtrics (Qualtrics International Inc) and ranked from lowest to highest. Using these data, the research team assigned initial (lowest ranking) and subsequent chapters to the participants in order. The Relational Playbook consists of 5 chapters, each delivered over a 2-month interval across 1 year (Figure 1). Participants receive weekly email and app notifications (“nudges”) linking to flash card–based learning modules. Each module concludes with a brief comprehensive quiz and celebratory feedback to reinforce engagement. Modules end with details about the next chapter’s kick-off intervention to implement.

Figure 1. The Relational Playbook program weekly activities. This figure shows what a week in the Relational Playbook looks like for a cardiology nurse practitioner team. On Monday, they are instructed to take 5 to 15 minutes and learn new content by completing learning modules and watching short videos. The rest of the week, they implement their learnings and activities through 1 intervention each week, such as “Walk in My Shoes” or “gratitude huddles.” At the end of the week, they submit a weekly follow-up survey that is tailored to the assigned activity for the month to see whether they progressed with the activity and their team’s response.



The evaluation data were collected through surveys and interviews from the NP section chief (eg, primary participant) to measure implementation, engagement, and adoption outcomes. Primary implementation outcomes were the acceptability, appropriateness, and feasibility of the Relational Playbook on Whistle assessed using the Acceptability of Intervention Measure, Feasibility of Intervention Measure, and Intervention Appropriateness Measure [22] (Multimedia Appendix 3). These surveys assess the acceptability, appropriateness, and feasibility of the Relational Playbook on Whistle through statements such as “The Relational Playbook on Whistle meets my approval,” “The Relational Playbook on Whistle seems suitable,” and “The Relational Playbook on Whistle seems implementable.” Each item is rated on a 5-point scale (1=“completely disagree”; 5=“completely agree”) and analyzed using mean scores [22]. The secondary outcomes of engagement and adoption were assessed using all participant platform visit data and survey responses (n=5), supplemented by a follow-up interview with the NP section chief to contextualize the findings. Whistle’s reporting tools were used to track platform visits, module completions, survey completions, and responses.

Quantitative data, including platform use and survey responses, were summarized both by chapter and for the Relational

Playbook overall. Chapter and Playbook completion rates were calculated as the percentage of completed modules relative to the total number of modules using Microsoft Excel. Platform visit data were reviewed to confirm that all participants accessed the Relational Playbook content on Whistle at least once. For qualitative data, we used a rapid qualitative matrix approach [21]. Two team members (BC and MD) met to discuss data and reach consensus on the concepts; given the informal nature and small sample (n=1), all data were analyzed instead of stopping at a point of saturation. The initial matrix summary was developed by 1 team member using identified concepts and illustrative quotes from the data. A second team member independently reviewed and refined the matrix to ensure accuracy, completeness, and consistency in data representation. To enhance rigor, discrepancies were discussed and resolved collaboratively. The full analytic team then conducted a review of the finalized matrix, engaging in consensus building to identify cross-cutting concepts and key insights.

Ethical Considerations

This study was deemed an exempt human research study by the Colorado Multiple Institutional Review Board (17-1153) and did not require informed consent. All participant data were handled in accordance with institutional privacy and confidentiality guidelines.

Results

The NP section chief and 4 cardiology NP team members participated in the study, with the NP section chief acting as the primary implementer and evaluator due to their formal supervisory role. The NP team provides clinical care across various inpatient and outpatient settings (eg, heart failure clinic and structural heart and valve clinic) and meets virtually each month for updates and professional development.

Acceptability, Appropriateness, and Feasibility and Platform Visits

The NP section chief, the primary participant, strongly agreed (5/5) on all measures that the Relational Playbook on the Whistle platform was acceptable (Acceptability of Intervention Measure), appropriate (Intervention Appropriateness Measure), and feasible (Feasibility of Intervention Measure). They engaged with 86% (73/85) of the learning content and reflection surveys and adopted all 11 kick-off interventions at least once with their team. The 4 cardiology NP team members engaged fully with the introduction, and their engagement declined over the subsequent 5 chapters. During scheduled check-ins, NP team members reported that their busy schedules, their direct care responsibilities, and not leading their own teams made it harder for them to implement the Relational Playbook interventions as they were not directly applicable to their roles. They found the learning components valuable and noted that these resources enhanced their understanding of and engagement in the section chief's activities. However, the lack of applicability in their daily work led to disengagement with the platform. Figure 2 shows the completion rates by chapter for the Whistle-enabled Relational Playbook.

The NP section chief provided generally positive feedback on the kick-off interventions and reported that their team adopted a more positive outlook, identifying what mattered most to them, such as "'family,' 'friends/relationships,' 'fulfilling my responsibilities,' and 'being good at my job.'" They had specific successes with using debriefs:

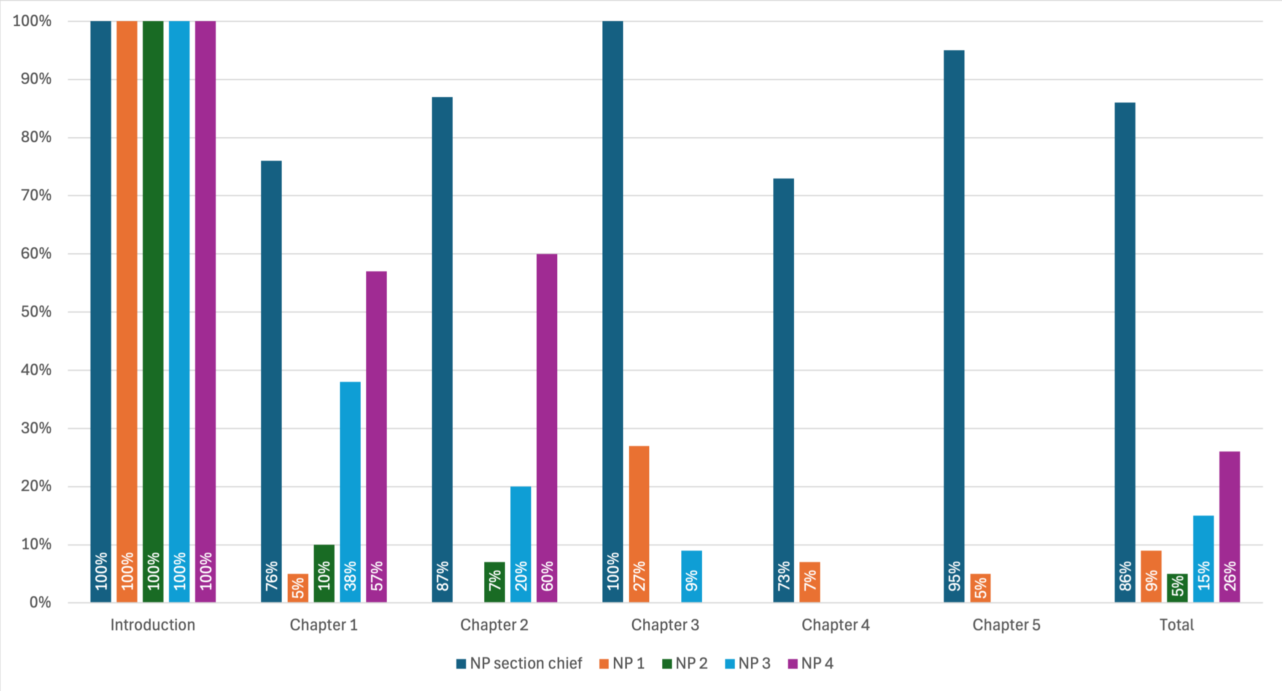
> *Worked well with a co-worker to solve a problem!*

However, the *Walk in My Shoes* and *Was It Worth It* interventions were more challenging to implement, as the NP section chief explained:

> *...I think it needs to be the right timing and people.*

They also reported adapting some interventions, such as replacing the "Stop, Start, Continue" group discussion with an online survey and incorporating the "What was a win this week" question from chapter 4 as a meeting icebreaker.

Figure 2. The Relational Playbook on Whistle completion rates. This figure displays the chapter completion rates for each participant alongside their total completion rate for the entire program. While all participants completed the introduction chapter, participation rates declined for everyone but the nurse practitioner (NP) section chief for chapters 1 to 5.



Interview Results

Platform Usability and Learning Content

The NP section chief primarily used the website, rating it as easy to use (4 out of 5 on a verbal ease-of-use scale) and preferable to the mobile app, which required frequent log-ins and multiple clicks to access content. They appreciated the ability to navigate seamlessly through the program and liked the push notifications (ie, nudges). The Relational Playbook content was described as "bite size enough to be done in one sitting and...easily digested." However, they observed that the Relational Playbook was designed for teams that "work together in a clinical way." Considering that the NP group did not physically work together, they suggested modifying the content to better reflect virtual team dynamics.

Relational Playbook Implementation

The NP section chief rated the implementation of the Relational Playbook practices as moderately easy (3 out of 5 on a verbal ease-of-implementation scale). They confirmed that the practices fostered a more positive team outlook, stating the following:

> *...there's some hard days.... And we focus a lot on the negative...instead of what went right. I liked that about the Playbook.*

They emphasized that the learning content only took 5 to 10 minutes to complete. Overall, the NP section chief described the Relational Playbook on Whistle as a valuable program:

> *You can always improve as a leader—I highly recommend it.*

Adaptations and Sustainment

The NP section chief suggested adaptations before expanding the program: (1) tailor Relational Playbook content for virtual teams that do not meet routinely in person, (2) condense the program to 6 months (from 1 year), (3) reduce nudges to every other week (from weekly), and (4) develop an educational module for team members without formal leadership roles. At the conclusion of the 1-year program, the NP section chief reported ongoing use of the huddles and appreciative inquiry practices.

Discussion

This feasibility study demonstrated that the Relational Playbook on Whistle is an acceptable, appropriate, and feasible intervention for a nurse leader. The NP section chief engaged with 86% (73/85) of the educational content and implemented all 11 kick-off interventions, confirming the platform's usability. Participant feedback emphasized the Relational Playbook's strengths, including its concise, "bite-sized" content; intuitive navigation; and direct relevance to clinical practice. By applying Relational Playbook practices, the NP section chief fostered a culture of learning and positivity within the team. The NP clinical team accessed the platform and participated intermittently. This may reflect the absence of opportunity for practicing NPs to put the leadership interventions into practice, the unique challenges of virtual teams that do not routinely work in person (noted above), or the assumption that leadership development is only for those who have formal leadership titles. Their reports of finding the education components valuable reinforce the section chief's recommendation for an educational module for team members without formal leadership roles.

The Whistle platform behavioral science features guided participants to set learning intentions, assume responsibility for their goals, and receive feedback on progress. While our study data did not allow for a granular analysis of each feature's individual contribution to engagement, this is an area that we will explore in future research. Rapid application of newly acquired skills in practice represents the gold standard of leadership development programs. Our single-team study process and findings align with recent work by Güntner et al [23], which reported that a web-based leadership transfer intervention positively influenced leaders' mindsets and self-regulated learning. The significance of these studies lies in demonstrating that digital microlearning interventions can effectively support leadership development in high-demand clinical environments, offering a scalable and cost-efficient alternative to traditional programs. Future studies of the Relational Playbook on Whistle will advance the evidence base for digital leadership training programs, ensuring positive outcomes in a cost-effective manner.

The partnership with Whistle Systems was an opportunity to integrate an evidence-based leadership development program into a digital technology innovation that delivered microlearning content using behavioral science and gamification principles. This technology overcame time constraints, a common barrier for busy nurse leaders [24,25], and promoted engagement and new habits. The Whistle platform's usability was rated favorably by the NP section chief, with the website preferred over the mobile app due to frequent re–log-ins and navigation challenges. Nudges effectively promoted engagement by linking directly to assigned content; however, a decrease in frequency was suggested to reduce response burden.

Additional behavior-driving tools offered by the Whistle platform were not leveraged in this feasibility study that could increase engagement and effectiveness among team members. These include real-time automated acknowledgments; hospital-branded Visa cards for monetary reward; peer or community recognition engagement through Whistle's "Town-Square" social feature; or the platform's artificial intelligence engine Robin, which tailors nudges informed by behavioral personalization algorithms to effectively prompt individuals while considering their unique motivational drivers [19]. Future iterations of the Relational Playbook on Whistle will include an educational module for team members in clinical roles to motivate them to learn and engage in culture change, content for virtual and hybrid teams, and additional Whistle tools.

This study's strengths include the real-world evaluation of the Relational Playbook on Whistle and its focus on clinical leadership development. The feasibility approach provided early insights into implementation outcomes, user experience, and potential program impact. However, several limitations should be noted: the small sample size and single-team design, reliance on 1 primary participant, absence of a control group, and lack of objective leadership or patient-related outcomes reduce the ability to attribute observed changes to the intervention. These factors limit generalizability, and findings should be interpreted with caution. Future research will address these limitations by including a larger, more diverse sample; detailed demographic data; a comparison group; and multisource ratings to capture changes in leader behavior and team culture before and after implementation.

The Relational Playbook on Whistle shows strong promise as an acceptable, appropriate, and feasible nurse leadership development program capable of addressing critical workforce challenges such as burnout, team dynamics, and leadership readiness. To maximize its impact, future iterations should include adaptations for virtual teams, streamline program delivery, actively engage all team members, assess the impact on patient safety, and evaluate cost-effectiveness compared to traditional leadership programs. Scaling the Relational Playbook across diverse clinical settings will require strategic collaboration with technology partners to ensure accessibility, flexibility, and sustained implementation. By leveraging digital platforms for leadership development, health care organizations can accelerate skill acquisition, strengthen team culture, and build resilient leaders in an increasingly complex care environment.

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Data Availability

The datasets generated or analyzed during this study are available from the corresponding author on reasonable request after US Department of Veterans Affairs permissions are obtained for release.

Authors' Contributions

MD and HMG conceived the intervention and study design. MD, HMG, and BC designed, collected, analyzed, and interpreted the mixed methods data. All authors contributed to writing and approved the final manuscript.

Conflicts of Interest

MD, BC, and HMG receive salaries from the US Department of Veterans Affairs. The other author declares no other conflicts of interest.

Multimedia Appendix 1
Screenshots from the Whistle platform showing its unique features, with the Relational Playbook's educational content reformatted into a microlearning flash card model incorporating short text, colored images, videos, and kick-off interventions.
[DOCX File, 849 KB - nursing_v9i1e79188_app1.docx]

Multimedia Appendix 2
The 13-item Learning Environment Assessment Tool (LEAT) is an abbreviated version of the validated 64-item Learning Environment Survey. The LEAT assesses key aspects of supportive learning environments, and each item is rated on a 3-point scale (1="rarely," 2="sometimes," and 3="almost always").
[DOCX File, 27 KB - nursing_v9i1e79188_app2.docx]

Multimedia Appendix 3
Primary implementation outcomes assessed using the Acceptability of Intervention Measure, Feasibility of Intervention Measure, and Intervention Appropriateness Measure tailored to the Relational Playbook on Whistle. Each item is rated on a 5-point scale (1="completely disagree"; 5="completely agree") and analyzed using mean scores.
[DOCX File, 49 KB - nursing_v9i1e79188_app3.docx]

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Abbreviations

NP: nurse practitioner
VHA: Veterans Health Administration

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Nurses' Expectations of a Knowledge Management System in Nursing Practice: Qualitative Study

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Abstract

Background: Evidence-based practice is essential for delivering safe, high-quality nursing care; however, its implementation remains challenging due to barriers such as limited knowledge, a lack of supportive organizational culture, and insufficient access to relevant knowledge at the point of care. Knowledge management systems (KMSs) have the potential to bridge this gap by integrating evidence into the nursing process through technological support. Despite growing interest, the integration of KMS into daily nursing practice is still underexplored, especially from the perspective of frontline nurses.

Objective: The aim of this study was to explore nurses' perspectives on the requirements for a KMS that supports evidence-based practice at the point of care, with a focus on usability, process integration into the electronic nursing care plan and patient chart, and implementation challenges and benefits.

Methods: A qualitative study was conducted in a Swiss hospital using observations, focus groups, and individual interviews with 6 registered nurses, 9 advanced practice nurses, 2 nursing managers, and 1 head physician. Data were analyzed using thematic analysis.

Results: The analysis revealed four main categories and ten subcategories: (1) content of the KMS, (2) personal and structural factors of knowledge management, (3) technical conditions of the KMS, and (4) implementation of a KMS. Participants emphasized the need for an intuitively structured, process-integrated system that links evidence-based information directly to nursing interventions in the electronic nursing care plan and patient chart. Organizational support, interprofessional collaboration, and clear responsibilities were identified as critical for successful implementation.

Conclusions: There is a clear need for a KMS that is user-friendly, seamlessly integrated into clinical workflows, and supports quick, reliable access to evidence-based knowledge. A KMS could enhance nurses' access to reliable knowledge, promote evidence-based decision-making, and strengthen professional confidence at the point of care. By embedding evidence directly into the electronic nursing care plan and patient chart, such systems can streamline workflows, reduce time spent searching for information, and support more consistent application of best practices. These capabilities may improve information retrieval and contribute to a safer, more consistent nursing practice.

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KEYWORDS

evidence-based practice; knowledge management; knowledge management system; qualitative research; point of care; nursing

Introduction

Background

Delivering safe, high-quality patient care is a central goal of health care institutions [1] and evidence-based practice (EBP) plays a key role in achieving this [2]. Despite strong advocacy, the integration of scientific evidence into everyday nursing practice remains inconsistent [3]. Studies report that barriers such as insufficient EBP knowledge and skills, lack of mentors and facilitators, perceptions that EBP takes too much time, unsupportive organizational cultures, and environments hinder nurses from using evidence at the point of care [2,3]. At the same time, there is an exponential growth in the body of evidence-based knowledge, which needs to be accessed and integrated into daily nursing practices in a timely and contextually relevant manner [4].

To address these challenges, the concept of knowledge management, widely used in other industries, is gaining traction in health care settings [5]. Knowledge management refers to programs or systems to create, capture, store, organize, and share knowledge and information effectively within organizations [6]. In health care settings, knowledge management has the potential to strengthen nursing performance [7] by facilitating access to both scientific knowledge and the expertise or practice knowledge of team members [5]. However, effective knowledge management in nursing practice requires more than just access; it requires integration into clinical workflows, supportive leadership, and a culture of continuous learning [6,8].

Knowledge management systems (KMSs), as a technological solution, offer a way to embed both evidence-based and practice-based knowledge directly into the nursing process [4]. KMSs are designed to support and enhance organizational processes for creating, storing, retrieving, transmitting, and applying knowledge [9]. When effectively designed and implemented, KMSs can support nurses in making informed decisions, promote EBP, and improve the quality of nursing care [9,10]. Despite this potential, research shows that such systems are rarely used in health care, especially in nursing contexts. To date, there are few descriptions of the development, implementation, and evaluation of KMSs in nursing practice [4]. There is a need to investigate factors on the adoption of a KMSs that are integrated into the nursing process in hospitals from different perspectives [11].

Prior Work and Research Gap

In a prior study, Ranegger et al [12] demonstrated the theoretical feasibility of linking evidence-based knowledge to standardized nursing interventions through a mapping project. While this work provided an essential foundation for embedding evidence in structured nursing documentation, it did not explore how such a system could meet the practical and contextual needs of nurses in clinical settings. Consequently, little is known about what nurses expect from a KMS, how they envision it supporting their workflow, and which organizational factors are required for successful implementation [12].

Aim of This Study

Building on this gap, our study focuses on advancing current research on KMSs in the health care sector by adding a user-centered perspective to support nurses at the point of care.

Therefore, the aim of this study was to qualitatively explore nurses' perspectives on the requirements for a KMS that supports EBP at the point of care, with a focus on usability, process integration into the electronic nursing care plan and patient chart, and implementation challenges and benefits. By identifying these requirements, this study contributes to the development of a KMS that is not only theoretically feasible but also contextually relevant, usable, and sustainable in clinical practice.

Methods

Study Design

An exploratory qualitative study design based on inductive thematic analysis was conducted to gain an in-depth understanding of nurses' perspectives, expectations, and experiences related to the development and implementation of a KMS to support EBP at the point of care. The study followed the COREQ (Consolidated Criteria for Reporting Qualitative Research) guidelines to ensure methodological rigor and transparency [13]. The study was underpinned by a pragmatic theoretical orientation, which assumes that knowledge is constructed through experience and that research should focus on understanding real-world problems and generating practical solutions. This framework guided the exploration of nurses' expectations of a KMS, emphasizing the practical relevance of the findings for system design and implementation.

Researchers' Characteristics

Two researchers collected the data. The first researcher was a female research associate with expertise and training in nursing and health sciences. She holds a master's degree in public health, is specialized in EBP, and has worked as a nurse previously. The second researcher was a male research associate with a master's degree in information systems with research experience in digital health. The researchers were not known to the participants before the study. Participants were informed about the researchers' professional backgrounds, institutional affiliations, and the aim of the study. They also knew about the researchers' roles within the project and that participation was voluntary and anonymous. The researchers were aware that their professional backgrounds could influence how they collected and analyzed data. They therefore reflected these potential biases throughout the analysis to support a balanced understanding of the data.

Participants and Setting

The study was conducted in a hospital in Switzerland that is part of a private hospital group comprising 3 hospitals. The hospital group employs approximately 2500 staff and treats over 140,000 patients annually, including around 27,000 inpatients. At the time of the study, a new intranet was planned to centralize knowledge resources and improve search capabilities.

The study focused on nurses with diverse work experience and role profiles because the KMS was intended primarily for nursing practice. Additionally, 1 physician was included to provide an interprofessional perspective, as physicians are involved in the current system. Only 1 physician was included because the study primarily focused on nursing workflows and physician involvement in the planned KMS was limited during the recruitment period. A purposive sampling strategy was applied via the head of the nursing development department to recruit participants for observations, individual interviews, and focus group interviews. All participants were directly or indirectly involved in nursing-related knowledge management, either as users of or contributors to knowledge sources. Eligibility criteria included active involvement in nursing care or related managerial or educational functions within the hospital. The initial plan was to invite 15 to 20 participants, which was achieved, with 18 individuals confirming attendance.

Data Collection

Prior to data collection, an observation guide and a semistructured interview guide were developed based on a literature review. The researchers first conducted independently 4 hours of open, participatory observation on a ward in November 2023, focusing on the activities of 3 registered nurses during their shifts on a surgical and internal medicine ward and took field notes according to the observation guide. These 3 nurses were not further part of the interviews.

Subsequently, all interviews were conducted using the semistructured interview guide, which was adapted after the observations. The 2 authors held 2 face-to-face focus group interviews in the hospital, with participants grouped by professional hierarchy to encourage open discussion. The first focus group involved 9 advanced nurse practitioners (ANPs) with master's degrees from different wards in the participating hospital (92 min). The second focus group comprised 3 registered nurses with a diploma degree from the surgical ward to capture another perspective (50 min). Three additional online interviews using Microsoft Teams (30 min each) were held with a head physician, a division manager in nursing care, and a co-nursing manager to include different viewpoints. Sociodemographic data from all participants were collected verbally (Table 1). All interviews were conducted between November 2023 and January 2024 and were audio-recorded. Field notes were taken during the interviews. No repeated interviews were carried out.

Table . Sociodemographic characteristics (N=18).

Sociodemographic characteristics	Value
Sex, female, n (%)	18 (100)
Role, n (%)	
Advanced practice nurse	9 (50)
Registered nurse	6 (33.4)
Nursing management	2 (11.1)
Physician	1 (5.5)
Field of work, n (%)	
Surgical	8 (44.4)
Internal medicine	5 (27.8)
Other (eg, orthopedics and oncology)	3 (16.7)
Expert in a field (eg, delirium and breast care)	2 (11.1)
Years of working experience, n (%)	
<5	1 (5.5)
5-10	7 (38.9)
10-15	5 (27.8)
>15	5 (27.8)

Observation notes were translated, summarized, and thematically clustered. The single and focus group interviews were audio-recorded and transcribed by hand. Data analysis took place in parallel with data collection. Data saturation was considered achieved after the third online interview. Consistency between the 2 data collectors was ensured through continuous discussion during data collection and analysis to align interpretation and maintain reflexivity.

Data Management and Analysis

Thematic analysis was conducted following the 6-phase approach described by Braun and Clarke [14]. In addition to the categories already formed a priori through a literature review and by developing the semistructured interview guide, 1 author performed the initial coding of all transcripts using MAXQDA 2022 [15]. Coding decisions and theme development were subsequently discussed with 2 additional authors to ensure analytic consistency and to confirm the relevance of identified categories. Disagreements were resolved through discussion until consensus was achieved. The analysis resulted in main categories and subcategories, which were then translated from German to English.

Ethical Considerations

All participants were informed verbally about the purpose and procedures of the study, data confidentiality, and voluntary participation. Informed consent was obtained before participation, and withdrawal of consent was permitted at any stage, including after data collection. Audio recordings were transcribed verbatim, anonymized to remove any potentially identifiable information, and assigned participant codes before recordings were subsequently deleted. All data were stored securely on password-protected institutional servers in accordance with data protection regulations. No participants withdrew consent for the use of their data in this study. According to Swiss legislation, this study did not require approval by a cantonal ethics committee. In accordance with the Swiss Human Research Act (Humanforschungsgesetz, HFG), ethical approval is mandatory only for research involving human participants where health-related personal data are collected or where interventions are performed [16]. The present study focused exclusively on healthcare professionals' perspectives on KMSs. No patients were involved, no health-related personal data were collected, and no interventions were performed. Therefore, the study does not fall within the scope of the Swiss Human Research Act and did not require formal ethical approval by a Swiss ethics committee.

However, the study was followed in accordance with the World Medical Association's Declaration of Helsinki.

Results

Sociodemographic Characteristics

All 18 participants were nurses with different degrees and roles, except 1 was a head physician. The participants from the observations and interviews had at least 1 year of professional experience and worked in different roles and fields in the hospital (Table 1).

Categories

The thematic analysis resulted in 4 main categories with 10 subcategories, each of which will be discussed in the following sections (Table 2).

Table . Main categories and subcategories of the thematic analysis.

Main categories	Subcategories
Content of KMS[a]	• Information sources • Format of information
Personal and structural factors of knowledge management	• Information retrieval skills • Time pressure and efficiency
Technical conditions of KMS	• Integration into workflow • Knowledge access and architecture
Implementation of a KMS	• Barriers • Facilitators • Expected benefits • Potential quality indicators

[a]KMS: knowledge management system.

Content of KMS

Information Sources

Participants described a clear distinction in information sources used by different roles. At the point of care, registered nurses primarily relied on in-house nursing instructions and team members, which was also observed.

In contrast, ANPs accessed a wider range of formal evidence sources, including databases, guidelines, professional networks, and conferences, which they used to update or develop new nursing instructions. Although digital advancements were mentioned, none of the participants reported using artificial intelligence (AI) tools in their knowledge work. Instead, maintaining clear, up-to-date, and evidence-based nursing instructions was viewed as a central way to ensure consistent practice. Most ANPs and nurses from focus groups would support the inclusion of brief synopses of studies explaining changes and evidence updates in the in-house nursing instructions. These would offer nurses an optional, deeper insight into the rationale behind changes. However, some ANPs and the co-nursing manager were critical of this and questioned whether nurses at the point of care would be using this due to the high workload and limited skills in scientific working.

Format of Information

Participants acknowledged that the current nursing instructions were logically structured and helpful, often featuring tables of contents and uniform formatting. Nurses were instructed to use nursing standards as the main source of information in nursing practice. At the time point of the interviews and observations, it was therefore important that the nursing standards were written in simple language and regularly updated according to the latest evidence.

Registered nurses and ANPs from both focus groups and observations expressed a need for varied formats as a source of information, such as checklists, videos, and schematics, as long as the content remained concise and practice-oriented. The information in the KMS should not be overloaded and it should summarize the most important information as briefly as possible, as an ANP said:

> *I think you have to be careful not to overload nurses with information, to be honest. You have to focus on what you really need in practice. The more it is broken down to the practical situation, the more the knowledge is used.* [P1]

Personal and Structural Factors of Knowledge Management

Information Retrieval Skills

Participants reported that while they were able to locate nursing instructions within their own specialty, accessing materials outside of their immediate practice area was often time-consuming and frustrating. Nurses, particularly those who were new, part-time, or less experienced, struggled to find information when documents were not intuitively filed or when search paths were long and complex. A nurse confirmed this during the observation. Many participants noted that there was no systematic onboarding to teach information-seeking or navigation strategies. Although some suggested additional training, they emphasized that intuitive structure and powerful search functions were more impactful than teaching workarounds. An ANP summarized it as follows:

> *If the search function is poor, it doesn't matter how well you know the system. You still can't find what you need.* [P2]

Time Pressure and Efficiency

Time constraints were a significant concern in information use and acquisition across all participants. Nurses commonly relied on team members and ANPs to obtain information quickly, particularly during high workload periods. In the observations, the nurses asked more experienced nurses or a physician in some cases before searching available documents. All participants would find it helpful to have faster access to information sources at the point of care. These sources should be process integrated, which means embedded in the electronic nursing care plan and patient chart. An ANP said:

> *I often hear that nurses know that a certain nursing instruction exists. They still ask me as an ANP if I can't just tell them the answer quickly so that they do not have to search for the document.* [P1]

Technical Conditions of KMS

Integration Into Workflow

Participants envisioned a KMS integrated into every phase of the nursing process, from patient admission and assessment to diagnosis, intervention, and evaluation. They found it important that the information would be available and could be retrieved exactly when they needed it. The nurses from the focus groups saw the greatest benefit in linking information to nursing interventions, for example, to check how a central venous catheter needs to be connected. The head physician also recognized potential in areas like diagnosis support and medication information:

> *For example, if I select permanent catheters in the nursing care plan, the relevant nursing instruction should be stored there. If access to the information is clearly visible in the nursing care plan, my attention would be drawn to it and I can just click on it. And then the information just comes up. Because if it is not obvious and I don't see it, I won't click on it and won't get to the information. It has to be obvious to me.* [P5]

Knowledge Access and Architecture

All participants criticized the current dual document storage system, which resulted from an ongoing transition to a new intranet. Most participants found the folder structure confusing and the search function ineffective due to a lack of semantic features. Old or irrelevant documents still appeared in search results, adding to the inefficiency. An ANP mentioned:

> *With the folder system, for example, there are folders from the pharmacy, where I think there is a great need for training. Because sometimes you go to an instruction but do not realize that there is also something about [eg,] potassium substitution. And there would be very helpful practical [nursing] instructions. But [most nurses] do not know that they exist.* [P2]

Suggestions from the participants were to install links in the electronic nursing care plan and patient chart with direct access to information. Two ANPs had the idea to create question mark buttons or to provide the information when clicking on nursing interventions or diagnoses of the electronic nursing care plan and patient chart (eg, dressing a wound, assessing the risk of malnutrition, and administering a medication), which was supported by the other ANPs. Links to documents should always point to the latest version, avoiding discrepancies between sources. An additional idea from the interviewed head physician was to link medication prescriptions directly to the electronic nursing care plan and patient chart with instructions for administration. Additionally, powerful search functions and filter options to quickly find relevant information would be helpful for nurses. The goal from the interviewed division manager in nursing care would be a single-source approach where updated instructions were universally accessible. The division maker in nursing care, therefore, said:

> *It must be ensured that the latest version of the nursing instruction is available via the KMS. For example, if you open a link to the nursing instruction from the electronic nursing care plan, the revisions made should also be changed in this document […]. And if something is changed there, I always have the latest version, no matter where I access the document from.* [P7]

Implementation of a KMS

Barriers

Time, money, and personnel constraints were mentioned as the main barriers to the development and implementation of a KMS. The co-nursing manager stressed that the decision-maker of the hospital needs to be convinced of the KMS, as it requires financial investment. The head nurse emphasized that time and financial resources of the hospital must be used sparingly and that the benefits need to outweigh the costs. Additionally, the lack of clarity around responsibilities for integrating KMS content into hospital IT systems was problematic from the head nurses' perspective.

Facilitators

The ANPs saw themselves as responsible for content conceptualization within the KMS. They proposed that IT staff and KMS providers manage the structural and technical implementation. Strong interprofessional collaboration, clear role descriptions, and leadership support were emphasized as important, as an ANP said:

> *The conceptual aspect is for sure with us ANPs. Anything else would be inefficient. But we would not be unhappy if someone else takes care of linking the documents between KMS and the hospital information system.* [P8]

Expected Benefits

Participants believed the KMS would facilitate faster information retrieval, better alignment with current standards, and improved interdisciplinary collaboration. From the head nurse's point of view, this meant that knowledge in nursing could be better preserved and shared. The nurses were convinced that documents were more likely to be used if they were integrated into the nursing process and could be accessed quickly. This could also increase the nurses' sense of safety, as they would always use the correct and updated documents. Moreover, the responsibility for finding the right document would no longer lie with the nurses themselves, as a registered nurse said:

> *And I think it would be of particular benefit to patients, and that is an interprofessional interest. If the nursing staff can stand up afterwards and say, these are our instructions, we have to implement them. The better you know the content of the nursing instructions and the faster you find them, the better you can argue.* [P9]

Potential Quality Indicators

Participants proposed a range of indicators on how to measure the effectiveness of the KMS. The ANPs mentioned direct KMS-related indicators such as time to retrieve information (eg, reduced time to find nursing instructions), task-completion rate (eg, conducting a nursing intervention), need for help in terms of knowledge retrieval (eg, contacting ANP), and user satisfaction with the system. Indirect quality indicators could be downstream outcomes such as quality of care and patient safety. The nurses from the second focus group mentioned the nurses' subjective sense of security when performing nursing interventions as an additional indicator. The head physician and co-nursing manager particularly mentioned the quality of the intra- and interdisciplinary communication, including the perceived ease and frequency of collaboration as further quality indicators. The co-nursing manager said:

> *For me, relevant indicators are the satisfaction and nurses' sense of security in their daily work. The nurses need the information to provide the patient with adequate care.* [P6]

The participants emphasized that an effective KMS should directly support clinical decision-making and increase confidence during care delivery. Nurses frequently linked quick access to correct information with improved performance, lower stress levels, and better patient outcomes. The ANPs and registered nurses believed that evaluating the system's impact should go beyond technical metrics and include experiential factors, such as how secure, informed, and supported they felt while using the system. Furthermore, participants stressed that if a KMS was truly helpful, it would minimize the need for ad hoc knowledge-seeking from team members, reduce errors, and encourage standardized practice across wards. An ANP mentioned:

> *If the information is easy to access whenever they need it, the more they use this information. This, I guess, brings satisfaction because nurses do not have to search a long time for the information and this also indicates a higher sense of security because they know, where they find the information and are well informed.* [P3]

Discussion

Main Results

This study explored nurses' expectations and needs for a KMS integrated into the electronic nursing care plan and patient chart. Participants found the existing hospital information system fragmented and time-consuming. In-house nursing instructions were well-structured but difficult to access due to a confusing filing system and poor search functionality. Nurses often relied on colleagues or ANPs for quick answers, especially under time pressure. Nurses expressed a strong need for a KMS that was integrated into the electronic nursing care plan and patient chart. They envisioned context-sensitive information access, such as clickable links or icons, at each step of the nursing process, from assessment through intervention to evaluation. The system should offer a simplified structure, powerful search functions, and information presented in practical, user-friendly formats like checklists, videos, or brief summaries. To support safe and efficient care, nurses emphasized that information must be both easily retrievable and always up to date. They saw clarity about responsibilities for maintaining the system as essential. Ultimately, they imagined that a well-designed KMS would enhance care quality, streamline workflows, and strengthen nurses' professional confidence at the point of care.

Integrating Knowledge Into Clinical Workflow

Our results show that the current system does not adequately support quick and reliable access to nursing-relevant information at the point of care. Nurses reported relying on team members or navigating complex document systems, often under time pressure. This aligns with findings that emphasize the importance of integrating knowledge tools directly into clinical workflows to reduce search time and cognitive load [4]. Existing help buttons and intranet instructions were appreciated; however, they were not sufficient for efficient knowledge access during daily work. This underscores the importance of embedding knowledge directly into digital workflows. Chorney et al [9] recommended this because they found that integrating KMS into clinical systems significantly improved access and usage. Knowledge embedded in systems not only reduces variation of information and nursing interventions but also supports EBP, given that the content is reliable and up to date [17]. This resonates with the Technology Acceptance Model, which emphasizes perceived usefulness and ease of use as key predictors of usage [18]. The desire for an intuitively designed, workflow-integrated KMS illustrates that these dimensions are central to successful use and implementation.

Information Literacy and the Role of Training

Nurses described variability in their ability to retrieve and apply information, especially among new staff, part-time workers, or those returning from leave. This reflects a broader challenge of information and digital literacy in nursing practice. Training was seen as critical to ensuring consistent access to and use of available knowledge resources. These findings are consistent with earlier studies that show age and experience influence confidence with electronic clinical systems [10] and that tailored onboarding and continued training support more effective system use [17]. Moreover, nurses' literacy influences their attitudes towards and intentions to use KMS [19]. While technical solutions are necessary, they must be accompanied by accessible training formats and support structures to ensure equitable use across roles and experience levels [17].

Evidence Flow and the Role of ANPs

Our study revealed a distinct division of tasks around knowledge sources: while nurses primarily relied on in-house nursing instructions and team members, ANPs engaged with external evidence sources. This distinction reflects the layered process of knowledge use, translation, and transfer outlined by Shahmoradi et al [4]. ANPs acted as translators, adapting external evidence to the hospital's context, while nurses at the point of care used this adapted knowledge. In addition to the application of nursing instructions, information was also transferred via other communication channels such as direct exchange, emails, or newsletters. This confirms findings from Al-Busaidi [20], who emphasized that knowledge transfer in health care often depends on informal systems that are neither systematic nor easily evaluated.

KMS Quality, Functionality, and Usability

A consistent theme in the interviews was the desire for a system that was intuitive, accessible, and available throughout the nursing process. This aligns with previous findings that ease of access and integration into clinical routines are critical success factors for KMS adoption [9]. Participants suggested that its functionalities should include a logical filing system, powerful search capabilities, and support for multiple content formats. This reflects a need for information to be both concise and adaptable to diverse learning preferences [9].

The absence of AI use among participants in the period before and during data collection in 2023 and 2024 also reflects broader hesitations in clinical environments. While AI integration was not expected by participants, its future role in enhancing clinical KMS remains a promising area for development [4]. Regardless of the technology used, the success of the KMS depends on its ability to fit seamlessly into the existing workflow and meet users' needs for quick and trustworthy information [20].

Evaluation and Trust in the System

Participants proposed a range of indicators to evaluate a future KMS, including efficiency gains, time savings, and perceived improvements in quality of care. These are consistent with indicators described by Al-Busaidi [20], who emphasized both organizational and individual-level outcomes such as improved learning, collaboration, and job satisfaction. Nurses in the interviews also framed evaluation in terms of emotional and ethical relief, particularly the idea that linked and validated instructions could reduce their burden of manually searching the "right" document. This does not imply a reduction in professional responsibility but highlights how a well-maintained KMS can support nurses in fulfilling their responsibilities more safely and confidently. This emotional dimension adds a new perspective in understanding trust in digital systems. Trust is shaped not only by technical reliability but also by how systems redistribute responsibility and reduce the risk of error [11]. When knowledge is institutionalized within a centrally maintained KMS, nurses can rely on the organization rather than the individual for ensuring accuracy. This shift reflects a rebalancing of cognitive and ethical responsibility, which can enhance professional confidence and perceived safety in clinical decision-making [21,22].

Organizational Conditions for Success

From the point of view of the head physician, division manager in nursing care, and co-nursing manager interviewed, organizational support emerged as an important factor for KMS success. They highlighted the need for leadership support, funding, and clear roles. These themes are confirmed across multiple studies, which identify infrastructure, staffing, policy support, and leadership engagement as critical to implementation success [1,20]. The findings also align with the Normalization Process Theory, which highlights the processes through which new interventions become embedded in everyday practice [23]. The constructs of shared understanding, cognitive participation, and practical integration are evident in participants' emphasis on collaboration and institutional backing. Organizational culture also plays a key role, as collaborative and open cultures have been found to facilitate KMS adoption more effectively than hierarchical, profit-driven environments [11]. Interviewed ANPs acknowledged the potential value of a KMS, particularly in terms of reducing redundant work and saving time. These findings support the statement from Chorney et al [9], that the success of a KMS is not only a technical or clinical matter, but also a strategic one. For sustainable implementation, the system must align with institutional priorities, demonstrate clear value, and receive long-term support from decision-makers in the setting [20].

Limitations

The main strength of the study was the inclusion of nurses with different levels of work experience and role profiles. This approach allowed for the consideration of multiple perspectives in the implementation of a KMS that was grounded in practical nursing requirements. The interdisciplinary research team balanced clinical and technical expertise but acknowledged that professional backgrounds might have influenced interpretation. Reflexivity was maintained through ongoing discussion to ensure balanced representation of participants' views. Conducting the study in a single hospital allowed for detailed observation of local workflows and knowledge management practices but limits the transferability of findings to other settings with different structures or digital maturity. Another limitation concerns the conceptual nature of the topic, as the study explored expectations for a KMS that has not yet been developed. Finally, the data were collected in German and then translated into English. These translations were rigorously checked by authors fluent in both languages.

Implications for Nursing Practice and Research

Our findings underscore the importance of designing a KMS that supports nurses' real-time information needs at the point of care. Seamless integration into the electronic nursing care plan and patient chart, intuitive navigation, and access to up-to-date, evidence-based instructions in various formats were seen as essential. Nurse managers should prioritize training, onboarding processes, and continuous support, especially for new, part-time, or returning staff.

There is a need for further research on the design and usability of KMS tools, especially those that leverage emerging technologies such as AI for knowledge synthesis and decision support. Future studies should also explore the implementation and effects of KMS at the point of care. Further investigation into the quality indicators identified by nurses for measuring KMS impact could support the development of validated evaluation frameworks. Future projects from the authors focus on developing and piloting an AI-supported KMS. It aims to provide personalized, evidence-based recommendations tailored to nurses' skill levels and workflows, thereby enhancing safety, quality, and efficiency at the point of care.

Conclusions

Participants expressed a clear need for a KMS that is user-friendly, seamlessly integrated into clinical workflows, and supports quick, reliable access to evidence-based knowledge. A well-designed KMS may have the potential to not only improve care quality and efficiency but also to enhance nurses' confidence and sense of safety in their daily work.

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Authors' Contributions

Conceptualization: RR, JV (equal), SZ (supporting)
Data curation: MV, JV (equal)
Formal analysis: MV
Funding acquisition: RR, JV (equal)
Methodology: MV, SM, GW-J, RR, JV (equal)
Project administration: JV
Writing – original draft: MV
Writing – review & editing: SM, GW-J, RR, SZ, JV (equal)

Conflicts of Interest

The authors declare that they have no competing interests. LEP provides health care intervention classifications but no knowledge management system and therefore has no competing interests in this study.

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Abbreviations

AI: artificial intelligence
ANP: advanced nurse practitioner
COREQ: Consolidated Criteria for Reporting Qualitative Research
EBP: evidence-based practice
KMS: knowledge management system

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Insights Into Factors Affecting Nurses' Knowledge of and Attitudes Toward AI and Implications for Successful AI Integration in Critical Care: Cross-Sectional Study

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Abstract

Background: Assessing the current landscape of nurses' knowledge and attitudes is a critical first step in facilitating a smooth and effective transition toward artificial intelligence (AI)–enhanced critical care.

Objective: This study aimed to assess the levels of and factors affecting the knowledge of and general attitudes toward AI in critical care among nurses.

Methods: A cross-sectional correlational design was used with 203 critical care nurses in Hail, Saudi Arabia, using the Nurses' AI Knowledge Questionnaire and the 20-item General Attitudes Toward Artificial Intelligence Scale from May 2025 to July 2025. Data were analyzed using 2-tailed *t* tests, ANOVA, Pearson correlation, and multivariable linear regression. Statistical significance was set at *P*<.05.

Results: Critical care nurses demonstrated moderate knowledge of (mean score 4.93, SD 1.78) and positive attitudes toward AI (mean score 64.39, SD 8.26). A moderate positive correlation was found between knowledge of and attitudes toward AI (r=0.45; *P*<.001). In multivariable analyses, older age was associated with lower knowledge (≥40 years: β=−1.29, 95% CI −2.12 to −0.45; *P*=.003) and less positive attitudes (β=−8.97, 95% CI −12.49 to −5.44; *P*<.001). Female nurses reported lower knowledge (β=−0.69, 95% CI −1.20 to −0.19; *P*=.007) and less positive attitudes (β=−2.65, 95% CI −4.78 to −0.52; *P*=.02) than male nurses. Greater experience (>5 years) was positively associated with knowledge (β=1.20, 95% CI 0.65 - 1.75; *P*<.001) and attitudes (β=8.08, 95% CI 5.76 - 10.41; *P*<.001).

Conclusions: Critical care nurses in Hail demonstrated moderate knowledge of and positive attitudes toward AI, which varied based on their demographic and professional characteristics. These findings highlight the need to strengthen AI literacy and provide targeted support to groups with lower scores, which may enhance readiness for AI integration in critical care settings.

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KEYWORDS

artificial intelligence; AI; knowledge; attitudes; factors; critical care nurses; Saudi Arabia

Introduction

The global health care model is undergoing a great revolution directed by the rapid incorporation of artificial intelligence (AI) [1,2]. AI is defined as a system designed to perceive the environment and take action to achieve specific goals [3]. AI encompasses machine learning, natural language processing, and robotics [2,4]. In medicine, AI has vast and promising potential for enhancing diagnostic precision; personalizing treatment plans; optimizing operational efficiency; and, ultimately, improving patient outcomes [5,6]. This technological shift aligns with global initiatives such as Vision 2030, which actively encourages innovation and digital transformation within its health sector to build a robust, data-driven health care system [7,8].

Critical care units, including intensive care units and emergency departments, represent environments with exceptionally high pressure [9]. Clinicians in these settings are required to process large amounts of complex, real-time patient data to make swift decisions. AI applications can be leveraged for the early detection of patient deterioration, prediction of sepsis, forecasting intensive care unit length of stay, and managing ventilatory support. These capabilities support clinical decision-making and potentially reduce human burden [10]. By automating routine tasks and administrative burdens, AI can free critical care nurses (CCNs) and physicians to focus on more complex clinical reasoning and direct patient care. This shift enhances both the efficiency and humanistic aspects of treatment [11].

As frontline clinicians, nurses are pivotal to the successful adoption of new technologies in clinical practice [12]. Their role involves continuous patient monitoring, assessment, and execution of complex care plans, making them key end users of AI-driven tools. Therefore, the effective integration of AI into critical care is linked to nurses' acceptance, which is shaped by their knowledge, attitudes, and willingness to incorporate these technologies into their workflow [13,14]. However, the introduction of AI in the nursing domain has sparked debate. While some view AI as a tool to augment nursing practice and mitigate workload, others perceive it as a threat to the essential human-to-human interactions that form the bedrock of compassionate care. This difference in perspective raises concerns about dehumanization and ethical implications [15-17].

A significant barrier to AI's integration is the current underrepresentation of nurses in the development, implementation, and evaluation of AI systems for health care [18,19]. This gap can lead to a misalignment among technological solutions, actual clinical needs, and workflow. Furthermore, studies have indicated that nurses' perceptions of AI are mixed and vary widely based on their understanding of its capabilities, reliability, and potential to replace human judgment [20]. Therefore, assessing the current landscape of nurses' knowledge and attitudes is a critical first step in facilitating a smooth and effective transition toward AI-enhanced critical care.

Previous research has begun to explore health care professionals' perspectives on AI, but studies focused on CCNs within the Middle Eastern context, particularly in Saudi Arabia, remain limited. Understanding the demographic, educational, and experiential factors that influence these perceptions is crucial for developing targeted educational and training programs. As critical care environments become increasingly technologically advanced, ensuring that the nursing workforce is not only proficient but also confident and ethically grounded in using AI is paramount.

This study aimed to bridge this knowledge gap by assessing CCNs' level of knowledge of and general attitudes toward AI in Hail, Saudi Arabia. The findings provide valuable insights for hospital administrators, educators, and policymakers in designing strategies that foster AI literacy and address concerns. The ultimate goal is to harness the full potential of AI to support rather than replace the critical role of nurses in delivering high-acuity patient care.

Methods

Design, Setting, Population, and Sample

A cross-sectional correlational design was used in this study. The target population of this study comprised CCNs employed in public hospitals located in the Hail region. After obtaining institutional review board approval, meetings were conducted with the heads of critical care units across participating hospitals. In addition, formal communication was established with continuing nursing education offices within these institutions. The survey was designed using Google Forms. The link to the questionnaire and informed consent form was disseminated to the CCNs. Participants were first given an electronic information sheet outlining the study's goals, procedures, risks, benefits, confidentiality measures, and voluntary nature of participation. Data collection was conducted over 3 months, from May 2025 to July 2025. Eligibility criteria required participants to have at least 1 year of continuous experience working in critical care departments, ensuring that only nurses with sufficient exposure to clinical practice in critical situations were included. Nurses serving primarily in administrative roles, as well as those with less than 1 year of critical care department experience, were excluded to maintain a focus on direct patient care providers with adequate professional backgrounds. The required sample size was determined using OpenEpi (version 3.01). On the basis of an estimated total population of approximately 420 CCNs in the region, the minimum sample size necessary to achieve adequate statistical power was 201, with a 95% confidence level and 5% margin of error. To enhance representativeness and mitigate the potential impact of nonresponses, 220 self-administered questionnaires were distributed. Of these 220 questionnaires, 203 (92.3%) were returned. The electronic survey required responses to all the items before submission; therefore, there were no missing data.

Instruments

The questionnaire consisted of 3 parts. In the first part, the characteristics of the nurses, including their age, sex, marital status, educational level, years of experience, type of shift work, unit type, and prior experience with AI in health care, were examined. We used a previously validated tool by Swed et al [21] (the Nurses' AI Knowledge Questionnaire) in the second segment of the questionnaire to gauge nurses' awareness of AI. It consists of 7 yes-or-no questions regarding common AI terms used in health care designed to gauge nurses' familiarity with this key vocabulary. The scoring system is as follows: "yes" answers are scored as 1 point, and "no" answers are scored as 0 points. The total score ranges from 0 to 7, with a higher score indicating a higher level of knowledge regarding AI terminology [21]. As Swed et al [21] noted, the Cronbach α value of 0.795 demonstrated the tool's internal consistency among the subscales. In this study, the reliability of this instrument was confirmed with a Cronbach α of 0.765.

The 20-item General Attitudes Toward Artificial Intelligence Scale (GAAIS) created by Schepman and Rodway [22] constituted the third section of the questionnaire. It gauged nurses' opinions on the use of AI in medical environments. The items are divided into positive (12 items) and negative (8 items). Positive items are scored on a 5-point Likert-type scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree." Negative items are reverse scored, with 1 denoting "strongly agree" and 5 denoting "strongly disagree." Thus, the scores range from 20 to 100, with higher scores on each subscale reflecting more positive attitudes [22]. According to Schepman and Rodway [22], the GAAIS has demonstrated a high degree of internal consistency, with Cronbach α values for the 12 positive items and 8 negative items being 0.88 and 0.82, respectively. In this study, reliability was confirmed with a Cronbach α of 0.969 for positive items and 0.952 for negative items.

Ethical Considerations

Institutional review board approval was obtained from the University of Hail (H-2025-718) on March 10, 2025, and from the Ministry of Health (2025-37) on March 18, 2025. In compliance with institutional review board approval, informed consent was obtained electronically: participants were required to study the information page before completing and submitting the survey, which constituted informed consent. The participants' anonymity and confidentiality were maintained throughout the study. As the survey platform required all items to be completed before submission, there were no partial responses or missing data. No compensation or incentives were provided for participation in the study.

Data Analysis

SPSS Statistics (version 27; IBM Corp) was used to analyze the data. The Shapiro-Wilk test was used to test for normality of the data (P>.05). Independent-sample t tests and one-way ANOVA were used to investigate the relationship between the dependent and independent variables. Using multivariable linear regression analysis, significant factors affecting CCNs' knowledge and attitudes were identified. Correlations between variables were assessed using the Pearson correlation coefficient. The P value was set at less than .05.

Results

Table 1 shows that most participants were aged 20 to 29 years (121/203, 59.6%), male (129/203, 63.5%), and single (140/203, 69%). Most nurses held a bachelor's degree (141/203, 69.5%), worked rotating shifts (131/203, 64.5%), and had 5 years or less of nursing experience (117/203, 57.6%). Younger nurses showed significantly higher knowledge of (P=.01) and more positive attitudes toward AI (P=.002) than older nurses. Male nurses reported higher knowledge and more positive attitudes than female nurses (P<.001 in both cases). Single nurses scored higher on knowledge (P=.03) and attitudes (P=.046) than married nurses. Nurses with a master's degree had higher knowledge (P=.02) and more positive attitudes (P<.001) than those with a bachelor's degree. Additionally, nurses with more than 5 years of experience exhibited higher knowledge (P=.02) and more positive attitudes (P<.001) than less experienced nurses.

Table . Relationship between critical care nurses' (CCNs) sociodemographic characteristics and knowledge of and attitudes toward artificial intelligence (N=203).

Variable and categories	CCNs, n (%)	Knowledge			Attitudes		
		Score (0-7), mean (SD)	*t* test (*df*) or *F* test (*df*)	*P* value	Score (20-100), mean (SD)	*t* test (*df*) or *F* test (*df*)	*P* value
Age (years)			4.61 (2)[a]	.01		6.55 (2)[a]	.002
20-29	121 (59.6)	5.20 (1.68)			65.60 (8.16)		
30-39	60 (29.6)	4.68 (1.94)			63.96 (8.44)		
≥40	22 (10.8)	4.09 (1.60)			58.90 (5.99)		
Sex			3.78 (201)[b]	<.001		3.54 (201)[b]	<.001
Male	129 (63.5)	5.27 (1.65)			65.90 (8.32)		
Female	74 (36.5)	4.32 (1.85)			61.75 (7.53)		
Marital status			2.20 (201)[b]	.03		1.88 (201)[b]	.046
Single	140 (69.0)	5.11 (1.71)			65.12 (8.62)		
Married	63 (31.0)	4.52 (1.88)			62.77 (7.22)		
Educational level			−2.35 (201)[b]	.02		−4.02 (201)[b]	<.001
Bachelor's	141 (69.5)	4.73 (1.80)			62.90 (7.17)		
Master's	62 (30.5)	5.37 (1.68)			67.79 (9.56)		
Shift type			−0.41 (201)[b]	.68		−1.09 (201)[b]	.28
Day	72 (35.5)	4.86 (1.78)			63.54 (7.79)		
Rotating	131 (64.5)	4.96 (1.79)			64.86 (8.51)		
Experience (years)			−2.41 (201)[b]	.02		−4.38 (201)[b]	<.001
≤5	117 (57.6)	4.67 (1.78)			62.30 (6.91)		
>5	86 (42.4)	5.27 (1.73)			67.23 (9.12)		

[a]*F* test.

[b]2-tailed *t* test.

The mean score for CCNs' knowledge of AI was 4.93 (SD 1.78; range 2 - 7), indicating a moderate level of knowledge. The mean score for attitudes was 64.39 (SD 8.26; range 47 - 95), reflecting a generally positive attitude toward AI (Table 2).

Table 3 shows that there was a moderate positive correlation between CCNs' knowledge of and attitudes toward AI (r=0.45; P<.001). This finding indicates that higher knowledge levels are associated with more positive attitudes.

Table . Means of critical care nurses' knowledge of and attitudes toward artificial intelligence (N=203).

Variable	Score, mean (SD; range)
Knowledge (0-7)	4.93 (1.78; 2-7)
Attitudes (20-100)	64.39 (8.26; 47-95)

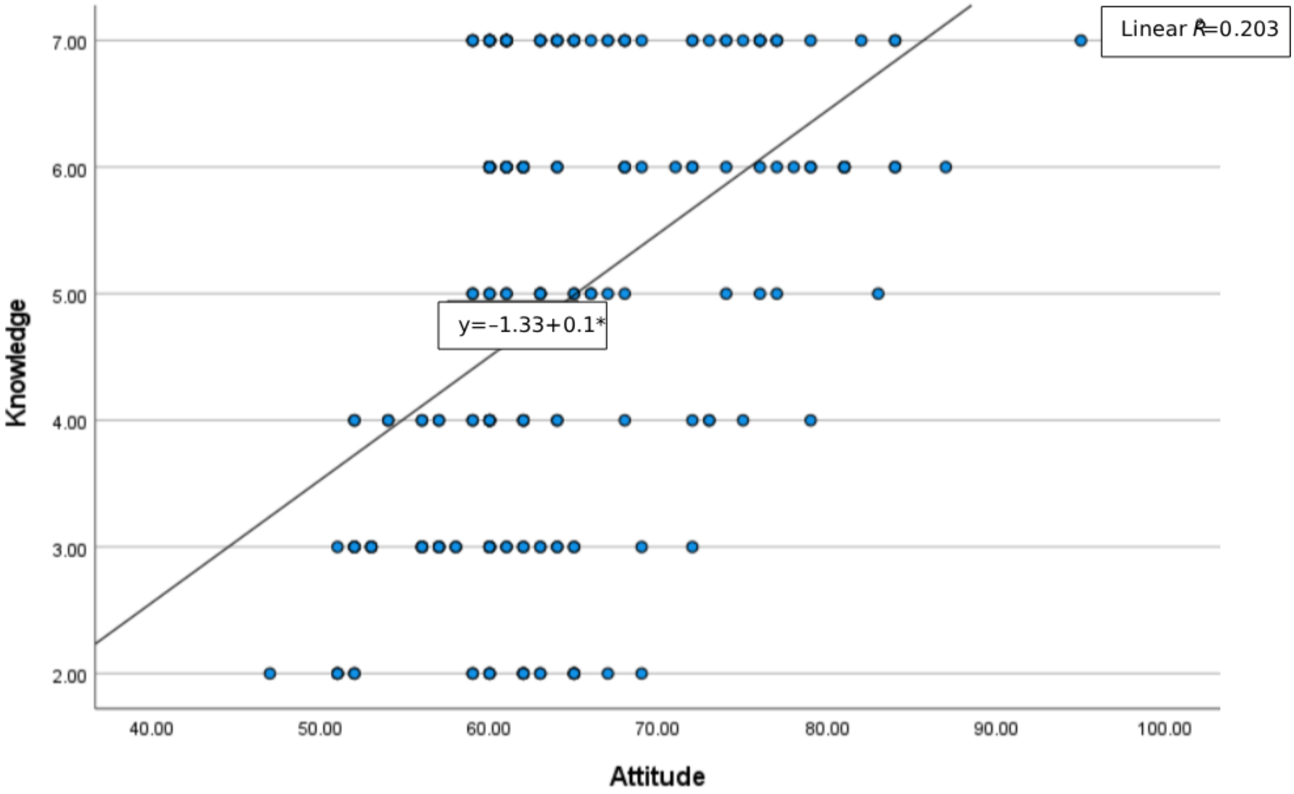
Table . Correlation between study variables (N=203).

	Knowledge	Attitudes
Knowledge	1	0.45
Attitudes	0.45[a]	1

[a]Correlation is significant at the .01 level (2 tailed).

Figure 1 illustrates the moderate positive correlation between CCNs' knowledge of and attitudes toward AI. The scatterplot shows that higher attitude scores were associated with higher knowledge levels. The regression line indicates a significant positive linear relationship (R^2=0.20, P<.001), suggesting that attitudes were associated with approximately 20% of the variance in knowledge.

Figure 1. Scatterplot of the correlation between critical care nurses' knowledge of and attitudes toward artificial intelligence.



The regression models identified several sociodemographic predictors of CCNs' knowledge of and attitudes toward AI. Age and sex were found to be significant predictors of knowledge. Nurses aged 30 to 39 years (β=–0.80; *P*=.02) and those aged ≥40 years (β=–1.29; *P*=.003) had lower knowledge scores than those aged 20 to 29 years. Similarly, female nurses reported significantly lower knowledge scores than their male counterparts (β=−0.69; *P*=.007). In contrast, nurses with more than 5 years of experience had significantly higher knowledge levels (β=1.20; *P*<.001). The model's R^2 was 0.19 (adjusted R^2=0.17; *P*<.001), indicating that the included predictors were associated with approximately 19.4% of the variability in knowledge scores.

Age, sex, educational level, and experience were significant predictors of attitudes. Nurses aged 30 to 39 years (β=–4.81; *P*=.001) and those aged ≥40 years (β=–8.97; *P*<.001) reported less positive attitudes than those aged 20 to 29 years. Female nurses had significantly less positive attitudes than male nurses (β=–2.65; *P*=.02). Conversely, nurses with a master's degree (β=3.38; *P*=.002) and those with more than 5 years of experience (β=8.08; *P*<.001) demonstrated more positive attitudes. The model's R^2 was 0.33 (adjusted R^2=0.31; *P*<.001), indicating that the included predictors were associated with approximately 33.2% of the variability in attitude scores (Table 4).

Table . Multiple linear regression for factors affecting critical care nurses' knowledge of and attitudes toward artificial intelligence.

Factor	Knowledge[a]		Attitudes[b]	
	β (95% CI)	*P* value	β (95% CI)	*P* value
Age (years)				
20-29	Reference	Reference	Reference	Reference
30-39	−0.80 (−1.47 to –0.14)	.02	−4.81 (−7.59 to –2.02)	.001
≥40	−1.29 (−2.12 to –0.45)	.003	−8.97 (−12.49 to –5.44)	<.001
Gender				
Male	Reference	Reference	Reference	Reference
Female	−0.69 (−1.20 to –0.19)	.007	−2.65 (−4.78 to –0.52)	.02
Marital status				
Single	Reference	Reference	Reference	Reference
Married	−0.44 (−0.98 to 0.10)	.11	−1.73 (−4.01 to 0.55)	.14
Educational level				
Bachelor's degree	Reference	Reference	Reference	Reference
Master's degree	0.40 (−0.10 to 0.90)	.12	3.38 (1.270 to 5.492)	.002
Experience (years)				
≤5	Reference	Reference	Reference	Reference
>5	1.20 (0.65 to 1.75)	<.001	8.08 (5.76 to 10.41)	<.001

[a]R^2=0.19; adjusted R^2=0.17; *P*<.001.
[b]R^2=0.33; adjusted R^2=0.31; *P*<.001.

Discussion

CCNs' Knowledge of and Attitudes Toward AI

This study provides a timely investigation of CCNs' knowledge of and attitudes toward AI in the Hail region of Saudi Arabia, a context undergoing rapid digital transformation as part of Vision 2030. The findings revealed a moderate level of AI knowledge (mean score 4.93, SD 1.78) and a generally positive attitude (mean score 64.39, SD 8.26) among CCNs. Crucially, a significant positive correlation was established, indicating that higher levels of AI knowledge were associated with more favorable attitudes. This aligns with the technology acceptance model (TAM), which posits that perceived usefulness and ease of use are key determinants of technology adoption and that these perceptions are inherently linked to an individual's understanding of the technology [23-25]. Our results suggest that educational interventions aimed at improving AI literacy could be a powerful lever for enhancing acceptance among the nursing workforce.

Predictors of CCNs' Knowledge of and Attitudes Toward AI

Sociodemographic analyses yielded insightful results. Younger nurses (aged 20-29 years) exhibited significantly higher knowledge and more positive attitudes than their older counterparts. This generational divide is consistent with the broader literature on technology adoption, where younger individuals, often "digital natives," tend to be more comfortable and familiar with emerging technologies [26,27]. This finding underscores the need for age-tailored training programs that support more experienced nurses in developing comparable levels of perceived ease of use and usefulness, thereby reducing TAM-related barriers among older staff while leveraging their clinical expertise.

Gender emerged as a significant predictor, with male nurses reporting higher knowledge and more positive attitudes than female nurses. This disparity may reflect broader societal and educational trends in the science, technology, engineering, and mathematics fields, where gender gaps in confidence and participation persist [28]. In the nursing context, which is predominantly female in many countries but has a different demographic profile in regions such as Saudi Arabia, this finding underscores the need for equitable access to AI training and leadership opportunities. Ensuring that these opportunities are encouraging and available to all genders is essential to preventing a new form of digital gender divide within the profession. From a TAM perspective, such differences may translate into unequal perceptions of ease of use and self-efficacy with AI systems, highlighting the importance of designing AI training and leadership opportunities that actively foster confidence and perceived control among women to prevent a digital gender divide in nursing.

Educational attainment has a strong positive influence. Nurses with a master's degree had significantly more positive attitudes and higher knowledge scores than those with a bachelor's degree. This finding reinforces the pivotal role of advanced education in fostering a forward-looking, evidence-based, and innovative mindset. This suggests that integrating AI concepts and applications into postgraduate nursing curricula is essential for preparing future nurse leaders [6,29]. Furthermore, contrary to what might be assumed, nurses with more than 5 years of experience reported higher knowledge and more positive attitudes. This compelling finding challenges the notion that experienced clinicians are resistant to change. Instead, it implies that experienced nurses, with their developed clinical expertise, may better appreciate AI's potential to alleviate cognitive burdens, reduce errors, and enhance patient safety [11].

The regression models indicated that 19.4% of the variance in knowledge and 33.2% of the variance in attitudes were related to demographic factors. However, other variables not measured in this study also played a significant role. These could include organizational culture, quality of previous technology implementation experiences, perceived organizational support for training, and the level of trust in the institution's data governance and ethical frameworks [30,31]. Future research should explore these organizational and psychological determinants to provide a more holistic understanding of the factors that influence AI integration in nursing.

Correlation Between CCNs' Knowledge of and Attitudes Toward AI

The moderate positive correlation between knowledge and attitude (r=0.45; P<.001) strongly implies that resistance or skepticism toward AI is not unchangeable but can be mitigated through education and exposure. Within the TAM framework, this implies that structured education and meaningful hands-on experience can reshape nurses' beliefs about AI's usefulness and ease of use, moving them from passive compliance to active, informed adoption of AI tools in clinical workflows. This finding aligns with the work by Dornan [32], who suggested that a basic understanding of AI is essential for its acceptance and use in clinical practice. When nurses understand how AI works, what it can offer, and what its limits are, the technology becomes less intimidating [32]. This awareness helps them move from being passive recipients of change to being active and informed participants. Such a shift encourages genuine engagement rather than simple compliance [32]. Therefore, the observed link highlights the need for targeted education programs designed to build nurses' confidence and skills in working with AI, ensuring that technology, rather than distance, enhances nursing care. Thus, the primary barrier is not an inherent opposition to technology but a lack of structured and accessible education on what AI truly entails in nursing practice.

Implications for Nursing Education and Practice

The findings underscore the need for specific measures to improve AI preparedness among nurses through education. Older, female, and less experienced nurses had less knowledge of and a negative attitude toward AI, suggesting possible gaps in confidence and exposure that must be addressed through systematic training activities. Incorporating fundamental AI principles and practical applications into undergraduate and postgraduate nursing courses is critical for ensuring that all future nurses are prepared to work with developing technology. In nursing practice, continuing professional development programs that include practical training, simulation-based learning, and case-based scenarios can help improve comprehension and minimize anxiety. Furthermore, nursing professionals with a more optimistic mindset can act as clinical representatives to assist in collaborative learning and ensure the smooth integration of AI in critical care settings. Improving AI literacy across the nursing profession will eventually lead to safer and more efficient clinical practice and successful incorporation of AI-driven strategies in patient care.

These findings are particularly important in the context of Saudi Arabia's ambitious health sector reforms. For AI to be successfully leveraged to build a robust, data-driven health care system as envisioned in Vision 2030, the readiness of the nursing workforce is fundamental. Aligning educational strategies, professional development, and organizational policies with TAM principles by explicitly targeting perceived usefulness, ease of use, and supportive conditions can help translate the current foundational willingness among nurses into sustained, confident use of AI in everyday practice. Our study confirms that foundational willingness is present but must be actively cultivated through targeted, demographically sensitive, and continuous educational strategies.

Strengths and Limitations

This study has several strengths. First, it addresses a significant gap in the literature by focusing specifically on CCNs in the underresearched Middle Eastern context, thus providing valuable insights for regional policymaking and educational planning. The use of validated instruments such as the Nurses' AI Knowledge Questionnaire and the GAAIS enhances the reliability and validity of the findings. Furthermore, the high response rate (203/220, 92.3% returned questionnaires) and rigorous sample size calculation strengthened the statistical power and representativeness of the results for the target population in Hail.

Despite these strengths, this study has several limitations that must be acknowledged. The cross-sectional correlational design captures a snapshot in time and cannot establish causality between the variables. This study was conducted in a single region of Saudi Arabia (Hail), which may limit the generalizability of the findings to other regions or countries with different cultural and health care infrastructures. The reliance on self-reported data for knowledge and attitudes is susceptible to social desirability bias, in which participants may have provided answers that they believed were expected rather than their true beliefs. Finally, the knowledge assessment was based on a 7-item yes-or-no questionnaire, which, while reliable, may not capture the full depth and nuance of a nurse's understanding of AI concepts and applications.

Recommendations

On the basis of this study's findings, the following recommendations are proposed.

Recommendations for Practice

Health care institutions should implement structured, ongoing AI education programs that build basic literacy for all CCNs and provide advanced modules for those in higher-responsibility roles. These programs should use practical, critical care examples to enhance perceived usefulness and ease of use. Targeted support is also needed for older and female nurses who showed lower knowledge and more negative attitudes through tailored workshops, mentorship, and simulation-based training to ensure equitable AI readiness. Additionally, nurses with master's degrees and more than 5 years of experience should be leveraged as AI champions to mentor colleagues and support effective implementation across critical care teams.

Recommendations for Education

Nursing schools and universities should integrate core AI content—concepts, clinical applications, ethics, and limitations—into undergraduate curricula while expanding advanced, practice-oriented AI training in postgraduate programs, reflecting the strong association between higher education and more positive perceptions. Alignment between academic preparation and workplace training will create a continuous pipeline of nurses who are both knowledgeable about and favorably disposed toward AI in critical care.

Recommendations for Policy

Hospital leadership and AI developers should systematically involve CCNs from diverse age groups, genders, and educational backgrounds in the design, piloting, and evaluation of AI tools because the regression results suggest that attitudes and knowledge are shaped partly by contextual and experiential factors beyond demographics alone. Participatory implementation can improve the perceived relevance and usability of AI systems, thereby reinforcing the positive relationship between knowledge and attitudes and supporting Saudi Arabia's Vision 2030 for a technology-driven, nurse-ready health care system.

Conclusions

This study demonstrated that CCNs in Hail, Saudi Arabia, possess a moderate level of knowledge and a generally positive attitude toward AI, with a clear correlation between the 2. Key sociodemographic factors, including age, sex, educational level, and clinical experience, significantly influenced these perceptions. The findings underscore that the successful integration of AI into critical care is not a technological challenge but a human-centric one. Readiness of the nursing workforce is a critical determinant of success. By investing in comprehensive, inclusive, and continuous education and actively involving nurses in the development process, health care leaders can harness the full potential of AI. This will ensure that these powerful technologies act as supportive tools that augment the clinical judgment and compassionate care provided by nurses, ultimately leading to enhanced patient outcomes and the realization of a technologically advanced, efficient, and resilient health care system as envisioned in the Saudi Vision 2030.

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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: HA
Data curation: HA, SMA, NA, KAS, HL, SAA
Formal analysis: SAA
Investigation: HA, SMA, NA, KAS, HL
Methodology: HA, SAA
Resources: HA, SAA
Validation: HA
Visualization: HA
Writing – original draft: HA
Writing – review & editing: HA, SMA, NA, KAS, HL, SAA
All authors read, revised, and accepted the final version of the manuscript for publication.

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence
CCN: critical care nurse
GAAIS: General Attitudes Toward Artificial Intelligence Scale
TAM: technology acceptance model

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Perception of AI Symptom Models in Oncology Nursing: Mixed Methods Evaluation Study

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Abstract

Background: Patients undergoing cancer treatment experience a significant symptom burden. The standard process of symptom management includes patient reporting and clinical response following symptom escalation. Emerging predictive symptom models use artificial intelligence (AI) components of machine learning and deep learning to identify the risk of symptom deterioration, facilitating earlier intervention to prevent downstream effects. However, integrating predictive symptom models into clinical practice will require oncology nurses to adopt innovative approaches.

Objective: This study aims to explore oncology nurses' perceptions of the use of predictive symptom models in cancer care and the factors influencing the adoption of this symptom care innovation.

Methods: The evaluation was guided by the Rogers Diffusion of Innovation Theory, which describes the process of how individuals adopt new technologies. The investigators developed an interview guide that asked oncology nurses to rate their perceptions of AI symptom models on a Likert scale. Participants were also asked to provide qualitative comments to support their ratings for each question, in order to better understand the key factors that would influence AI predictive model adoption. Investigators analyzed demographic data and Likert ratings with descriptive statistics. Qualitative analysis of participant comments included content analysis and inductive coding to identify themes. Nurses' perception of factors that would influence the adoption of AI symptom models, based on the Rogers theory, included relative advantage, compatibility, complexity, trialability, and observability.

Results: Responses of 15 oncology nurses with more than 1 year of experience in oncology were analyzed. There was high agreement among nurse participants that an AI model could improve symptom management for patients with cancer (n=10, 67%) and increase early intervention to prevent the escalation of symptoms (n=12, 86%). All participants (N=15) agreed that receiving symptom information would be helpful. Nearly three-quarters of participants (n=11, 73%) endorsed that the information would save time. Most (n=12, 80%) recommended that clinicians receive information about the predicted symptom deterioration of their patients. Among open-ended responses, key themes were consistent with factors identified in the Diffusion of Innovation theory including: (1) perceptions related to the AI model (compatibility or complexity), (2) nurses' perception of patients' benefit (observability), (3) improved clinical processes (relative advantage or observability), (4) apprehension over model accuracy and impact (compatibility or trialability or observability), and (5) implementation or adoption (trialability or complexity or observability).

Conclusions: Oncology nurses agree that predictive symptom models could help improve symptom management for patients undergoing cancer treatment. However, nurses noted that transparency in the factors included in the AI model was essential, that nurses should be involved in the development and testing of models, and that the observability of the benefit in symptom care would need to be evident for ultimate adoption.

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KEYWORDS

artificial intelligence; AI; oncology; nursing; symptom management; implementation

Introduction

Patients undergoing cancer treatment experience a wide range of symptoms that impact functional status, quality of life, and health care use [1-3]. Currently, symptom reporting is a reactive process based on patient reporting, followed by a response for poorly controlled symptoms. Oncology nurses have historically screened patients both at clinical visits and via phone triage when patients report increasing symptom burden [3]. Increasingly, but slowly, clinical workflows are implementing symptom monitoring with electronic patient-reported outcome (ePRO) systems, which enable patients to report symptoms electronically and allow oncology clinicians to respond accordingly [4]. However, the ePRO-based symptom management decreases care escalations, which is notable given that worsening of symptoms is a primary driver of health care use among patients with cancer [3]. However, oncology symptoms can change rapidly, and some, such as fever, require prompt evaluation and clinical action [5,6]. While responsive ePRO reporting systems have improved patient symptom burden, high levels of symptoms and health care use persist. ePRO symptom models remain reactive, with detection following a patient reporting a change and lacking the ability to anticipate symptom escalations.

One application of artificial intelligence (AI) is the use of computer-based models to analyze large quantities of data, in this case, symptom data. Predictive symptom models attempt to evaluate data and detect a change prior to patient symptom escalation. AI models are being tested using retrospective and prospective data [7]. AI models, paired with ePRO collection, are being developed to enable predictive and anticipatory warnings that may help categorize patients at an increased risk of symptom escalation [8]. AI models use patient-generated data to predict the likelihood of a specific outcome or a set of outcomes [8]. Models to diagnose both diseases and symptoms, as well as health care use, are being integrated into oncology use cases [7,9]. Predictive symptom models, which inform the identification of symptom patterns, show promise as a mechanism to enhance the accuracy of symptom detection before escalation [7,10]. AI-derived alerting models, using machine learning (ML) or deep learning methods, have the potential to predict emerging symptom escalations. These models seek to prioritize patients at increased risk for changes before symptom escalation. Detecting symptoms, such as an impending fever, before the patient experiences it can facilitate earlier intervention and better outcomes [11]. Alternative predictive approaches are necessary to detect dynamic symptom changes while reducing the burden of symptom reporting.

Transitioning to proactive care models requires a complete shift, both cognitively and operationally, for both patients and clinicians. Moving from a reactive reporting structure to a predictive symptom management model requires adoption by the oncology team. Notably, the implementation of this shift will require the engagement of oncology nurses, who will be the clinicians responsible for responding to AI-based alerts.

Few studies have examined nurses' perceptions of implementing AI-based symptom models [12]. A recent study that assessed nurse perspectives on ML-based clinical decision support systems broadly found that previous experience with technology and nurse perceived engagement in the development process, among other factors, influenced perceived use of ML clinical decision support systems [13]. The use of AI in the clinical setting is expanding, and a key theme consistently identified by nurses, nurse informaticists, and nurse leaders regarding the development, implementation, and adoption of AI-based tools is the importance of engaging nurse end-users at the beginning of the development process [14-16]. Thus, the purpose of this evaluation was to examine nurses' willingness to adopt AI-derived alert notifications about impending symptom escalations. In anticipation of implementing these AI-based symptom management systems, this exploration addresses an existing gap in the literature regarding oncology nurses' perceptions, including usefulness and anticipated efficiency, of AI-derived symptom prediction models for cancer symptom management.

The Rogers Diffusion of Innovation Theory describes the process of how users decide to participate in the adoption of new technologies [17] and framed our work to nurses' consideration to adopt AI. Using AI-based models in clinical practice will require a significant transition from current symptom evaluation processes, and oncology nurses, who are largely responsible for symptom triage, will need to adopt and use this innovation in care management workflows. Perception of the innovation, rather than the innovation itself, is key to adoption. The Diffusion of Innovation theory identifies 5 perceived attributes that influence adoption, including relative advantage, for this study whether the AI predictive models are perceived as improving current symptom monitoring and would benefit patients; compatibility—whether the AI predictive models are consistent with symptom treatment values, past experiences, and the needs of nurses providing symptom care; complexity—whether AI predictive models are seen as easy to understand and use; trialability—whether the AI predictive models can be piloted and tried out; and observability—whether the symptom management benefits of the AI predictive models can be seen by the nurses. According to the theory, adoption occurs at varying speeds based on individual characteristics and perceptions, such that a small percentage of the population will be innovators and early adopters, and others are more likely to adopt later after others have accepted the innovation. The focus of this study is on these factors and how they may influence nurses' perceptions and decision-making about the adoption of AI predictive symptom models.

Methods

Design, Setting, and Participants

We conducted a mixed methods exploration of oncology nurses' perspectives regarding the use of AI-based symptom predictive models to detect symptom changes in patients with cancer. The use of both structured questionnaire (eg, Likert-scale questions) and interview questions allowed for a more in-depth analysis of perspectives regarding the adoption of AI predictive symptom models and is well-suited for implementation research [18] Specifically, we conducted interviews with participants using both structured, Likert-scale–based questions and open-ended questions.

A convenience sample of registered nurses with at least 1 year of experience in oncology from across the United States was recruited to participate in this project. Participants were excluded if they lacked fluency in spoken or written English, lacked access to Zoom (Zoom Communications, Inc) web-conferencing technology or were unable to meet in person, or if they had less than 1 year of experience as a nurse in oncology. Recruitment methods included direct professional referrals, social media (such as LinkedIn and Facebook), and snowball sampling. Investigators contacted participants via email to schedule interviews. Interviews, the duration of which ranged from 20 to 30 minutes, were conducted in December 2024 and January 2025 via web teleconferencing platform (Zoom) and in-person by 2 investigators (BN and EAS). Interviews were not recorded or transcribed, though detailed notes were kept by the investigators who conducted the interviews and included capturing verbatim quotes from participants.

Individual Interviews

The team developed the interview guide (Multimedia Appendix 1) to gather information on the acceptability of implementing AI predictive symptom monitoring and management. The interview guide was initially drafted by 2 investigators (BN and EAS) and feedback was obtained from other members of the team before being finalized (Multimedia Appendix 1). Before starting the interview, as outlined in the interview guide, the concept of an AI-based symptom model was presented to the participants. The description was broad in that it included general model types but emphasized the predictive capability of AI algorithms in the identification of symptom deterioration. In addition to demographic questions, the final interview guide consisted of 6 total Likert-scale questions, in which participants responded to statements about the hypothetical clinical usefulness and efficiency of a symptom prediction model, indicating their agreement or disagreement using the Likert scale (1=“Strongly Disagree“ to 5=“Strongly Agree”). Following each Likert-scale question, participants were asked to provide open-ended comments in response to the Likert-scale question that they had previously answered. Three additional open-ended questions were meant to elicit additional information, for example, “If you received a notification that your patient is at high risk for experiencing worsening symptoms in the next 24 hours, what would you do?”

Saturation was assessed on an ongoing basis. No new information was elicited, and subsequently, no new codes were identified over the final 5 interviews, indicating that we achieved content-level saturation.

Data Analysis

Quantitative Analysis

Descriptive analyses, including means and SDs, were calculated using demographic data to describe the sample. Due to the small sample size, we rounded frequencies (percentages) to the whole number. Additionally, investigators evaluated the frequency of Likert ratings by participants through descriptive statistics. The Likert-scale ratings were on a 1 to 5 rating with responses initially coded based on a 1 to 5 rating (1=“Strongly disagree,” 2=“Disagree,” 3=“Neutral,” 4=“Agree,” and 5=“Strongly agree”). However, in further analyses, we combined ratings of 1 to 2 and 3 to 5 to create categorical ratings of “Disagree,” “Neutral,” and “Agree.” Methodologically, this approach is used to improve interpretability in smaller sample sizes, which have limited responses in multiple categories [19]. Our quantitative analysis of Likert-scale responses ultimately provided a clearer picture of the reportable trends within the sample.

Qualitative Analysis

For qualitative analysis, the team members (BN and EAS) used open coding and initially coded qualitative responses independently. After resolving disagreements and reaching consensus on codes, the investigators recoded each qualitative interview. Data were then analyzed using thematic analysis which involved several steps: data familiarization, keyword selection, identification of initial themes, and comparison of the investigators’ initial themes.

Triangulation

In keeping with a mixed methods approach, the investigators synthesized quantitative and qualitative data and identified findings that converged, complemented, or diverged across data modalities [20,21]. Quantitative data from Likert-scale responses were triangulated concurrently with qualitative, open-ended responses to the questions and/or follow-up prompts. Finally, the investigators compared the codes for the factors within the Diffusion of Innovation Model. Participant quotes were used to represent themes. We used the GRAMMS (Good Reporting of a Mixed Methods Study) guidelines to aid clarity of reporting (Checklist 1) [22].

Ethical Considerations

The University of Utah Institutional Review Board reviewed the project protocol and deemed it a quality improvement project and not human participants research (00166873). Each participant was informed of the purpose of the project, including that participation was and could be discontinued at any time for any reason. Verbal consent was obtained prior to proceeding with the interview. No compensation was provided to the participants. In accordance with the rigor of human participants research, the study team followed procedures to protect the participants’ privacy and confidentiality, including deidentifying participant data, not sharing data outside of the study team, and storing data securely on password-encrypted computers.

Results

User Statistics

Sample characteristics are summarized in Table 1. The sample included 15 nurses who self-identified as working in oncology for more than 1 year. Participants were all female (15/15, 100%) with a mean age of 44.6 (SD 11.44) years. The cohort consisted of an experienced group of nurses, with an average of 18.33 (SD 9.82) years of nursing experience. Most of this experience (mean 14.10, SD 9.92 y) was in oncology. Participants reported working in diverse oncology settings, including inpatient oncology and outpatient infusion, as well as in roles related to quality improvement and patient navigation (Table 1). Furthermore, the sample was highly educated, with 8 out of 15 (53%) having completed a master's degree (Table 1).

Table . Participant demographics (N=15).

Characteristics	Participants
Age (y), mean (SD)	44.6 (11.44)
Years of experience, mean (SD)	18.33 (9.82)
Years of experience in oncology	14.10 (9.92)
Highest level of education, n (%)	
Diploma	1 (7)
Bachelor's degree	4 (27)
Master's degree	8 (53)
Doctoral	2 (13)
Practice environment, n (%)	
Inpatient oncology	4 (26)
Outpatient oncology	8 (53)
Quality	1 (7)
Navigation	2 (13)

Quantitative Evaluation

Results are presented in categorical (agree or disagree) percentages for the 6 Likert-scale questions (Table 2). All nurse participants overwhelmingly agreed that receiving the symptom information would be helpful, signaling compatibility with existing values. Furthermore, 12 out of 15 (86%) nurses believed that an AI model would enable early intervention to prevent the escalation of symptoms, aligning with this view. Most nurses (12/15, 86%) also thought that an AI model would allow the relative advantage of early intervention to prevent the escalation of symptoms. A smaller majority, or 10 out of 15 (67%) nurses, agreed that an AI model could improve symptom management for patients with cancer. The remaining one-third or 5 out of 15 (33%) participants were neutral about whether the symptom prediction model could help improve symptom management related to the disease. There was similar agreement on the expectation that a symptom prediction model would enhance a patient's quality of life, with 10 out of 15 (67%) nurses agreeing. From an efficiency perspective, 11 out of 15 (73%) nurses felt that the information may save time. Despite nurses obtaining significant volumes of clinical information during a clinical day, 12 out of 15 (80%) nurses recommended that clinicians receive information about the predicted deterioration of their patients.

Table . Perceptions of artificial intelligence (AI) predictive ratings' value in oncology symptom management (N=15).

Topic	Disagree, n (%)	Neutral, n (%)	Agree, n (%)
Knowing that a patient is at risk of symptom deterioration earlier is helpful information for me to have as an oncology clinician	0 (0)	0 (0)	15 (100)
I expect that information from an AI model would allow me to intervene earlier, preventing an escalation of patient symptoms.	0 (0)	2 (13)	12 (86)
I would recommend oncology clinicians receive information about predicted deterioration from an AI algorithm when caring for patients with cancer.	1 (7)	2 (13)	12 (80)
Having this information might save me time and/or help improve my efficiency in helping my patients reduce their symptom burden	1 (7)	3 (20)	11 (73)
I expect information from an AI model would add to reducing symptom burden and improve my patients' quality of life.	2 (13)	3 (20)	10 (67)
I expect information from an AI model would help me better manage symptoms related to cancer treatment or disease.	0 (0)	5 (33)	10 (67)

Only 1 out of 15 (7%) respondents indicated that they believed AI-based symptom models would not improve efficiency or would not recommend that oncology clinicians receive information regarding patient deterioration from an AI symptom model. A small number, 2 out of 15 (13%) nurses indicated that AI-based symptom models would not reduce symptom burden or improve quality of life. These concerns reflect fears of complexity, given the complete shift in operational paradigm. A higher percentage of respondents, ranging from 13% to 33%, were neutral in their responses, indicating that they were still considering the information on the innovation.

Qualitative Evaluation

Themes

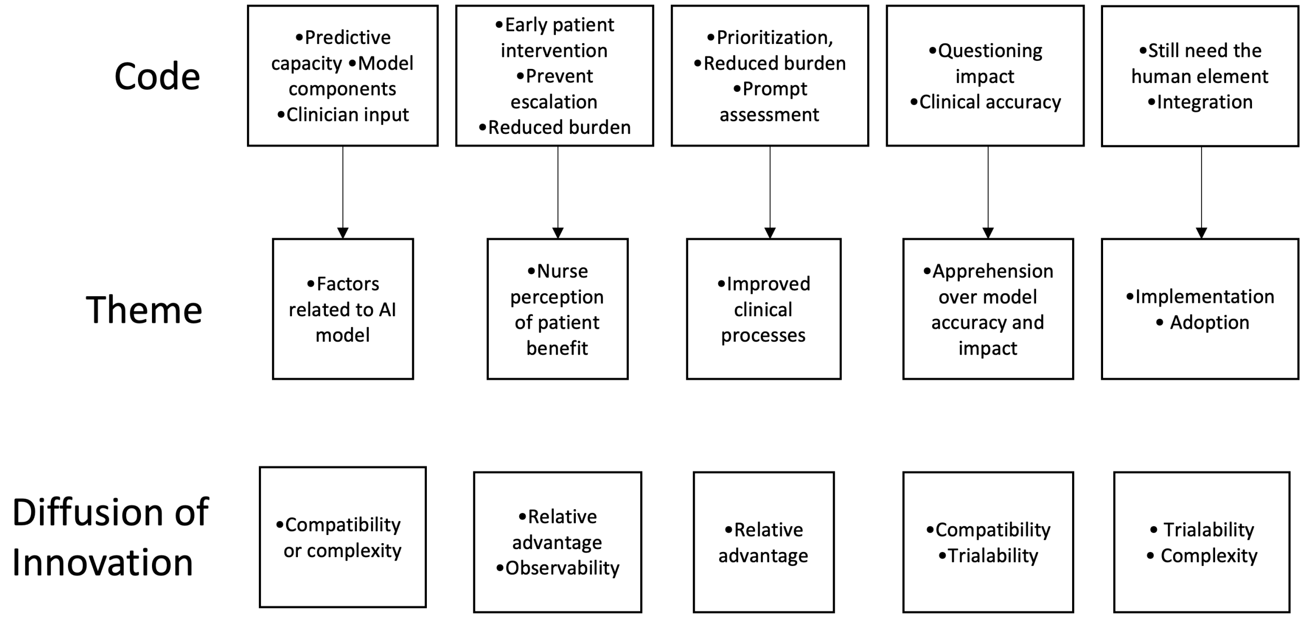
Participants' comments further explained their perceptions about the development of symptom prediction models, including: (1) factors related to the AI model (compatibility or complexity), (2) nurse perception of patient benefit (relative advantage or observability), (3) improved clinical processes (relative advantage), (4) apprehension over model accuracy and impact (compatibility or trialability), and (5) implementation or adoption (trialability or complexity). Table 3 displays the identified themes, perceptions influencing adoption, and select quotes. Figure 1 highlights the development of themes from codes and the attributes of the Diffusion of Innovation Theory.

Table . Themes, codes, participant number, and quotes.

Themes	Perception attributes	Codes	Exemplar quote(s)
Factors related to the AI[a] model	• Compatibility • Complexity	• Predictive capacity • Model components • Clinician input	*I think it might help if the algorithm says the patient is likely to develop a fever. What would I do with that information if there were no infectious symptoms? It might be helpful if managing a lot of patients helps someone to rise to the top for check-ins.* [Participant 11] *Depends on where they get their data from. We already know when chemotherapy induced nausea will occur... so if AI is using appropriate standardized resources, I would be fine with that.* [Participant 8]
Nurse perception of patient benefit	• Relative advantage	• Early patient intervention • Prevent escalation • Reduced burden	*...a lot of time patients wait until symptoms are worse to call. We can intervene sooner.* [Participant 14] *Oncology patients can deteriorate quickly, this could help get symptoms before out of control to avoid ER/ hospital visit.* [Participant 1] *If a [model] did exist I would highly recommend [it] to prevent or mitigate life events to help prevent life or death.* [Participant 6]
Improved clinical processes	• Relative advantage	• Prioritization • Reduced burden • Prompt assessment	*Prioritization should occur digitally, rather than me doing it, adding more to my work burden.* [Participant 12] *Delays in care, due [to patient] burden of calling in. The RN reaching out directly could increase patient satisfaction and response.* [Participant 12]
Apprehension over model accuracy and impact	• Compatibility • Trialability • Observability	• Questioning impact • Clinical accuracy	*Based on clinical practice, you can usually pinpoint those patients anyway.* [Participant 12] *I don't really know if I would fully trust every time until it proves itself.* [Participant 3]
Implementation or adoption	• Complexity • Trialability • Observability	• Still need the human element • Integration • Workflow • Communication of model output (eg, notifications, text) • Ease of use • Alert fatigue	*AI can't supersede one-on-one contact.* [Participant 10] *[I] would want notifications if they are interruptions… I would want [them] to be relevant.* [Participant 12]

[a]AI: artificial intelligence.

Figure 1. Codes, themes, and diffusion of innovation category. AI: artificial intelligence.



Factors in the AI Model

Themes focused heavily on nurses' ability to understand the factors within the model and test it to assess its predictive capacity, components, and provide input into its development. Predictive capacity refers to the model's ability to make accurate assessments of future behavior. For example, participants emphasized the importance of the model being accurate and relevant to the patient's clinical presentation, reflecting the need for compatibility with existing systems. For example, one participant stated:

> *[I would want to know] … what led to notification, reason behind alert… what was their trend before… algorithm that shows patients who exhibit X also show Y, in the context of what's going on with the specific patient.* [Participant 15]

Participants also commented on specific factors necessary as model components, such as temperature and respiration. Nurses strongly emphasized the importance of involving oncology clinicians in the development of the AI model, highlighting their need to understand its compatibility with current systems.

Patient Benefit

Another theme identified was the benefits to patients, which included codes for early patient intervention, prevention of escalation, and reduced patient burden, all of which are compatible with current systems. Early patient intervention, as noted by many participants, was identified as a benefit of AI-based symptom management and is defined as having contact with the patient in a manner that occurs earlier than standard care as a relative advantage. For example, participants noted that a model could allow them "to intervene earlier before symptoms progress into dangerous situations" (Participant 2) or "prevent hospitalization and improve quality of life by managing symptoms at home" (Participant 8). Early intervention is the mechanism by which ePRO alerting systems have effectively decreased escalations of care from a current setting to a higher level of care, such as an emergency room. Other participants disagreed that patients would benefit more than they already do, with one participant stating:

> *I don't think the AI model will provide much additional information...Nurses already watch for specific symptoms.* [Participant 13]

Nurse participants also focused heavily on reducing the burden of cancer care delivery on patients. They highlighted the fact that the combination of early intervention, for example, early symptom detection, can prevent later-stage symptoms and care escalations, thereby improving the experience of cancer care, which aligns with the goals of current systems, but may also represent perceived advantages over the current system.

Enhanced Clinical Processes

Participants could envision that an AI-based symptom model may enhance the process of clinical care by improving prioritization and response times, thereby facilitating the prompt assessment of clinically significant changes in a manner superior to current systems. Additionally, participants felt that the process of care could decrease clinical burden, for example, stating "being able to streamline information would be helpful" (Participant 7). Nurses also reported wanting to reduce the patient's need for reporting and the burden of care escalations to clinicians. However, some participants also expressed concerns that the model could increase clinical burden and highlighted concerns about complexity, noting:

> *The nurse will have to contact the patient. Just because they have an alert doesn't mean they will have the symptoms.* [Participant 10]

Model Accuracy

Participants also reported it would be imperative to test the model to verify its accuracy, noting that nurses would be more likely to use a model they could participate in testing. Participants cautioned that patient engagement may influence the clinical accuracy of the tool. Many nurses have progressed beyond the initial knowledge stage and are now considering not only whether, but also how, systems should adopt AI symptom models. Nurses have experience in integrating new technologies into clinical practice; as such, they understand the importance of accepting innovation to facilitate its diffusion and optimal use. Nurse participants also reported some apprehension about the use of AI models. Specifically, participants voiced concerns about the effectiveness and clinical use. Participants noted that training the model with the correct inputs would be crucial in confirming the model's accuracy.

Implementation Processes

Nurses' comments emphasized that decision-making also depends on the practical implementation of AI-based models. Evaluation and trialability of escalation alerts would be necessary for both initial and long-term adoption. Participants reported that AI-based predictive alerts for symptom management will not replace human nurse assessment and response. Participants also noted that the integration into the workflow needs to be seamless. There were many comments related to the importance of ensuring that communication of model output to nurses and other clinical staff does not increase the time burden, though many thought it would. For example, one participant noted, "I don't know it will save time, [it] may add time, but that is the sacrifice to catch something early" (Participant 12). Furthermore, most participants expressed a firm belief that a model could be easy to use and would not contribute to alert fatigue.

Discussion

Principal Findings

The majority of our sample of nurses agree with statements that support the use of AI-based symptom models, reflecting nurses' belief that these models may represent a relative advantage to current practice. The themes that nurse participants identified as essential to the adoption of AI symptom models aligned with the Diffusion of Innovation Theory. Nurses have recognized that the compatibility of AI-based symptom models holds promise for predicting, detecting, and enabling a response to changes in patient symptoms. Nurses' strong agreement to receive symptom information via new models revealed an overall favorable view of this type of model and alignment with existing values. These models align with nurses' strong commitment to providing patients with the best possible care, and by fostering the potential for AI-based symptom management models to improve patient care. Specific benefits identified by participants include improving clinician response by increasing the information clinicians receive and reducing patient burden through the elimination of unnecessary reporting or care escalations. This type of agreement indicates that nurses have progressed beyond the knowledge stage in the innovation process, toward identifying the necessary information to adopt the use of models. Overall, oncology nurses have positive views regarding the perceived advantages for patients and the compatibility with current care. This study demonstrates that many nurses have positive perceptions of the advantages and usability of AI-based symptom models and are now considering the implementation and use beyond the potential value.

Despite support for adoption, nurses urged caution in the development and implementation of these models. In particular, nurses emphasized the importance of involving end-users in the development, pilot testing, and implementation of these models, as this will help determine their value and appropriate integration into clinical workflow, thereby facilitating their adoption. Nurses have experience in integrating new technologies into clinical practice; as such, they understand the importance of accepting innovation to facilitate its diffusion and optimal use. This aligns with a framework developed for designing and implementing AI models from a systematic review, which recommends the inclusion of health care providers in development and implementation [8].

Nurse participants recognized the importance of trialability through accurately training and testing models, as well as ensuring that the data sources used are adequate to positively impact patient outcomes. Nurses strongly felt that model development requires the careful selection of clinically appropriate inputs, such as the inclusion of temperature and laboratory values, to support clinically accurate results. Confirming models that are appropriate for the input data and the desired outcomes is necessary for accuracy. As frontline users, nurses who currently assess patient symptoms should be included in model factor selection and testing. Often, these models are developed in collaboration with other clinical providers, and yet nurses will be the ones to receive the alerts and need to triage them. Trialability and observability for nurses, not just physicians, are keys to adoption. These themes are consistent with the recommendations for transparency in the development of AI-based clinical models, ensuring that both clinicians and patients understand and agree on the inputs to the model [23]. Creating transparent and explainable models is a step toward combating the perpetuation of healthcare bias in AI models and will facilitate long-term adoption [24,25].

While participants identified the need to understand model inputs and testing, they also reported a need to see the model's impact on outcome to feel confident in making clinical decisions based on the model, again underscoring the importance of observability. Model outcome achievement depends on the implementation of models as designed. For this to occur, there must be transparency and trialability of both inputs and clinical outcomes. For example, our early work developing a predictive model demonstrated the ability to predict symptom escalation more accurately in short intervals than at longer intervals [10]. Transparency will enable clinical teams to implement models for the purpose they were developed, thereby supporting accuracy. Efforts to transform and train models for additional uses will need to follow proper rigor to ensure the models are adapted and updated effectively. Transparency and inclusion in development will enable oncology nurses to effectively use AI-based models.

Experienced oncology nurses in our sample reported both a strong interest in using and some reluctance to immediately trust AI-based symptom models. While involving nurses in the development and implementation will facilitate trust, oncology nurses may lack the education and training to understand how these models work. An extensive national survey of nurses revealed that only 30% of nurses are aware of how AI is used in nursing practice [26]. Although information regarding the use and daily applications has increased in the last several years, this highlights the need to provide AI education to both students and to disseminate it to nurses at the point of care delivery. Future work should specifically evaluate the education needs of oncology nurses regarding AI-based symptom models.

With many clinical symptom escalation models still in development, gaining a clear understanding of nurse perceptions regarding the use, decision to adopt, and maintenance of these models is essential. Our examination revealed that oncology nurses share similar concerns to those documented in the literature regarding the use of clinical predictive models, including alert fatigue and increased time burden, which represent a source of complexity [27]. Additional barriers to adoption of AI technology in healthcare include ethics, technological considerations such as data access and infrastructure, and liability and regulatory issues [28]. However, as evidenced in our results, nurses also hold favorable perceptions that these models have advantages and align with current treatment values, prioritizing the reduction of cancer symptom burden. Implementation strategies that could be used to overcome adoption barriers include, but are not limited to, identifying implementation champions as well as ensuring adequate interpretability of the model [29,30]. AI-based symptom models have the potential to improve patient outcomes and enhance clinical processes when implemented thoughtfully into the clinical workflow. As the end users of AI-based symptom management models, nurses should be involved as content experts, beginning with model development and continuing through the design, integration, and evaluation of the model into workflows, to maximize both short-term implementation and long-term adoption. However, additional research is needed to identify which implementation strategies are effective at promoting the adoption and sustained use of AI-based symptom management models.

Limitations

We sought to elicit oncology nurses' initial thoughts on AI-based symptom prediction models. We should continue to inductively evaluate nurses' adoption of AI. Our exploration was limited by a small sample size and a homogenous population that was skewed by age (older) and education levels (high) that impacts the generalizability of our findings. This may be attributable to our convenience sampling approach and the fact that participants recommended other individuals who were recruited to participate, possibly introducing selection bias. Both the sample skew and homogeneity may have influenced the overall positive perceptions of an AI model for use in symptom management. Additionally, the use of unrecorded and note-based qualitative data analysis may have limited our ability to accurately assess content-level saturation; however, we believe that the detailed notes taken by interviewers permitted accurate assessment of content-level saturation. Finally, while we used the Rogers Diffusion Theory of Innovation to improve the descriptive analysis of the qualitative themes, it may limit our understanding of the responses and future work. Further work should survey a larger sample of nurses to understand oncology nurses' perceptions of AI symptom models and consider the impact of education levels on their views regarding AI. Additionally, future work should highlight the gaps in nurses' understanding of the application of AI in clinical care. The inclusion of end users in the design and testing of AI-based models facilitates adoption, and additional work should concentrate on and focus on implementation processes, which include user-centered design testing of best practices, such as alerting, alert visualization, and responses to care.

Conclusions

Overall, nurses showed a positive attitude toward the adoption of AI-based symptom models, particularly highlighting the perceived advantages of such models and their compatibility with nurses' goals of enhancing the patient experience. Proper use of AI symptom prediction models creates the opportunity to decrease the burden of patient reporting of cancer symptoms, improve clinician responsiveness, and enable prompt intervention to reduce unnecessary care and escalations. To facilitate the seamless integration of AI-based symptom models, thoughtful inclusive design strategies must include end users to test and modify transparent clinical models for long-term adoption.

Acknowledgments

There was no use of artificial intelligence, including generative artificial intelligence, in the development of the study or in the generation of text, tables, figures, or informational content of this manuscript.

Data Availability

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

Authors' Contributions

Conceptualization: BN, EAS, AS, JF, KM
Data curation: BN, EAS
Formal analysis: BN, EAS
Methodology: BN, EAS
Software: BN, EAS
Validation: AS, JF, KM
Visualization: EAS

Writing–original draft: BN, EAS, KM
Writing–review and editing: BN, EAS, AS, JF, KM

Bridget Nicholson is a consultant for Daymark Health. All other authors have nothing to disclose.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Symptom Care at Home (SCH) artificial intelligence (AI) model interview script.
[DOCX File, 33 KB - nursing_v9i1e82283_app1.docx]

Checklist 1
GRAMMS Checklist.
[DOCX File, 8 KB - nursing_v9i1e82283_app2.docx]

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Abbreviations

AI: artificial intelligence
ePRO: electronic patient-reported outcome
GRAMMS: Good Reporting of a Mixed Methods Study
ML: machine learning

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Retraction: Comparative Effectiveness of Health Communication Strategies in Nursing: A Mixed Methods Study of Internet, mHealth, and Social Media Versus Traditional Methods

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The JMIR Publications Editorial Office is retracting the article "Comparative Effectiveness of Health Communication Strategies in Nursing: A Mixed Methods Study of Internet, mHealth, and Social Media Versus Traditional Methods" by Hamarash et al [1]. This follows an investigation that identified concerns regarding the integrity of the peer-review process that occurred for this article. We regret that these issues were not identified prior to publication.

Not all authors agreed with the retraction.

Reference

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Community Health Nurses' Knowledge and Perceptions of AI in Canada: National Cross-Sectional Survey

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Abstract

Background: Artificial intelligence (AI) continues to expand into nursing and health care. Many examples of AI applications driven by machine or deep learning are in use. Examples include wearable devices or alerts for risk prediction. AI tends to be promoted by nonnurses, creating a risk that AI is not designed to best serve registered nurses. Community health nurses (CHNs) are a small but essential group. CHNs' familiarity with AI and their perceptions about its effect on their practice are unknown.

Objective: The research aims to understand CHNs' awareness, knowledge, and perceptions of AI in practice and gain insights to better involve them in AI.

Methods: An online cross-sectional Canadian survey targeting CHNs was conducted from April to July 2023. Descriptive statistics summarized respondents' characteristics and perceptions of AI, followed by a chi-square test used to determine a relationship between respondents' level of AI knowledge and their AI perceptions, with odds ratio (OR) to determine the strength of association.

Results: A total of 228 CHNs participated with varying response rates per question. Most respondents were female (172/188, 91.5%), average age of 45.5 (SD 11.7) years, and an average of 13.5 (SD 10.1) years of community practice experience. Most respondents (205/228, 89.9%) felt they welcomed technology into their practice. They reported their understanding of AI technologies as "good" (95/220, 43.2%) and "not good" (125/220, 56.8%). Overall, 39.6% (80/202) of respondents felt uncomfortable with the development of AI. They agreed that AI should be part of education (143/203, 70.4%), professional development (152/202, 75.2%), and that they should be consulted (195/203, 96.1%). Many respondents had concerns related to professional accountability if they accepted a wrong AI recommendation (157/202, 77.7%) or if they dismissed a correct AI recommendation (149/202, 73.8%). Respondents with "good" AI knowledge were significantly associated with, and twice as likely to indicate nursing will be revolutionized (P=.007; OR 2.28, 95% CI 1.25-4.18), nursing will be more exciting (P=.001; OR 2.52, 95% CI 1.42-4.47), health care will be more exciting (P=.004; OR 2.3, 95% CI 1.30-4.06), and agreed that AI is part of nursing (P=.01; OR 2.1, 95% CI 1.19-3.68). Respondents with "not good" AI knowledge were significantly associated with, and more likely to feel uncomfortable with AI developments (χ^2_1=4.2, P=.04; OR 1.84, 95% CI 1.03-3.3).

Conclusions: CHNs reporting "good" AI knowledge had more favorable perceptions toward AI. Overall, CHNs had professional concerns about accepting or dismissing AI recommendations. Potential solutions include educational resources to ensure that CHNs have a sound basis for AI in their practice, which would promote their comfort with AI. Further research should explore how CHNs could be better involved in all aspects of AI introduced into their practice.

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KEYWORDS

registered nurses; community health nurses; artificial intelligence; survey; machine learning

Introduction

Background

Artificial intelligence (AI) covers a broad array of AI-driven applications supported by machine learning (ML) or deep learning, which have potential utility in health care and nursing practice. Many examples of AI-driven care applications exist, from wearable devices for automated detection of signs and symptoms [1], automated assessment of outcomes to support the need for a different level of care [2,3], client-specific automated predictions of risks [4-7], and bots to answer inquiries and send reminders [8]. Despite widespread uptake and use, AI is commonly driven by nonnurses (ie, scientists, engineers, and the technology industry) [9,10] and physicians [11]. The lack of participation by registered nurses (RNs) creates a risk that AI will not be designed to best serve RNs who are expected to use AI applications and their outcomes in clinical practice [11-13]. Likewise, it is unknown whether community health nurses (CHNs) have thought about how AI applications could change their practice or how AI might be useful to inform clinical practice.

The community setting has a smaller group of RNs compared to the acute care sector [14]. CHNs are RNs who provide essential services in a variety of roles (eg, home health, public health, and primary care) within community settings (eg, clients' home and schools) [15]. Home health clients are most often older adults with multiple comorbidities [2], or individuals who have chronic [16,17] and unstable conditions [18]. Public health clients can be any age, as the focus of care is on promoting better health with service delivery to groups or individuals [15]. Within these settings, CHNs make the best care decisions based on the information that exists, as well as considering other subtleties that can affect these decisions. Regardless of the setting in the community, CHNs have increased autonomy [15,17,19], and clients have reduced nursing oversight because of time between visits [20]. This decreases the amount and frequency of the client-specific data collected. Further, CHNs focus on human connections and building trustful relationships while recognizing the strengths of individuals and communities to promote and improve their health [15]. These features support the importance of having CHNs who understand the practice area involved in AI.

Nursing research within the community sector is expanding to include a focus on the use of AI (eg, ML) as a method to improve real-time risk predictions [5,20,21] and to assist with better planning or targeting of service delivery [16]. Although involving CHNs would be key to raising the right questions for AI, as well as advising and validating results [22], few researchers are reporting this type of CHN involvement in AI development. More commonly, researchers are using existing collected data [16,21,23]. This passive involvement misses the opportunity of actively involving CHNs who are familiar with the data they collect and how it may add insight to clinical issues. However, in one example, a nonnurse researcher [24] describes using CHNs to advise and evaluate throughout an AI project, concluding that nursing input validated outcomes and facilitated acceptance of the AI algorithm into practice. Hence, nursing involvement provides a relevant perspective and knowledge that influences their informed decisions, which ensures clinical relevance and accuracy of AI and related ML [24,25]. These revelations add impetus to examine CHNs' perceptions of AI in their practice and to consider how they could be better involved.

Purpose Statement

This study aims to establish a baseline understanding of Canadian CHNs' awareness, knowledge, and perceptions of current and future effects of AI on their clinical practice. This will help to gain insights into how CHNs could be better involved in AI. Therefore, the research questions guiding this study include: (1) Are CHNs aware of the emergence of AI, including ML applications, in nursing? (2) What are CHNs' main sources of knowledge for learning about current day-to-day AI? (3) How do CHNs describe their level of knowledge of AI technologies? (4) Is there a relationship between CHNs' level of knowledge of AI technologies and their perceptions of the effects of AI on clinical practice, professional accountability, and the usefulness of AI applications? (5) What AI competencies do CHNs perceive as being needed in their community practice?

Methods

Ethical Considerations

Research approval was granted from the University of Northern British Columbia (UNBC) Research Ethics Board (REB 6009080), April 2023, to conduct a single cross-sectional open survey using SurveyMonkey licensed through UNBC. The survey landing page included an informational letter to provide study details. After reading the information on the landing page, respondents were asked to voluntarily consent electronically to participate in the study. Upon confirmation of informed consent, participants were then given access to this survey. If a participant did not consent, they received a thank-you message, and access to the survey closed automatically. All aspects of data collection, storage, and analysis were password-protected and housed on an encrypted UNBC server. The invitations advertised a random draw of 5 e-gift cards at the end of the survey period as an incentive to participate in the survey.

Instrument Design

A total of 11 research papers, which used surveys to examine attitudes and perceptions toward AI, were screened for relevance to this research study's instrument design. Two papers [26,27] were validating their General Attitudes Artificial Intelligence Scale to classify individuals with positive or negative feelings toward AI. The remaining 9 research studies targeted RNs [28], nursing students [29], radiologists [30,31], physicians [32], medical students [33], a mix of health care professionals [34,35], and consumers [36]. All except Swan [28] had their survey questions included in the publication or supplemental information. A request to preview and use Swan's survey, if applicable, was granted (BA Swan, RN, PhD, personal communication, November 30, 2022).

Swan's survey was selected due to its purposeful design for use with nursing professionals. It included similar questions to the other previewed surveys, indicating that common survey topics were covered. Further, Swan's survey was adapted by adding questions important to this study. In the adapted survey, the first question to address computer expertise was sourced from Schepman and Rodway [27], who suggested that individuals with computer expertise would be more positive about AI. Questions 32 and 33 were added from Esmaeilzadeh [36] with slight modifications to address professional accountability. More details on the survey and its adaptation are found in Multimedia Appendix 1. Swan's survey had not been tested or piloted before deployment of the survey (BA Swan, RN, PhD, personal communication December 21, 2022).

The revised survey was reviewed for clarity by a retired community nursing manager with over 35 years of community experience, as a public health nurse in direct care and management. It was confirmed that the survey took 20 minutes to complete, and a direct question exploring how nurses should be involved with AI was suggested. Therefore, Q37 "How should nurses be involved in artificial intelligence that influences their practice?" was added.

The final version consisted of 37 content questions (referencing aspects of AI) plus a demographic section, which was used to describe respondents' representation across Canada, as well as their level of experience and current position. The survey was recreated on the survey platform. Complete wording of each survey item and types of questions are found in Multimedia Appendix 1.

Recruitment

The target population was RNs licensed in Canada who practiced in the community setting (eg, home care and public health) or RNs who had a community nursing focus (eg, researchers, educators, administrators, and clinical informatic nurses). Collectively, the term CHNs will be used. The survey was only offered in English. The size of the targeted population was unknown. Canadian workforce data reported that 32,074 direct care RNs were employed in community health in 2023 [14]; however, this does not account for the others not providing direct care (eg, researchers, educators, and administrators) included in the population of interest. Therefore, an online calculator [37] was used with the parameters of 20,000 for an unknown population, distribution at 50%, with 5% margin of error and a 95% CI, indicating a sample size of 377 was needed. The emergence of AI into clinical practice remains a new field. Therefore, the power analysis was a reference point to guide this exploratory research study.

The participants were recruited by an "invitation to participate letter," which had the live link to the survey embedded into its content. This was shared through nursing sources by monthly newsletters, email lists (eg, existing organizational and collegial connections), and informal networks (eg, colleague-to-colleague and social media). Two national organizations, Community Health Nurses of Canada and Canadian Nursing Informatics Association, canvassed their membership by broadcast messages and posts in their monthly e-newsletter. Each provincial and territorial nursing association or licensing body was contacted by email, briefly explaining the research and asking if they would circulate it to their members. Licensing bodies recommended that the researcher contact the nursing associations. One provincial licensing body agreed to send out the invitations by email to their members who identified as working in the community and had previously consented to be contacted for research purposes. The nursing associations kept the invitation in their monthly newsletters, or posts on their social media sites, or sent by broadcast message to their members until the survey closed. The survey was live from April 24 to July 30, 2023.

Data Management

On the survey closure date, the full dataset was exported from the survey platform to SPSS Statistics (version 29; IBM Corp). All computer IP addresses were removed, as well as respondents who provided consent but did not complete any survey questions. As it was expected that CHNs may complete this survey using a shared workstation, multiple responses from the same IP address were included as long as they were completed at different times, for different durations, and represented unique participant responses. The use of the same IP addresses was limited to 10 instances and met the above criteria. The geographical locations were grouped into regions to determine Canada-wide representation: Eastern (Prince Edward Island, Newfoundland & Labrador, New Brunswick, and Nova Scotia), Central (Ontario and Quebec), Western (Manitoba, Saskatchewan, Alberta, and British Columbia), and Northern (Yukon, Northwest Territories, and Nunavut). Questions that offered "other" as a choice were reviewed and recoded into the appropriate existing choices already provided; otherwise, it was left as "other." All word responses were coded for a numerical value to enable analysis (eg, Likert scale responses). Surveys that were blank (n=5) were removed. Cases with missing data (greatest in the demographic section) were kept, thus maximizing the number of responses for any given question. Therefore, the count n/N and percent are presented per question, except for multiple response questions, where n values and percent are given, because participants could respond to more than one option. Chi-square analysis was conducted to examine the relationship between respondents' reported AI knowledge (Q6) and respondents' perceptions of AI in their practice (Q10-Q20 and Q22-Q35, Q21 "other" was not included). All questions were examined for their missing or incomplete data. Variation in response rates could be due to respondents' choices not to answer or complete the survey. Therefore, to minimize the potential for response bias, all questions with a less than 15% missing data rate were kept. The core set of survey questions used to examine the research questions met this proportion of missing variables, with response rates as follows: Q6 (220/228, 96.5%), Q10-Q20 (206/228, 90.4% to 208/228, 91.2%), and Q22-Q35 (202/228, 88.6% to 207/228, 90.8%). The missing data for these questions is as follows: Q6 (3.5%), Q10-Q20 (range 8.8% to 9.6%), and for Q22-Q35 (range 9.2% to 11.4%).

Data Analysis

Both descriptive and inferential statistics were used to examine the data. Descriptive analysis summarized respondents' characteristics and their perceptions of AI in nursing. Inferential statistics examined the relationship between their reported AI knowledge (Q6) and their perceptions of the current and future effects of AI on nursing and health care.

The chi-square test for independence was used to determine an association between CHNs reported level of knowledge of AI technologies (independent variables) and their perceptions of the effects of AI (dependent variables). The CHNs were grouped by their reported level of knowledge of AI technologies to allow for comparison. CHNs described their level of knowledge of AI technologies as "excellent," "very good," "good," "fair," or "none." They were grouped as "good" level of knowledge if they indicated "good" to "excellent" and "not good" level of knowledge if they indicated "fair" or "none." The reference category chi-square test for independence was a primarily "good" level of AI knowledge; however, a "not good" level of AI knowledge was the reference category for Q26 (comfort with AI development), Q32 (concern with AI offering wrong recommendation), and Q33 (concern with dismissing appropriate AI recommendation) to promote ease in explaining the results. All statements related to CHNs' perception or attitudes about AI were a 5-point Likert scale from strongly agree (5), agree (4), neutral (3), disagree (2), and strongly disagree (1). The responses for these questions were grouped as "agree" if the respondent indicated "agree" or "strongly agree" and grouped as "not agree" if they indicated "neutral," "disagree," or "strongly disagree." Neutral was grouped with "not agree" because it was interpreted that this group of respondents had no definitive feeling either way on the subject. As the aim of the research was to gain an understanding of how to better involve nurses in AI, it was concluded that these "neutral" respondents, along with "not agree," may need more targeted strategies to better involve them. Further, the transformed response "agree or not agree" was clarified by the sentiment being examined to ease understanding. The dependent variables were considered: comfortable or not comfortable with AI development, AI applications useful or not useful, effects of AI agree or not agree, and professional accountability concerned or not concerned. Odds ratios were calculated for chi-square tests that were significant to determine the strength of association.

Correction (ie, Yates and Bonferroni) methods for statistical testing were not used. Yates continuity correction was not used because the sample size was considered large enough (range 202 to 208) to support a Pearson chi-square [38]. It is noted that the item "nurse should be consulted" produced cells under 5 (not agree); however, this seemed a reasonable result and would not benefit from Yates correction. The Bonferroni post hoc was not used because it can be too restrictive [39]. The Bonferroni post hoc (0.05/25=0.002) is given for reference only and includes the 25 items (Q10-Q20 and Q22-Q35) examined for association.

The open-text question asking the respondents "How should registered nurses be involved in AI?" was examined for types of responses. Some examples of these responses included how CHNs could be engaged in AI technologies, for example, education, advising, or consulting. These responses were quantified with the frequencies reported.

Results

Overview

A total of 296 potential respondents opened the survey, 261 met recruitment criteria, with 233 (89.3%) providing consent. As reported, blank surveys (n=5) were not included. A total of 228 surveys were included in the analyses. The response rate fluctuated per question, with the response rate better at the start of the survey and waning by the final demographic section. The item, "community years experience," had the most nonresponses (52/228, 22.8%).

Sample Characteristics

Sample characteristics (Table 1) helped to describe the sample that responded to the survey. The respondents' average age was 45.5 (SD 11.7) years, with 58.4% (104/178) younger than 50 years. Most respondents identified as female (172/188, 91.5%). The average overall years of experience for RNs was 19.8 (SD 12.2) years, with most (161/179, 89.9%) ranging from 5 years to over 35 years of experience. For community practice, the average years of experience was 13.5 (SD 10.1) years, with many (129/176, 73.3%) ranging from 5 years to over 35 years of experience. The sample had representation from the 4 Canadian regions: Eastern (47/186, 25.3%), Central (72/186, 38.7%), Western (65/186, 34.9%), and Northern (2/186, 1.1%). The practice descriptions are multiple-response questions. The reported practice settings (Table 2) included public health (65/191, 22.3%), home care (56/191, 19.2%), community health centers (44/191, 15.1%), primary care (41/191, 14%), and case management (16/191, 5.5%). Approximately half indicated they provided direct care (108/191, 51.4%), and the majority (115/190, 60.5%) held a bachelor's degree.

Table . Sample characteristics of respondents.

Characteristic	Participants
Gender, n (%)[a]	
Male	16 (8.5)
Female	172 (91.5)
Age (years), means (SD)	45.5 (11.7)
Age (years), n (%)[b]	
25-29	13 (7.3)
30-34	26 (14.6)
35-39	29 (16.3)
40-44	17 (9.6)
45-49	19 (10.7)
50-54	30 (16.9)
55-59	21 (11.8)
60 and older	23 (12.9)
RN[c] experience (years), means (SD)	19.8 (12.2)
RN experience (years), n (%)[d]	
Less than 5 years	18 (10.1)
5-9	24 (13.4)
10-14	29 (16.2)
15-19	22 (12.3)
20-24	18 (10.1)
25-29	21 (11.7)
30-34	22 (12.3)
35 and greater	25 (14)
Community experience (years), means (SD)	13.5 (10.1)
Community experience (years), n (%)[e]	
Less than 5 years	47 (26.7)
5-9	24 (13.6)
10-14	30 (17)
15-19	26 (14.8)
20-24	13 (7.4)
25-29	19 (10.8)
30-34	13 (7.4)
35 and greater	4 (2.3)
Geographic location, n (%)[f]	
Eastern Canada	47 (25.3)
Central Canada	72 (38.7)
Western Canada	65 (34.9)
Northern Canada	2 (1.1)

[a]N=188.
[b]N=178.
[c]RN: registered nurse.

[d]N=179.
[e]N=176.
[f]N=186.

Table . Education and employment data of respondents.

Characteristic	Participants
Education level, n (%)[a]	
Diploma	27 (14.2)
Bachelor	115 (60.5)
Masters	38 (20)
Doctoral or PhD	10 (5.3)
Employment sector, n (%)[b],[c]	
Public	140 (70.4)
Private	45 (22.6)
Academia	14 (7)
Practice setting, n (%)[b],[d]	
Health informatics	12 (4.1)
Community health	44 (15.1)
Case management	16 (5.5)
Older adult	13 (4.5)
Home care	56 (19.2)
Hospice palliative	11 (3.8)
Primary care	41 (14)
Community mental health	9 (3.1)
Public health	65 (22.3)
College or university	18 (6.2)
Other	7 (2.4)
Current position (years), n (%)[b],[d]	
Direct care	108 (51.4)
Nurse informatician	6 (2.9)
Manager or administrator	34 (16.2)
Staff education	23 (11)
Researcher	6 (2.9)
Faculty	19 (9)
Strategic planning	5 (4.3)
Other	9 (4.3)

[a]N=190.
[b]Multiple response questions, n summed in each section, may be greater than N.
[c]N=187.
[d]N=191.

Acceptance of Technology and Competent Users of Technology

The survey questions 1 and 2 were used to explore the CHNs' acceptance of technology into their practice, and how they described their computer use. Almost all participants (205/228, 89.9%) agreed or strongly agreed to welcoming technology into their practice. More than half (129/227, 56.8%) identified as competent users of the internet and standard applications, and another 36.6% (83/227) indicated they were users of specialist applications. The survey, included in Multimedia Appendix 1, is subdivided into sections related to the headings addressing each of the research questions.

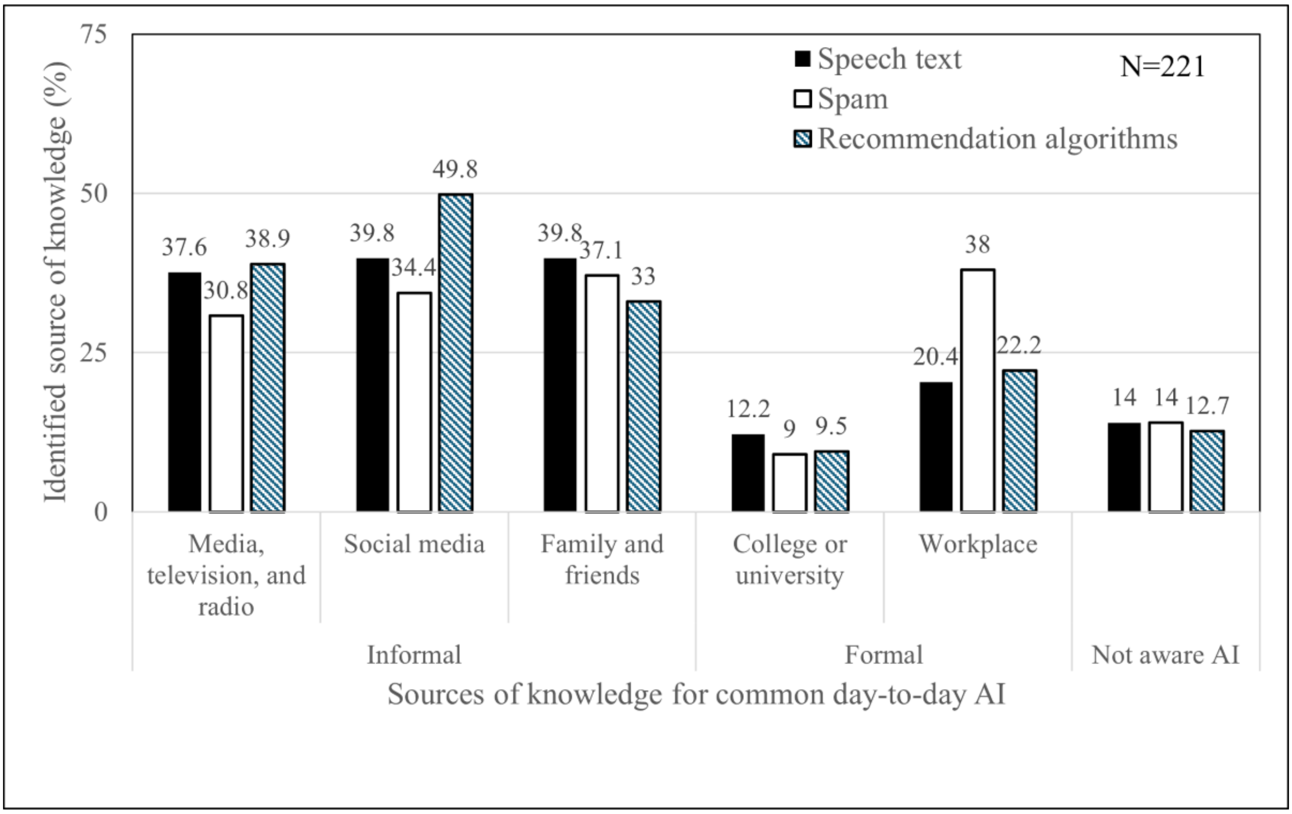
CHNs' Awareness of the Emergence of AI, Including ML Applications, in Nursing

CHNs' awareness of AI (Q8) in health care was more prevalent than their awareness of AI in nursing. The respondents were aware of AI (multiple response questions) in health care (123/220, 55.9%), but fewer were aware of AI in nursing (67/220, 30.5%). This was similar for ML and deep learning (Q9): respondents had heard of it in health care (84/220, 38.2%), and fewer had heard of it in nursing (35/220, 15.9%).

CHNs' Main Sources of Knowledge for Learning About Current Day-to-Day AI

The key sources of knowledge for learning about current day-to-day AI (Q3-Q5) varied between informal and formal methods. The respondents' major source of knowledge (multiple response questions) of common forms of day-to-day AI applications (Figure 1; ie, speech-text, spam, and recommendation algorithms) was informal resources such as media, television, or radio (range 68/221, 30.8% to 86/221, 38.9%); social media (range 76/221, 34.4% to 110/221, 49.8%); and family and friends (range 73/221, 33% to 88/221, 39.8%). Formal sources were indicated less often: colleges and universities (range 20/221, 9% to 27/221, 12.2%) and workplace (range 45/221, 20.4% to 84/221, 38%). It is worth noting that some respondents were not aware that these applications (speech-to-text, spam, and recommendation algorithms) were forms of AI (range 28/221, 12.7% to 31/221, 14%).

Figure 1. Respondents' key sources of knowledge for day-to-day artificial intelligence. AI: artificial intelligence.



CHNs' Description of Their Level of Knowledge of AI Technologies

Respondents described their understanding of the technologies used in AI (Q6) as none (42/220, 19.1%), fair (83/220, 37.7%), good (67/220, 30.5%), very good (23/220, 10.5%), and excellent (5/220, 2.3%). These results were grouped into 2 levels of AI knowledge: "good" level of knowledge included good to excellent (95/220, 43.2%), and "not good" level of knowledge used fair and none (125/220, 56.8%). Level of AI knowledge (Q6) was used in the chi-square test, as AI was more commonly known with a more balanced representation. For ML or deep learning (Q7), it was a similar trend, more nurses indicated "not good" level of knowledge (148/220, 67.3%) than "good" level of knowledge (72/220, 32.7%).

The Relationship Between CHNs' Level of Knowledge of AI Technologies and Their Perceptions of the Effects of AI on Clinical Practice, Professional Accountability, and the Usefulness of AI Applications.

Effects of AI on Clinical Practice

Questions 22 to 31 and 34 to 35 examined the respondents' perception of the effects of AI on their practice. An overview of respondents' perceptions indicated 39.6% (80/202) felt uncomfortable with the developments in AI, ML, and deep learning. Over half (133/206, 64.6%) of the respondents agreed that AI would revolutionize both health care and nursing. Few respondents agreed that the human nurse, 10.2% (21/205), or members of the interprofessional team, 12.6% (26/207), would be replaced. Almost half of respondents felt AI would make nursing more exciting, 44.1% (89/202), and similarly, health care more exciting, 47.5% (96/202). Likewise, 44.8% (91/203) perceived AI to be part of nursing. Many respondents (143/203, 70.4%) felt that AI should be part of nursing education and included in professional development (152/202, 75.2%). Most respondents agreed they should be consulted (195/203, 96.1%) about AI, as well as having the opportunity to raise relevant nursing questions (189/202, 93.6%).

Examination with the chi-square test for independence (Table 3) was used to determine if there was a relationship between the respondents' reported AI knowledge and their perceptions of the potential effects of AI on clinical practice. For Q26, the reference category for level of AI knowledge was "not good." There was a significant relationship between respondents reporting "not good" level of AI knowledge and their perception of "feel uncomfortable" (ie, "agree" with statement) with AI developments (χ^2_1=4.2, *P*=.04; α=.05; small effect ϕ=.15). Respondents reporting "not good" AI knowledge were 1.84 (95% CI 1.03-3.3) times more likely to indicate developments in AI made them feel uncomfortable.

Table . Respondents' perceptions of current and future effects of AI[a] on clinical practice related to their level of AI knowledge.

Questions	Knowledge level	Effects		Chi-square (*df*)	Effect (ϕ)	OR[b] (95% CI)	*P* value
		Agree n (%)	Not agree n (%)				
Q22 revolutionize nursing				7.3 (1)	0.19	2.28 (1.25-4.18)	.007
	Good	66 (75)	22 (25)				
	Not good	67 (56.8)	51 (43.2)				
Q23 revolutionize health care				2.3 (1)	0.11	1.58 (0.88-2.86)	.13
	Good	62 (70.5)	26 (29.5)				
	Not good	71 (60.2)	47 (39.8)				
Q24 replace human RN[c]				0.85 (1)	0.07	1.53 (0.62-3.78)	.36
	Good	11 (12.5)	77 (87.5)				
	Not good	10 (8.5)	107 (91.5)				
Q25 replace interprofessional team member				0.2 (1)	0.03	1.18 (0.52-2.70)	.69
	Good	12 (13.6)	76 (86.4)				
	Not good	14 (11.8)	105 (88.2)				
Q26 uncomfortable with AI developments[d]				4.2 (1)	0.15	1.84 (1.03-3.3)	.04
	Not good	53 (45.7)	63 (54.3)				
	Good	27 (31.4)	59 (68.6)				
Q27 nursing will be more exciting				10.1 (1)	0.22	2.52 (1.42-4.47)	.001
	Good	49 (57)	37 (43)				
	Not good	40 (34.5)	76 (65.5)				
Q28 health care will be more exciting				8.3 (1)	0.20	2.3 (1.30-4.06)	.004
	Good	51 (59.3)	35 (40.7)				
	Not good	45 (38.8)	71 (61.2)				
Q29 AI is part of nursing practice				6.6 (1)	0.18	2.1 (1.19-3.68)	.01
	Good	48 (55.2)	39 (44.8)				
	Not good	43 (37.1)	73 (62.9)				
Q30 AI included in nursing education				0.7 (1)	0.06	1.3 (0.71-2.4)	.40
	Good	64 (73.6)	23 (26.4)				
	Not good	79 (68.1)	37 (37.9)				
Q31 AI included in professional development				2.0 (1)	0.10	1.6 (0.83-3.14)	.16
	Good	69 (80.2)	17 (19.8)				
	Not good	83 (71.6)	33 (28.4)				
Q34 nurses should be consulted				0.2 (1)	−0.03	0.74 (0.18-3.05)	.68
	Good	83 (95.4)	4 (4.6)				
	Not good	112 (96.6)	4 (3.4)				
Q35 identify relevant AI nursing questions				2.0 (1)	−0.10	0.44 (0.14-1.39)	.15
	Good	78 (90.7)	8 (9.3)				
	Not good	111 (95.7)	5 (4.3)				

[a]AI: artificial intelligence.
[b]OR: odds ratio.
[c]RN: registered nurse.
[d]Reference category was set to "good" for all variables with the exception of Q26 where the reference category was set to "not good."

The remaining statements (Q22-Q25 and Q27-Q35) used the reference category "good" level of AI knowledge. There were significant relationships between "good" level of AI knowledge and the following perceptions. Respondents perceived AI would revolutionize nursing (χ^2_1=7.3, *P*=.007; α=.05; small to moderate effect ϕ=.19) and were 2.28 times more likely to agree that nursing would be revolutionized (95% CI 1.25-4.18). Respondents perceived AI would make both nursing (χ^2_1=10.1, *P*=.001, α=.05, small to moderate effect ϕ=.22) and health care (χ^2_1=8.3, *P*=.004, α=.05, small to moderate effect ϕ=.20) more exciting. Respectively, these respondents were 2.52 times more likely (95% CI 1.42-4.47) and 2.3 times more likely (95% CI 1.30-4.06) to perceive that AI will make nursing and health care more exciting. These respondents perceived that AI is part of nursing practice (χ^2_1=6.6, *P*=.01; α=.05; small to moderate effect ϕ=.18) and were 2.1 times more likely to agree that AI is part of nursing practice (95% CI 1.19-3.68).

There was no association observed between level of AI knowledge and perceived effects: for revolutionizing health care (*P*=.13) nor between level of AI knowledge and perceived effects for replacing human RN (*P*=.36) or replacing interprofessional team members (*P*=.69). There was no association between level of AI knowledge and perception that AI should be part of nursing education (*P*=.4), part of professional development (*P*=.16), nurses should be consulted (*P*=.68), or nurses should identify relevant nursing questions for AI (*P*=.15).

Professional Accountability

Two statements (Q32 and Q33) used "what if" scenarios to examine CHNs' perceptions of AI and professional accountability. One described an AI providing the wrong recommendation, and the other described a correct recommendation that was dismissed by the nurse. Respondents expressed concern regarding their responsibility in both scenarios. The majority, 77.7% (157/202), were concerned if AI offered the wrong recommendation, and likewise, 73.8% (149/202), if an appropriate AI recommendation was dismissed. Examination with chi-square test for independence (Table 4) with "not good" as the reference category revealed no association between level of AI knowledge and perceived concern if AI provided a wrong recommendation (*P*=.06). Conversely, the chi-square test for independence suggested a significant association between a "not good" level of AI knowledge and perceived concern if a correct recommendation was dismissed (χ^2_1=3.98, *P*=.046; α=.05; small effect ϕ=.14). Respondents reporting "not good" AI knowledge were 1.9 times more likely to be concerned with dismissing an appropriate AI recommendation (95% CI 1.01-3.57).

Table . Respondents' perceptions of concern with professional accountability related to their level of AI[a] knowledge.

Questions	Knowledge level	Concern		Chi-square (*df*)	ϕ	OR[b] (95% CI)	*P* value
		Agree n (%)	Not agree n (%)				
Q32 if AI offers wrong recommendations				3.7 (1)	0.14	1.9 (0.98-3.74)	.06
	Not good	95 (82.6)	20 (17.4)				
	Good	62 (71.3)	25 (28.7)				
Q33 if correct recommendation is dismissed				3.98 (1)	0.14	1.9 (1.01-3.57)	.046
	Not good	91 (79.1)	24 (20.9)				
	Good	58 (66.7)	29 (33.3)				

[a]AI: artificial intelligence.
[b]OR: odds ratio.

Usefulness of AI Applications

Q10-Q20 examined the respondents' perceptions of the utility of various AI applications. Respondents perceived that overall, each AI application would be useful (Figure 2), with agreement ranging from 68.6% (142/207) to 88% (183/208). Most respondents indicated Q15 bots (183/208, 88%), Q18 risk prediction (161/208, 77.4%), and Q20 summarizing narrative text from a client's notes (160/207, 77.3%) would be useful. Further examination to determine if the level of AI knowledge was associated with CHNs' perception of the utility of AI application revealed that in all but one example, there was no association between level of AI knowledge and their perception of utility (Table 5). There was a significant association between a "good" level of AI knowledge and perception of utility for Q13 transition management (χ^2_1=7.9, *P*=.005, α=.05, small to moderate effect ϕ=.2). Respondents reporting "good" AI knowledge were 2.45 times more likely to agree that transition management would be useful (95% CI 1.3-4.63).

Figure 2. Respondents' perception of the utility of AI applications. AI: artificial intelligence.

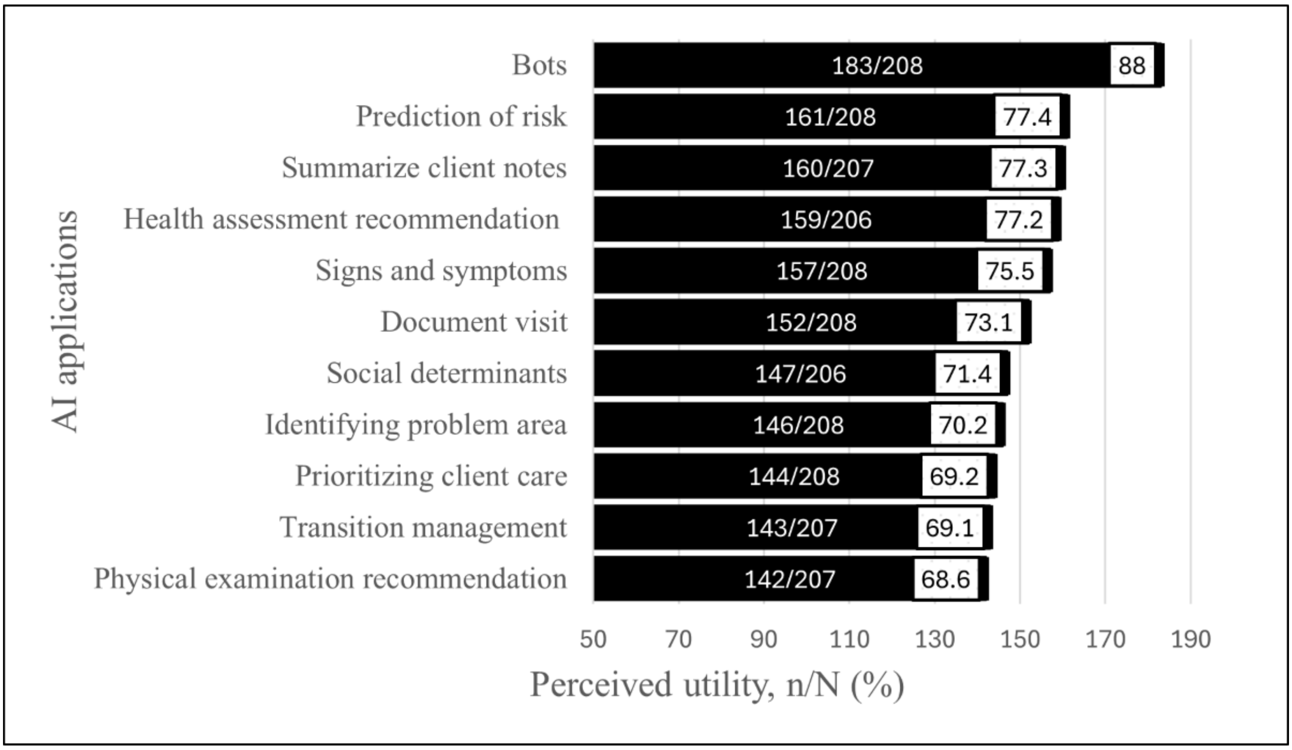


Table . Respondents' perception of the utility of AI[a] applications related to their level of AI knowledge.

Questions	Knowledge level	Utility of AI		Chi-square (*df*)	ϕ	OR[b] (95% CI)	*P* value
		Agree n (%)	Not agree n (%)				
Q10 signs and symptoms				0.27 (1)	0.034	1.18 (0.62-2.26)	.61
	Good	68 (77.3)	20 (22.7)				
	Not good	89 (74.2)	31 (25.8)				
Q11 social determinants				0.8 (1)	0.06	1.3 (0.72-2.48)	.36
	Good	65 (74.7)	22 (25.3)				
	Not good	82 (68.9)	37 (31.1)				
Q12 prioritizing client care				0.9 (1)	0.07	1.3 (0.73-2.45)	.35
	Good	64 (72.7)	24 (27.3)				
	Not good	80 (66.7)	40 (33.3)				
Q13 transition management				7.9 (1)	0.20	2.45 (1.30-4.63)	.005
	Good	70 (79.5)	18 (20.5)				
	Not good	73 (61.3)	46 (38.7)				
Q14 problem area				3.7 (1)	0.13	1.83 (0.98-3.42)	.06
	Good	68 (77.3)	20 (22.7)				
	Not good	78 (65)	42 (35)				
Q15 bots				0.03 (1)	−0.01	0.93 (0.40-2.15)	.86
	Good	77 (87.5)	11 (12.5)				
	Not good	106 (88.3)	14 (11.7)				
Q16 health assessments				0.1 (1)	−0.02	0.90 (0.47-1.74)	.76
	Good	67 (76.1)	21 (23.9)				
	Not good	92 (78)	26 (22)				
Q17 physical assessment				0.04 (1)	−0.01	0.94 (0.52-1.7)	.84
	Good	59 (67.8)	28 (32.2)				
	Not good	83 (69.2)	37 (30.8)				
Q18 prediction of risk				0.4 (1)	0.04	1.24 (0.64-2.41)	.53
	Good	70 (79.5)	18 (20.5)				
	Not good	91 (75.8)	29 (24.2)				
Q19 documentation of visit				3.2 (1)	0.13	1.8 (0.95-3.44)	.07
	Good	70 (79.5)	18 (20.5)				
	Not good	82 (68.3)	38 (31.7)				
Q20 summarize client notes				1.6 (1)	0.09	1.54 (0.78-3.05)	.21
	Good	71 (81.6)	16 (18.4)				
	Not good	89 (74.2)	31 (25.8)				

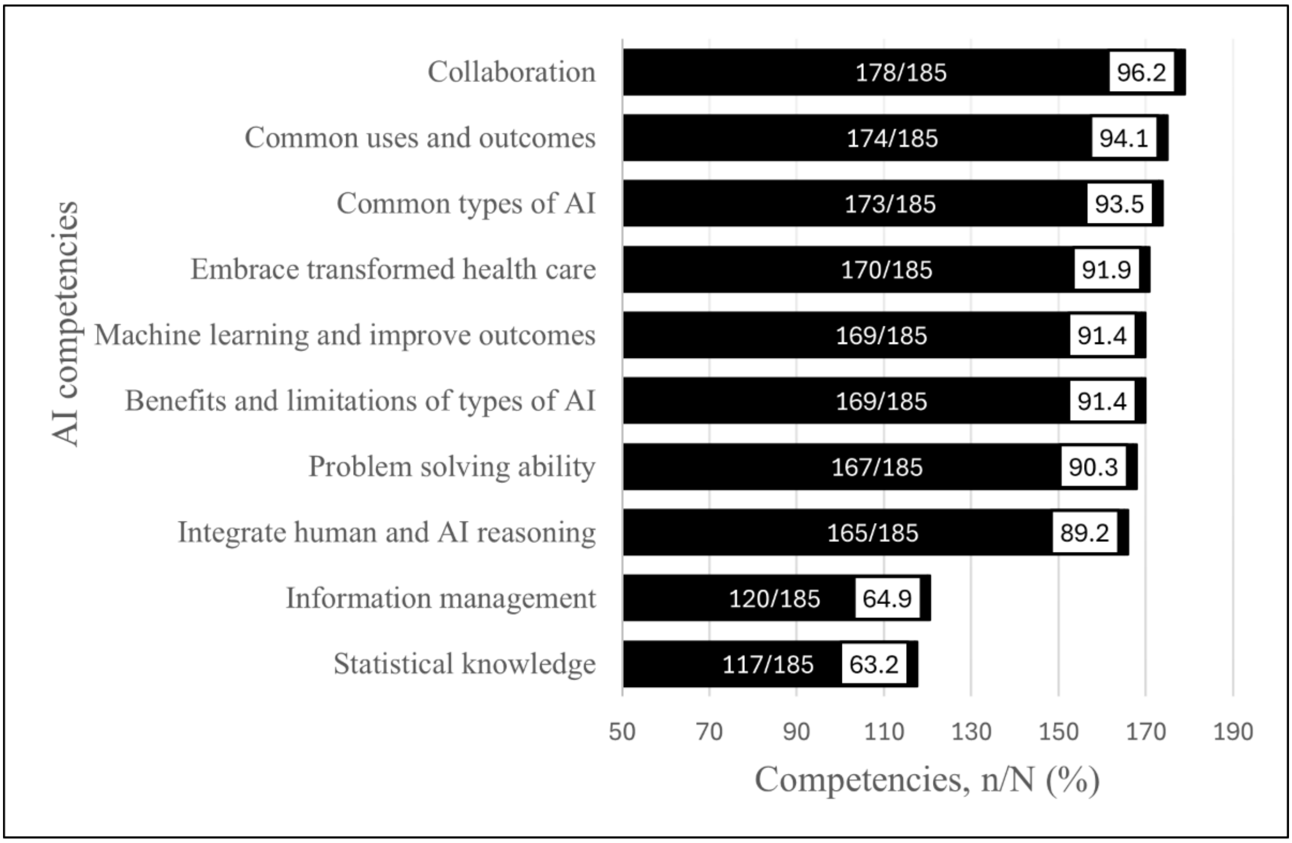
[a]AI: artificial intelligence.

[b]OR: odds ratio.

AI Competencies CHNs Perceive as Being Needed in Their Community Practice

The survey (Q36) offered 10 competencies for respondents to indicate which were needed by CHNs (multiple-response question). The 3 competencies most identified as needed (Figure 3) were (1) communications, collaboration, and cross-functional knowledge (178/185, 96.2%); (2) knowledge of common uses and outcomes of AI (174/185, 94.1%); and (3) knowledge of common types of AI (173/185, 93.5%). The competency identified least was statistical knowledge, which also covered skills related to clinical analytics, data management, and algorithm awareness (117/185, 63.2%). Complete wording of each competency is found in Multimedia Appendix 1.

Figure 3. Competencies identified by respondents as needed by CHNs to integrate AI into clinical practice. AI: artificial intelligence; CHN: community health nurse.



Insights on How CHNs Could Be Better Involved in AI

An open-ended question (Q37) asked how respondents thought they should be involved. It produced (70/228, 30.7%) responses, which provided insights into nurse involvement and their perspectives on related aspects of AI in their practice. Respondents expressed a need for further education (21/70, 30%) using phrases like "learn," "knowledge acquisition," "stay up to date," and "education." Most respondents (57/70, 81.4%) cited numerous roles or functions where nurses should be involved: raising relevant questions (5/70, 7.1%); advising and consulting (24/70, 34.3%); planning, development, and implementing (14/70, 20%); evaluation (12/70, 17.1%); change management (5/70, 7.1%); regulation, policy, and ethics (7/70, 10%); and all phases (13/70, 18.6%). They used terms like "key stakeholders" and "subject matter experts." They felt nurses needed to be involved to make AI relevant. Respondents (7/70, 10%) specifically identified that direct care (front-line and end user) CHNs should be involved. Some respondents (8/70, 11.4%) referred to AI as a tool or an additional resource. Other respondents (13/70, 18.6%) acknowledged their apprehension with AI being introduced into practice. Respondents (6/70, 8.6%) referred to the need to be mindful about the human relationship with phrases like "relationships are key aspects of community health nursing" and "human connection care can not be replaced."

Discussion

Principal Findings

The main findings indicated CHNs differ in their level of knowledge and perceptions of AI technologies in nursing and health care. Many CHNs have a limited awareness of AI emerging in health care and report even less awareness of AI emerging in nursing practice. The main sources of information for day-to-day AI applications are predominantly informal methods (eg, social media) compared to academic and workplace sources. Some CHNs are unaware that common day-to-day applications are AI-driven. Fewer CHNs describe their knowledge of AI technologies as "good." However, the CHNs who describe their AI knowledge as "good" are twice as likely to be optimistic or have favorable perceptions of AI effects, such as revolutionizing nursing, making nursing more exciting, and agreeing that AI is part of nursing. Whereas CHNs with "not good" AI knowledge are almost twice as likely to feel uncomfortable with AI development. Regardless of the level of AI knowledge, most CHNs agree they should be involved in AI by consulting and raising nurse-relevant questions in various phases of AI development, such as implementation and ongoing evaluation. The results substantiate the need for appropriate AI education for CHNs to prepare them to participate in AI that will influence their practice.

CHNs have a limited awareness of AI emerging in nursing practice (30.5%), which aligns with results found in similar nursing research [28,40]. However, other questions in this current research are used to gain further insights into why their understanding of various AI technologies might be limited. CHNs use informal (eg, social media, and family and friends) methods of learning about common day-to-day AI applications, with 12.7% (28/221) to 14% (31/221) of respondents being unaware that these common forms (ie, speech to text, spam, and recommendation algorithms) are driven by AI. This limited awareness could be related to relying on informal sources of knowledge. CHNs may turn to readily available sources of information because of convenience. Likewise, being aware of spam from work-related sources could be as simple as "don't see a reply, check your spam folder," while having no real understanding of the algorithms that recognize and reroute spam. This lack of understanding whether an application is driven by AI has been linked to clinical practice by another study [40] where 22% of Canadian nurses did not know if AI is used in their practice area. Similarly, Coakley et al [31] identified that approximately 40% of radiographers did not recognize work-related AI-driven applications. This raises a potential concern that CHNs may be using AI-driven applications within their practice unbeknownst to them. Lastly, over half (125/220, 56.8%) of CHNs describe their knowledge of AI technologies as "not good." This limited awareness of AI in nursing and lack of knowledge of AI technology highlights a knowledge deficit, stressing the importance of AI education for CHNs.

The composition of the survey sample strengthens the clinical value of the results. First, this Canadian sample is an experienced group of CHNs, both in years of practice as an RN and years of experience in the community sector. They describe themselves as competent and welcoming of technology. This was expected because Canada has been striving since 2000 to improve digital health connections (eg, electronic health records) within the Canadian health care system [41]. A current report [40] confirms a continual uptake in digital technology. This steady increase of new technologies into practice (eg, electronic health records and electronic assessments) emphasizes CHNs' adaptability and resiliency to new technologies in their practice, considering these decisions are made at higher levels in the organization rather than from staff who are expected to use them [42]. Second, more than half of the survey respondents provide direct care services. This means they are familiar with community practice, its clinical data, and provision of care at the client level, and have the potential to offer pragmatic insights. Third, this group of CHNs includes end users who are seldom involved in the development of AI. They are, however, important stakeholders in ensuring clinical relevance in new technology [22,24]. The various characteristics (eg, experienced, competent, and end users) of this CHN sample provide validity and relevance to the results.

A common technique for assessing the level of knowledge across surveys is asking the respondent to indicate their level of AI knowledge. Most surveys use this subjective method, finding fewer respondents rate their level of AI knowledge as "good" compared to "not good" level of knowledge) [28,32,40,43,44], aligning with the current study (level of knowledge "good" 95/220, 43.2% versus "not good" 125/220, 56.8%). None of the cited surveys uses the difference in knowledge level to compare groups and their perceptions.

The subjective evaluation of CHNs' level of AI knowledge may be underestimated or overestimated. However, professionally, CHNs self-reflect on practice and learning gaps, so they have familiarity in evaluating their competencies [45]. It seems plausible to use the self-identified AI knowledge level as a starting point to determine if there is a relationship between the level of knowledge and CHNs' perceptions of AI. The 2 groups of "good" and "not good" knowledge level of AI technologies in this study suggest that the level of AI knowledge affects some of the AI perceptions of CHNs.

The CHNs reporting "not good" level of knowledge are almost two times more likely to indicate that they are uncomfortable with the developments in AI. Intuitively, this makes sense. It can be argued that having "good" AI knowledge provides a method to evaluate the benefits or disadvantages of AI and perhaps provides some control [46]. CHNs reporting a "good" level of knowledge are more than two times more likely to feel nursing will be revolutionized, nursing and health care will become more exciting, and agree that AI is part of nursing practice. Therefore, CHNs with a "good" level of AI knowledge are more optimistic about the future effects of AI [46]. The differences between AI perceptions for CHNs with a "good" level of knowledge versus a "not good" level further stress the necessity for education and ongoing learning opportunities to decrease apprehension and promote optimism around AI [46].

Regardless of their level of knowledge, few CHNs believe that human RNs (21/205, 10.2%) or interprofessional team members (26/207, 12.6%) will be replaced by AI. This sentiment aligns with that of Swan [28]. The underlying belief that human touch is integral to nursing care, along with humans' ability to reconsider and change care when an unexpected situation arises, supports human RNs and other interprofessional members' continued importance to the care team [47-49]. CHNs' responses (Q37) defend the importance of human involvement: "relationships are a key aspect of community health nursing" and "human connection care can not be replaced." CHNs' belief that they will not be replaced does not address how they think their role within health care will change. This aspect should be examined in future research.

Professional accountability is a central feature for all regulated professionals. Several studies include some reference to the issue (eg, medical liability). This current study demonstrates a mixed outcome. There is no association between the level of AI knowledge and concern with AI providing a wrong recommendation, versus an association between the level of AI knowledge and concern with dismissing a correct recommendation. Still, the clinical importance should be addressed because most CHNs, regardless of their level of AI knowledge, have concerns about who would be held responsible for either accepting a wrong recommendation (157/202, 77.7%) or dismissing a correct recommendation (149/202, 73.8%). Other studies confirm that professionals have concerns about the use of AI in practice [32,40,43]. Further research needs to explore what CHNs feel they require to help address and remediate their concerns.

Although CHNs have a limited understanding of AI, more than two-thirds perceived the examples of AI-driven applications as useful. It suggests that, superficially, they perceived a value in the application to their practice setting. Positive perceptions of the utility of AI applications trend across surveys [28,33,40,43]. However, it is unknown why CHNs perceive the AI applications as useful to them; that is, whether it is the function of replacing a task or the function of supporting decision-making that is important. Future research should follow the open text response “start by asking nurses what they feel could be automated,” thus gaining an understanding of what makes an application useful.

A more comprehensive picture of how CHNs should be involved in AI becomes apparent through the open text responses. First, CHNs confirm their need to “learn,” for “knowledge acquisition,” to “stay up to date,” and “education” as important prerequisites to being involved in AI. Although the quantitative sample identifies the necessity of AI to be included in nursing education and professional development, the open text responses connect AI education to facilitating CHNs’ involvement (participation). Second, the open text responses share a wide range of ways CHNs can be involved. It verifies the importance of including all levels of nurses, specifically noting direct care nurses, and validates that CHNs need to be engaged during all phases of AI. Areas of involvement include: raising relevant questions, planning, development, implementing, evaluation, and monitoring to ensure AI is clinically relevant and accurate. Third, they recognize that their involvement includes regulation, workplace policies, and ethical frameworks to guide their practice because AI is a tool. Fourth, they readily admit to being apprehensive, citing concerns with loss of some of their skills (eg, assessment) along with the human connection and relationship with clients because of AI. This loss of human connection because of technology is also a common concern explored in the literature [49,50]. Further research should continue to examine how CHNs can be better involved.

Clinical Implications and Recommendations

This research reveals 2 interrelated concepts, preparation and participation. These are both essential to better involve CHNs. The first, preparation, acknowledges the importance of education and ongoing professional development. This builds the foundation that will support CHNs to become involved. AI needs to be consciously integrated both in nursing education and ongoing professional development, with attention to a standardized curriculum to ensure all nurses have a basic understanding of AI. Specific areas of concentration should address professional accountability. This will provide CHNs with knowledge to evaluate AI outputs as part of their decision-making, as well as planning and ameliorating perceived future effects of AI. The second, participation, addresses the various aspects of involving CHNs to identify relevant questions and to contribute their nursing perspective to all phases of development and implementation of AI. Professional nursing groups and health care organizations are instrumental in ensuring that the right mix of CHNs, from end user to leadership, have participation on AI advisory committees. Although this research was initiated to examine the perceptions of CHNs about AI in clinical practice, it now raises the necessity of further research to expand on these results by conducting small group consultations to gain an in-depth understanding of how best to involve CHNs.

Strengths and Limitations

The strengths of this study include establishing baseline knowledge and perceptions of AI among Canadian CHNs. An effort was made to recruit the appropriate sample population by targeting national nursing groups as well as provincial and territorial nursing organizations. This survey identifies the need for appropriate education (preparation) and confirms that CHNs want to be involved (participation). It explores the use of the self-reported level of knowledge to determine differences between the “good” and “not good” levels of knowledge.

Several limitations exist. The original survey that was foundational to this study did not have psychometric or reliability testing done. Further testing and reporting of reliability is recommended as a future step. In this variation of the survey, only 1 experienced community nurse was used to determine face validity. A notable limitation of the research is the length of the instrument, as nonresponses increased as the survey progressed. The multiple response questions allowed for several responses, which may have blurred the interpretation. For example, under “current position,” a respondent could have 2 different positions within the community, for example, direct care and educator. Self-reported knowledge is subjective; we are unable to verify what the respondents know or do not know or evaluate the expertise of their knowledge. However, CHNs who feel they have knowledge were more favorable or optimistic about AI within their practice. This study did not examine whether respondents had AI-related practical experience or whether current AI is integrated into their practice. Each survey statement or question is briefly explained or described, for example, “AI will revolutionize nursing by supporting health promotion and disease prevention, helping create personalized treatment plans, speeding up administrative tasks.” Each respondent could interpret it differently depending on their understanding of how this might occur and their experience with any of the concepts in the descriptor. There were no respondents identified from Prince Edward Island, Saskatchewan, or the Northwest Territories. With a nonresponse rate (42/228, 18.4%) for this question, it could not be determined where the missing respondents were located. An online survey has challenges. The recommended number of 377 respondents to have a 5% error margin was not achieved. The true response rate is unknown because it is unknown how many CHNs received the recruitment invitations due to the method used to recruit respondents. Respondents’ bias or selective reporting may have occurred because it was an online survey; only nurses who could access the survey could respond. Additionally, using the term AI in the survey title may have only interested a select group of nurses. As well, the survey was only offered in English, limiting the participation and insights from Francophone nursing colleagues. Lastly, for analysis, the chi-square test can only test for the association of the categorical variables, not causation.

Conclusions

The survey results provide insights into the proposed research questions. Only a third of CHNs are aware that AI is emerging in nursing practice. CHNs use informal sources of knowledge (eg, family and friends) to learn about day-to-day AI applications, with some unaware that these day-to-day applications are AI-driven. This raises the concern that CHNs may be using AI in their practice without realizing that the technology they are using is AI-based. CHNs who report better AI knowledge tend to be more optimistic (ie, “more exciting”) and less uncomfortable about AI and its effects on practice. However, many CHNs have concerns with AI and their professional accountability. Many CHNs agree that AI as a topic should be included in nursing education as well as professional development. This study identifies that most CHNs want to be involved in AI, highlighting that they want to be consulted and given opportunities to raise nurse-relevant questions. An important step to better involve CHNs should address the availability of appropriate and consistent education. This will help to promote the awareness of AI in nursing and alleviate professional concerns, thus preparing CHNs to be better involved.

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Data Availability

The data are presented in the main paper.

Authors' Contributions

Conceptualization: MHB, LC, SF
Data curation: MHB, SF
Formal analysis: MHB, SF, LC, PJ
Investigation: MHB
Methodology: MHB, SF, DB, LC, PJ
Project administration: MHB
Supervision: SF, DB, LC, PJ
Validation: MHB, SF, DB, LC, PJ
Visualization: MHB, SF, DB, LC, PJ
Writing – original draft: MHB
Writing – review & editing: MHB, SF, DB, LC, PJ

Conflicts of Interest

None declared.

Multimedia Appendix 1
Survey instrument.
[DOCX File, 39 KB - nursing_v9i1e78560_app1.docx]

Checklist 1
CHERRIES checklist.
[DOCX File, 26 KB - nursing_v9i1e78560_app2.docx]

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Abbreviations:

AI: artificial intelligence
CHN: Community Health Nurse
ML: machine learning
OR: odds ratio
RN: registered nurse
UNBC: University of Northern British Columbia

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