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Artificial Intelligence–Enhanced Wound Care to Improve Access, Efficacy, and Equity in Wound Care for Older Adults in Rural and Remote Regions of Canada

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Abstract

Wound care is an increasing global challenge, with older adults among those most affected. As populations age, the demand for effective and efficient wound care increases. Over the years, various wound assessment and care techniques have been developed, including digital wound care technology (DWCT), which uses innovative artificial intelligence (AI). Many older adults, especially those living in rural and remote areas, face significant barriers in obtaining timely and effective wound care, leading to poorer health outcomes and increased health care costs related to wound care. These challenges underscore the urgent need to implement wound care models that equitably improve access to care and enhance clinical outcomes, particularly for older adults, to promote healthy aging and age-in-place. Based on evidence from the literature and the initial implementation of a DWCT in 2 community health systems in Ontario, this viewpoint paper encourages clinicians and health care leaders to embrace and expand the implementation of an AI-driven DWCT to address inequities in access to high-quality, timely care. The experiences from these implementations indicate that the use of AI can support clinical decision-making and extend access to care for individuals in rural and remote communities in Canada. By leveraging DWCT powered by AI, health care providers can enhance the accuracy and consistency of wound assessments, improve communication, streamline care processes, and more effectively allocate resources, ultimately aiming to reduce disparities in wound care outcomes.

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KEYWORDS
wound care; AI; equity; artificial intelligence

Introduction

Wound care represents a growing challenge worldwide, particularly impacting older adults [1]. As populations age, the demand for effective and efficient wound care increases, driven by the growing number of older adults with multiple chronic conditions that predispose them to complex wounds and longer healing times. Many older adults, especially those living in rural and remote areas, face significant barriers in obtaining timely and effective wound care, leading to poorer health outcomes and increased health care costs [2]. These challenges underscore the urgent need to implement wound care models, which equitably improve access to care and enhance clinical outcomes. Traditionally, wound assessment is conducted visually to evaluate anatomical, physiological, and mechanical domains [3] or with subjective methods such as the Pressure Ulcer scale for Healing (PUSH) and Pressure Sore Status Tool (PAST) scales; these methods are widely used, can lack accuracy and consistency, leading to variable wound evaluation reports when administered by different clinicians [4].

With advances in science and technology, a range of instruments has been developed to address the growing demand for wound care. Among these, noninvasive imaging techniques have received particular attention for their potential to support wound assessment and monitoring. A systematic review of 20 studies done in 2015 summarized available approaches, including 2D stereophotogrammetry and 3D imaging methods. The authors concluded that 2D imaging is a practical wound measurement technique, offering ease of use and reliable assessments of wound size and healing progress; however, they noted that its inability to capture wound depth limits its value for care planning [5]. Building on this, a 2022 scoping review of 156 global studies examined the development, evaluation, and implementation of digital health technologies (eg, imaging and measurement) for wound care [6]. This review highlighted growing adoption of digital tools, citing evidence of their acceptability, feasibility, effectiveness, and clinical impact. At the same time, it identified important challenges, including limited evidence in hard-to-reach populations (eg, those in remote regions), low uptake linked to noninclusive design processes, and uncertainty around cost-effectiveness. It is essential to note that this review was not specifically tailored to older adults, a population at elevated risk of wound development and delayed healing due to comorbid conditions, and who also experience disproportionate barriers to care arising from age-related, geographic, and socioeconomic factors.

This study is a forward-looking perspective that highlights the current context of wound care in Canada and explores the potential for artificial intelligence (AI) driven digital wound care technology (DWCT) to improve access, efficiency, and equity. The authorship of this study reflects the multiple perspectives shaping this work, including 2 community health systems implementing a DWCT, the evaluation team supporting that implementation, academic and government partners advancing digital health innovation, and representatives from the company developing the technology. By bringing together these complementary experiences, we aim to provide a salient commentary on the merits of AI-augmented DWCT and its potential to advance equity, access, and efficiency in wound care in Canada.

The initial implementation of a DWCT in 2 rural and/or remote community health care systems, presented here as case studies, illustrates the contextual challenges faced by health care providers and patients while also offering practical insights into the technology's application and benefits. Discussion of anticipated challenges in implementing AI technologies in wound care provides a roadmap for future research directions, including identification of potential facilitators and barriers to adoption and uptake of the DWCT in the 2 networked community health systems. The potential for AI in transforming health care delivery is vast, particularly in the field of wound care, and can play an important role in ensuring that all patients receive high-quality, equitable care across diverse geographies.

Wound Care in Canada

The Canadian population is experiencing a significant demographic shift, with older adults (65 years and older) rapidly becoming the fastest-growing demographic, and by 2051, they could represent 25% of the population [7]. Aging is associated with the accumulation of cellular and molecular damage within the body, which can manifest as frailty and/or chronic health conditions [8], which increases vulnerability to complex wounds, meaning the number of older adults needing wound care is anticipated to increase substantially in the future [9]. Although the exact prevalence of wounds requiring care in Canada is unclear, estimates suggest that up to CAD $11.1 billion (US $8.18 billion) are spent annually on wound care [9]. Approximately 1 in 500 Canadians develops nonhealing wounds [10], which significantly impacts the health care system [11]. In Ontario alone, 30% - 50% of health care delivery involves patients with wounds, predominantly affecting older adults who often heal at home [11].

In 2019, older adults constituted 17% of Canada's population but accounted for 47% of total health care costs [10]. Rural and remote areas of Canada are aging more rapidly than their urban counterparts [12]; yet, they often have fewer health resources, especially health human resources (HHR) [2]. This lack of access to timely treatment for complex wounds leads to improper treatment of up to 25% of Canadian patients [13]. Chronic wounds impose significant physical and emotional burdens, decreasing patients' quality of life and increasing health care costs [14,15]. Without regular, high-quality care, these wounds can lead to serious complications such as infections, hospitalization, amputation, and even death [1].

The complexity of wound care is exacerbated by limited opportunities for comprehensive wound care education for health care providers, who typically receive fewer than 10 hours of formal instruction [16]. During training, health care providers are taught to provide quality care and maintain optimal functioning, including the treatment of health conditions such as wounds, through supportive, preventive, therapeutic, palliative, and rehabilitative care. However, these professionals need additional training to fulfill the specific needs of care and their respective professional scope of practice. For example, the College of Ontario of Nurses specified the scope of practice for registered nurses (RNs), registered practical nurses (RPNs), and nurse practitioners (NPs), which includes 5 regulated acts, including performing a prescribed procedure below the dermis or a mucous membrane [17]. While this authorized act consists of wound assessment and wound care, which are at the entry level, nurses with advanced education, such as NPs, have an extended scope of practice and are authorized to diagnose, prescribe medications, and other treatments for clients [17]. Similarly, British Columbia has specified the pacified authorities at entry level and advanced level, which is presented in the Wound Care Canada by Freeman et al [18]. In addition, the British Columbia Provincial Nursing Skin & Wound Committee, in collaboration with the wound care clinicians from across all health authorities, has devised the wound assessment and treatment flow sheet: documentation guide (version 2, 2018) that specifies nurses' roles with regard to wound assessment and documentation for varying types of wounds [19].

Traditional methods for tracking wound healing progress, such as using a paper ruler and cotton swab for wound assessment, result in high clinical variability and a 44% error rate in infection identification [20]. Furthermore, health care education and wound care tools have traditionally been developed with lighter skin tones in mind, leading to inaccurate assessment for patients with darker skin [21]. Additionally, rural communities in Canada are diverse, not only in terms of geographic characteristics such as population size, density, or distance from urban centers, but also in social aspects, including social representation and resource availability [18,22,23]. There is growing concern regarding the shortage of health care providers in remote and rural regions, further intensifying the issue of care access for older adults. The Canadian Institute for Health Information reports on the declining trends of health professionals in rural or remote areas, including for nurses, NPs, and pharmacists over a decade, and stagnant growth for rural family physicians [2]. Reducing health disparities, particularly in rural and remote areas with finite resources, requires innovative solutions, including consultation models and enhanced access to best practice care [24]. These dual drivers, population aging and uneven resource distribution, underscore the urgent need for effective health care solutions that:

1. Enable individuals to age in place while living with aging-related health conditions, including chronic and complex wounds.
2. Support the provision of best-practice clinical care in areas where specialized health care human resources are limited.
3. Reduce the challenges associated with human error and biases.

To meet these needs, innovative technologies such as AI offer promising solutions that can enhance efficiency, access, and quality in health care delivery.

AI-Enhanced Wound Care as a Solution

AI has the potential to transform medical practices and service delivery in health care, including enhancing productivity, improving patients' flow, experience, care, and quality of life [25] and enhancing providers' experiences and safety [25,26]. The positive impacts of AI in clinical care include enhanced accuracy in diagnostics, improved patient engagement, and increased treatment support [25]. AI has been leveraged in wound care, providing more efficient and effective solutions for acute and chronic wounds [27]. AI-driven algorithms have proven effective in measuring wound dimensions and identifying prognostic features, such as tissue composition, granulation, slough, eschar, and exudate. These elements are crucial for assessing wound burden and predicting the healing trajectory [28].

Our Implementation Experience: Project and Team

To illustrate how AI-augmented wound care can enhance equity, access, and efficiency, we draw on our collective experiences implementing a DWCT in 2 networked Canadian community health systems. The following section describes the technology itself, the project sites, and the multidisciplinary team involved in its adoption, highlighting both practical considerations and lessons learned in real-world settings.

The Digital Wound Care Technology

The DWCT under implementation, Swift Skin and Wound (Swift), is developed by Swift Medical Inc. and is deployed in more than 5200 health care facilities internationally, spanning the continuum of care. Swift Skin and Wound is a software-based, noninvasive digital wound assessment application installed on smart devices. The software captures clear imaging enhanced by HealX (Swift Medical Inc), a Health Canada and US Food and Drug Administration–registered fiducial marker for real-time calibration of wound images on smart devices, using AI-driven algorithms that auto-trace wound edges, precisely measure wound surface area, and facilitate comprehensive documentation [29]. These features offer advanced analytical and tracking insights to clinicians, empowering them with data-driven assessments to support wound care management [28,29]. This DWCT also enhances communication among the interdisciplinary care team through the centralized dashboard portal, which provides a comprehensive, real-time view to support coordinated care management. The dashboard enables the care team to review patient information, track progress, and provide recommendations, facilitating coordination of care.

Recently, Swift Skin and Wound added additional features: AutoDepth, SmartTissue, and HealingIndex. AutoDepth automatically calculates the visible depth of wounds, measures the wound, and accurately identifies and records its deepest point on a smart device. SmartTissue detects and quantifies tissue types including epithelial, granulation, slough, and eschar within the wound bed, irrespective of skin tone, using deep learning and vision architectures designed to run locally on a wide range of smart devices [30]. HealingIndex uses deep learning and machine learning algorithms to analyze a range of wound characteristics, including wound size, tissue composition, wound type, location, and wound exudates' type and amount to predict healing trajectories of wounds [28]. By using these sophisticated AI-driven algorithms, providers can achieve rapid and precise assessments of wounds and their characteristics and use predictive modeling to project healing trajectories and inform clinical decision-making for care plans (Figure 1).

Figure 1. A sample wound on the ankle area, showing a clinical presentation where objective and consistent wound assessment, supported by an artificial intelligence–driven tool for measurement and tissue classification, can enhance effective monitoring, especially in settings with limited access to specialized expertise.

Evidence from implementations, mostly in US health systems, indicates that integrating Swift's DWCT into wound care programs can improve clinical outcomes [31,32], enhance operational efficiency [29,32], reduce costs [31-33], and increase clinician satisfaction [34].

While other digital wound care technologies exist, this viewpoint focuses on Swift's DWCT because the authorship team is uniquely positioned as active implementation partners in Canadian health systems. We draw on the published literature to provide context and evidence, but we triangulate these insights with our direct, real-world experience to highlight equity, access, and efficiency considerations that emerge in practice, providing insights that would be difficult to capture from literature alone.

Project Description

This project uses an implementation research approach to evaluate the adoption of the DWCT in 2 networked Canadian health systems, aiming to identify facilitators, barriers, and lessons for broader AI-driven wound care implementation.

Implementation Site 1: Giishkaandago'Ikwe Health Services

Giishkaandago'Ikwe Health Services (formerly Fort Frances Tribal Area Health Services) is an Indigenous-led health organization in Northwestern Ontario. The accredited organization provides holistic health services to the 10 Anishinaabe Communities of Southern Treaty 3. The Home and Community Care Program offers essential services in the home and community setting, including advanced wound care through a nurse-led DWCT tool.

Giishkaandago'Ikwe initiated implementation of the DWCT in February 2022 as a quality improvement initiative. This site has particular expertise in leveraging technology to provide care across remote geographic regions. Given the high amputation rates in the region, the home and community care team implemented the DWCT to strengthen decision-making for wound management through efficient documentation and communication, with the goal of enhancing healing rates and reducing amputations.

The interdisciplinary wound care team includes RNs, RPNs, including 2 Skin Wellness associate nurse (SWAN)–trained RPNs, personal support workers (PSWs), and a physiotherapist with advanced wound care training (Masters of Clinical Science in wound healing). In total, the team includes 14 wound care clinicians, supported by a wound care champion and a home and community care coordinator. Foot care nurses conduct wound assessments and communicate findings to the home care team, while other community health nurses contribute through public health programming and wound care support.

Team members complete an 8-hour online wound care training upon hire if they do not already have advanced wound care education. In addition, the team participates in an annual, full-day, hands-on internal wound care workshop to reinforce clinical skills. Weekly SWIFT rounds provide structured opportunities for case review, collaborative problem-solving, and ongoing knowledge exchange.

Implementation of the DWCT was completed over 1 month, supported by training and mentorship from both SWIFT and the site's internal champion (the home and community care coordinator). Initial training consisted of a 1-hour virtual session, followed by ongoing support throughout the implementation period. Due to the team's small size, strong collaboration, and existing wound care expertise, adoption of the technology was rapid and well integrated into practice. The AutoDepth feature has been actively used in patient care, and team members completed SmartTissue training in January 2025.

Implementation Site 2: Brightshores Health System (Brightshores)

Brightshores Health System is a comprehensive health care network serving the rural Gray and Bruce counties in Ontario, Canada. It operates 6 hospitals (Owen Sound, Meaford, Markdale, Southampton, Wiarton, and Lion's Head), each with 24/7 emergency departments. Brightshores services encompass medical and surgical services, including complex surgeries, total joint replacements, cancer treatments, advanced diagnostic imaging such as magnetic resonance imaging and computed tomography scans, and wound care. Across the system, over 400,000 visits per year are reported, and approximately 2200 staff members with over 250 dedicated physicians deliver patient care across the region, including wound care.

Implementation of the DWCT began in 2024, initially within the regional diabetic foot ulcer clinic. Within months, 35 clinical staff were trained as technology champions, and by October 2024, the DWCT was rolled out to multiple departments across all 6 hospitals. Initial training was performed in-person (2.5 h) with an asynchronous online portion (1.5 h) facilitated by the research team and a nurse specialized in wound, ostomy, and continence (NSWOC), with a focus on use of the AI technology, clinical data entry education, and workflow processes. Users included RNs, RPNs, clinical coordinators, NPs, nurse clinicians, and PSWs. Within 6 months, it was noted that the turnover of staff necessitated continuous training opportunities. An online training module has been developed specifically for the Brightshores sites, which will be more accessible and enable quicker onboarding for staff across multiple sites. Deployment of SmartTissue began in December 2024 and continues across sites.

Discussion

AI-Powered Digital Wound Care Could Improve Access, Enhance Efficiency, and Address Inequities

Overview

Wound care is a critical component of comprehensive home health services. The prevalence of older adults as recipients of home care is notable, with a substantial proportion necessitating wound care due to conditions such as pressure injuries, postsurgical recovery, and complications arising from venous ulcers. Older adults prefer to receive wound care in community settings [35], citing pain, transportation barriers, and risk of exposure to infection in the clinic as primary drivers of preference [36]. Patients and family caregivers frequently report feeling inadequately prepared to participate effectively and confidently in wound care [37]. The presence of nonhealing wounds and associated complications can profoundly affect quality of life, increasing risk of infections and hospitalization [38].

Access

In the Canadian context, the potential for an AI-enhanced DWCT to increase access to best practice care is particularly significant. The "Caring for Canadians" study highlights a significant gap between the supply and demand for HHR in Canada, a gap that is already evident and expected to widen over the next decade, with rural and remote communities feeling the impacts most acutely [39]. Specialist HHR, such as NSWOCs or additional training in wound care, is in high demand. However, recruiting and retaining specialized health care workers is challenging, which has led to the adoption of innovative, technology-enhanced care models to optimize resource use [2,24].

In Canada, geographic location is a primary factor determining access to care, with isolated and remote communities experiencing the highest levels of deprivation [40]. These communities are frequently located in northern regions of the provinces and territories and are often home to Indigenous groups [40]. First Nations, Métis, and Inuit people, along with those of African, Caribbean, Southeast Asian, and Latin descent, have higher prevalence and incidence of diabetes and higher rates of lower extremity amputation because of diabetic foot ulcers and peripheral arterial disease [41]. This is particularly evident in Indigenous populations, where the rate of major amputations due to diabetic wounds is up to 49 times higher than in non-Indigenous populations [42]. This may be attributable to poor access to health care, barriers to clear communication, cultural differences, and discrimination [43]. Within this context, the AI-augmented DWCT offers an opportunity to increase access to best practice care by leveraging available resources and supporting available staff to work at the frontiers of their scope of practice (Textbox 1).

Textbox 1. Case study: Giishkaandago'Ikwe Health Services.

The team at Giishkaandago'Ikwe Health Services uses digital wound care technology (DWCT) for all aspects of wound assessments. Leveraging this technology has strengthened communication internally and externally with care partners. Enhanced communication is central to improved outcomes, illustrated here through a client story.

A client was referred by the Emergency Department after seeking care for painful, reddened foot wounds that had worsened following several weeks of self-treatment. The team initiated a comprehensive wound assessment completed by a personal support worker (PSW) using the SWIFT app. PSWs are unregulated care providers who assist individuals with activities of daily living (ADLs) and instrumental activities of daily living (IADLs).

A holistic treatment plan was then created by the interdisciplinary team during SWIFT rounds. Giishkaandago'Ikwe Health Services mobilized available staff to provide care, ensuring they were supported to work to their full scope of practice. The client observed weekly progress through the app, which increased their engagement and adherence to the care plan. The team also used dashboard-generated reports to share wound progress with external health care providers.

Through this collaboration, the client's care was escalated appropriately, enabling timely access to vascular surgery and chiropody for specialized offloading. The client received these services in a tertiary center and was able to return home promptly, with the Giishkaandago'Ikwe team providing ongoing follow-up.

Despite a late start to wound care and the need for surgical intervention, the client's wounds fully healed within 5 months—an excellent outcome for a case at high risk of amputation. Importantly, the majority of the client's care occurred within their home community, minimizing disruption to their family and caregiving responsibilities. The ability to coordinate and communicate effectively across providers using DWCT was key to avoiding prolonged hospitalization and ensuring continuity of care close to home.

In the Giishkaandago'Ikwe Health Services case study, the DWCT enabled a PSW who had direct contact with the patient to complete a wound care assessment even though this typically would be conducted by nursing staff. The DWCT tool enabled the team member who was geographically co-located to effectively capture the data needed for the wound care team to create a full care plan, without requiring the patient or the specialist providers to travel. In such scenarios, AI-augmented DWCT can support an available staff member to work at the frontiers of the scope of practice while maintaining direct connections for clinical escalation and consultation when needed.

This is particularly relevant in the Canadian rural and remote context, where geography and inclement weather can act as a barrier to access. A 2020 review of barriers to equitable access identified the lack of year-round roads, extreme winter weather events, and the absence of rural and remote hospital staffing as key contributors to poor access to care in Indigenous communities [44]. That same review identified telehealth and telehealth-enabled consultation models as a mitigator of inequitable access. Furthermore, the review noted that telehealth enables community health workers and nurses to provide additional services in their local community and reduces the burden on patients to travel long distances to access care. This has important implications for equitable access, as community care providers typically have higher levels of trust and greater ability to provide culturally safe care [45].

The DWCT augments traditional "telehealth" in wound care by adding empirical data in the form of high-quality, time-lapsed photos in a "dashboard" that can be accessed by patients, caregivers, and the entire wound care team. This enables tracking of wound trajectory and gives contextual clinical data to geographically remote specialist providers such as NSWOCS, endocrinologists, and vascular surgeons. Additionally, the dashboard supports team communication as it offers a shared point of reference to facilitate collaborative care planning. In the context of an optimized scope of practice, this feature provides an additional layer of protection—ensuring specialized clinical oversight of geographically remote patients being cared for by practitioners working at the frontier of scope of practice. Furthermore, this supports staff who may not have clinical training in wound care by providing avenues for consultation and escalation to complement their clinical judgment. Ultimately, this benefits patients who receive care from a trusted provider in their community, while retaining the benefit of review and consultation from clinical experts.

The AI-augmented features of the DWCT expand access to best practice care by (1) enabling patients in remote communities to access services without necessitating travel, (2) empowering clinicians practicing in rural and remote communities to work with an optimized scope of practice, and (3) supporting communication and ensuring all members of the care team have access to relevant clinical information.

Efficiency

Optimization of clinical resources is required to ensure efficiency and maximize the number of patients who receive best practice care. The AI-enhanced DWCT tool can increase clinical efficiency by conducting rapid assessment of wounds and streamlining consultations and escalations [28]. A key component of effective wound care is assessment of wound size. Traditionally, this is done with paper rulers, and the wound size is calculated using a formula that multiplies length by width. However, this traditional method is ill-suited to irregularly shaped wounds, leading to overestimation of size in 36% - 74% of nonrectangular wounds [46-48]. Patients with darker skin tones, wounds characterized by diffuse edges, irregular shapes, necrotic tissue, or unhealthy surrounding tissue are more prone to having their wounds overestimated in size [46]. A more accurate calculation of wound size can be captured using a tracing method, where transparency film is placed over the wound and outlined, but this is reported to be time-consuming [49]. Accurate and objective measurement of wounds is essential as a change in wound size is a key predictor of wound healing trajectory [5]. Digital wound measurements powered by AI are emerging as a more efficient and accurate means to measure wounds [46,50-52] (Textbox 2).

Textbox 2. Case Study: Brightshores Health System.

Brightshores Health System is spread throughout 8600 square kilometers in Southwestern Ontario. Residents are among the oldest average age in the province, with the fastest-growing segment of the population aged between 65 and 84 years. The region has a significant population of patients with chronic disease and wounds, but Brightshores is limited to 1.4 Nurses Specialized in Wound, Ostomy, and Continence (NSWOC's) for the 6 hospital sites.

This means that daily, multiple wounds can present at any one of Brightshores hospitals, and the reality of limited resources means limited and delayed response time. Furthermore, without access to specialists and with limited tools, frontline nursing staff struggle to accurately assess wounds. The DWCT has presented an opportunity for frontline staff to take photos of wounds, allowing for accurate and detailed assessments that can be digitally accessed by the NSWOC and all providers within the circle of care. Providing frontline staff at all 6 hospital sites with a tool to accurately assess wounds allowed for a reduction in reliance upon the NSWOC.

Within the first year, over 1000 km of NSWOC travel time has been saved, allowing them to devote more time to direct patient care. Since the implementation of this DWCT, initial trends show a promising decline in amputation rates and fewer visits of outpatient wound care patients attending the emergency departments due to wound complications, compared to the previous year. Patients are reporting that their assessments performed with the DWCT are more comfortable than traditional methods and are reporting that the use of DWCT has improved their wound care experience.

In one patient's story, the patient felt discouraged about the lack of visual improvement they were able to detect with their eyes. With the use of the DWCT and historical measurements, the patient was able to monitor progressive wound closure, aligning with compliance to treatment recommendations, and was happy to experience a full wound closure within a month of using Swift.

Brightshores' continued hope is that the use of this technology will empower nurses to gain confidence and become more involved in wound assessments, enabling prioritization of wound care, and that this technology will enable patients to see progression in healing over time.

This case study highlights the benefits of tools that enable the clinical care team to optimize their time and streamline processes for escalating concerns to specialized care resources. Use of the DWCT is faster and clinically equivalent in accuracy compared to manual methods of wound measurement and capture [29,53]. Enhanced DWCT reduces the overall time required for wound measurement and documentation and has been shown to result in an average time saving of 1.01 - 2.39 minutes per wound assessment when compared to the traditional manual methods [29]. Given the known constraints on clinicians' time, burden of documentation, and anticipated workforce shortages, these time savings represent an opportunity to increase both efficiency and access.

AI tools can also help identify and escalate wounds that require review. HealingIndex is a new feature of the DWCT that uses machine learning algorithms to assess the photographs of the wounds that are submitted by clinicians. This tool analyzes the photo to identify wound characteristics associated with healing including wound size, tissue composition, and exudates, to predict the healing trajectories of the wound. The HealingIndex AI Model uses deep learning techniques to examine patient wound records, images, and characteristics, producing a score from the AI model that indicates the level of risk for delayed healing and potential deterioration [28].

While traditional care pathways rely on clinicians identifying and escalating wounds that are deteriorating or at risk of deteriorating, the HealingIndex automates these processes using a predictive algorithm. This allows the wound care team to rapidly identify and prioritize wounds that require specialist input. This identification reduces the risk of deterioration and complications that necessitate hospitalization or amputation, reducing overall health care costs associated with wound complications [1,31,38]. Furthermore, the use of this AI tool can identify wounds at risk for slow healing, which may require an adapted wound management protocol. By reducing complications and adapting the treatment of slow-healing wounds, the AI tool can reduce the overall costs associated with wound care [31]. Early identification of wound deterioration is crucial as it allows timely intervention, preventing progression and potentially leading to significant savings for the health care system through avoidance of unnecessary costs [34].

The use of the predictive algorithm may also augment clinical decision-making by identifying wounds that are healing effectively and therefore may not need daily or thrice-weekly dressing changes. Reducing the frequency of dressing changes reduces supply costs and frees patient and provider time. Reducing the frequency of dressing changes to once a week, where clinically appropriate, can free up thousands of hours of nursing time over the course of a year [54]. Overall, the AI-powered DWCT can enhance clinical efficiency by automating escalation and review processes.

Additionally, the DWCT platform provides opportunities for asynchronous collaboration. Specialists are able to review patient records, including high-resolution time-lapse photos, and provide recommendations without requiring geographic co-location or congruent timing. This enables the specialist wound care nursing team to optimize their time by reducing travel between sites, reducing administrative burden, and creating care plans that can be executed by staff located near the patient. This offers the benefits of not only efficiency but also equity, as access to best practice care and consultation is no longer limited to the fortunate few who can be reviewed by the specialist nurses in person. In rural and remote parts of Canada, which, as noted above, are struggling to recruit and retain skilled providers, these tools enable more patients to access specialist consultation and review without necessitating travel.

AI-powered DWCT can support increased efficiency by (1) reducing time spent on manual assessment and measurement of wounds; (2) automating escalation by flagging deteriorating wounds for review, which enables prioritization of at-risk patients for intervention; and (3) enabling collaboration between frontline staff and specialist wound care resources without requiring geographic colocation or time alignment.

Equity

Universality and accessibility are embedded within Canada's Health Act, and equity must be centered as a priority. Inequities in the Canadian health system exist, especially related to disparities in health outcomes for rural and remote populations, and disproportionately affect First Nations, Inuit, and Métis communities who face burdens associated with travel and costs [44]. Rural health care policies are often guided by urban care models, which can exacerbate these inequities for rural communities [24].

Many rural, remote, and Indigenous communities experience inequitable access and poor outcomes, which may be attributable in part to resource shortages. Additionally, human biases, racism, colonial legacies, and historically unbalanced relationships between service users and providers also play a key role. Nyugen et al [44] explicitly state "Colonization and historical intergenerational traumas... have plagued the survivors and later generations with physical and mental trauma," and "...many Health Care providers do not acknowledge the impact of colonization on the Indigenous community and disregard the social determinants of health as explanations for illness." This, in turn, manifests as culturally inappropriate health services, which deter people from seeking health care.

In this context, the AI-enhanced DWCT can support more equitable care by enabling community care providers with existing, trusting relationships to provide culturally safe care. This approach is aligned with mitigation strategies proposed by Indigenous health experts who highlight the importance of community partnerships and provision of culturally safe care [44,45].

Furthermore, patients with darker skin tones disproportionately experience poor wound outcomes, which may be attributable to both inequities in social determinants of health and limitations in provider ability to accurately identify clinically relevant changes in tissue in pigmented skin [55]. Johnson et al [55] note that erythema is an excellent example, as its presentation varies based on skin tone, and historically, medical education has failed to account for diverse skin tones in training and published literature [21]. Darker skin tone is associated with overestimation of wound size when using standard "width X length" measurements [46]. In comparison, the DWCT with AI-augmented AutoTrace, AutoDepth, and SmartTissue is able to provide accurate measurements and can enable color calibration to adjust for light conditions and skin pigmentation [46]. Thus, the use of the AI-enhanced DWTC can support more accurate measurements and potentially overcome some of the implicit biases that health care providers manifest.

Next Steps

While AI-enhanced tools offer immense promise to support better care efficiency and outcomes, there are several key considerations that must be addressed to ensure equitable and trustworthy implementation. One of the pressing concerns is the representation of diverse patient populations in AI systems. When datasets fail to capture diversity across factors such as skin tone, age, and other demographic variables, resulting models can produce biased or inaccurate outputs. These biases are particularly problematic in clinical contexts like wound care, where diagnostic accuracy is critical. Diverse groups, such as individuals with darker skin tones or older adults, are often underrepresented in training datasets, leading to biases in AI outcomes. This underrepresentation can result in inaccurate diagnoses or recommendations, which are harmful and counter to the goals of quality wound care. Human biases embedded in AI systems can become enshrined or even amplified if not intentionally designed with equity in mind [25]. Such biases arise when AI models are trained on datasets that do not adequately represent the diversity of the population, including those most likely to experience wounds, such as older adults [56]. Chu et al [56] emphasize the known challenges of ageism in AI, noting that models often overlook older adults due to insufficient data representation. To counteract these biases, it is essential to increase the diversity of AI training datasets and maintain robust evaluation protocols that ensure accuracy and interrater reliability across patient populations. These safeguards are crucial in mitigating the risks of bias and ensuring that AI systems are fair and inclusive.

In addition to addressing bias, overcoming skepticism and implementation barriers is crucial for the successful adoption of AI-enhanced technologies, particularly among older adults. While the stereotype of older adults as technophobic is increasingly being disproven [57], structural barriers such as the cost of technology and access to reliable internet remain significant hurdles for many older adults in rural and remote communities [58]. Despite these challenges, patients are generally open to the use of AI in health care if appropriate regulatory and safety oversights are in place [59]. Pilot studies, such as those by Wang et al [52] and Raismam et al [60], show promising results regarding patient acceptance of AI for wound care [52,60] while Mohammed et al [34] highlight positive provider acceptance [34]. These studies indicate a growing receptiveness toward an AI-augmented DWCT, but continued exploration into unique barriers, especially those pertinent to the Canadian context, is necessary.

The evaluation being conducted by this team will enhance understanding of implementing AI-enhanced DWCT in rural and remote communities in Canada. This evaluation will identify specific barriers and facilitators of adoption, ultimately leading to the creation of a framework that supports wider adoption and integration of technologies to support healthy aging. By addressing these issues, the path toward equitable, efficient, and widespread use of AI technologies in health care becomes clearer, fostering a more inclusive technological future.

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Conflicts of Interest

Authors HTM and RDJF are current employees of Swift Medical Inc. Other authors have no conflicts to declare.

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Abbreviations

AI: artificial intelligence
DWCT: digital wound care technology
HHR: health human resource
NP: nurse practitioner
NSWOC: Nurses Specialized in Wound, Ostomy, and Continence
PAST: Pressure Sore Status Tool
PSW: personal support worker
PUSH: Pressure Ulcer Scale for Healing
RN: registered nurse
RPN: registered practical nurse
SWAN: Skin Wellness associate nurse

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From Concept to Practice: Lessons From the Balanced Nursing Teams Decision-Support System

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Abstract

The global nursing workforce crisis demands a shift from reactive staffing to strategic workforce optimization through data-driven decision-support systems. This viewpoint paper reflects on the development and attempted implementation of the balanced nursing teams system, a decision-support tool integrating approximately 250 data points—of which roughly 150 are extracted from existing organizational systems (human resources, scheduling, electronic health records, quality registries) through flexible import mechanisms, and the remainder collected through a built-in 360-degree staff survey with automated analysis—across 10 domains to evaluate nursing team balance between capacity, performance, and outcomes. Following crowdfunding by 18 Belgian health care organizations, balanced nursing teams were implemented across 8 diverse settings (home health care, general hospitals, academic centers) between 2019 and 2023. Using the Human-Organization-Technology fit framework, we analyze why evidence-informed, organization-endorsed digital innovations struggle to achieve adoption. Our analysis reveals 3 interdependent barrier categories: technological fragmentation (vendor lock-in, legacy systems, prohibitive integration costs), organizational siloing (Chief Nursing Officers [CNOs] lacking budgetary authority, nursing framed as peripheral to strategic priorities), and managerial hesitance (fear of punitive data use, cognitive overload from staffing crises). These barriers were worsened by the substantial data-integration burden that the system's breadth imposed on organizations with limited digital maturity. Critically, only one site (ie, a nurse-led home health care organization where leadership held both strategic authority and resource control) achieved sustained implementation. This contrast demonstrates that workforce optimization through data depends not on software maturity alone, but on achieving simultaneous fit across human, organizational, and technological domains. We argue that the persistent marginalization of nursing leadership within hospital governance structures represents the fundamental barrier to digital transformation in nursing workforce management. The urgency paradox is striking: while nursing represents health care organizations' highest operational cost and most direct patient interface, workforce optimization tools are consistently deprioritized in favor of regulatory compliance systems and billing infrastructure. Bridging this gap requires systemic investment in nursing leadership authority, data interoperability standards, and recognition that data-driven workforce decisions are strategic imperatives rather than operational luxuries.

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KEYWORDS

nursing workforce management; clinical decision-support systems; implementation science; sociotechnical barriers; nursing leadership

Introduction

Overview

The global nursing workforce crisis extends beyond simple shortages. Persistent mismatches between staffing levels, skill mix, and patient demand have been linked to missed care, adverse outcomes, and failure to rescue, ultimately compromising both patient and staff outcomes [1-4]. While policymakers have focused primarily on increasing the number of nurses entering the workforce, evidence indicates that expanding supply alone does not resolve the underlying staffing challenges [5,6]. The retention of experienced nurses depends on the work environment quality and team performance [7], yet high turnover continues to impose substantial financial and operational burdens on health care organizations [8].

Current staffing models, such as mandatory nurse-to-patient ratios, fail to capture the complexity of nursing team dynamics, skill mix optimization, and broader contextual factors that determine whether care teams can effectively meet patient demands [9]. Addressing this challenge requires a shift from ratio-based workforce planning towards data-informed team design that integrates human, organizational, and contextual dimensions of nursing care [9].

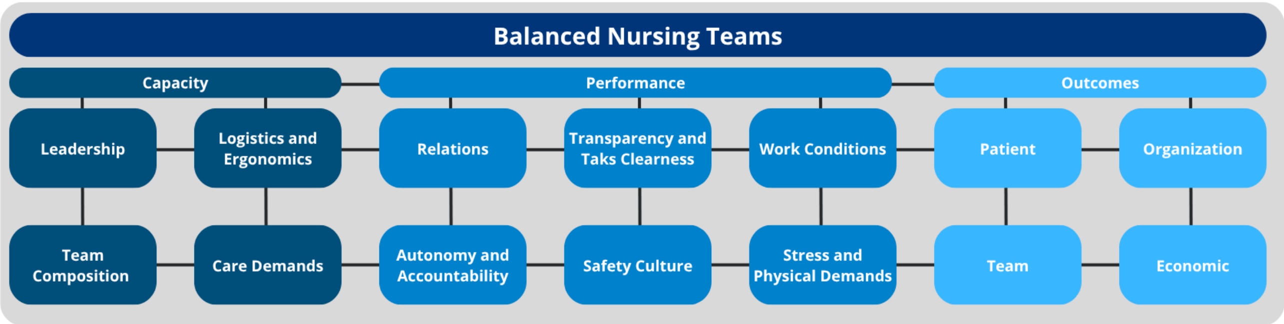
This viewpoint paper offers a critical reflection on the sociotechnical challenges of implementing digital workforce innovation in nursing. Drawing from our experience developing and testing the balanced nursing teams (BNuT) decision-support system across 8 Belgian health care organizations, we examine why evidence-informed, practitioner-endorsed digital tools struggle to achieve real-world adoption. Rather than presenting a traditional implementation study, we provide an analytical perspective on the systemic barriers that constrain digital transformation in nursing workforce management, offering lessons for researchers, health care organizations, and policymakers pursuing similar innovations.

A Nursing Teams Composition and Staffing Decision-Support System: BNuT

In response to these challenges, the BNuT initiative was launched in 2018 through a collaboration between a member organization of Belgian health care organizations and 2 research groups. The project originated from a clear practical demand: develop an instrument that enables evidence-based, proactive, and data-driven decisions regarding nursing team composition. Following proof-of-concept development, 18 health care institutions collectively crowdfunded the project, reflecting broad recognition of this critical gap in nursing workforce management.

BNuT was conceived as a computerized decision-support instrument designed to optimize team composition and team functioning in ways that existing tools cannot. While most workforce software estimates patient demand or calculates staffing levels based on mandatory ratios [10], these systems rely heavily on manual governance and contextual adjustment. In contrast, BNuT integrates data across multiple domains—including relational dynamics, autonomy, care demand, leadership, logistics, and safety—into a unified team-level model of workforce balance (Figure 1).

Figure 1. Conceptual model of the balanced nursing teams (BNuT) system. The figure depicts the 10 subcomponents supporting the BNuT decision-support system, organized into 2 overarching categories: capacity domains (team composition, care demands, staffing, and skill mix) and performance domains (leadership, logistics, safety culture, workload distribution, team dynamics, and professional development). These domains collectively inform the assessment of team balance, ranging from negative imbalance through optimal balance to positive imbalance.



The system estimates team balance on a continuum ranging from negative imbalance (eg, excessive workload and high risk of burnout) through optimal balance to positive imbalance (eg, over-capacitated teams and high risk of boreout). This continuum builds on earlier conceptualization of a balanced care team as one in which capacity, including care demands and team composition (4 domains) and operational performance processes (6 domains), is strategically aligned to optimize outcomes for both staff and patients, as well as organizational and economic outcomes [9]. Sustained imbalance between the 10 domains undermines both care quality and workforce sustainability. BNuT aims to operationalize this principle by assessing the alignment between nursing workforce organization and patient care needs, translating complex multidimensional data into actionable, evidence-based visual indicators for team and managerial decision-making.

The development of BNuT followed a staged approach designed to progressively establish validity and relevance. The underlying model was empirically grounded in a systematic scoping review that identified 35 factors across 9 domains of balanced team functioning [9]. The indicator set was subsequently refined through structured codevelopment with nursing managers from participating institutions, who assessed each variable's clinical importance, data availability, and interpretive complexity. The application itself was co-designed with end users through user-story workshops that shaped functionality, interface design, and workflow integration. This iterative process established content validity, ensured practical relevance, and confirmed usability. However, criterion validation against patient and staff outcomes, which was originally planned via the operational deployment in participating hospitals, could not be completed. This validation gap was caused by the sociotechnical barriers described in this paper, as they prevented the successful implementation necessary for outcome evaluation. BNuT should therefore be understood as a theoretically and empirically informed decision-support prototype. Its outcome validation remains contingent on achieving the organizational conditions for sustained use.

Aim and Analytical Framework

This paper provides a reflective analysis of the sociotechnical challenges encountered during the development and testing of BNuT. We move beyond technical specifications to examine why digital innovations supported by both evidence and organizational demand struggle to achieve real-world adoption. Our analysis uses the Human-Organization-Technology fit (HOT-fit) framework [11], a model specifically developed for evaluating health information systems. This framework maps the 3 principal barrier categories observed in our work and highlights how interactions among human, organizational, and technological factors jointly shape implementation outcomes. Each dimension is examined systematically, followed by an integrative reflection demonstrating how compounding barriers can obstruct implementation even when individual system components function as designed. This viewpoint does not present outcome validation of the BNuT system; rather, it offers a structured reflective analysis of implementation dynamics, informed by 8 years of engagement with participating organizations and stakeholders across the Belgian health care field.

The insights presented in this viewpoint are grounded in 8 years of sustained engagement with the BNuT project (2018 - 2026), encompassing the full cycle from conceptualization and codevelopment to attempted implementation across 18 health care institutions. During this period, the author team engaged in extensive, iterative dialogues with stakeholders across all levels of the health care system (eg, frontline nurses, nursing managers, CNOs, data managers, data protection officers, IT departments, and external development partners) through codevelopment workshops, pilot testing sessions, steering committee meetings, and formal presentations to prospective adopters and investors. Each of these interactions generated feedback that progressively shaped the team's understanding of the barriers and enablers discussed in this paper. The reflections synthesized here emerged iteratively from this long-term, multi-stakeholder engagement. This approach prioritizes ecological breadth and depth of immersion over the rigor of structured qualitative research. The HOT-fit framework [11] was applied retrospectively to organize and analyze these accumulated insights, providing an analytical foundation.

The BNuT System and Implementation Context

BNuT Concept and Architecture

Health care organizations face a fundamental data paradox in nursing workforce management. While data seems abundant, the information remains siloed across systems, leaving leaders without the integrated insight required for strategic workforce decisions. Existing information systems were primarily designed for billing and regulatory compliance rather than operational or strategic decision-making. As a result, critical data concerning team dynamics, workload distribution, competency mix, and patient demand remain fragmented across incompatible platforms, such as electronic health records (EHRs), scheduling tools, human resources (HR) databases, and quality registries. This fragmentation and the lack of comprehensive data warehouses or business intelligence tools leave nurse managers operating largely reactively, addressing daily staffing shortages without insight into long-term workforce patterns or their impact on safety, quality, and retention. Moreover, staff lack a data-informed understanding of their team capacity, performance, and outcomes, and must rely largely on perceptions. This data paradox has become increasingly consequential as contemporary health care systems face mounting pressures: cost containment imperatives, heightened quality and safety demands, and growing clinical hyperspecialization that requires more sophisticated approaches to team composition and skill-mix optimization.

BNuT aims to address these challenges through 2 interconnected objectives that shift workforce management from reactive to strategic. The first involves comprehensive data collection and processing to enable both cross-sectional analyses (capturing current team states) and longitudinal tracking (monitoring team evolution). This supports standardized decision-making capable of distinguishing between expected variance, acceptable fluctuations, and disruptive imbalances. The second objective focuses on integrating multiple data streams into meaningful composite indicators at the clinical microsystem level, encompassing workload intensity, competency distribution, leadership effectiveness, safety climate, and related domains to estimate the balance between team capacity, performance and care demands, and outcomes.

To achieve this, the system combines a 360-degree evidence-based survey, capturing staff perceptions on statements within each capacity and performance domain, and data drawn from existing organizational systems such as scheduling software, EHRs, and quality metrics. All data are synthesized using established evidence-based standards in nursing workforce research, ensuring that the resulting indicators reflect empirically supported relationships between the domains. Crucially, the unit of analysis is the clinical microsystem, acknowledging that patient and team outcomes emerge from collective team processes rather than individual performance metrics. The system supports dynamic management through continuous monitoring and benchmarking functions, allowing leaders to compare performance across teams, identify high-performing configurations, and support continuous improvement. Team involvement in discussing these data is paramount to support teams and leaders in understanding team strengths and weaknesses, to identify improvement priorities, and to assess the extent of readiness for innovation [12]. BNuT thus provides managers and leadership with both a helicopter view for strategic oversight and the ability to zoom in on specific teams or metrics when deeper investigation is required, thereby supporting decision-making at operational, tactical, and strategic levels.

Implementation Setting and Challenges

BNuT was implemented across 8 health care organizations representing diverse contexts, including home health care, general hospitals, and academic centers. Although the degree of adoption varied, each site revealed distinct yet interrelated sociotechnical barriers that influenced feasibility and uptake:

1. At the human level, hesitance and abstention emerged as key barriers. While these responses may originate as reactions to perceived risks, the resulting behavioral patterns—reluctance to engage, delayed adoption, or outright avoidance—function as implementation barriers. Nursing leaders and managers expressed concern that

BNuT-generated insights might be misused in their performance evaluations. There was also apprehension about receiving feedback without having the resources or organizational support to act on it, creating a sense of accountability without agency. The operational pressures of managing day-to-day staffing crises left little cognitive bandwidth for strategic workforce optimization. This environment discouraged engagement with reflective data tools, despite general support for the underlying vision.

2. At the organizational level, siloed priorities and hierarchical governance structures undermined implementation. Financial executives, facing severe budget constraints (particularly relevant given that approximately 40% of Belgian hospitals operate at a financial loss [13,14], perceived workforce optimization tools as an additional cost rather than an investment. Chief technology officers, while conceptually supportive, found it difficult to justify allocating scarce IT resources to early-stage, nurse-led projects lacking immediate financial return. This division between nursing leadership (operational authority) and executive governance (strategic control) created a structural misalignment that limited implementation feasibility.
3. At the technological level, integration of existing systems proved prohibitively complex and expensive due to vendor lock-in strategies, legacy system fragmentation, and deliberate data walling between platforms. Several hospitals had outsourced IT operations, transforming what could have been internal configuration tasks into costly external service requests requiring formal budget approval. IT departments, already constrained by workforce shortages and competing project portfolios, often struggled to prioritize nurse-led digital innovations.

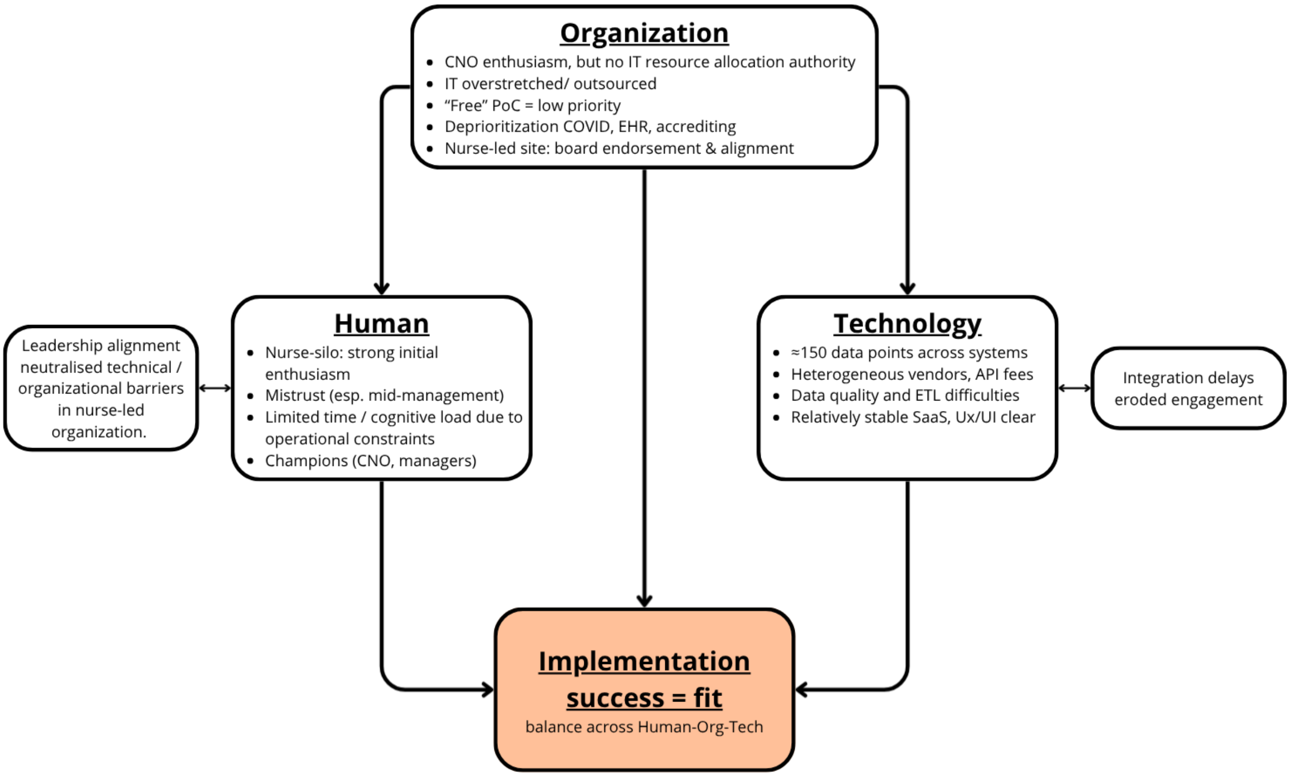
Out of the 8 health care organizations, one site achieved substantial success offering a contrasting perspective. Operating as a nurse-led home health organization, its leadership culture embedded the vision of data-driven workforce optimization from the outset. Alignment between operational need, executive vision, and organizational authority enabled integration of BNuT into management routines. This contrast underscores the critical role of organizational alignment and leadership ownership in realizing the potential of sociotechnical innovations such as BNuT.

The 3 Dimensions of Barriers

Identifying the HOT-Fit

The implementation experiences of the BNuT project were examined through the HOT-fit framework [11]. The framework provides a sociotechnical lens for analyzing how system adoption and sustainability depend on the alignment, or fit, between 3 interacting domains: human, organizational, and technological. Our reflections demonstrate that BNuT's implementation challenges were not isolated to any single dimension. Rather, success depended on achieving an equilibrium across domains, and an imbalance in one frequently undermined progress in the others (Figure 2). This section reflects on lessons learned within each domain and concludes by considering the interdomain dynamics that shaped implementation outcomes.

Figure 2. HOT-fit framework applied to the BNuT implementation. The diagram illustrates the 3 interacting domains of the HOT-fit model and their relationships in the context of the BNuT decision-support system. Arrows represent interdependencies: successful implementation (fit) occurs only when all domains are simultaneously aligned. Callouts highlight two key observations: (1) strong fit within the organizational domain—where nursing leadership held both strategic authority and operational responsibility—enabled the nurse-led organization to overcome technical barriers, and (2) data-integration delays eroded user engagement. API: application programming interface; BNuT: balanced nursing teams; CNO: chief nursing officer; EHR: electronic health record; ETL: extract-transform-load; HOT: Human-Organization-Technology; PoC: proof of concept; SaaS: software-as-a-service; UX/UI: user experience/user interface.



Human: Trust, Empowerment, and Cognitive Capacity

Across the participating organizations, nursing leaders were consistently enthusiastic about BNuT's conceptual promise. The idea of a data-driven instrument capable of translating complex workforce information into actionable team-level insights resonated strongly with their daily struggles. Notably, the project itself originated from nursing leaders' explicit requests for better decision support tools, making BNuT a response to practitioner demand rather than a top-down research initiative. Early skepticism during prototype demonstrations largely dissipated once realistic use cases were presented. The urgency of developing such a system was widely acknowledged, and many leaders expressed relief that a project finally addressed the persistent gap between workforce research and managerial decision support.

> *The added value that this tool will be able to give us in the future was clear to everyone in the meeting. It will enable us to make an in-depth analysis based on objective data about the functioning of a team and also indicate on which elements action is required to remedy this.* [Chief Nursing Officer, participating hospital]

> *BNuT provides a most powerful lens for every nurse manager. Gain personal leadership and team insights to transform your department with data-driven decisions for better care and satisfied staff.* [Nurse Manager involved in BNuT pilot testing]

However, this enthusiasm coexisted with overconfidence regarding implementation feasibility. Many nursing leaders underestimated the organizational and technical barriers involved and overestimated their own authority to overcome them. Hospitals with advanced data infrastructures were paradoxically more hesitant, perceiving BNuT as "yet another system" rather than as a complement to existing business-intelligence tools. These organizations typically requested an Application Programming Interface (API) to integrate BNuT's algorithms into their own dashboards rather than adopting the full platform. Conversely, smaller organizations, particularly those without internal analytics capacity, perceived BNuT as uniquely valuable but lacked the resources to integrate it.

Hesitance surrounding data use proved a recurrent issue, though its nature differed markedly across organizational levels. Among frontline nurses, concerns were minimal once the survey's anonymity was assured; they generally perceived BNuT as a supportive and developmental tool rather than a threat. In contrast, hesitance and some mistrust were concentrated among junior and mid-level managers, who feared that aggregated results, particularly those reflecting leadership climate or organizational support, could be interpreted punitively by higher management. In one large university hospital, even the CNO voiced concern that unfavorable scores on "organizational leadership" might be politically exploited by other executives. These perceptions reveal the asymmetrical distribution of vulnerability within hierarchical hospital structures: while staff trusted the system's safeguards, middle management occupied a position where performance data could plausibly affect professional standing.

Demonstrations and early pilots substantially increased perceived usefulness. Once users saw how disparate data streams converged into interpretable insights, engagement improved markedly. A frequently cited example involved incident reporting: one team appeared to have a disproportionately high number of reported safety incidents. Initially interpreted as poor performance, the BNuT analysis revealed that this team simultaneously scored highest on safety culture, indicating a healthy incidence-reporting climate. Such cases illustrated how integrated data interpretation could challenge misperceptions and reframe organizational learning.

Despite these successes, cognitive and temporal constraints limited sustained engagement. Nursing managers facing chronic staffing shortages and operational crises had little time to interact with a strategic-level dashboard. The tool's intuitive design mitigated digital-literacy barriers, yet the absence of formal onboarding and the overall cognitive load of crisis management restricted deeper adoption. Champions, typically CNOs or middle managers, emerged in nearly all sites, but their influence was constrained by limited institutional authority. Over time, enthusiasm at the human level could not compensate for systemic resource constraints and organizational inertia.

However, it must also be acknowledged that the system's own scope likely contributed to the cognitive and governance burden experienced by potential adopters. BNuT encompasses 10 domains and integrates approximately 250 data points, of which roughly 150 are to be extracted from organizational systems. While the user-facing interface was specifically designed to simplify interpretation by reducing this complexity to composite indicators and visual summaries, the underlying data requirements imposed demands on organizational processes that were substantial, particularly for institutions already operating under severe resource constraints. For organizations with limited digital maturity, the gap between the system's data needs and the institution's capacity to deliver that data may have been too large, regardless of the tool's analytical value. In retrospect, a more modular deployment strategy might have lowered the threshold for initial adoption: beginning with a reduced core indicator set drawn from readily available data and progressively activating additional domains as organizational data capacity matured would have allowed trust, familiarity, and demonstrable value to develop incrementally before the full model was introduced.

Organizational: Leadership Alignment and Structural Inertia

The organizational context proved decisive. In all hospitals, the CNOs were strong advocates for BNuT, yet they lacked budgetary control. IT departments, already overstretched and managing numerous competing projects, had to allocate technical resources, while financial decisions ultimately rested with chief financial officers. Because the project was offered free of charge during the proof-of-concept phase, it competed poorly for attention against commercial initiatives with contractual obligations. In hindsight, requesting a modest financial buy-in might have enhanced commitment and prioritization by signaling ownership.

Both HR and IT departments often viewed BNuT as redundant. HR staff perceived it as encroaching on their existing tools, while IT departments regarded it as a low-priority research experiment. Chronic shortages of IT personnel further reduced their willingness to support time-consuming integrations. In several hospitals, IT services had been partially outsourced, transforming even minor configuration tasks into expensive external contracts. In some cases, hospitals lacked in-house capacity to access their own databases, as software vendors maintained exclusive control and charged high fees for basic queries. These arrangements effectively held data "hostage" and created a very high dependency on vendors for data extraction.

Organizational fit, the degree to which nursing leadership held authority corresponding with operational responsibility, emerged as the critical differentiator. In hierarchical organizations where the nursing department functioned as a silo, CNOs struggled to gain board-level approval. Projects framed as nurse-led were perceived as peripheral to strategic objectives. By contrast, the one nurse-led organization integrated BNuT into its formal strategic plan, supported by executive leadership and dedicated IT allocation. This fit between operational need, strategic vision, and resource authority was essential. It enabled the project to progress from conceptualization to sustained use, highlighting the necessity of structural empowerment for nursing leadership within governance systems.

> *We use BNuT as an integrated data and communication system in our organization to better understand our practices and outcomes in home health and to lead and manage our organization proactively.* [CEO Home Health Organization]

Competing institutional priorities further hindered progress. Post-COVID recovery, ongoing EHR upgrades, and accreditation audits absorbed most organizational attention. Because BNuT did not have immediate regulatory or financial implications, it was consistently deprioritized. Organizational culture also played a role: hospitals with participatory cultures tended to show greater openness to collaboration, whereas highly hierarchical institutions rarely progressed beyond exploratory discussions. Overall, BNuT's organizational challenges reflected the entrenched marginalization of nursing leadership within hospital governance, a systemic issue that extends beyond this specific innovation.

Technological: Interoperability, Data Quality, and Usability

The technological domain presented the most concrete and persistent barriers. BNuT requires integration of about 250 data points, where approximately 150 data points can be drawn from existing systems: HRs, scheduling, EHRs, quality registries, and even locally maintained spreadsheets. Each organization used a unique constellation of software vendors and data formats, often without shared standards. Even when multiple hospitals used the same vendor, integration had to be redeveloped from scratch due to licensing and cost restrictions.

Vendors frequently imposed additional charges for API access or custom data exports, and in several cases claimed that bespoke queries were required for every new request.

Manual preprocessing was initially necessary to conform to the BNuT data structure. Anticipating this challenge, the system was designed with a flexible, tiered integration architecture: organizations could upload data manually per data point through the web interface, push standardized files through an automated importer in an agreed-upon format, or connect directly to a PostgreSQL database structure into which raw data could be pushed with automated ETL processing. To further reduce this burden, the project contracted an external ETL specialist who configured direct connections to source systems where feasible. Despite this flexibility, the approach proved only partially effective due to heterogeneous database architectures, limited vendor documentation, and the cost of obtaining data exports from third-party software providers. Data quality issues were widespread: implausible values were common, and missingness varied widely between datasets. BNuT's algorithms were designed to tolerate partial missingness, except for a few core variables essential for standardization, but the variability still limited analytic robustness. The persistence of these barriers, even given the system's deliberately flexible architecture, underscores that the bottleneck was structural and rooted in vendor lock-in, fragmented data governance, and limited hospital IT capacity.

Despite these integration difficulties, the user-facing technology was well received. A professional user experience/user interface designer ensured that the interface was intuitive and visually clear, with a simplified radar chart summarizing 10 domains of team performance. Users could benchmark teams or explore subdomains with minimal training. The system was web-based (Software as a Service) and accessible through standard browsers, providing sufficient performance and stability for managerial use.

Maintenance and updates were provided by the research team in collaboration with a contracted developer. Hospitals were able to independently distribute surveys and upload local data, and feedback loops for technical improvement remained informal. Overall, the technical obstacles were concentrated in data extraction and integration rather than in software usability or performance.

A critical question arising from the BNuT experience is whether a model integrating approximately 250 data points was over-engineered. The breadth of the model reflects our conceptual ambition of capturing team balance across all domains identified as relevant in the empirical literature [9], an ambition that was codeveloped and endorsed by the participating organizations themselves. However, the practical consequence was a data-governance burden that exceeded the current capacity of most hospital sites, particularly those reliant on legacy systems, outsourced IT functions, or fragmented data architectures. Even the flexible integration mechanisms provided could not overcome the structural barriers imposed by vendor lock-in and the cost of data extraction from proprietary systems. This tension between comprehensiveness and feasibility represents a design challenge that is not unique to BNuT but characterizes many health information systems that attempt to bridge the gap between research-level measurement and operational reality [15]. Future iterations of such systems should consider adopting a modular architecture where a core set of indicators (operationalizable with minimal integration effort and immediately actionable for nursing managers) serves as the entry point, while the full model is reserved for organizations with sufficient digital infrastructure and data-governance capacity.

Interdomain Fit: A Prerequisite for Sustainability

Analysis across HOT-fit domains highlights that implementation success depended on achieving simultaneous fit across all 3 dimensions. The nurse-led organization illustrated how a strong fit within the organizational domain, where nursing leadership held both strategic authority and resource control, could compensate for barriers in other areas. Once executive endorsement was secured, IT resources were allocated, data-sharing agreements expedited, and BNuT was embedded in strategic planning. The same technical hurdles that halted progress elsewhere became manageable. Conversely, where one domain lacked fit, most commonly technology, momentum in the others dissipated.

In several hospitals, delays in data integration eroded enthusiasm among nursing leaders who initially championed the tool. Similarly, where organizational structures prevented nursing leadership from influencing IT or financial decisions, human-level motivation could not translate into implementation capacity. Positive feedback loops only emerged when success was visible and endorsed from the top: early demonstrable value encouraged further engagement and resource allocation, but such cycles remained rare.

Overall, these patterns confirm the HOT-fit framework's central proposition: the effectiveness of health information systems depends not merely on the functionality of individual components but on the equilibrium between them. Imbalance in any single domain propagates across the system, undermining overall fit. In BNuT's case, technological constraints, particularly data integration and interoperability, acted as the principal bottleneck, yet organizational and cultural dynamics determined whether these constraints could be overcome. Strong leadership endorsement, clear strategic positioning of nursing within governance structures, and proactive attention to data-trust and communication dynamics proved essential conditions for sustaining progress. The nurse-led success case offers a critical insight: when nursing leadership holds both strategic authority and operational responsibility, implementation becomes feasible. In this organization, the same technical challenges that stalled progress elsewhere were systematically addressed because nursing leadership could directly allocate resources, prioritize IT projects, and embed BNuT within strategic planning. This demonstrates that the barriers encountered elsewhere were not primarily technical but organizational. Conversely, when nursing remains positioned as a cost-center with limited influence over budgets and technology decisions, even technically sound innovations may struggle to take root. Achieving fit across human, organizational, and technological systems is therefore not only a condition for digital success but also a reflection of the broader power balance between clinical professions and institutional structures within health care.

Discussion

Principal Findings

The main finding of this reflective analysis is that the implementation of BNuT succeeded only where simultaneous alignment across human, organizational, and technological domains was achieved, specifically in a nurse-led home health organization where leadership held both strategic vision and budgetary authority. Across the 7 hospital sites, adoption was prevented by converging barriers: data interoperability failures driven by vendor lock-in and fragmented IT architectures, restricted nursing leadership authority within hierarchical governance structures, and the substantial data-governance demands imposed by the system's own breadth. These findings are not unique to the Belgian context but reflect structural dynamics widely documented in health informatics.

More specifically, the BNuT implementation illustrates how organizational complexity constrains decision-support adoption in nursing practice. Across sites, barriers arose primarily from misalignment between human, organizational, and technological domains, although BNuT's own data requirements may also have exceeded the digital capacity of participating institutions. This finding echoes long-standing observations within implementation science that the success of health information technology depends less on technical soundness than on contextual fit within existing workflows, governance, and professional cultures [16].

The predominance of technological barriers parallels systematic reviews showing that interoperability failures remain the most persistent obstacle to decision-support integration [17,18]. As in those studies, the inability to access or standardize data across HR, scheduling, and clinical systems eroded perceived reliability and constrained analytic capability. These "barriers of insufficiency" [17] reflect structural deficits in hospital IT resourcing rather than isolated project limitations, reinforcing the need for policy-level interoperability mandates.

The vendor lock-in and data fragmentation observed in the BNuT project are not isolated to the Belgian health care context. Internationally, similar dynamics have been extensively documented. In England, the National Programme for IT (NPfIT) was ultimately dismantled in 2011, in part because of vendor lock-in and the inability to achieve interoperability across hospital trusts [19,20]. Subsequent NHS strategies have mandated open standards and fast health care interoperability resources–based interoperability, yet in practice, vendor-controlled data architectures continue to impede secondary use of clinical and workforce data [21-23]. In the United States, the 21st Century Cures Act introduced explicit information-blocking provisions to prevent vendors from restricting data access, reflecting federal recognition that proprietary data practices constitute a systemic barrier to innovation [24]. Within the European Union, the proposed European Health Data Space regulation represents an emerging attempt to establish cross-border interoperability standards that could, in principle, reduce the per-project negotiation costs that proved limiting in the BNuT experience [25]. Collectively, these international examples confirm that the barriers encountered by BNuT reflect a structural problem in health IT governance, and that no amount of tool-level design can compensate when system-level interoperability standards are absent.

At the organizational level, the imbalance between nursing leadership enthusiasm and restricted resource authority emerged as decisive. BNuT encountered resistance not from overt opposition but from structural dependency on nonclinical decision-makers, reflecting what has been described as the "negotiation of control" in health care technology implementation [26]. When nursing leaders lacked access to financial or technical levers, implementation stalled despite clinical support [27]. This pattern may reflect broader international challenges: research suggests that even within integrated health systems, resource allocation and workflow redesign remain chronic bottlenecks [28], while CNO authority limitations and IT resource allocation challenges appear to be documented across health care systems globally [17,27]. The single nurse-led organization in our sample, where strategic and budgetary authority were unified under nursing leadership, achieved full operational use, empirically supporting the HOT-fit premise that fit across all domains is a prerequisite for sustainability.

The human dimension was characterized by enthusiasm to hesitation, abstention to mistrust. Nurses did not resist technology per se, but distrusted implementations perceived as top-down or evaluative [29]. The anonymity of BNuT's survey component mitigated some of these concerns, yet lingering fears of data misuse illustrate fragile power dynamics [26]. Time pressure and cognitive overload further limited engagement, with research showing that human-resource scarcity continues to undermine even well-designed interventions [17].

Taken together, our findings reinforce the view of health care organizations as complex adaptive systems in which technical, organizational, and human subsystems are tightly coupled [16]. Localized improvements in one domain cannot compensate for deficits in another. The nurse-led success case exemplifies this interdependence: strong executive sponsorship overcame technical and organizational inertia, producing a functioning sociotechnical equilibrium. In contrast, sites lacking such fit experienced cascading failure: data integration delays reduced managerial trust, which in turn decreased organizational priority. Implementation success thus required "all lights green," confirming HOT-fit's central premise that sustainable adoption depends on balanced interaction across domains.

The conceptual contribution of BNuT lies in extending decision support beyond patient-level staffing ratios towards team-level optimization, incorporating leadership, workload, and safety culture. This holistic approach addresses gaps identified in recent reviews of nursing decision-support systems, which report limited theoretical grounding and minimal postimplementation evaluation [30]. Yet the difficulties experienced in this project also underscore the persistent divide between research prototypes and operational systems. Bridging this divide will require not only improved technical integration but also structural empowerment of nursing leadership to act as equal partners in digital transformation.

The lessons from BNuT have concrete implications for the design of future nursing decision-support systems. First, scalability demands a shift from monolithic, all-or-nothing deployment towards modular architectures that allow organizations to adopt core functionality with minimal integration effort and progressively expand as digital maturity grows. An API-first, cloud-native design would reduce per-site configuration costs and enable integration with diverse IT ecosystems without requiring bespoke development for each vendor. Second, adaptability requires that indicator sets are configurable to organizational context: rather than imposing a fixed 250-variable model, future systems should allow institutions to select domains aligned with their strategic priorities and data availability, with the full model serving as an aspirational benchmark. Third, integrating predictive analytics, for example, flagging units where scheduled team composition falls below stability thresholds, or forecasting turnover risk based on employment pattern trends, would shift such tools from retrospective reporting towards prospective decision support, increasing their value for both unit-level workforce management and organization-wide strategic planning. Fourth, interoperability should be embedded by design rather than retrofitted: adopting open data standards and European Health Data Space–compatible data models from the outset would reduce dependency on vendor-specific export mechanisms. For clinical data, standards such as HL7 fast health care interoperability resources provide a foundation; however, workforce-specific data (including turnover, employment patterns, and team composition metrics) are not yet covered by existing interoperability standards, highlighting the need for standardized data models for nursing workforce analytics as a prerequisite for tools like BNuT.

Taken together, the findings demonstrate that sustainable digital innovation in health care depends on achieving fit across human, organizational, and technological systems. Where one domain fails, whether through technical fragmentation, limited leadership authority, or mistrust, momentum across the others may diminish. Conversely, fit across all domains enables small successes to compound into sustained adoption.

Furthermore, they reveal a troubling urgency paradox. Given mounting workforce shortages, cost pressures, and quality demands, strategic optimization of nursing team deployment should arguably be among health care organizations' highest priorities. The nursing workforce represents both the highest operational cost and the most direct interface between an organization and its patients. Yet across the sites studied, workforce optimization tools were consistently deprioritized in favor of regulatory compliance systems, billing infrastructure, or projects with more immediate financial returns. This misalignment between stated workforce priorities and actual resource allocation warrants attention from nursing leadership and policymakers alike. Translating these insights into practice yields several actionable lessons for the key stakeholders shaping the future of the nursing workforce.

Several limitations of this viewpoint must be acknowledged. First, the authors were the developers of BNuT, which creates an inherent risk of presenting the tool more favorably than an independent analysis might. We have tried to apply a self-critical lens, particularly in examining whether the system's own complexity contributed to adoption failure, but readers should interpret the analysis with this in mind. Second, the reflections presented here are grounded in 8 years of sustained stakeholder engagement rather than in formal qualitative data collection with recorded interviews, systematic coding, and member checking. This gives us considerable ecological breadth and depth of immersion, but lacks the methodological safeguards of structured qualitative research, and the insights may be subject to recall bias and selective interpretation. Third, all implementation attempts occurred within the Belgian health care system, with its specific configuration of hospital governance, vendor markets, and regulatory frameworks. Although we have drawn parallels with international experiences, direct generalizability to other jurisdictions should not be assumed. Fourth, criterion validation of BNuT against patient and staff outcomes was planned but could not be completed because the sociotechnical barriers described in this paper prevented sustained implementation. The system's effectiveness, therefore, remains empirically undemonstrated, and the tool should be understood as a theoretically informed prototype rather than a validated intervention. Fifth, the contrast between the single successful site and the 7 hospital sites should be interpreted with caution: the successful organization differed structurally in governance, scale, and patient population, and the comparison cannot isolate which specific factors were sufficient or necessary for adoption. Nonetheless, we believe that systematically documenting implementation failure through a structured analytical framework serves an important function in the health informatics literature, where publication bias towards successful cases limits collective learning.

Lessons Learned

The synthesis of our findings, summarized in Figure 2, yields actionable lessons for the diverse stakeholders involved in digital nursing innovation. While grounded in the BNuT experience, these insights reflect broader structural issues relevant to sociotechnical implementation in health care.

Researchers

For researchers developing digital decision-support tools, the BNuT case offers a sobering lesson. BNuT was developed bottom-up from explicit practitioner demand: nursing leaders requested better decision-support tools, and 18 health care organizations collectively crowdfunded its development. The project incorporated end user co-design throughout, with nursing managers and CNOs involved in iterative development cycles. Implementation science principles guided the approach, including stakeholder mapping, staged rollout, and continuous evaluation. Yet despite these methodological strengths, BNuT still encountered fundamental barriers that prevented adoption in most sites. This suggests that the obstacles to data-driven decision support in nursing may be more systemic than methodological: even well-designed, practitioner-endorsed innovations may fail when organizational structures do not grant nursing leadership the authority to implement them. Researchers should therefore embed evaluation within a sociotechnical framework from the outset, document contextual mechanisms rather than merely outputs, and advocate for the structural conditions that enable adoption, not only develop technically sound tools.

Health Care Organizations

For health care organizations, our analysis underlines that the success of nursing informatics projects depends on granting nursing leadership formal authority over budget and data infrastructure. CNO enthusiasm alone cannot compensate for siloed governance or outsourced IT functions where access to the health care organization's own data is locked by software vendors. Health care organizations need to address this issue in future contract negotiations with the software vendor so that access to their proper data can be faster, more flexible, and at a much lower additional cost. Organizations that positioned nursing as an equal partner in strategic planning achieved smoother integration and sustained use. Embedding nursing analytics tools such as BNuT within long-term workforce strategies, rather than treating them as stand-alone one-fits-all pilots, fosters alignment across organizational hierarchies and improves accountability.

Policymakers

For policymakers, the BNuT experience highlights that the barriers to digital nursing innovation are systemic rather than local. Fragmented data architectures, vendor lock-in, and inconsistent interpretations of data-protection regulation create environments where interoperability remains prohibitively expensive. Concretely, this requires policy action on multiple fronts. First, mandatory interoperability standards for health IT vendors would reduce the per-project negotiation costs that limited BNuT's data integration. Second, dedicated pilot funding mechanisms for nurse-led digital health innovation could provide the financial continuity that free proof-of-concept approaches cannot sustain. The BNuT experience suggests that offering a tool free of charge may paradoxically reduce organizational commitment; phased funding models tied to implementation milestones might better incentivize sustained engagement. Third, governance reforms that mandate nursing representation on hospital IT steering committees and digital transformation boards would address the chronic underrepresentation of nursing leadership that proved decisive across our implementation sites. Addressing these "barriers of insufficiency" [17] requires structural investment in digital infrastructure and governance. Equally essential is embedding nursing leadership within national digital health strategies. Policies that enable nurse leaders to access and use workforce data are not merely equity measures but economically rational interventions that enhance quality, safety, and system performance.

Conclusions

The BNuT experience demonstrates that the challenge of digital transformation in nursing may lie less in technology than in achieving fit across sociotechnical domains. Sustainable innovation appears to depend on the concurrent readiness of human, organizational, and technological systems, none of which can substitute for another. When fit is achieved, as in the nurse-led organization, digital tools can become enablers of strategic decision-making rather than isolated projects. The persistent barriers encountered across most sites reflect structural issues that extend far beyond any single system: the undervaluation of nursing leadership, fragmented data infrastructures, and chronic underinvestment in interoperability. Equally, our experience suggests that decision-support systems of this scope must be designed with explicit attention to the data-governance capacity of target organizations, adopting modular architectures that lower the threshold for initial adoption. Addressing these systemic imbalances—in interoperability governance, nursing leadership authority, and the design of implementation-ready tools—will be essential not only for future iterations of BNuT but for the broader success of nursing informatics as a driver of resilient and learning health care organizations.

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Authors' Contributions

SV contributed to conceptualization, project administration, visualization, writing of the original draft, and review and editing of the manuscript. PVB and FH contributed to conceptualization, supervision, validation, and review and editing of the manuscript. WDK contributed to the review and editing of the manuscript. The authors used a large language model (Anthropic Claude) to assist in the writing process, but remain fully responsible for the content.

Conflicts of Interest

None declared.

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Abbreviations

API: application programming interface
BNuT: balanced nursing teams
CNO: Chief Nursing Officer
EHR: electronic health record
HOT-fit: Human-Organization-Technology fit
HR: human resource
NPfIT: National Programme for IT

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Facilitating Digital Transformation in Nursing Through Nursing Development Units: Scoping Review

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Abstract

Background: Nursing Development Units (NDUs) are structured clinical environments designed to enhance professional development, collaboration, and organizational learning. While NDUs have been widely studied for their impact on nursing practice, their role in supporting digital transformation in health care has been less explicitly examined.

Objective: This scoping review aimed to map the characteristics, structures, and processes of NDUs and identify how these elements may relate to digital readiness and the integration of digital tools in nursing practice.

Methods: We conducted a scoping review of 40 publications describing NDUs. Data were coded iteratively to identify patterns at the individual, interpersonal, and organizational levels. Core elements and subcategories of NDUs were mapped, highlighting potential connections to capacities required for digital transformation.

Results: NDUs operate across three levels: (1) individual—fostering professional role development, leadership, and resilience; (2) interpersonal—promoting participatory cultures, collaborative practice, and shared unit visions; and (3) organizational—providing structured frameworks for practice philosophy, role development, resource and change management, and embedded evaluation systems. While most primary publications did not explicitly address digital competencies, the structures, reflective practices, and collaborative processes described represent foundational capacities for engaging with digital tools, innovation, and organizational change.

Conclusions: NDUs are characterized by multilevel structures and processes that enhance professional and organizational capacities. Although explicit evidence on digital transformation is limited, these capacities align with key prerequisites for the adoption and effective use of digital technologies in nursing practice. Further research is needed to examine how NDUs directly support digital innovation in clinical settings.

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KEYWORDS

nursing development unit; professional development; innovation in nursing; reflective practice; digital transformation; interdisciplinary collaboration; organizational learning; PRISMA

Introduction

Digital transformation is no longer a future scenario in health care but a present reality driven by artificial intelligence, remote monitoring, electronic health records, and data-informed decision-making [1-4]. While these innovations promise improved care quality, efficiency, and patient engagement, their implementation in nursing faces persistent challenges, including digital burnout, workflow disruption, resistance to change, and insufficient staff-centered design [5,6]. These barriers are not merely technical but rooted in organizational culture, leadership, and professional identity. Consequently, digital transformation in nursing often fails due to misalignment between technological innovations and clinical practice [6]. In this review, digital transformation in nursing is understood as a sociotechnical process. It involves technological adoption, changes in professional roles and competencies, and the adaptation of organizational routines and culture.

Nursing Development Units (NDUs) have emerged as a promising model to foster innovation and support digital transformation in nursing. NDUs are nursing-led, practice-based innovation hubs designed to integrate research, education, and clinical practice through reflective, participatory, and evidence-informed development cycles [7-9]. Unlike isolated pilot projects, NDUs are embedded within health care organizations and supported by dedicated leadership, resources, and evaluation systems, enabling long-term iterative learning and continuous improvement [10,11]. Their core mechanisms—structured reflection, participatory decision-making, and embedded evaluation—directly address known barriers to digital transformation by empowering nurses as cocreators of practice change.

Despite this potential, NDUs remain undertheorized in the context of digital health. Systematic mapping of their conceptual features, functional roles, and organizational frameworks—particularly regarding how they enable or constrain digital transformation—is lacking. Moreover, terminological variation (eg, “Clinical Development Unit,” “Practice Development Unit,” and “Nursing Professional Unit”) complicates cross-contextual comparisons and limits the transferability of insights [11-13]. This conceptual and methodological heterogeneity highlights a key research gap: the absence of a coherent, internationally applicable framework to understand how NDUs function as catalysts for digital innovation in nursing.

This scoping review aimed to address this gap by systematically mapping the international literature on NDUs, synthesizing their core conceptual features, functional roles, and organizational frameworks. The review also explored how NDUs engage with digital transformation—not as passive recipients of technology but as active spaces of knowledge translation [14], organizational change [15], and co-design [16]. A scoping review methodology was chosen due to the conceptual complexity, terminological diffusion, and limited existing synthesis of the NDU concept [17,18]. This approach allows for a comprehensive, transparent, and structured mapping of the literature, providing a foundation for future implementation models and strategies for digital innovation in nursing.

Methods

This scoping review followed the Joanna Briggs Institute methodology [17] and the framework by Arksey and O’Malley [18], which encompasses 4 phases: identifying relevant publications, selecting publications, extracting data, and synthesizing findings. Reporting adhered to the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist to ensure transparency and reproducibility [19].

Search Strategy

A systematic literature search was conducted in May 2025 in the databases MEDLINE (via PubMed), ScienceDirect, EBSCO, Cochrane Library, and Europe PMC. Supplementary searches in Google Scholar and LIVIVO captured gray literature and publications not indexed in biomedical databases. Results were sorted by relevance, and all retrieved records were screened without a stopping rule to maximize sensitivity.

The primary database search used the exact phrase “Nursing Development Unit” to prioritize conceptual precision. No additional filters (eg, publication year, study design, or language) were applied to capture the complete literature on NDUs. This decision was grounded in the historically established use of the term. In the literature, “NDU” often denotes a defined organizational model rather than a generic practice development activity. We anticipated that broader search strings (eg, including “Practice Development Unit” or “Clinical Development Unit”) would markedly increase retrieval in the main databases. Much of this literature is conceptually adjacent but heterogeneous (eg, general practice development, quality improvement, or clinical education units) and does not necessarily reflect the NDU model targeted in this review.

To reduce the risk of missing relevant publications due to terminological variation, we complemented the core database search with supplementary searches and screened for records that provided structural or process descriptions consistent with NDUs (eg, “Clinical Development Unit,” “Practice Development Unit,” “Nursing Clinical Development Unit,” and “Nursing Professorial Unit”). The full MEDLINE search syntax is provided in Multimedia Appendix 1.

Publications were included if they described structural, functional, or organizational characteristics of NDUs, as well as development processes and implementation strategies. Publications primarily evaluating effectiveness or outcomes (eg, patient metrics and clinical performance) were excluded as the focus was on conceptual mapping rather than outcome assessment. Disease- or population-specific NDUs were included only if they provided insights into NDU structures or processes. Only English- or German-language publications with available full texts were considered. English was used to ensure coverage of the international literature, whereas German-language publications were included for feasibility given the review team’s proficiency. Textbox 1 summarizes the eligibility criteria.

Textbox 1. Inclusion and exclusion criteria.

Inclusion criteria

- Empirical and conceptual publications with abstracts available
- Language: German or English
- Description of content-related aspects, progressive development process, and implementation strategies of Nursing Development Units (NDUs)

Exclusion criteria

- Disease-specific focus (unless NDU structures or processes were described)
- Evaluation of NDUs (effectiveness or outcomes)
- Full text not available

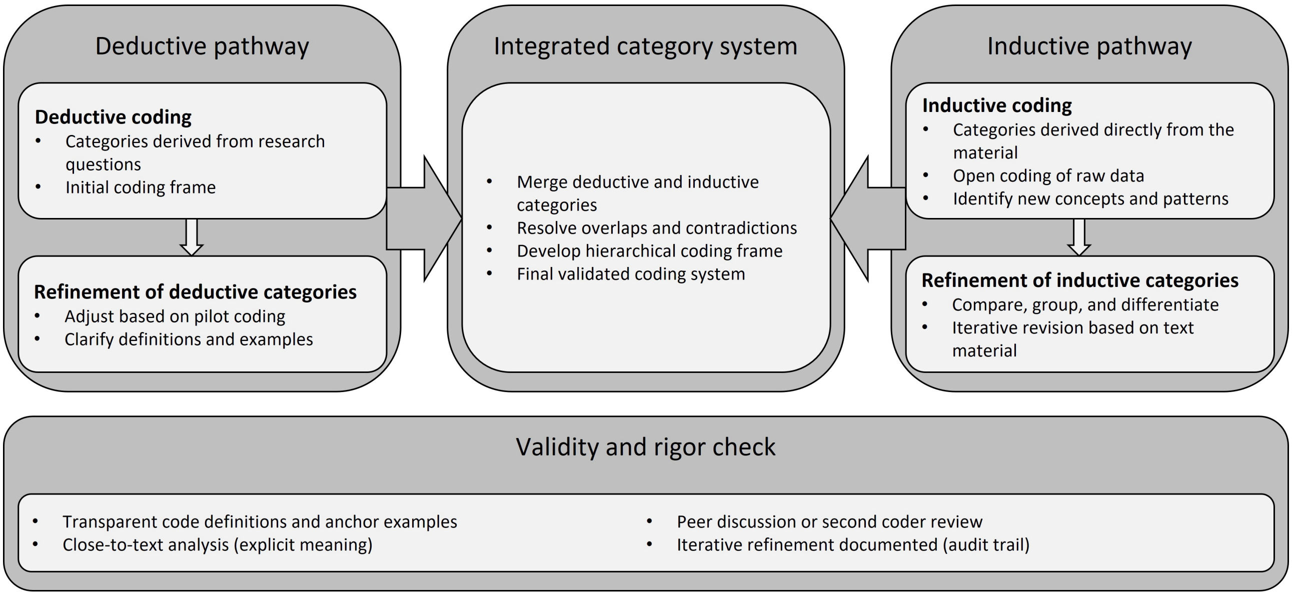
Publication Selection and Data Extraction

Duplicate records were manually removed based on title, author, digital object identifier, journal, and year. Three reviewers (AG, PM, and KG) independently screened titles and abstracts, and any record deemed eligible by at least one reviewer progressed to full-text review. The involvement of 3 reviewers at this stage was chosen to efficiently manage the large number of retrieved records.

Full-text screening was performed independently by 2 reviewers (AG and KG) using predefined inclusion and exclusion criteria, with disagreements resolved through discussion. All included publications were full-text documents (peer-reviewed articles or gray literature reports) that underwent thematic analysis. Data extraction followed a standardized charting framework capturing structural, functional, and organizational characteristics; development and implementation processes; and references to digital transformation where present. Each publication was extracted by a single reviewer, with the framework ensuring consistency. Given the more in-depth nature of full-text assessment, the involvement of 2 reviewers was considered sufficient to ensure consistency and methodological rigor.

A qualitative synthesis was conducted using the structured qualitative content analysis by Kuckartz and Rädiker [20], as recommended by Levac et al [21]. Thematic categories emerged through an iterative process: (1) deductive mapping of initial categories from the research questions (eg, "leadership identity"), (2) inductive coding of all publications to identify recurring patterns, and (3) aggregation of overlapping patterns into the final thematic structure through team consensus. Category definitions, anchor examples, and iterative coding refinement ensured analytical rigor. Figure 1 [20] illustrates the process.

Figure 1. Qualitative content analysis process according to Kuckartz and Rädiker [20] (applied in this review).



Ethical Considerations

As this study was a scoping review of published literature, it did not involve human participants, and therefore, ethics approval was not required.

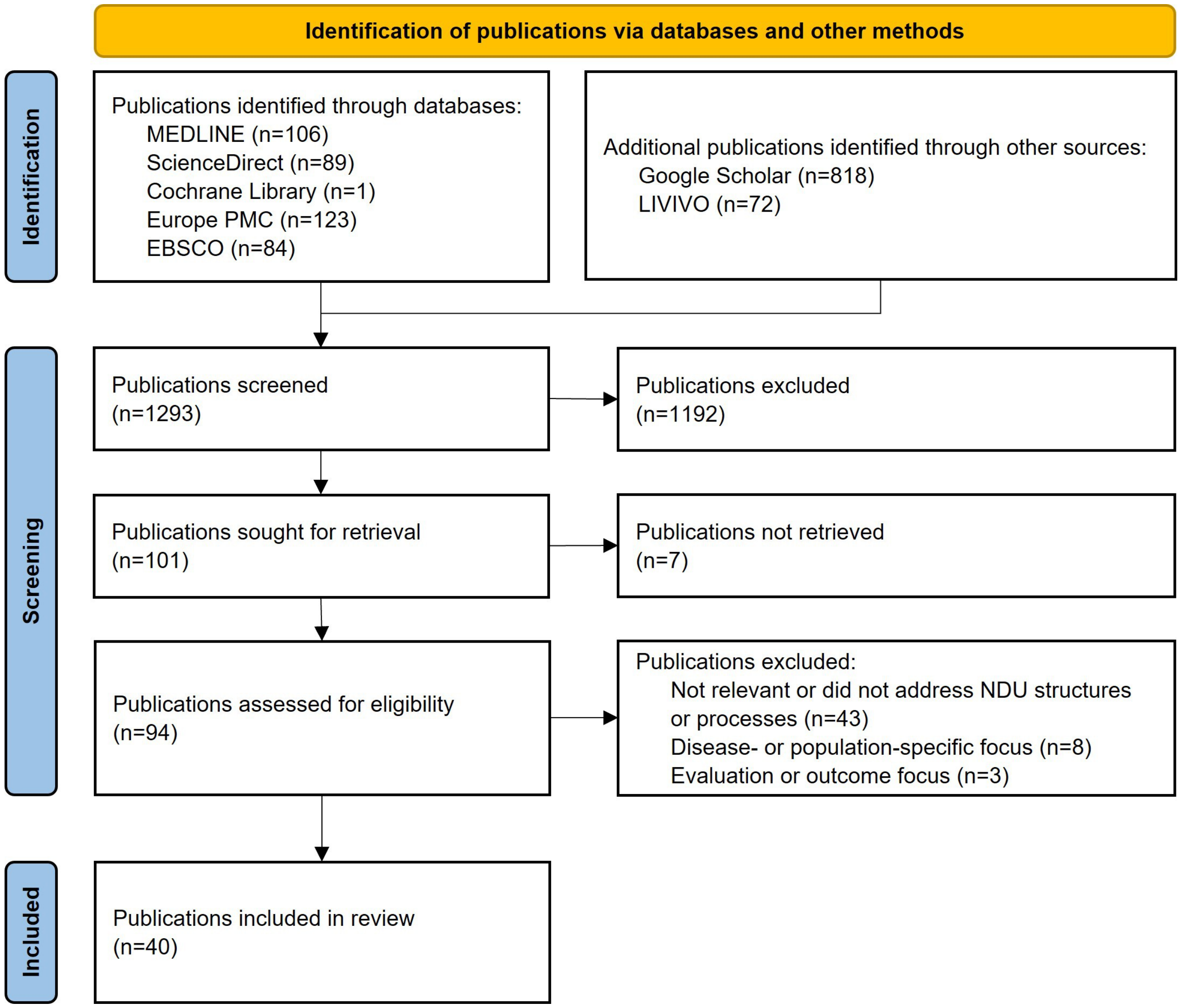
Results

Publication Selection

The database search conducted in May 2025 yielded 1293 records: 106 (8.2%) from MEDLINE (via PubMed), 818 (63.3%) from Google Scholar, 72 (5.6%) from LIVIVO, 89

(6.9%) from ScienceDirect, 1 (0.1%) from the Cochrane Library, 123 (9.5%) from Europe PMC, and 84 (6.5%) from EBSCO. After removing duplicates and screening titles and abstracts, of the 1293 publications, 101 (7.8%) underwent full-text review. Applying the predefined eligibility criteria resulted in 40 publications included for in-depth analysis. No unresolved disagreements occurred during the selection process. The publication selection process is illustrated in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart (Figure 2 [22]).

Figure 2. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart illustrating the study selection process (adapted from Moher et al [22]). NDU: Nursing Development Unit.



Main Characteristics of the Included Publications

The 40 included publications originated from the United Kingdom (n=26, 65%) and Australia (n=14, 35%) and covered the period from 1991 to 2017. Most publications were in English (n=39, 97.5%), with 2.5% (n=1) in German. Study designs comprised qualitative, quantitative, mixed methods, and conceptual approaches. The publications examined how professional roles, leadership, collaborative practices, organizational structures, and reflective processes shape nursing practice. Publication characteristics are summarized in Table 1.

Table . Characteristics of the included publications (N=40).

Study	Country	Design	Focus	Purpose
Atsalos and Greenwood [8], 2001	Australia	Qualitative	Leadership experiences in NDUs[a]	To explore leadership experiences of nurses working in NDUs under conditions of organizational stress
Atsalos et al [23], 2007	Australia	Qualitative	Experiences of nurse leaders in NDUs	To explore the experiences of nurse leaders involved in developing Clinical Development Units into centers of nursing excellence
Avallone and Gibbon [24], 1998	United Kingdom	Cross-sectional survey	Nurses' perceptions of their work environment in an NDU	To examine nurses' perceptions of their work environment within an NDU
Bell and Procter [25], 1998	United Kingdom	Qualitative	Experiences of nurses working in an NDU	To explore nurses' experiences of involvement in nursing research within an NDU
Bland [10], 1997	United Kingdom	Case study	Development of an emergency nurse practitioner role	To describe the development of the emergency nurse practitioner role within an accident and emergency NDU
Bowles and Bowles [26], 2000	United Kingdom	Quantitative	Transformational leadership in NDUs vs conventional units	To compare transformational leadership in NDUs and conventional clinical settings
Cannard [27], 1996	United Kingdom	Quantitative	Aromatherapy to promote relaxation and stress reduction	To describe the implementation of aromatherapy as a practice development initiative within an NDU
Christensen and Craft [28], 2017	Australia	Conceptual	Translating research into nursing practice	To discuss strategies for translating nursing research into practice through an NDU
Christian and Norman [29], 1998	United Kingdom	Qualitative	Clinical leadership in NDUs	To examine approaches to clinical leadership development within NDUs in England
Draper [30], 1996	United Kingdom	Narrative review	Opportunities for evaluation of NDUs	To critically examine the purposes, characteristics, and effectiveness of NDUs
Duffield [31], 2005	Australia	Evaluation study	Masterclass for unit managers	To evaluate the design and delivery of a leadership masterclass for nursing unit managers
Gerrish [7], 2001	United Kingdom	Evaluation study	Evaluation of NDUs	To evaluate a Nursing and Practice Development Unit accreditation program
Gerrish and Ferguson [32], 2000	United Kingdom	Qualitative	Factors influencing NDU progress	To identify factors influencing the development and progress of NDUs
Graham [33], 1996	United Kingdom	Conceptual	Conceptual framework for NDUs	To present a conceptual framework supporting reflective practice and practice development within NDUs
Graham [34], 2000	United Kingdom	Qualitative	Reflective practice in mental health nurses	To examine reflective practice processes among mental health nurses working in an NDU

Study	Country	Design	Focus	Purpose
Graham [35], 2003	United Kingdom	Qualitative	Leadership perspectives in NDUs	To explore leadership perspectives within an NDU from academic and clinical viewpoints
Greenwood [36], 2000	Australia	Qualitative	Clinical Development Units: challenges and issues	To describe the characteristics, achievements, and challenges of Clinical Development Units
Greenwood [12], 1997	Australia	Qualitative	Accreditation of NDUs	To describe NDUs and examine models of accreditation
Greenwood [37], 1999	Australia	Case study	Western Sydney approach	To describe the establishment and leadership preparation approach of a Clinical Development Unit network in western Sydney, New South Wales
Greenwood and Kearns [38], 1996	Australia	Qualitative	Establishing a transcultural NDU	To describe the establishment of a transcultural NDU in an Australian context
Greenwood [13], 2000	Australia	Qualitative	Issues surrounding establishment and survival of NDUs	To examine challenges related to the establishment and sustainability of NDUs
Greenwood and Parsons [39], 2002	Australia	Evaluation study	Evaluation of a leadership preparation program	To evaluate a leadership preparation program for Clinical Development Unit leaders
Happell and Martin [40], 2002	Australia	Qualitative	Changing mental health nursing culture	To describe the implementation of a nursing Clinical Development Unit program in mental health nursing
Happell and Martin [41], 2004	Australia	Evaluation study	Evaluation of the Nursing Clinical Development Unit program	To evaluate outcomes of a Nursing Clinical Development Unit program in mental health nursing
Happell and Martin [42], 2005	Australia	Evaluation study	Changing the culture of mental health nursing	To assess the impact of a Nursing Clinical Development Unit program on mental health nursing culture
Johns [43], 1991	United Kingdom	Conceptual	Holistic model of nursing practice	To present a holistic model of nursing practice developed within an NDU
Keatinge and Scarfe [44], 1998	United Kingdom	Qualitative	NDUs in dementia care	To describe the establishment of an NDU in dementia care
Keatinge et al [45], 2000	United Kingdom	Action research	Nursing management of agitation in institutionalized residents with dementia	To examine nursing management of agitation in dementia care through participatory action research within an NDU
Malby [46], 1996	United Kingdom	Qualitative	Overview of NDUs in the United Kingdom	To provide an overview of the development and implementation of NDUs in the United Kingdom
Manley [47], 1997	United Kingdom	Action research	Advanced practitioner and consultant nurse role	To develop and examine an advanced practitioner role through action research within an NDU context

Study	Country	Design	Focus	Purpose
Parsons and Mott [11], 2003	Australia	Qualitative	Toward Clinical Development Units	To describe the principles and processes underpinning Clinical Development Units
Pearson [48], 1997	United Kingdom	Evaluation study	King's Fund Centre NDU network	To assess the progress and direction of the King's Fund Centre NDU network
Redfern and Stevens [49], 1998	United Kingdom	Qualitative	NDU structure and orientation	To describe the structure, aims, and organization of NDUs
Redfern and Murrells [50], 1998	United Kingdom	Qualitative	Research, audit, and networking activity in NDUs	To compare research, audit, and networking activities between NDUs and non-NDUs
Redfern et al [51], 1997	United Kingdom	Qualitative	Evaluation of NDUs	To evaluate the value and core characteristics of NDUs
Ryan [52], 1994	United Kingdom	Qualitative	Improving discharge planning	To describe practice development activities aimed at improving discharge planning within an NDU
Schiereck [53], 2000	United Kingdom	Qualitative	Social interaction in NDUs	To examine social interactions between nurses and patients within an NDU
Scholes [54], 1996	United Kingdom	Qualitative	Role transition and emotional labor	To explore the impact of working in an NDU on practitioners' role transition and emotional labor
Vaughan [9], 1998	United Kingdom	Qualitative	History of NDU programs	To compare the development trajectories of 2 NDU programs
Wright [55], 2007	United Kingdom	Qualitative	Contribution to quality	To examine the concept of NDUs and their contribution to quality in nursing practice

[a]NDU: Nursing Development Unit.

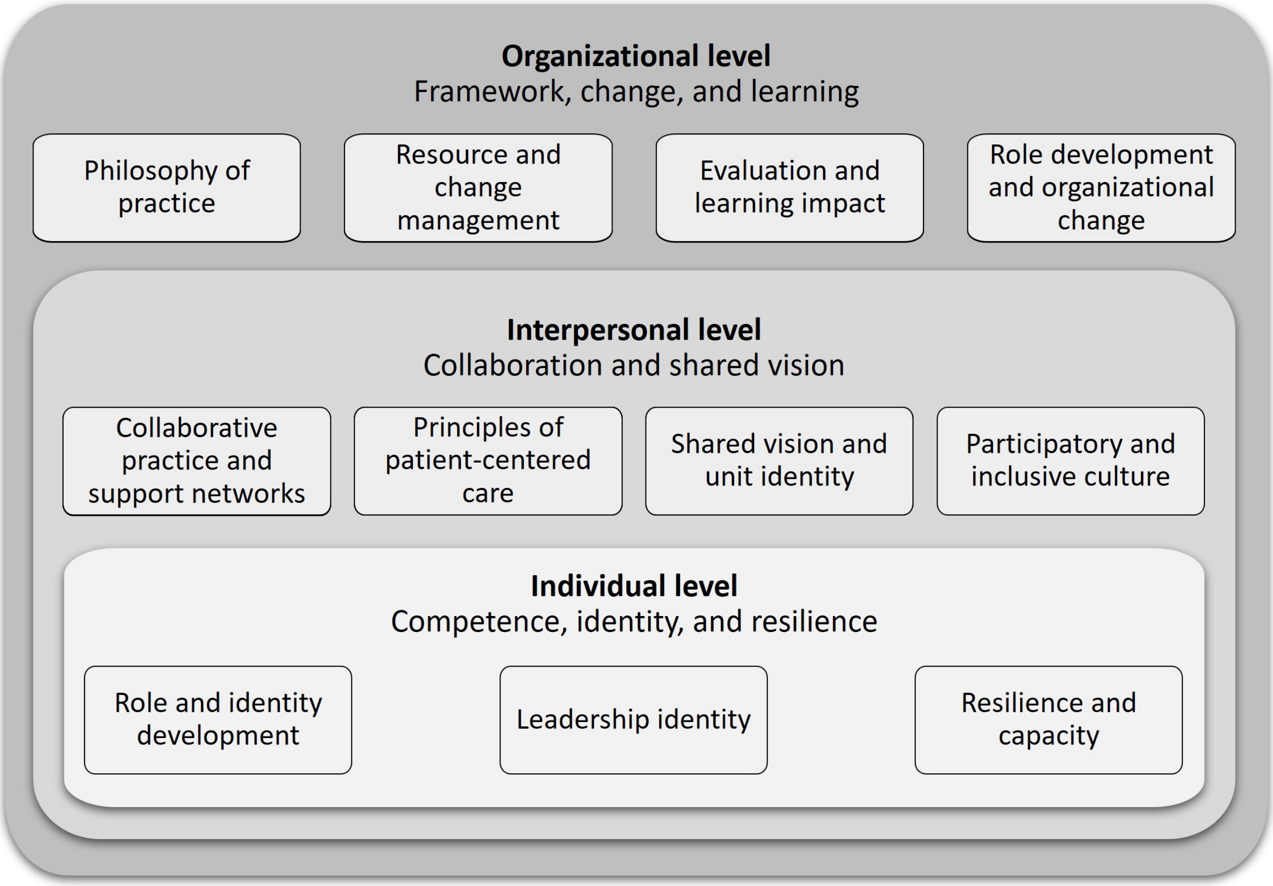
Core Elements of NDUs

Overview

The literature consistently described NDUs as operating across 3 interrelated levels: individual, interpersonal, and organizational (Figure 3). These levels structure descriptions of professional development, collaboration, and organizational learning. This framework emerged inductively from the data through iterative coding of all included publications, reflecting patterns observed in the literature rather than a pre-established theoretical model.

Several characteristics identified at these levels—such as competence development, participatory practices, and embedded learning structures—are discussed in the broader literature on organizational readiness for change and digital transformation. While explicit engagement with digital technologies was seldom reported in the included publications, the identified capacities and practices indicated potential enablers for adopting digital tools and supporting digital innovation in nursing.

Figure 3. Core elements of a Nursing Development Unit inductively synthesized from the included publications.



Individual Level: Competence, Identity, and Resilience

NDUs were described as settings in which professional roles, leadership capabilities, and personal resilience are addressed. Activities included reflective practice, integration of ethical and evidence-based principles, and adaptation to evolving clinical demands. Table 2 maps publications contributing to individual-level components.

A clear understanding of professional roles, the integration of personal and shared philosophies of practice, and the development of self-efficacy and professional coherence were described as central elements of role and identity development [23,43]. Several publications highlighted intrinsic motivation and self-awareness in relation to personal growth and competence development [23].

Table . Mapping publications to individual-level components of Nursing Development Units (n=17).

Level and subcategory	Publications
Individual	
Role and identity development	[8,10,23,25,33-35,43,45,47,54]
Leadership identity	[8,23,26,29,31,35,39]
Resilience and capacity	[27,34,44,45,54]

Reflective practice was described as integrating ethical considerations, clinical judgment, and personal values into everyday care [43]. The literature reported structured forms of reflection, including written protocols, workshops, and reflective models, which were used to support critical inquiry into values, roles, and routines and articulate emerging professional identities within NDUs [33,34]. Modular training programs addressing clinical and research competencies were described across several publications and commonly linked to supervision and assessment processes [10].

Leadership identity was addressed in a subset of publications (7/17, 41.2%), which described clinical leaders as taking on facilitative and innovative roles and as supporting team processes. At the same time, challenges such as variable staff motivation and uncertainty regarding the NDU concept were reported [8,23]. Leadership support structures, including mentorship, networking, and formal development programs, were described in relation to team support during periods of change [31].

Several publications (5/17, 29.4%) described NDUs as contexts in which professional resilience is addressed, particularly in relation to iterative development processes and challenges associated with time constraints, emotional labor, and organizational obstacles [23,43]. Staff perceptions reported in the literature included high expectations, impatience for visible progress, and difficulties adjusting to evolving roles [43].

Across the included publications, reflective practice, continuous competence development, and leadership identity were recurrently described at the individual level. While the reviewed publications did not explicitly address digital competencies or digital practices, they outlined professional capacities—such as critical reflection, adaptability, and role clarity—that are frequently discussed in the broader literature in relation to organizational and technological change.

Interpersonal Level: Collaboration and Shared Vision

Across the included publications, NDUs were described as fostering participatory and inclusive cultures, supporting collaborative practices, and facilitating the development of shared visions and unit identities. Several publications reported that team interactions and decision-making processes emphasized principles of patient-centered care. Table 3 summarizes the publications contributing to the interpersonal-level subcategories.

Participatory and inclusive cultures were described as involving collaboration, shared decision-making, and ongoing improvement [32,53]. Publications reported that traditional nursing boundaries were sometimes transcended, enabling staff to engage in collective reflection, articulate unit philosophies, formulate action plans, and evaluate progress. Bottom-up approaches, including staff participation as coresearchers, were described in relation to collective ownership of practice change [32,45].

Table . Mapping publications to interpersonal-level components of Nursing Development Units (n=30).

Level and subcategory	Publications
Interpersonal	
Participatory and inclusive culture	[8,23-25,32,34,40,42,43,53,54]
Collaborative practice and support networks	[24,25,34,37,39,41,45,47,50,52,53]
Shared vision and unit identity	[9,11-13,28,33,36-38,40,42,44,46,49]
Principles of patient-centered care	[8,27,38,43,44,52,53]

Collaborative practices and support networks were described as developing through mentorship and interdisciplinary teamwork, supporting staff in addressing challenges and continuing professional growth [23,49]. Strategic planning processes were reported to clarify team needs, anticipate obstacles, and link practice activities to evidence generation. Several publications described collaborative planning as fostering shared ownership and a collective vision for change [54]. Partnerships with academic institutions were reported to support training, research, and innovation [9,49].

Shared vision and unit identity were described as contributing to team coherence. Staff involvement in defining the NDU's purpose, intended outcomes, and guiding principles was frequently reported [43,45,54]. The literature highlighted that shared philosophies of practice grounded in clinical realities and staff perspectives can reinforce team coherence and collective identity [43]. Exposure to experiences from other NDUs was reported to help manage expectations, facilitate collective problem-solving, and support ongoing development [44].

Patient-centered care was described as emphasizing trust, sensitivity, shared decision-making, and patient autonomy [8,43]. Evidence-based approaches were reported across NDUs, although implementation varied. Some publications reported extensive evaluation frameworks, whereas others focused on routine questioning and evidence-informed decisions [9]. Integration with relational care models such as primary nursing was described as an example of applying patient-centered principles in practice [8,43,53].

Across the reviewed publications, participatory cultures, collaborative planning, and shared decision-making were consistently reported as central interpersonal characteristics of NDUs. Although digital technologies were not explicitly addressed, these interactional patterns reflected approaches commonly discussed in the broader literature for co-designing and implementing complex interventions, including digital tools in health care settings.

Organizational Level: Framework, Change, and Learning

At the organizational level, NDUs were described as involving frameworks and structures that support practice development, change, and learning. Several publications highlighted overarching philosophies of practice, structured role development, and embedded evaluation systems as recurring elements. Table 4 summarizes the publications contributing to the organizational-level subcategories.

Table . Mapping publications to organizational-level components of Nursing Development Units (n=31).

Level and subcategory	Publications
Organizational	
Philosophy of practice	[7,9,11-13,28,33,35-38,40-44,46,48-51,55]
Resource and change management	[9,12,13,26,31,32,36-39,41,44,46,48,49,51,55]
Role development and organizational change	[10,11,29,33,35,37,43,47,51]
Evaluation and learning impact	[7,28,30-32,39,41,48,50-53,55]

Philosophies of practice were described as providing frameworks of values, guiding principles, and standards that inform unit culture and practice [51]. Role development and organizational change were reported in relation to clarifying responsibilities, establishing decision-making processes, and supporting structural adjustments to avoid duplication and facilitate innovation [33,53].

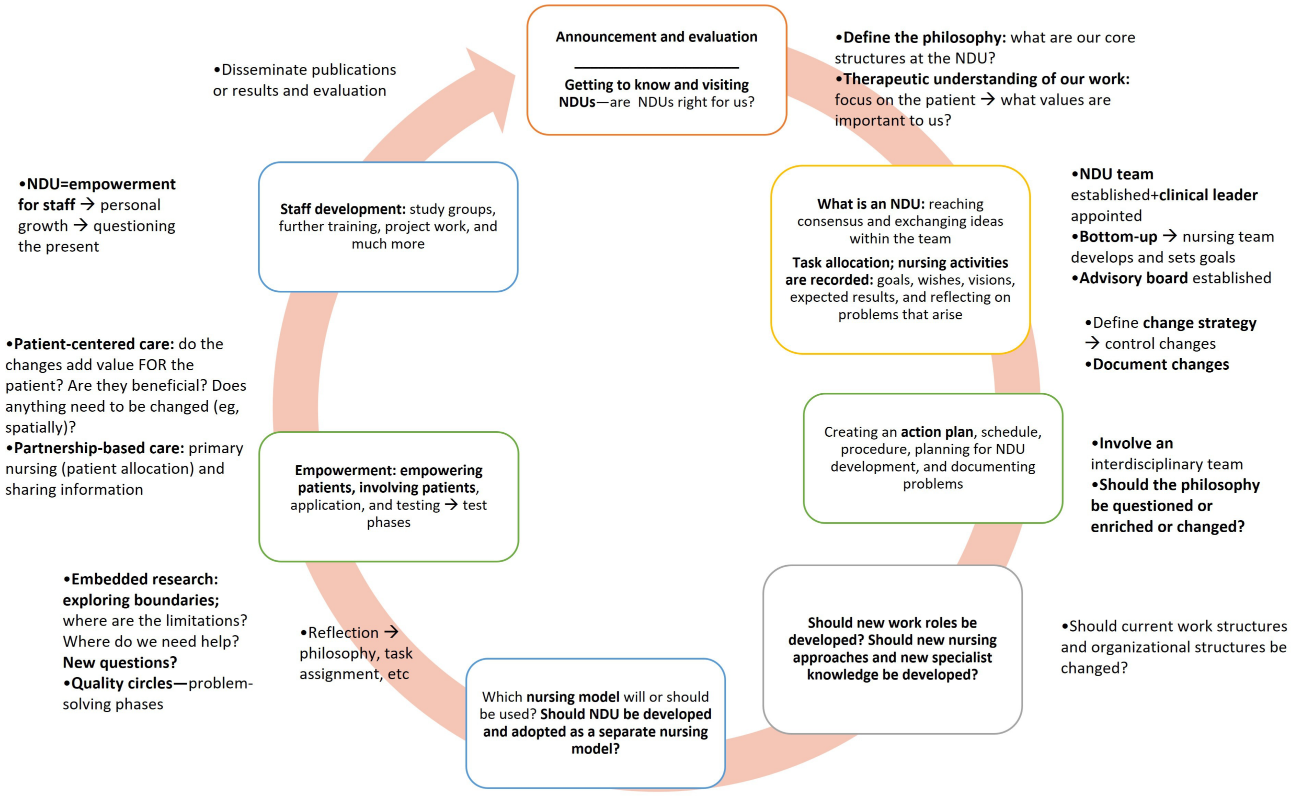
Management of resources and change was described in the literature as including strategies to allocate time and materials, address resistance, and respond to operational pressures [49,53]. Evaluation and learning systems were reported to support reflective processes, facilitate improvements based on evidence, and connect practice to research and learning across disciplines [50,51,53]. Iterative development processes using structured strategies, participatory approaches, and strategic planning were described as approaches to respond to local needs while maintaining growth and improvement [10,11,29,50,51,53,54].

Embedded evaluation systems and iterative learning cycles were frequently reported as integral to NDU development. While these publications did not specifically address digital innovations, the described organizational infrastructures and learning mechanisms were consistent with approaches that are widely considered relevant for implementing and adapting complex interventions, including digital tools in health care settings.

Development and Implementation Process of NDUs

NDU development was reported as a multiyear, iterative process involving alignment of organizational structures, professional identity formation, and collaborative teamwork (Figure 4). Implementation evolves through cycles of reflection, strategic planning, practice-based experimentation, and evidence-informed evaluation grounded in a shared philosophy of practice that incorporates diverse staff perspectives and emphasizes holistic, patient-centered nursing [8,11,43,55].

Figure 4. Progressive development toward a Nursing Development Unit (NDU) synthesized inductively from the included publications.



Implementation practices reported included client-centered care, nurse empowerment, and evidence-based routines [11,29]. Adaptations to local cultural, staffing, and regional conditions were described as supporting flexibility while maintaining core principles [49]. Staff engagement in data collection and analysis was reported to facilitate learning, support innovation uptake, and foster interdisciplinary thinking [50,51,53].

Challenges reported in the literature included staff turnover, limited acceptance by other health care professionals, high workloads, and gaps between theory and practice. Sustained leadership support and team commitment were described as important factors for maintaining NDU development over time [28].

Discussion

Core Characteristics of NDUs: A Foundation for Innovation

This scoping review mapped the structural and procedural characteristics of NDUs across individual, interpersonal, and organizational levels based on 40 international publications from the United Kingdom and Australia spanning 1991 to 2017. The findings confirm NDUs as multilevel, practice-based innovation spaces that foster professional development, collaborative cultures, and structured learning. These characteristics are not merely descriptive but reflect a coherent framework for supporting continuous improvement and evidence-informed practice.

At the individual level, NDUs are not merely settings for skill development but spaces for professional identity formation. The emphasis on reflective practice, leadership identity, and resilience suggests that NDUs support nurses in navigating complex clinical realities and evolving roles [10,23,33,43]. This process fosters psychological safety and self-efficacy—conditions that are increasingly recognized as essential for adaptive learning and innovation [56,57].

At the interpersonal level, NDUs function as cocreation platforms. The documented practices of shared decision-making, collaborative planning, and peer learning indicate a culture where knowledge is coproduced rather than imposed in a top-down manner [23,32,45,50]. This participatory orientation aligns with contemporary models of human-centered design and may reduce resistance to change—especially when introducing new technologies [16,58].

At the organizational level, NDUs are defined by structured learning cycles and embedded evaluation systems. Their iterative development process—rooted in reflection, experimentation, and feedback—mirrors established frameworks for organizational change [10,11,29,50,51,53]. This suggests that NDUs are not static entities but dynamic systems capable of continuous adaptation, a quality that is critical in rapidly evolving digital health environments [59,60].

Crucially, these characteristics are not isolated features but interconnected processes that reinforce one another. For example, individual reflection is amplified through team dialogue, team collaboration is guided by organizational frameworks, and organizational learning is sustained through individual and team engagement. This synergistic interplay positions NDUs as potential organizational incubators for innovation—although the extent to which they support digital transformation remains to be empirically tested.

Implications for Digital Transformation: A Cautious Interpretive Framework

While the included publications did not explicitly address digital technologies, the identified characteristics of NDUs suggest potential conditions that may support digital transformation in nursing. This section presents these connections as interpretive transfer hypotheses—plausible inferences based on conceptual alignment with known prerequisites for successful technology adoption.

NDUs may support digital transformation by fostering the professional and organizational capacities required for technology integration. For instance, reflective practice and continuous competence development—core to NDUs—can help nurses critically engage with digital tools, align them with ethical and clinical values, and integrate them meaningfully into care routines [33,34,43]. This supports the development of a digital professional identity where technology use is not seen as an external imposition but as an extension of nursing expertise [5,6,61,62].

The participatory culture of NDUs—characterized by shared decision-making, co-design, and peer learning—may reduce resistance to change and improve the fit of digital tools with clinical workflows [16,63-65]. By involving nurses in the design, testing, and evaluation of digital solutions, NDUs could serve as safe spaces for experimentation, where failures are reframed as learning opportunities [15,16]. This aligns with human-centered design principles and may enhance user acceptance and long-term sustainability [58].

At the organizational level, the structured frameworks for change management, iterative evaluation, and evidence-based practice in NDUs mirror the adaptive and learning-oriented processes needed for digital implementation [7,15,50,51]. The emphasis on feedback loops, strategic planning, and continuous improvement provides a robust infrastructure for managing the uncertainties and disruptions associated with digital innovation [60,66].

However, these implications must be interpreted with caution. The evidence base is limited in both temporal and technological scope: most included studies (39/40, 97.5%) were published before 2007, and none explicitly examined digital tools or competencies. Therefore, the claim that NDUs "support digital transformation" should not be understood as a proven causal relationship but rather as a plausible hypothesis that requires empirical validation in contemporary digital contexts.

Strengths and Limitations

This review's strength lies in its systematic and transparent approach guided by established frameworks (Joanna Briggs Institute and PRISMA-ScR guidelines). The inclusion of diverse study types and international literature provides a broad understanding of NDU development and implementation. The independent screening and iterative data extraction process enhances rigor, transparency, and generalizability.

Several limitations must be acknowledged. First, while this review focused on publications explicitly labeled as "Nursing Development Unit," it is possible that related concepts or alternative labels (eg, "Clinical Development Unit" and "Practice Development Unit") exist in more recent (digital) nursing literature and may share similar mechanisms for supporting innovation and technology adoption. Although supplementary searches were conducted, our decision to anchor the database search to the exact phrase "Nursing Development Unit" may have led to missed publications describing comparable models under different terminology. Consequently, our synthesis should be interpreted as mapping the literature that explicitly self-identified as "NDU" rather than exhaustively capturing all international Practice Development Unit models. Second, the age of the included publications (mostly published before 2007) limits the direct applicability of the findings to current digital health landscapes, where technologies such as artificial intelligence, real-time monitoring, and interoperable electronic health records are increasingly central. Third, the lack of outcome evaluations and the heterogeneity of definitions and implementation contexts reduce the comparability of the findings. Fourth, the exclusion of non–English- and non–German-language publications may have introduced language bias. Fifth, the absence of a formal quality appraisal—typical in scoping reviews that prioritize conceptual mapping over effect estimation—limits the comprehensive assessment of the robustness of individual findings.

These limitations underscore the need for future research to explicitly link NDU principles with digital transformation using contemporary case studies, mixed methods designs, and outcome-focused evaluations.

Conclusions: A Foundation for Future Inquiry

This review demonstrates that NDUs are structured environments that promote professionalization, collaboration, and learning through multilevel processes. While the evidence base does not directly support claims about digital transformation, the core characteristics of NDUs—reflective practice, participatory cultures, and iterative learning—may offer enabling conditions for the adoption and integration of digital technologies in nursing.

However, these connections remain theoretical and require empirical testing. Future research should investigate how NDUs can be adapted to support digital innovation, with a focus on digital competencies, workflow integration, ethical considerations, and staff well-being. Only through such research can we determine whether NDUs are indeed a viable foundation for digital transformation in nursing or whether new models are needed to meet the demands of the digital age.

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Data Availability

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

Conflicts of Interest

None declared.

Multimedia Appendix 1
Search strategy.
[DOCX File, 13 KB - nursing_v9i1e89051_app1.docx]

Checklist 1
PRISMA-ScR checklist.
[PDF File, 104 KB - nursing_v9i1e89051_app2.pdf]

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Abbreviations

NDU: Nursing Development Unit
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PRISMA-ScR : Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews

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Nursing Informaticians in Spain: Scoping Review and Expert-Validated Gap Analysis

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Abstract

Background: The role of nursing informaticians is well-established in countries like the United States, Canada, and Australia, supported by competency frameworks and educational programs that enable nurses to lead technological integration in health care. However, in Spain, this role is not formally recognized, and specialized university training is scarce, creating a significant gap in digital health leadership among nurses.

Objective: The study aimed to analyze the international landscape of the nursing informatician role, comparatively focusing on the situation in Spain, to subsequently identify the specific gaps for its implementation through experts' views and insights.

Methods: First, a scoping review following the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) guidelines was conducted in English and Spanish using scientific evidence searched in PubMed, Scopus, CINAHL, and Web of Science from 2018 to the present, as well as gray literature on the topic. A total of 55 published studies were included after screening 1356 records and 10 gray literature documents. Subsequently, findings were validated through a gap analysis comprising a panel of 10 experts selected according to their experience in digital literacy.

Results: The review identified 6 core competencies for nursing informaticians: information management, cybersecurity, patient safety, evaluation and development of clinical information systems, leadership and coordination of digital tools, implementation of new technologies and specialized applications, and education and digitalization in health. Internationally, training is delivered via postgraduate programs, certifications, and leadership initiatives. Experts validated the relevance of these competencies for Spain (rated 5/5) and the applicability and desirability of implementing training programs (rated 4.8/5). Key barriers identified were the lack of official recognition, scarce training, and organizational resistance to change.

Conclusions: There is a contrast between the established role of nursing informaticians internationally and its absence in Spain. The lack of a formal framework and specific training programs is the primary barrier. Implementing validated competencies and tailored educational strategies is crucial for Spain to advance its digital health transformation and empower nursing leadership in technology.

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KEYWORDS

nursing informatics; nursing informaticians; enfermeras especialistas en sistemas de información; digital health; competency-based education

Introduction

Global Perspective

Nursing informatics (NI) is a discipline that has gained relevance in recent years due to the increasing integration of information and communication technologies. The definition of NI includes the integration of information technologies in patient care and the clinical setting. Digital transformation facilitates and enhances diagnosis, data management, information, and optimization of processes. This can lead to improved quality of care and efficiency of the health care system [1]. Within this transformation, NI emerges as a crucial discipline that integrates nursing science, information technology, innovative technologies, and data analytics to manage and communicate data, information, technology integration, and nursing practice [1,2]. The professionals who lead this charge are nursing informaticians (in Spanish "Enfermeras Especialistas en Sistemas de Información" or "Enfermeras Informáticas" [EESIs]), who serve as the vital connection between clinical practice, information systems, and technical teams [3].

Literature Review

In countries like the United States, Canada, and Australia, this advanced role is well-established and robustly supported. The presence of professional bodies such as the American Medical Informatics Association, the Healthcare Information and Management Systems Society, the Canadian Nursing Informatics Association, and the Health Informatics Society of Australia provides a structured framework for professional development. These frameworks help define the role of nursing informaticians as a link between clinical practice and information systems that analyze, design, implement, and evaluate health information technologies. "Nursing informatician" is a generic term that includes variations depending on the formative level and leadership. For example, "nurse informaticist" or "nursing informatics specialist" is a common and specific job title for a professional with advanced knowledge [4]. Other alternatives are "chief nursing informatics officer," an executive role that provides an informatics strategy focused on nursing practice, and "chief X informatics officer," which includes clinical informatics leaders from various disciplines [5]. Furthermore, universities in these nations have prioritized the integration of informatics competencies into nursing curricula, empowering graduates to lead the use of technology in clinical practice [6]. This combination of professional communities, academic programs, and defined competency frameworks enables nursing informaticians to lead high-impact projects in the digital transformation of health care systems.

This leadership is present in several key areas. For instance, nursing informaticians can contribute to the development of interactive digital platforms to supervise and ensure the quality of clinical placements. In this context, a user-centered design has proven fundamental to successful adoption by supervisors and students [7,8]. Their expertise becomes essential in guiding institutions through the creation or development of e-learning platforms, where success depends on a broad and systematic analysis of needs rather than on technical specifications alone [9]. Moreover, they command the "co-creation" of educational resources, mostly virtual teaching packages. This methodology involves end users in the design process, creating training tools perceived as relevant and useful by them [10].

Emerging technologies, such as artificial intelligence, language processing models, big data, and 3D printing, can also be part of these nurses' competencies. However, without appropriate training and a legislative framework, the integration of these advances into clinical practice can be challenging. Their training enables them to stay updated on technological advancements [11].

These examples of NI competencies that are commonly assumed in the international context by their role underscore a profound functional gap in Spain. There, the nursing informatician's role is not formally recognized, and relevant university training is scarce. This absence raises a key question: "Why is the concept of nursing informaticians developed and implemented globally while absent in Spain?" As experts point out, digital health in the country faces significant challenges due to a lack of specialized training and a defined competency framework for nursing in this field [8]. This requires defining specific competencies that go beyond just using clinical information systems [12]. Furthermore, nursing students' basic digital literacy in their current studies is insufficient [13], so specialized training becomes essential to prepare future nurses to use and integrate technology in health care [14].

Research Objectives

Given the differences between international and national paradigms, a comprehensive analysis was required. This led to a 2-phase study design comprising 2 objectives: the first was to analyze the international scientific and gray literature on the nursing informaticians' role, comparatively focusing on the situation in Spain. The second objective consisted of validating these findings by identifying the specific barriers and opportunities for implementing the role in Spain according to experts' views and insights.

Methods

In line with the objectives, the design was divided into 2 phases: the first was related to the main objective for the scoping review, and the second phase focused on the second aim related to a gap analysis.

Phase 1

A scoping review was chosen to conduct a comprehensive analysis of existing literature, identify research gaps in publications, and examine the diverse evidence surrounding the nursing informaticians' role, as well as gray literature. Analysis is required before drawing specific conclusions [15]. To guide this review, a research question was framed using the population, concept, context framework:

- Population: the nursing profession and, specifically, the role of nursing informaticians
- Concept: professional roles, competencies, training models, barriers, and facilitators for the implementation of the nursing informaticians' role
- Context: the international health care landscape, considering experienced countries in NI, is used as a benchmark to analyze the existing gap in the Spanish health care system

The scoping review was conducted following the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) guidelines (Checklist 1) [16]. A comprehensive search strategy was developed to reflect the international scope and the specific focus on Spain. Key terms in both languages, English and Spanish, included "nursing informatics," "nursing informatics," "nursing informaticians," "informática aplicada a la enfermería," "enfermeras especialistas en sistemas de información," and "enfermería informática." The search was performed for articles published from 2018 to the present across high-impact databases: PubMed, Scopus, CINAHL, and Web of Science. Filters for language, document type, and full-text accessibility were applied. To ensure a comprehensive overview, the search was supplemented with gray literature from international NI associations, relevant institutional documents, and university curricula in Spain related to the discipline.

Inclusion and Exclusion Criteria

Articles selected during the methodological analysis process contained one or more of the keywords corresponding to NI and nursing informaticians. In the next step, the content of the screened articles was studied to determine their relevance to the current study.

During the screening process, the following exclusion criteria were applied to scientific articles:

- Nonspecific article content despite mentioning the search terms
- Low academic quality: studies with inconsistent methodology or insufficient bibliographic support
- Full text unavailable
- Article irretrievable from repositories

After screening, a review of all literature was conducted following the steps recommended by the Joanna Briggs Institute (Table 1) for conducting scoping reviews. This process included identifying the research question, searching for relevant evidence, selecting studies, extracting data, and presenting the results [15].

Table . Joanna Briggs Institute appraisal tools.

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Reid L et al [1]. Defining nursing informatics: a narrative review.	Narrative Review	JBI[a] Critical Appraisal Checklist for Textual Evidence: Narrative	1[b]	1	1	1	1	3[c]	3	1	3	1	1	1
Sensmeier J [2]. The value and impact of the alliance for nursing informatics.	Program Evaluation	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	—[d]	—	—	—	—	1
Kirchner RB [3]. Presentando a la enfermera especialista en sistemas de información.	Narrative Article	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	—	—	—	—	—	1
Benavente-Rubio A [6]. El rol de enfermería en la salud digital.	Systematic Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	3	3	1	1	1	1	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Konstantinidis ST [7]. HEALINTAL digital interactive platform for European and national placements audit for medicine and allied health professions following a user-centered design.	Book chapter	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	—	—	—	—	—	1
Papamalis F [8]. Ensuring quality health care practice for doctors and medical allied professionals through a digital interactive audit platform.	Conference paper	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	—	—	—	—	—	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Baggia A [9]. Ecosystem of organizations in the digital age: Conference proceedings.	Conference paper	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	—	—	—	—	—	1
Konstantinidis S [10]. Co-creation of a virtual interactive teaching package for auditors of health care placements-towards assurance of quality of health care traineeships.	Conference paper	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	—	—	—	—	—	1
Ball MJ. et al [11]. The health informatics series: evolving with a new discipline.	Narrative Review	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	—	—	—	—	—	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
León Molina J [12]. Papel de enfermería en el sistema de información hospitalario.	Narrative Article	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	—	—	—	—	—	1
Chipps J et al [13]. Nursing informatics skills relevance and competence.	Interview-based descriptive study	JBI Critical Appraisal Checklist for Qualitative Research	1	1	1	1	3	3	1	1	—	—	—	1
Backonja U [14]. How to support the nursing informatics leadership pipeline.	Descriptive cross-sectional study	JBI Critical Appraisal Checklist for Analytical Cross Sectional Studies	1	1	1	1	3	3	1	1	—	—	—	1
Peters MDJ [15]. Updated methodological guidance for the conduct of scoping reviews.	Publication guideline	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	1	1	—	—	—	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Page MJ et al [16]. Declaración PRISMA 2020.	Publication guideline	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	1	1	—	—	—	1
Luppa N and Suresh S [4]. Physician and nurse informatics collaboration.	White Paper	JBI Critical Appraisal Checklist for Textual Evidence: Policy	1	1	1	3	1	2[e]	1	—	—	—	—	1
Conte G et al [17]. Embracing digital and technological solutions in nursing.	Scoping Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	1	1	1	3	1	1	1
Farzandipour M et al [18]. Designing a national model for assessment of nursing informatics competency.	Quantitative study	JBI Critical Appraisal Checklist for Analytical Cross Sectional Studies	1	1	1	1	3	3	1	1	—	—	—	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Farokhzadian J et al [19]. Necessary prerequisites for evidence-based practice.	Cross-sectional study	JBI Critical Appraisal Checklist for Analytical Cross Sectional Studies	1	1	1	1	1	1	1	1	—	—	—	1
Kulju E et al [20]. Educational interventions and their effects on health care professionals' digital competence development.	Narrative Review	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	1	2	3	1	1	1
Saco P [21]. Informática aplicada a la enfermería.	University Subject Guide	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	2	1	1	—	—	—	—	—	1
Nes AAG et al [22]. Technological literacy in nursing education.	Systematic Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	1	1	1	3	1	1	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Yildiz M et al [23]. Hemşirelerde tiger temelli hemşirelik bilişimi yetkinlikleri.	Descriptive-correlational study	JBI Critical Appraisal Checklist for Analytical Cross-Sectional Studies	1	1	1	1	3	2	1	1	—	—	—	1
Canadian Nurses Association [24]. Nursing informatics.	Policy Brief	JBI Critical Appraisal Checklist for Textual Evidence: Policy	1	1	1	3	1	2	1	—	—	—	—	1
Ramos Rodríguez JM [25]. Las TICs en enfermería de práctica avanzada.	Narrative Article	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	—	—	—	—	—	1
González-Pardo Maza E [26]. Tecnología Big Data y su misión en el campo de la enfermería.	Narrative Review	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	—	—	—	—	—	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Reid L et al [27]. Nursing informatics: competency challenges for nursing faculty.	Scoping review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	1	1	1	3	1	1	1
AMIA[f] Policy Invitational [28]. Redefining our picture of health.	White Paper	JBI Critical Appraisal Checklist for Textual Evidence: Policy	1	1	1	1	1	1	1	—	—	—	—	1
Toffoletto MC and Ahumada Tello JD [29]. Telenursing in care, education, and management.	Integrative Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	3	3	1	3	1	1	1
Kaihlanen A et al [30]. Nursing informatics competence profiles and perceptions.	Cross-sectional study	JBI Critical Appraisal Checklist for Analytical Cross Sectional Studies	1	1	1	1	1	1	1	1	—	—	—	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Forman TM et al [31]. A review of clinical informatics competencies in nursing.	Systematic Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	3	3	1	3	1	1	1
Kleib M et al [32]. Approaches for defining and assessing nursing informatics competencies.	Scoping Review (protocol)	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	3	1	2	2	2	1	1
Kleib M et al [33]. Approaches for defining and assessing nursing informatics competencies.	Scoping Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	1	1	1	1	1	1	1
Davies A et al [34]. Core competencies for clinical informaticians.	Systematic Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	1	1	1	1	1	1	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Domingos CS et al [35]. A aplicação do processo de enfermagem informatizado.	Narrative Review	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	1	—	—	—	—	—	1
Nahm ES et al [36]. Cybersecurity essentials for nursing informaticists.	Narrative Review	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	3	1	3	3	1	1	1
Taylor-Pearson K et al [37]. The role of nurse informaticians in advancing 3D printing use in health care.	Systematic Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	1	1	1	3	1	1	1
Australia's Digital Health Community [5]. Leadership in clinical informatics.	White Paper	JBI Critical Appraisal Checklist for Textual Evidence: Policy	1	1	1	1	1	3	1	—	—	—	—	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Brown J et al [38]. Issues affecting nurses' capability to use digital technology.	Integrative Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	1	1	1	1	1	1	1
Gonzalo de Diego B et al [39]. Competencies in the robotics of care for nursing robotics.	Scoping Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	3	1	2	3	2	1	1
Nazeha N et al [40]. A digitally competent health workforce.	Scoping review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	1	1	1	1	1	1	1
Le Y et al [41]. A bibliometric and visualized analysis of nursing informatics competencies in China.	Bibliometric Review	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	3	3	1	1	—	—	—	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
von Gerich H et al [42]. Artificial intelligence-based technologies in nursing.	Scoping review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	1	1	1	3	1	1	1
Harerimana A et al [43]. Nursing informatics in undergraduate nursing education.	Scoping Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	3	1	1	1	1	1	1
Wynn M et al [44]. Digital nursing practice theory.	Scoping review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	3	1	1	3	1	1	1
Oh J et al [45]. Evaluation of the effects of flipped learning of a nursing informatics course.	Quasi-experimental study	JBI Critical Appraisal Checklist for Quasi-Experimental Studies	1	1	1	1	1	1	3	1	1	3	2	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Lokmic-Tomkins Z et al [46]. Perspectives on the implementation of health informatics curricula frameworks.	Qualitative study	JBI Critical Appraisal Checklist for Qualitative Research	1	1	1	1	3	2	1	1	—	—	—	1
Haupeltshofer A et al [47]. Promoting health literacy.	Scoping review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	1	1	1	3	1	1	1
Lee KH et al [48]. Empowering healthcare through comprehensive informatics education.	Narrative Review	JBI Critical Appraisal Checklist for Textual Evidence: Narrative	1	1	1	1	1	3	3	1	3	1	1	1

Main author [reference] and title	Article type	Critical appraisal tools	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Item 11	Include
Stunden A et al [49]. Nursing students' preparedness for the digitalized clinical environment.	Integrative Review	JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses	1	1	1	1	1	1	1	1	1	1	1	1

[a]JBI: Joanna Briggs Institute.

[b]1: yes (valid).

[c]3: No (not valid).

[d]Not applicable.

[e]2: unclear.

[f]AMIA: American Medical Informatics Association.

Data Extraction and Analysis

This review was conducted through manual data extraction by the researchers to maximize the quality of information selection. The search strategy was supplemented by reviewing gray literature, obtaining documents from relevant associations, and white papers on NI around the world. Some were deemed eligible, and others were excluded after a screening process. The data were then processed in an ordered format with the help of the Microsoft Office suite. This helped create a much more sensible and accurate starting point for the analysis using that software. This method likely ensures a high-quality review of the literature and, in turn, provides a rigorous summary of the evidence.

Artificial intelligence was used on a very limited basis to make only editorial corrections within the final manuscript in order to enhance writing quality and correct grammar, spelling, and structure in different article files. These tools were not used to extract or analyze results. This approach ensures the relevance and currency of the extracted data within the study context.

Phase 2

This phase aimed to validate the scoping review findings through a gap analysis, consisting of a cross-sectional expert panel consultation survey with quantitative items and related qualitative open-ended questions (this survey or questionnaire can be found in Multimedia Appendix 1). For this purpose, a panel of 10 national experts in NI was assembled. All participants volunteered to participate and were recruited through an open call issued by the authors. Experts were selected based on the following criteria: (1) 10 or more years of experience related to health and digital literacy environments in Spain, (2) extensive training in digital literacy, and (3) peer-recognized expertise within their professional field. Their sociodemographic characteristics are detailed in Table 2.

Table . Experts' sociodemographic characteristics.

ID	Gender	Age (y)	Years of experience	Highest education level	Current position	Main area of expertise	Autonomous community
E1	Male	46	22	PhD	University professor	Digital health literacy	Madrid
E2	Male	53	29	PhD	Director of Digital Strategy	Hospital information systems	Catalonia
E3	Female	49	25	Master's	Clinical Informatics Specialist	Clinical workflows and EHR[a]	Andalusia
E4	Female	57	31	PhD	Senior eHealth Researcher	Telemedicine and patient care	Madrid
E5	Female	40	16	Master's	Informatics Unit Supervisor	EHR implementation	Valencian Community
E6	Male	32	15	PhD	Digital Health Consultant	Data governance and security	Valencian Community
E7	Female	43	19	PhD	Health care Innovation Manager	Semantic interoperability	Galicia
E8	Female	56	33	PhD	Dean of Health Sciences	Ethics and legislation in eHealth	Castile and León
E9	Male	45	20	Master's	Advanced Practice Nurse	Big data and health analytics	Valencian Community
E10	Female	53	27	PhD	Director of Nursing Services	Leadership and digital change	Andalusia

[a]EHR: electronic health record.

Sample size was determined based on the principles of purposive sampling and data saturation. This approach is consistent with the methodological literature on Delphi studies and expert panels, where a sample of 10 to 20 highly specialized participants is considered sufficient to achieve a comprehensive depth of information and reach thematic saturation [50]. Qualitative comments from the experts were analyzed through a simplified thematic analysis to identify relevant information not captured by quantitative items. The quality and richness of the data provided by these experts were prioritized over a larger, less specialized sample. To ensure objectivity, anonymity among experts was maintained so that none of the experts knew the identity of the rest of the panel.

Ethical Considerations

The scoping review conducted in this study exclusively used publicly available data and literature. Therefore, it did not require ethical approval. For the gap analysis, all participating experts were informed of the study's objectives and provided written consent to participate before answering the questionnaire. Anonymity and confidentiality of their responses were guaranteed throughout the process. No compensation was provided to the participants.

Trial Registration

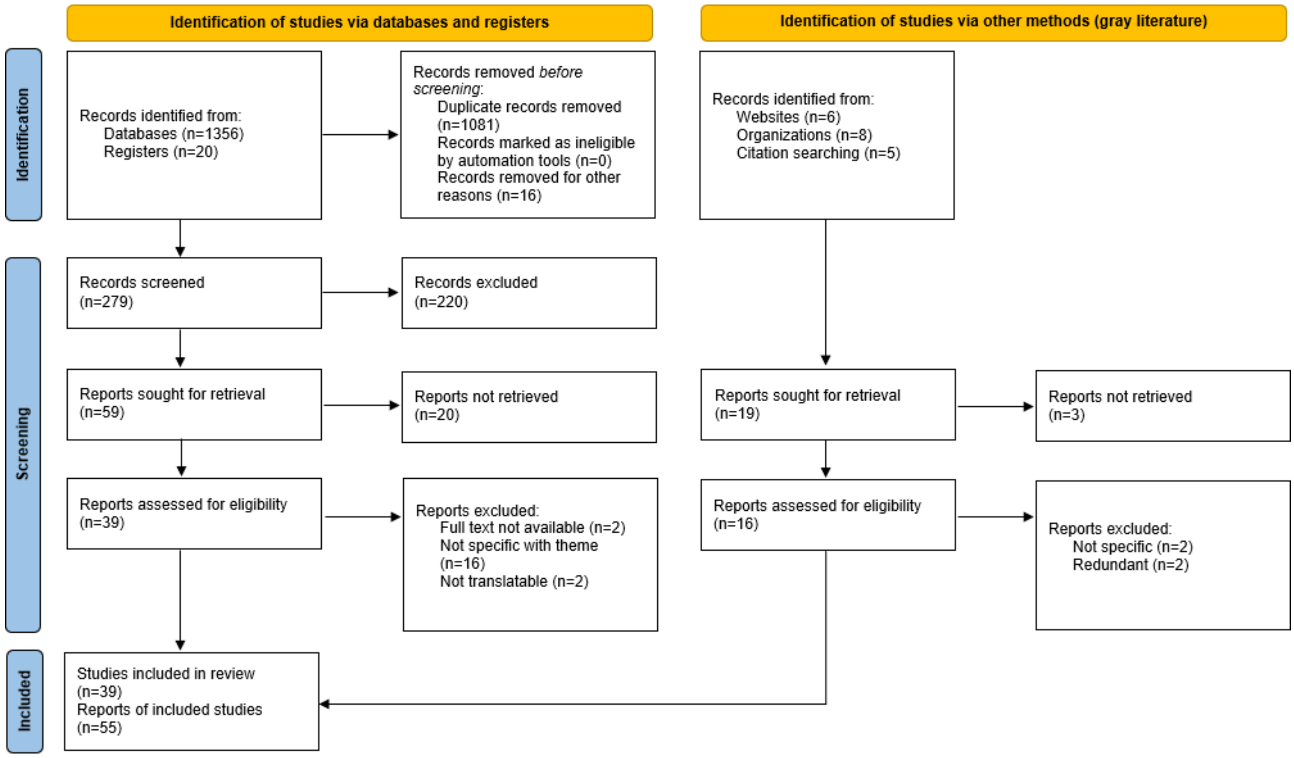
The results of a health care intervention on human subjects are not reported in this study; therefore, registration in a clinical trials registry was not applicable.

Results

Scientific Literature Review

The scoping review included 55 published studies (the full list is available in Multimedia Appendix 2). The literature review identified an increasing scientific output internationally on NI and the role of nursing informaticians (see the PRISMA [Preferred Reporting Items for Systematic Reviews and Meta-Analyses] flow diagram [Figure 1] for the process of the complete search [16]). However, production in Spanish is significantly lower.

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram.



Academic Training

During the study and after an exhaustive literature analysis, several training methods were identified that are used to impart the necessary knowledge and skills to nursing informaticians in clinical practice (Table 3).

Table . Academic training.

Academic training	Description	References
Undergraduate and postgraduate programs	Degrees incorporating health information systems, data analysis, and emerging technologies.	[1,17-19]
Research projects and theses	Advanced training (Master's/PhD) focused on investigating specific NI[a] problems to develop analytical skills.	[18]
Practical training and rotations	Supervised clinical placements allowing the application of theoretical knowledge in real-world settings.	[2,17,19]
Simulations and labs	Use of EHR[b] simulators and informatics laboratories for safe, interactive learning.	[17,26,27]
Continuing education	Professional certifications, seminars, and workshops for updating skills (eg, cybersecurity, data management).	[2,20,23,24,29]
Leadership programs	Mentorship initiatives for emerging leaders (eg, Alliance for Nursing Informatics Emerging Leaders Program).	[2,25]

[a]NI: nursing informatics.

[b]EHR: electronic health record.

In summary, training in NI is conducted through a combination of academic programs, competency models, continuing education, clinical placements, simulations, online courses, seminars, workshops, research projects, and leadership training. These training methods must be developed to increase knowledge about NI [30] and evaluated to ensure that nurses acquire the necessary competencies to effectively implement and use information systems in clinical practice, as well as to integrate new technologies into the clinical environment [31].

Competencies

As a result of the consulted literature and its exhaustive analysis, essential competencies for nursing informaticians have been identified [32,33]. These competencies are fundamental to understanding the functions they would fulfill in this nursing leadership role within the Spanish health care system. They are structured into 6 general competencies (Table 4).

Table . Competencies.

Competencies	Description	References
Information management	Includes the collection, storage, organization, and analysis of health data. Nursing informaticians must ensure patient privacy (applying current regulations) regarding their private information at all times. It also implies establishing standardized nursing documentation models for efficient and accurate information (NI[a] process), as well as the use of standardized taxonomies. Measures nursing care complexity and ensures privacy.	[35,36,51,52]
Cybersecurity and patient safety	The integration of new technologies must prioritize patient safety, minimizing risks. In turn, the accuracy and reliability of data must be guaranteed, as well as their confidentiality.	[36,37]
Evaluation and development of clinical information systems	Analysis and management, creation, evaluation, and modification of hospital information systems to improve the quality of care. They must be practical and relevant to nursing practice. They must also integrate connectivity with new technologies.	[36]
Leadership and coordination of digital tools	Leadership in digital communication and patient care management using advanced digital tools are important competencies.	[5,14,36]
Implementation of new technologies and specialized applications	Integration of artificial intelligence, 3D printing, metaverse, big data, and robotics. Nursing informaticians as technological experts integrating and promoting these technologies.	[37-40]
Education and digitalization in health	Continuing education in new technologies is crucial to prepare health professionals. Nursing informaticians must be trained to transmit knowledge in information technologies and the use of emerging technologies to health care professionals in their environment.	[41,42]

[a]NI: nursing informatics.

Contextual Framework

The successful implementation of nursing informaticians requires the definition, training, and aptitude of nurses in digital competencies within a specific contextual framework. This framework must include both generalist nurses and nursing informaticians [17,38,47].

All nurses must have the opportunity to receive training and qualifications as expert users to fully leverage the possibilities offered by technology while also knowing how to mitigate information overload [5,38]. Generally, younger nurses tend to possess more positive training, education, and attitudes toward technology; however, all professionals must be provided with opportunities adapted to their existing knowledge to undergo training in digital transformation [17,38]. Strategies must be established to combat computer illiteracy, structural problems (such as lack of staff and financial resources), and limited access to new technologies, which constitute the most common barriers. Likewise, these conditions must be met while ensuring the privacy and security of obtained data, servers, and devices to guarantee the safety of both patients and professionals [28,38].

Specific leadership roles in digital transformation will be assumed by nursing informaticians [5,17]. Their objective must be to increase system efficiency and improve the quality of care through evidence-based data in an interdisciplinary, coordinated, and patient-centered manner [4,5,17,24].

Benefits

Based on the literature, the implementation of the nursing informaticians' role in Spain presents several potential benefits, inspired by the experiences of other countries (Table 5).

Table . Benefits.

Benefits	Description	References
Improved management and use of health information systems	Nursing informaticians combine clinical nursing knowledge with an understanding of information sciences, acting as a connection between nurses and technical teams	[1,3,4,23,28,32,33,47]
Leadership in the adoption of new technologies	Responsible for developing and implementing ICTs[a] in the clinical setting	[3,8,14,22,24,38,47]
Optimization of the development and implementation of the electronic health record	Nursing informaticians ensure that EHR[b] systems are designed to facilitate compatibility with care and traceability of clinical practice	[3,18,30,38,42]
Contribution to nursing research	Participating in the research and implementation of digitalization solutions, as well as the collection, processing, and interpretation of large datasets	[6,14,15,28,29,40,46]
Effective application of the NP[c], care complexity, and resource allocation	Strengthening evidence-based practice and consolidating nursing as a science. Nursing informaticians can ensure the effective application of the NP and promote the use of standardized taxonomies. Furthermore, the use of structured data allows quantifying care complexity. Consequently, nursing informaticians become essential for designing systems that move from operational documentation to predictive decision-making	[8,19,23,35,42,51-53]

[a]ICT: information and communication technology.

[b]EHR: electronic health record.

[c]NP: nursing process.

Barriers

Potential barriers to its implementation have been identified (Table 6).

Table . Barriers.

Barriers	Description	References
Lack of formal recognition and specific training programs in Spain.	Currently, training in NI[a] is limited.	[13,19,25,32,33,35,42,48]
Need to improve digital literacy in nursing.	Current competencies in applied informatics are insufficient.	[8,13,19,26,35,38,42]
Challenges in the integration of technologies and systems.	Includes a plurality of terminologies and a lack of experience among nurses.	[6,43,49]
Absence of a national digital health competency framework specific to nursing.	Essential for defining and acquiring the competencies of nursing informaticians.	[6,17,43]
Resistance to change and a lack of understanding of the value of structured data.	On the part of some professionals.	[17,26,42]
Limitations in accessing and using clinical nursing data.	Depend on electronic records.	[2,6,13,42,43]
Need for investment and resources.	For the training and integration of these professionals.	[5,6,14,20,38,46]

[a]NI: nursing informatics.

Expert-Validated Gap Analysis

Following the scoping review, the opinions of a panel of 10 experts in the field of NI were gathered. Using a form, they evaluated the results retrieved from the scoping review based on their extensive experience. They rated items on a scale from 1 (strongly disagree) to 5 (strongly agree) and wrote down their perspectives on each aspect from the scoping review.

Academic Training

The applicability and desirability of implementing specific training programs for nursing informaticians were overwhelmingly rated very positively by the experts (4.5/5). The proposals for their implementation are diverse:

- Continuing education: the importance of “continuing education from professional associations” is emphasized, including “practical workshops” and accessible courses. A “hybrid training model, in small teams, by knowledge level and very real needs applied to the specific practice of the work area” is proposed.
- Methodology: the development of a “modular and progressive curriculum, with training in digital competencies from the degree level, interdisciplinary master’s programs, and accredited continuing education, integrating mixed methodologies (in-person and online), digital clinical simulations, and practicums in real health care settings” is valued.
- Collaboration: the need for universities, in collaboration with professional associations and technology companies, to work in symbiosis to develop the most relevant content is emphasized.
- Implementation phases: some experts suggest “starting with pilot experiences in hospitals that are already digitized” or “initially through postgraduate training, possibly due to low demand,” to later integrate it into the undergraduate degree.
- Culture and recognition: the importance of “creating the culture and the social or professional symbolic image of this role before its future implementation” and the need for a “prior change in the culture of digital literacy among nursing professionals” are highlighted.

Competencies

The competencies described in the scoping review received the highest rating (4.7/5), along with the benefits. The experts consider that the competencies identified for nursing informaticians are “highly relevant and applicable within the Spanish health care system, as they directly respond to current and emerging needs”:

- Key benefits: it is highlighted that they are crucial for “patient safety” and the “improvement in quality of care, potential for research, and analysis of results.”
- Adaptation to the environment: it is acknowledged that they must be “adapted to our reality: limited resources, differences between autonomous communities, and the need for more practical training.”
- Transdisciplinary role: it is suggested that nursing informaticians “should be integrated into transdisciplinary teams in research, as well as in management or decision-making regarding the design, development, validation, and implementation of new technologies.”
- European trend: it is pointed out that “they correlate with basic European digital competencies, therefore showing traceability with our educational system.”

Benefits

There was broad recognition among experts (4.7/5) of the multiple benefits that implementing the EESI role would bring:

- Improved quality and efficiency: an “optimization in the management and use of health information systems” is expected, improving “care continuity, interoperability […] and the traceability of care.”
- Leadership in digital transformation: EESIs would provide “key leadership in the adoption and implementation of information and communication technologies.” One expert believes that “nursing is the most qualified profession to enhance its training in digital competencies and lead technological projects.”
- Boost to research: “nursing research would be promoted through the analysis of clinical data, allowing evidence to be generated from practice.”
- Strengthening the profession: the EESI role would help to “revalue the nursing profession as a key agent in the digital transformation of health.” The aim is for nurses to lead technological change, “(that we) do not just follow it.”
- Patient benefits: “care plans and health education, monitoring of care plans,” and the promotion of “active patient participation in their care process” are mentioned.

Barriers

The experts’ ratings in this section were the most varied (4.4/5). Although the majority continue to identify significant obstacles, one expert is optimistic, noting that “all the classically identified barriers are being progressively addressed, which creates a more favorable and realistic scenario for the effective implementation of nursing informaticians’ “role,” while the others refer to these previously identified barriers:

- Lack of recognition and regulatory framework: the “absence of official recognition of the role” and the lack of a “regulatory framework and defined policies” are crucial.
- Training and digital literacy: the “scarce specific training at the national level (and a) low level of digital literacy in the nursing community” are mentioned. One expert indicates that “the main barrier is the nursing professionals themselves, due to a lack of time and a culture of digital competencies.”
- Resistance to change and organizational culture: “resistance to change from health care professionals accustomed to more traditional work models,” and the “lack of clinical leadership from nurses who are experts in information systems” are relevant.
- Resources and infrastructure: “scarce economic, technological, and human resources” and “difficulties in systems integration and terminological standardization” are impediments.

Main Findings

This study reveals a significant dichotomy between the internationally recognized role of the nursing informaticians and their unrecognized role within the Spanish health care system. Through a scoping review, the international evidence has been synthesized, delineating a clear framework of competencies, training models, and benefits associated with this specialized role. Second, the expert-validated gap analysis confirmed that this framework is not only relevant because of its benefits but also essential for the Spanish context nowadays. Barriers that impede its implementation were also identified. The consensus among experts (4.7/5 for benefits and competencies) underscores a professional and academic mandate to bridge this gap.

Findings articulate 6 core competencies for the nursing informaticians: information management, cybersecurity and patient safety, evaluation and development of clinical information systems, leadership and coordination of digital tools, implementation of new technologies and specialized applications, and education and digitalization in health. These are more than technical skills, as they represent functions such as empowering nurses to act as the central professionals between clinical practice, information technology, and organizational strategy [3,29]. The strong validation by Spanish experts (4.7/5) confirms their applicability and designates a direction for future educational and professional development programs regarding this role.

Discussion

Comparison With Spanish Legal Framework

The status of NI in Spain has proven to be distanced from that of countries such as the United States, Canada, and Australia, where professional associations like the American Medical Informatics Association and the Healthcare Information and Management Systems Society have led the integration of nursing informaticians as those responsible for driving digital transformation [2,8,12,23,25]. A critical analysis of the Spanish legal framework reveals the structural nature of this gap. While international nursing informaticians possess advanced competencies in systems design, cybersecurity, and data leadership, the current regulation of the nursing profession in Spain—specifically Order CIN/2134/2008, which regulates the nursing degree [54], and Royal Decree 954/2015 on nursing prescription [55]—limits digital competencies to the user level.

Both regulations solely and explicitly define the digital competency of nurses in Spain as "applying technologies and information systems" [54,55]. This creates a dichotomy: the legislation exclusively restricts nurses to using existing tools, whereas the health care system increasingly demands qualified specialists to evaluate, design, and lead the implementation of new tools. This restriction within the legal framework illustrates why Spanish nursing staff often feel insufficiently prepared for the digitized clinical environment, echoing findings from Australia [13,49].

Frameworks for Transformation and Cultural Change

A proposed conceptual framework as a driver for change could be the Technology Informatics Guiding Education Reform, with the intent of moving from basic computer literacy toward information management and innovation leadership. The progression of these competencies would reflect the Data-Information-Knowledge-Wisdom model, in which nursing informaticians in Spain would guide digital transformation by using health information and resources to create solutions adapted to the Spanish context.

Overcoming these barriers requires a deliberate and structured strategy, similar to that already achieved by other international pioneers. The emphasis placed by the experts consulted in this study on the "lack of a digital literacy culture" and "resistance from the professionals themselves" points to the need for a cultural shift. Technical training must be accompanied by an evolution of the organizational culture that values data-driven care and nursing leadership in technology.

Implications for Practice, Policy, and Future Research

The findings of this study have significant implications: hospital and health care managers can use the validated competency framework from this study to formally introduce the role requirements. Providing nurses with specialized training and empowering them to lead improvement projects related to information systems or the implementation of new digital tools could potentially create momentum and demonstrate the value of the role so that they are not only technical but also strategic for making nursing care visible [17,26,42,51].

Results suggest a call to action for policymakers and regulatory bodies in Spain, such as the Ministry of Health and National Agency for Quality Assessment and Accreditation, to integrate nursing informaticians' competencies into nursing curricula. This could begin with undergraduate introductions and extend to interdisciplinary master's programs, as suggested by the experts. Collaboration among academia, professional associations, and technology companies is essential to ensure that this training is relevant, practical, and aligned with the needs of the health care system.

Longitudinal studies are needed to evaluate the impact of pilot training programs on nursing competencies. Further research should also focus on developing and validating a standardized instrument to assess NI competencies specifically tailored to the Spanish health care context.

Limitations

This study has several limitations that should be acknowledged. First, the search was limited to studies published in English, Spanish, and Portuguese, which may have excluded relevant literature in other languages. The manuscript has been carefully reviewed by a native English speaker, although some phrasing or constructs may still reflect the linguistic influences of the researchers' native language. Second, the search of gray literature may not have captured all relevant institutional documents or unpublished curricula. Third, the expert panel was selected through purposive sampling to ensure richness of data. Although thematic saturation was reached, the sample was limited to 10 participants. Furthermore, a potential selection bias exists due to the voluntary nature of the recruitment (open call); the experts may possess a baseline "pro-technology" attitude, which could have influenced the highly positive ratings compared to what might be observed in a generalist nursing population. Fourth, the protocol for this scoping review was not prospectively registered in a public repository such as PROSPERO (International Prospective Register of Systematic Reviews). However, the study was conducted following a detailed internal protocol developed by the authors following the PRISMA-ScR and Joanna Briggs Institute guidelines. Finally, a potential publication bias in the literature was spotted, where successful implementations of NI are more likely to be reported than failures. This could skew the international perspective. Future research should address the operational and budgetary requirements needed to change the organizational governance model for implementing the nursing informaticians' role.

Conclusions

This 2-phase study provides a comprehensive and critical diagnosis of the situation of NI and their role in Spain. It revealed a gap between the nation's current reality and the established international standard. The lack of a conceptual framework, specialized university training, and official recognition for the nursing informaticians' role are the principal barriers preventing nursing informaticians from leading the digital transformation of health care.

The international literature findings were validated by national experts, creating an actionable roadmap. The identified competencies offer a robust foundation for designing educational programs. The successful training models from other countries provide a blueprint for their implementation. The experts' high level of agreement was unequivocal: the nursing informaticians' role is imperative for improving patient safety, optimizing system efficiency, and furthering the development of NI as a scientific discipline in Spain.

Challenges are significant, although the pathway forward is clear. This research serves as a foundational call to action for policymakers, academic institutions, and health care leaders: building regulatory, educational, and organizational infrastructure is needed to empower a new generation of nursing leaders equipped to lead the future of digital health in Spain.

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Data Availability

The data extracted and analyzed during the scoping review are available from the corresponding author upon reasonable request. The individual responses from the experts are not publicly available to protect participant privacy.

Authors' Contributions

AMM conceived the study and its design. MLC and AMM conducted the literature search, screening, and data extraction. PVR participated in the data extraction and adequacy due to her technological background. MLC and AMM developed the questionnaire and the gap analysis with the experts. All authors drafted the manuscript, critically revised it for intellectual content, and approved the final version for publication.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Gap analysis questionnaire.
[PDF File, 209 KB - nursing_v9i1e83373_app1.pdf]

Multimedia Appendix 2
Scoping review chart 1.
[DOCX File, 1723 KB - nursing_v9i1e83373_app2.docx]

Checklist 1
PRISMA checklist.
[PDF File, 509 KB - nursing_v9i1e83373_app3.pdf]

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Abbreviations

EESI: Enfermeras Especialistas en Sistemas de Información
NI: nursing informatics
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews
PROSPERO: International Prospective Register of Systematic Reviews

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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

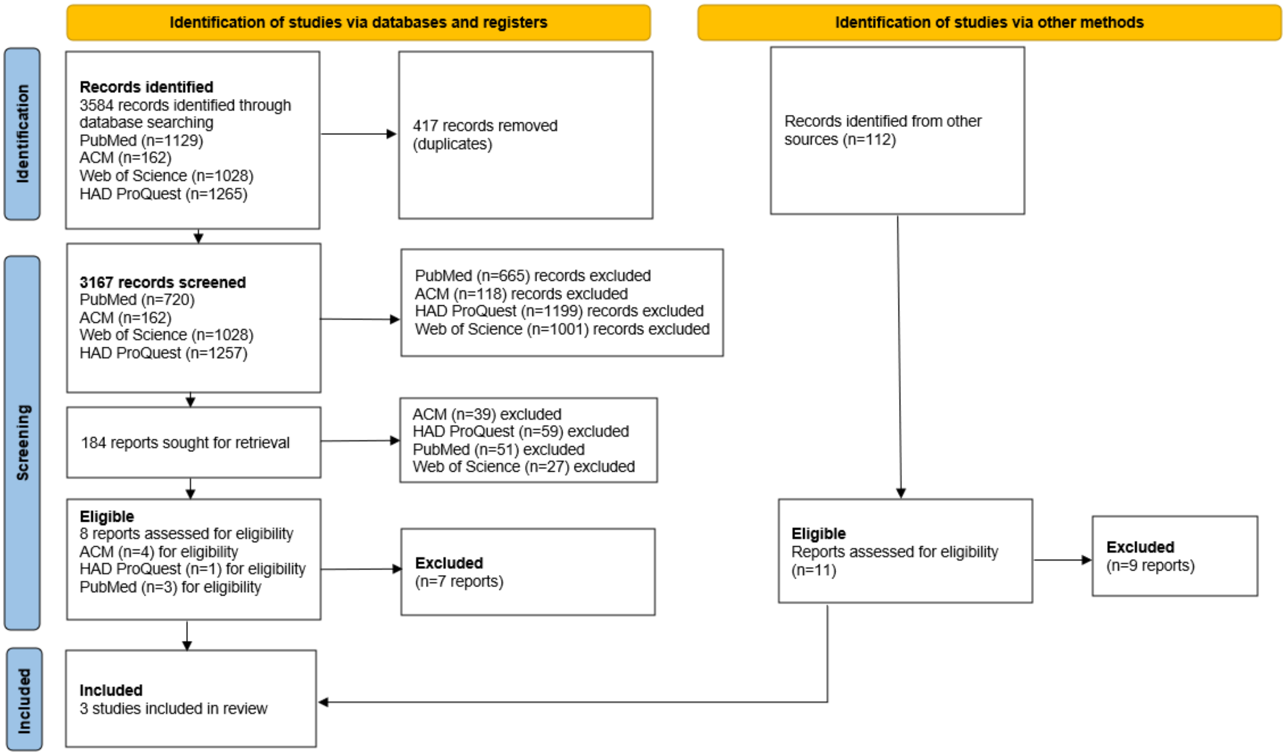
With regard to the synthesis approach, due to the heterogeneity of the included studies (technologies, outcome measures, countries), a narrative synthesis approach was applied keeping in mind the principles of thematic content analysis [48]. Data were coded inductively to identify recurring themes related 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.

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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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Simulation-Based Training for Nursing Students to Improve Patient Safety: Systematic Review

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Abstract

Background: Patient safety is a fundamental pillar of health care quality. Simulation-based training provides a controlled environment for nursing students to develop safety competencies and error-recognition skills before clinical practice.

Objective: This systematic review aimed to describe and characterize the simulation-based education features and modalities used to address patient safety outcomes in undergraduate nursing students, identifying the strategies that contribute to improvements in safety-related competencies.

Methods: A systematic review was conducted following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines across PubMed, Web of Science, Scopus, CINAHL, Cochrane, and Lilacs (2019‐2024). Inclusion criteria focused on original studies involving undergraduate nursing students and simulation interventions measuring patient safety outcomes. Studies in languages other than English, Spanish, or Portuguese were excluded. Two reviewers independently performed study selection and data extraction. Methodological quality was assessed using Joanna Briggs Institute tools, applying a 60% quality threshold for inclusion. Results were synthesized through a narrative approach.

Results: A total of 20 studies from 12 countries were included. The methodological quality was high (n=14) and moderate (n=6). Findings revealed that high-fidelity simulation and virtual reality are the primary strategies used. Simulation proved effective in enhancing both technical skills (medication administration accuracy) and nontechnical skills (communication via SBAR [Situation, Background, Assessment, Recommendation] and ISBAR [Identification, Situation, Background, Assessment, Recommendation] tools, teamwork, and adverse event reporting). Key strategies contributing to safety included repetitive practice and interprofessional simulation, which significantly improved error detection and clinical judgment.

Conclusions: Simulation is an essential pedagogical strategy for preparing nursing students to deliver safe care. Practical implications include the need to integrate structured simulation into nursing curricula to bridge the theory-practice gap. Future research should prioritize longitudinal designs to assess the retention of these safety skills in clinical settings and develop standardized metrics for measuring patient safety outcomes.

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KEYWORDS

nursing students; simulation training; patient safety; nursing; systematic review; PRISMA; Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Introduction

Overview

Patient safety is a fundamental pillar of quality health care, aimed at minimizing risks and preventing harm during medical care [1]. According to the World Health Organization (WHO), this concept is defined as "the absence of avoidable harm to a patient and the reduction to an acceptable minimum of the risk of unnecessary harm associated with healthcare" [2]. Despite its importance, safety failures remain a critical global issue; more than 1 in 10 patients suffer harm during treatment, leading to more than 3 million deaths annually. Consequently, unsafe care must be recognized as both a major public health crisis and a significant economic burden [3].

The study of these failures gained international prominence following the landmark report "To Err is Human," published in 2000 by the National Academy of Sciences. This study revealed that the cost of medical errors extends beyond economics, deeply affecting patient satisfaction, professional morale, and overall trust in the health system [4]. To address these challenges, a comprehensive monitoring approach is required. This involves the proactive identification of hazards, continuous process improvement, and the promotion of a safety culture that actively engages both health care professionals and patients [1].

Patient safety culture is a complex phenomenon in which values, attitudes, competencies, and behaviors influence how health care professionals perceive and manage safety risks [2]. A comprehensive framework for patient safety culture consists of leadership, teamwork, evidence-based practice, communication, learning, just culture, and patient-centered care [5]. This concept is integrated with WHO resolution WHA72.6 [6], which prioritizes concrete measures to prevent avoidable harm in health care, such as strategies for safe medication, error-free surgery, infection control, sepsis management, reliable diagnostics, and adequate hygiene in facilities. This multidimensional framework highlights the systemic nature of safety culture and the central role of leadership and communication in preventing adverse events.

The occurrence of safety incidents is rarely the result of a single individual's actions but rather the culmination of various systemic factors [4]. These include rapid technological advances, increasingly complex care processes, inadequate policies, and an aging population with multiple chronic comorbidities [2]. Because incidents often stem from multiple overlapping causes, focusing on individual blame fails to address the underlying systemic issues, making it likely that the same errors will recur [2,4]. To mitigate these risks, the Global Patient Safety Action Plan 2021-2030 outlines strategic activities designed to identify, evaluate, and manage risks throughout the health care continuum, with the ultimate goal of preventing harm or minimizing its impact [7].

Training and education in safe practices are essential to maintaining and improving standards of care and ensuring that health systems can adapt and respond to emerging challenges in health care [1]. In this context, simulation, defined as any technique that extends or replaces real-world experiences to promote reflective learning, has established itself as a key strategy for improving research on patient safety incidents [8].

Clinical simulation has proven effective as a teaching strategy for developing both technical and nontechnical skills, including communication, teamwork, leadership, and critical thinking [9,10]. This approach allows for the creation of structured, meaningful, and reflective learning environments that facilitate the effective and safe resolution of complex situations, in line with the competencies to be acquired [8-10].

Clinical scenarios form the basis of clinical simulation, as they allow learning experiences to be structured with different levels of complexity in line with training objectives [11]. A key element in their design is fidelity, understood as the degree to which the simulation reproduces the conditions of actual clinical practice [12], which can be classified as low, medium, or high depending on the resources used and the educational goals. Low-fidelity simulation typically focuses on the acquisition of basic technical skills using task trainers, simple manikins, or case studies, while medium and high levels incorporate more complex scenarios and greater realism. Similarly, the simulation modality refers to the format used to develop the training experience. According to the Healthcare Simulation Dictionary, these modalities can include role-playing, virtual or online simulations, task trainers, high-tech mannequins, or immersive simulations with standardized patients (SPs) or trained actors [12]. Thus, the combination of modality and fidelity level allows simulation to be adapted to different educational contexts and clinical competencies [11]. Immersive simulation, particularly when based on realistic clinical scenarios, offers strong opportunities to develop competencies and promote changes in thinking and practice. Its effectiveness is enhanced when followed by structured debriefing, enabling reflective analysis and identification of improvement strategies [9].

Nursing professionals, from their formative stage, need to be actively trained to provide safe care, and effective communication is essential to reduce health errors [13,14]. A culture of open communication facilitates enhanced team interactions and equips students with efficacious strategies to deploy in their practice, thereby fostering critical thinking and emergency management skills. The formation of effective interprofessional teams through simulation-based learning has been linked to improved patient outcomes, a reduction in medical errors, and the delivery of high-quality care [15]. The students have acquired knowledge and have been instructed in the guidelines for conducting practices more safely. However, they encounter obstacles when attempting to communicate and report errors, as they perceive themselves to have a lower status and are sometimes fearful of the potential consequences [16].

A coalition of international scientific societies with expertise in simulation has issued a call for the integration of simulation-based learning into the curricula of undergraduate and postgraduate programs. This initiative is designed to foster a culture of safety [17]. It is also imperative that the simulation be designed in such a way that it does not compromise the psychological and physical integrity of the participants, while also ensuring the safety of the training process [18].

Previous reviews on educational interventions in patient safety highlight considerable methodological heterogeneity and limited evidence regarding the specific impact of simulation [19]. One review found that although patient safety competence was frequently assessed, only 2 studies used simulation, and none examined behavioral changes, limiting conclusions about real clinical impact [18]. A published protocol targeting nursing students also considers simulation among various teaching methods, but anticipates substantial variability that may hinder conclusions about its differential effectiveness [20].

Another systematic review reported improvements in knowledge, clinical skills, and confidence through simulation-based learning; however, it included varying fidelity levels and did not specifically address patient safety outcomes, limiting applicability to this domain [21]. Similarly, quantitative syntheses confirm the benefits of simulation but do not analyze its transfer to patient safety in real health care contexts [22]. A comparison between SPs and role-playing showed improvements in communication skills, yet without linking findings to objective patient safety indicators [23]. Finally, an exploratory review associated simulation with greater competence and confidence but did not differentiate between levels of evidence or modalities, limiting the strength of its recommendations [24].

Overall, despite suggested benefits, the literature shows methodological heterogeneity, limited analysis of behavioral outcomes, and insufficient connection to specific patient safety indicators, raising the question of the actual effect of simulation-based learning on patient safety outcomes in nursing students.

Objective

Since 2020, with the closure of in-person training activities and the impossibility of clinical practices, justified by immediate public health needs: preventing the transmission of infections, facilitating social distancing, and responding to government orders, the need for education and training that adapts to the new demands of the health system has become evident [25,26].

The use of simulation methodology in the education of nursing students can be a strategy that improves the application of the theoretical concepts learned and clinical practice, to provide safe and quality care. The objectives of this systematic review were (1) to determine the effect of simulation-based education on patient safety outcomes in nursing students, (2) to identify the aspects related to patient safety that have been the subject of the use of simulation, and (3) to describe and characterize simulation-based education features and modalities used to address patient safety outcomes in undergraduate nursing students.

Methods

Design

A systematic review was carried out during the months of February and March 2024, following the checklist of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement [27]. The review followed the PRISMA 2020 guidelines and was designed and presented as a systematic review rather than an exploratory review, to accurately determine the effect of simulation-based education on patient safety outcomes, establishing strict predefined eligibility criteria, quality assessment, and structured synthesis of evidence (Checklist 1).

Search Strategy

A systematic search was carried out from 2019 to 2024 in the databases: PubMed, Web of Science, Scopus, CINAHL, Cochrane, and Lilacs. These databases were selected to ensure broad coverage of biomedical, nursing, educational, and multidisciplinary research, as well as to minimize publication and indexing bias. To guide the search, we started from the PIO (Population, Intervention, Outcomes) question (Table 1).

The terms were adapted to the controlled language of the MeSH (Medical Subject Headings) and Descriptors in Health Sciences, in addition to CINAHL subject headings (Table 2).

Table . Keywords PIO[a].

PIO question	Keywords	MeSH[b]	DeCS[c]
Population	Nursing students	Nursing students	Estudiantes de enfermería
Intervention	Training through simulation techniques	Simulation training	Simulación
Outcomes	Improving patient safety	Patient safety	Seguridad del paciente

[a]PIO: Population, Intervention, Outcomes.

[b]MeSH: Medical Subject Headings.

[c]DeCS: Descriptors in Health Sciences in Spanish.

Table . Search strategy.

Base	Search strategy	Number of articles
PubMed	((“education, nursing”[MeSH Terms] OR (“education”[All Fields] AND “nursing”[All Fields]) OR “nursing education”[All Fields] OR “education nursing”[All Fields] OR (“nursing education research”[MeSH Terms] OR (“nursing”[All Fields] AND “education”[All Fields] AND “research”[All Fields]) OR “nursing education research”[All Fields])) AND "2019/02/27 00:00”:“3000/01/01 05:00”[Date - Publication] AND ((“students, nursing”[MeSH Terms] OR (“students”[All Fields] AND “nursing”[All Fields]) OR “nursing students”[All Fields] OR (“nursing”[All Fields] AND “students”[All Fields])) AND (“simulation training”[MeSH Terms] OR (“simulation”[All Fields] AND “training”[All Fields]) OR “simulation training”[All Fields]) AND (“patient safety”[MeSH Terms] OR (“patient”[All Fields] AND “safety”[All Fields]) OR “patient safety”[All Fields]) AND "2019/02/27 00:00”:“3000/01/01 05:00”[Date - Publication] AND "2019/02/27 00:00”:“3000/01/01 05:00”[Date - Publication] AND "2019/02/27 00:00”:“3000/01/01 05:00”[Date - Publication])) AND (y_5[Filter])	92
Scopus	(TITLE-ABS-KEY (nursing AND students) AND TITLE-ABS-KEY (simulation AND training) AND TITLE-ABS-KEY (nursing AND education) AND TITLE-ABS-KEY (patient AND safety)) AND PUBYEAR >2018	109
WoS[a]	(((TS=(nursing students)) AND TS=(simulation training)) AND TS=(nursing education)) AND TS=(patient safety) Last 5 years	136
LILACS	(estudiantes de enfermería) AND (simulación) AND (educación en enfermería) AND (seguridad del paciente) AND (year_cluster:[2019 TO 2024])	14
CINAHL	nursing students AND nursing education AND (simulation training or simulation education or simulation learning) AND (patient safety or patient outcomes or quality of care) Limiters - Publication Date: 20190101 - 20241231	133
Cochrane	(*simulation training) AND (nursing students):ti,ab,kw AND (patient safety):ti,ab,kw (Word variations have been searched) con año de publicación de 2019 hasta 2024, fecha de publicación en la Biblioteca Cochrane Entre Jan 2019 y Feb 2024, en Ensayos	32

[a]WoS: Web of Science.

Inclusion and Exclusion Criteria

The inclusion criteria were articles written in English, Spanish, and Portuguese, which were primary studies on the use of simulation in the undergraduate stages of nursing to maintain patient safety, such as communication, teamwork, medication safety, clinical performance linked to safety, without differentiating the type of simulator used. Although initially it was decided to include only nursing students, it was later decided to also include studies involving medical students in the case of communication or teamwork.

Exclusion criteria were considered qualitative studies, reviews, editorials, personal experiences, and those quantitative articles that were not peer reviewed, studies that dealt exclusively with student satisfaction and perception with the simulation methodology, studies in which among the participants there were already graduated professionals, and those in which at least one of the objectives did not deal with safety, studies on the use of simulators that were specific for learning specialized care, studies referring to the design of simulation scenarios or the development of modifications of educational strategies related to simulation.

Article Selection, Methodological Quality Assessment, and Risk of Bias

The articles obtained were exported to the Zotero bibliographic manager. After removing duplicates, articles were selected by title and abstract during online sessions by 2 researchers. When discrepancies arose, another revisor was contacted for a final decision. Full texts of the remaining articles were obtained to assess eligibility. Two reviewers thoroughly assessed the full texts to determine study inclusion, resolving discrepancies through discussion and, when necessary, with the involvement of a third reviewer. Two reviewers determined that articles met eligibility criteria. References from secondary articles, such as reviews and scoping reviews, were also reviewed to assess their potential inclusion of those articles that met the objectives of this study. Those selected underwent a quality evaluation by 2 authors independently using the Joanna Briggs Institute (JBI) Critical Appraisal Tools [28] according to study design (the checklist for randomized controlled trials [RCTs] [29], the checklist for quasi-experimental studies [30], and the checklist for analytical cross-sectional studies [31]).

The methodological quality of all included studies was assessed independently by 2 reviewers using the JBI Critical Appraisal Tools according to the study design: the checklist for RCTs, quasi-experimental studies, and analytical cross-sectional studies. Discrepancies were resolved by consensus with a third reviewer. Studies meeting ≥60% of the applicable JBI criteria were included in the final synthesis. Considering that the JBI critical appraisal tools do not establish universal cutoff points for classifying methodological quality, leaving this decision to the discretion of review teams, a 60% threshold was applied as a pragmatic criterion to balance the inclusion of methodologically acceptable studies while avoiding overly restrictive exclusions, thereby ensuring the availability of sufficient evidence for analysis [28].

Data Extraction and Synthesis

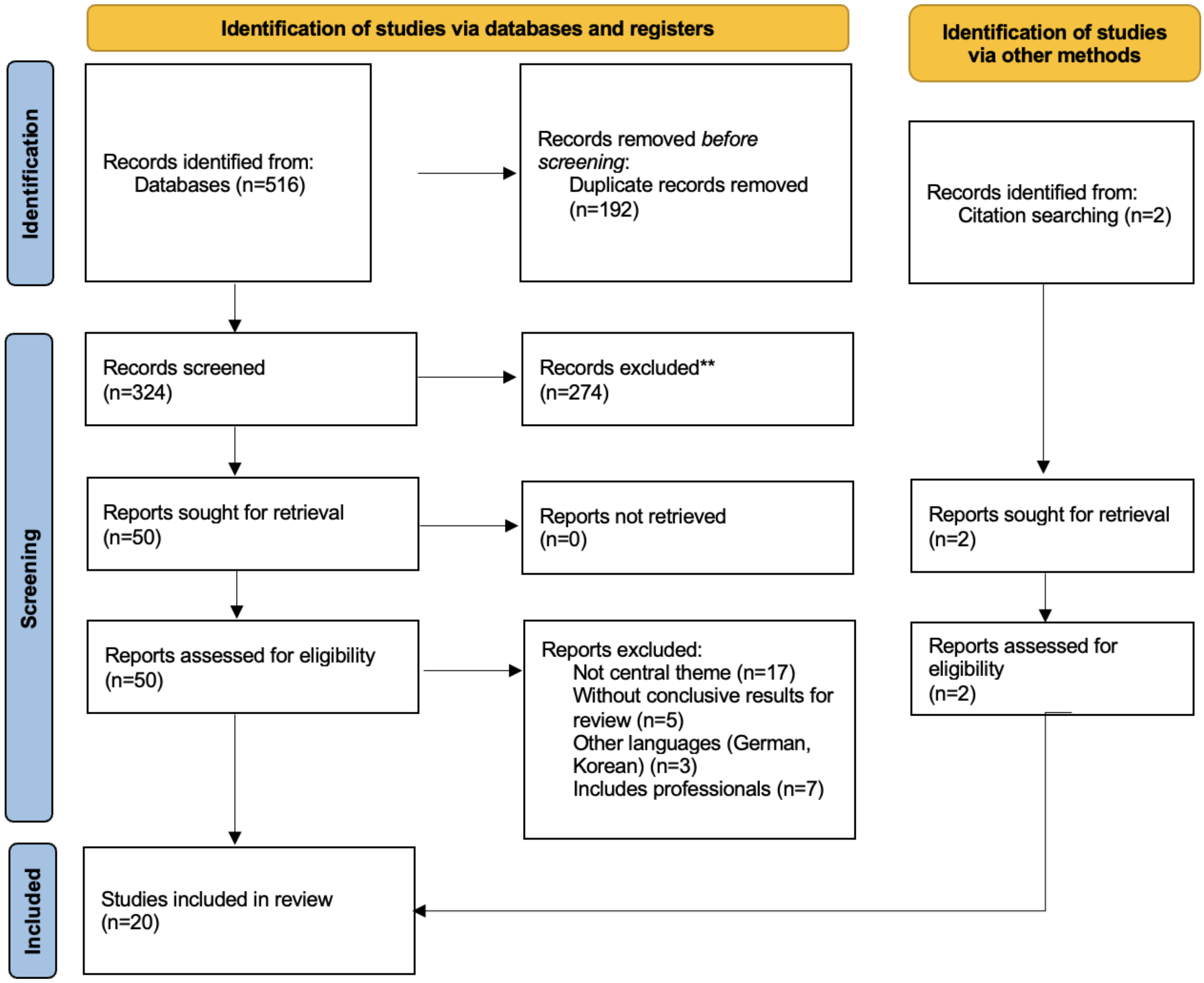
The authors independently extracted data from the studies into a Microsoft Excel spreadsheet. The sheet recorded data on the author, year of publication, country, age of participants, type of study, objective, scales and instruments used, results and conclusions, limitations, safety aspects covered, type of simulation, types of interventions performed, and simulated cases (Table S7 in Multimedia Appendix 1 [32-51] and Table S8 in Multimedia Appendix 2 [32-51]). Given the diversity among the included studies, clinical and methodological heterogeneity (diverse domains, modalities, and durations), noncomparable instruments, and incomplete statistical reporting (missing effect sizes and variances), a narrative synthesis was conducted, guided by the principles of thematic content analysis.

Results

Study Selection

The selection process is shown in Figure 1.

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



Characteristics of Included Studies

A total of 20 studies [32-51] met the inclusion criteria for this review. The primary characteristics of these studies are detailed in Table 3. The included articles were published between 2019 and 2024. The country with the highest number of studies was Korea with 6 studies [32,34,36,37,41,48], followed by the United States [32,40,45] and China [39,43,49], with 3 studies each. Spain [42,50] and Taiwan [46,51] contributed 2 studies each. Germany [35], Ireland [47], and Indonesia [38] contributed 1 study each. One study was led by an international team (Canada, England, Scotland, and Australia) [44]. For the purpose of counting, each of the 20 studies [32-51] was assigned to the country of the coordinating institution, and the multicountry study was considered as a single study with international participation.

Table . Characteristics of included studies.

Author (year), country	Participants	Type of study and assignment	Objectives	Data collection scales and instruments	Results and conclusions	Limitations
Breen et al [47] (2019), Ireland	Total 90: 45 nursing students 3rd course, 45 last-year medical students. Year: 2016.	ECA 3 groups: e-learning (E)[a], E+standard simulation (E+S)[b], competency-based progression simulation and e-learning (E+PBP)[c]. Randomized	To determine the effectiveness of a competency-based training (PBP)[d] for clinical communication.	National Early Warning Score (NEWS)[e] based on the ISBAR[f] tool	Communication competence was achieved by 2/29 (7%) in E, 3/23 (13%) in E+S, and 15/25 (60%) in competency-based progression. Competency-based training was significantly more effective (*P*<.001)	Single center; undergraduate sample; short training duration
Son and Kim [36] (2019), Korea	98 Nursing students. CG[g]: 41, IG[h]: 57 Course 3rd Year: 2017 Age: 22 - 23 Gender: Women	Quasi-experimental. Pretest-posttest design of nonequivalent control group. Convenience sampling	Effectiveness of communication education based on SEGUE[i] between students and patients.	Communication competence and effectiveness measured by a self-report questionnaire and by teacher and standardized patient ratings of the students	Intervention students showed significantly greater improvements in communication competence and efficacy than controls (In terms of performance, as assessed by lecturers and students, the *P* value is <.001, the standardized patient score is 0.042, and the communication effectiveness score is 0.004).	Single institution; small control group
Jeong and Kim [37] (2020), Korea	54 nursing students. IG: 26, CG: 28 Grade: 3rd Year: 2018 Age: 20 - 40 average 23 Gender: Women, only 1 man	Clinical trial (pre-post). Simple blind	Develop a fall simulation program using the SBAR[j] communication technique	Knowledge of falls and attitude toward falls scale, post-fall evaluation protocol (AHRQ[k]). GICC-15[l] and Dunsford adapted structured communication	SBAR-based simulation significantly improved structured fall-related communication compared with controls.	No long-term follow-up; single-blind design
Liaw et al [49] (2020), China	120 medical and nursing students. IG: 60, CG: 60 Grade: 3rd-4th year. Year: 2018. Mean age 22.17 (SD 2.07) years. Gender: Women (81, 67.5%)	RCT[m] (pretest-posttest) Randomized	To evaluate a team training program using VR[n] versus conventional live simulations on the performance of communication skills and teamwork	ATHCT[o] and ISVS[p]. Baseline, posttest, and 2 months after	Both groups improved teamwork attitudes; VR training was noninferior with higher follow-up ISVS.	Self-reported outcomes; single-center design
Sanko and McKay [33] (2020), United States	231 nursing students from 2016 (CG: 68), 2017 (IG: 85), and 2018 (CG: 78) patient safety courses.	Clinical trial (2 cohorts years different intervention and control groups). Convenience sampling	To assess whether exposure to simulation scenarios to enhance systematic thinking influenced adverse event reporting and the type	Simulated AERS[q]. System Thinking Scale (STS)[r]	Systems thinking scores increased significantly after simulation, and adverse event reporting improved (*P*<.001).	Single-site sample; simulated reporting system
Lee and Kim [34] (2020), Korea	194 nursing students. 47 teams (4 and 3 components) Course: higher level. Year: 2015 - 2016	Prospective observational convenience sampling	To examine the relationships between nursing students' team task performance and SBAR-R[s] communication.	Measurement of team task performance and communication using developed checklists based on SBAR-R	Higher SBAR-R scores were significantly associated with better team task performance (*P*=.004).	Single university; limited scope

Author (year), country	Participants	Type of study and assignment	Objectives	Data collection scales and instruments	Results and conclusions	Limitations
Wai et al [48] (2021), Korea	46 students: 19 medical, 27 nursing. Interprofessional teams. Grade: Final year medicine (5th), 3rd-4th year nursing. Gender: 63% female students.	Mixed methods convenience sampling	To compare the effectiveness of combined classroom plus clinical simulation versus clinical simulation alone on attitudes, perceptions, and teamwork performance.	HFAS[t] Survey. Teamwork performance using TBL-SAI[u] focus group interview	Both groups improved teamwork attitudes (P=.04) with no added benefit from classroom teaching	Small sample; limited power
Musharyanti et al [38] (2021), Indonesia	95 nursing students IG:55. CG: 40.	Quasi-experimental. Nonequivalent randomized control group.	To compare drug safety knowledge and skills after safety training with the 4C/ID[v] teaching method.	MCQs[w] and 2 checklists developed ad hoc on patient safety and medication administration	Intervention students achieved significantly higher safety knowledge and skills than controls (P<.001).	No baseline testing
Du et al [39] (2021), China	47 nursing students.CG:21, IG:26 Grade: 2nd Year 2019. Age 17 - 27 Gender: 44 women -3 men	Controlled trial. Simple blind.	To assess the risk of pressure ulcer development in 3 different scenarios	OSCE[x] adapted to different scenarios Pressure Ulcer Knowledge Assessment Tool (PUKAT 2.0)[y]	OSCE-based simulation significantly improved assessment performance (P<.001).	Small sample. Single center
Lee and Lim [32] (2021), Korea	30 nursing students. Grade: Final year. Year: 2018. Average age 22.17 Gender: women	Quasi-experimental (pre-post). Convenience sampling	Develop, implement, and verify the effectiveness of a simulation-based handover education program.	Communication tool adapted from SBAR. Knowledge questionnaire developed by authors. Self-efficacy (adapted questionnaire).PASS-BAR[z]	Simulation significantly improved handover knowledge, self-efficacy, and performance (P≤.001).	No control group; all-female sample
Craig et al [40] (2021), United States	83 nursing students. CG:35. IG:45 Grade: 3rd.	Quasi-experimental. Convenience sampling	To examine the effects of an educational strategy using a simulation program on medication management.	MSKA[aa] and MSCEC[ab]	Simulation significantly improved medication administration skills (P<.001).	Single-site study
Raurell-Torreda et al [50] (2021), Spain	93 nursing students. IG: 48, CG:45 Course: 3rd, 1 medical student in 5th year. Age: CG: 22.3±5.2- IG: 23.3±6.8 Gender: 78.5% women	Clinical Trial Randomized	Evaluate the impact of SBAR training on interprofessional teamwork skills (role-related and communication) and nontechnical skills.	KidSIM-TPS[ac] and CSET[ad] (nontechnical skills)	Intervention students showed significant improvements in teamwork behaviors (P≤.004).	Partial implementation
Park and Kim [41] (2021), Korea	91 nursing students. IG: 47, CG: 44. Final year of nursing Academic year 2018/19. Age: IG 22.59±1.23, CG 22.86±1.39 Gender:+77% women	Clinical Trial Randomized	Analyze the impact of simulated patient deterioration on situational awareness and patient safety competence-attitude.	SAGAT[ae] modified; PSCSE[af] modified.	Simulation significantly improved situational awareness and safety attitudes (P<.001).	Single university
Chen et al [51] 2022, Taiwan	54 students: 18 medical students and 36 nursing students Grade: 4th year nursing, 5th year medicine Year: 2019 Gender: 70% Women	Mixed methods Randomized	Determine the importance of interprofessional training on competence, teamwork attitudes, and safety.	MTP[ag], TBP[ah], TA[ai], and PSA[aj]	Both groups achieved comparable competence gains; qualitative data supported learning benefits	Small sample

Author (year), country	Participants	Type of study and assignment	Objectives	Data collection scales and instruments	Results and conclusions	Limitations
Pol-Castañeda et al [42] (2022), Spain	179 nursing students. Grade: 2nd Academic year 2018/19 Age: 60% between 18‐25 Gender: 89% women	Mixed methods Convenience sampling	To assess the acquisition of skills in safe medication administration by nursing students	Questionnaire. adapted from the. MASAT[ak]	Simulation improved most medication skills except documentation.	Assessment variability
Goldsworthy et al (2022), Canada, England, Scotland, and Australia [44]	88 nursing students 5 diverse university sites in 4 countries Grade: 3rd-4th Pandemic year 2020?	Quasi-experimental Convenience sampling	Explore the impact of a virtual simulation on to recognize and respond to a rapidly deteriorating patient.	10-item Clinical Self-Efficacy Survey designed 20-item multiple-choice test on evidence-based practice	Virtual simulation significantly improved knowledge scores (*P*=.001).	Nonrandomized design
Li et al [43] (2023), China	205 nursing students.IG:103, CG: 102. Grade: 2nd Academic year 2020/21. Mean age CG: 19.65 (SD 0.75) years, IG:19.78 (SD 0.77) years. Gender: women 87%‐89%	Quasi-experimental (2-tailed) Convenience sampling	Exploring the effects of an online course (SPOC)[al] combined with simulation-based training in a patient safety education program.	PSCSE	Patient safety competence scores were significantly higher in intervention students (*P*<.001).	Single-center study
Haerlin et al [45] (2023), United States	193 nursing students: Group Clinical experience: 51, Group Manequins:44, Group VR: 57. Academic year 2021/22. Age: 19-53 (median 21). Gender: 81.6% female	Quasi-experimental Convenience sampling	Compare differences in learning and practice in patient care as a function of the learner’s training experience.	Competency by CCEI[am] and LCJR[an]. Clinical Learning CLECS[ao] 2.0	Manikin-based simulation produced equal or superior outcomes compared with other modalities.	Regional sample
Chou et al [46] (2024), Taiwan	84 nursing students IG: 42 and CG: 42. Grade: 2nd Year: 2022. Mean age 20.3 (SD 0.46) years. Gender: 80% women	Clinical Trial Randomized	To examine the effectiveness of a VR communication simulation in the acquisition of communication skills in the fundamentals of nursing practice.	Kalamazoo Consensus Statement Essential Elements Communication Checklist, “Communication Self-Assessment Scale” modified, Development and Testing of a Perceived Stress Scale for Nursing Students in Clinical Practice and a learning satisfaction	Kalamazoo Consensus Statement Essential Elements Communication Checklist, “Communication Self-Assessment Scale” modified, Development and Testing of a Perceived Stress Scale for Nursing Students in Clinical Practice and a learning satisfaction	Short intervention; self-report bias

Author (year), country	Participants	Type of study and assignment	Objectives	Data collection scales and instruments	Results and conclusions	Limitations
Heier et al [35] (2024), Germany	221 Students, 154 medical and 67 nursing students (IG: 66 medical, 28 nursing/CG: 88 medical, 39 nursing) Course: 3rd year medical and 1st-2nd year nursing students. Year: October 2021-March 2023. Mean age 24 (SD 3.9) years. Gender: 51.13% women	Mixed methods Convenience sampling	Develop joint communication skills training for nursing and medical students in professional error communication.	Adaptation of G-IPAS[ap] "Teamwork,Roles and Responsibilities," "Patient- centeredness" and a self-developed interprofessional error communication scale	Adaptation of G-IPAS "Teamwork,Roles and Responsibilities," "Patient- centeredness" and a self-developed interprofessional error communication scale	Nonrandomized design

[a]E: e-learning.
[b]E+S: e-learning plus standard simulation group.
[c]E+PBP: e-learning plus competency-based progression simulation group.
[d]PBP: progression-based performance/competency-based progression.
[e]NEWS: National Early Warning Score.
[f]ISBAR: Identification, Situation, Background, Assessment, Recommendation.
[g]CG: control group.
[h]IG: intervention group.
[i]SEGUE: Set the stage, Elicit information, Give information, Understand the patient's perspective, End the encounter.
[j]SBAR: Situation, Background, Assessment, Recommendation.
[k]AHRQ: Agency for Healthcare Research and Quality.
[l]GICC-15: General Interpersonal Communication Competency (15 items).
[m]RCT: randomized controlled trial.
[n]VR: virtual reality.
[o]ATHCT: Attitudes Toward Interprofessional Health Care Team.
[p]ISVS: Interprofessional Socialization and Valuing Scale.
[q]AERS: Adverse Event Reporting System.
[r]STS: Systems Thinking Scale.
[s]SBAR-R: Situation, Background, Assessment, Recommendation, Read-back.
[t]HFAS: Human Factors Attitude Survey.
[u]TBL-SAI: Team-Based Learning Student Assessment Instrument.
[v]4C/ID: Four-Component Instructional Design.
[w]MCQ: multiple choice questionnaire.
[x]OSCE: Objective Structured Clinical Examination.
[y]PUKAT: Pressure Ulcer Knowledge Assessment Tool.
[z]PASS-BAR: Patient Safety Screen-Based Assessment Record (handover tool).
[aa]MSKA: Medication Safety Knowledge Assessment.
[ab]MSCEC: Medication Safety Critical Elements Checklist.
[ac]KidSIM-TPS: KidSIM -Program Team Performance Scale.
[ad]CSET: Clinical Simulation Evaluation Tool.
[ae]SAGAT: Situational Awareness Global Assessment Technique.
[af]PSCSE: Patient Safety Competency Self-Evaluation.
[ag]MTP: Medical Task Performance.
[ah]TBP: Team Behavior Performance.
[ai]TA: Teamwork Attitude.
[aj] PSA: Patient Safety Attitude.
[ak]MASAT: Medication Administration Safety Assessment Tool.
[al]SPOC: Small Private Online Course.
[am]CCEI: Creighton Competency Evaluation Instrument.

[an]LCJR: Lasater Clinical Judgment Rubric.

[ao]CLECS: Clinical Learning Environment Comparison Survey.

[ap]G-IPAS: German Interprofessional Attitudes Scale.

The study designs varied, encompassing 8 RCTs [33,37,39,41,46,47,49,50], 11 quasi-gstudies [32,35,36,38,40,42-45,48,51], and 1 analytical cross-sectional study [34]. The participant samples predominantly consisted of undergraduate nursing and/or medical students at various stages of their training. The objectives of the studies commonly focused on evaluating the use of simulation-based training on competencies essential for patient safety, such as interprofessional communication, teamwork, and clinical reasoning. The studies that included only nursing students were 14 [32-34,36-46] and the remaining 6 were studies with a mixture of nursing and medical students [35,47-51], although one of them only included 1 medical student [50].

The total number of participants included was 2494. The study with the least participation grouped 30 students [41] and the one with the highest participation had 231 [42]. Most participants were women (more than 60%); in one of the studies, all participants belonged to a women's nursing school [41].

The studies were carried out from 2015 [34] to 2023 [35]; 5 of them did not report the age of the participants, and 4 did not report the academic year in which the participants were enrolled, their sex, or the year the study was conducted.

Measurement tools varied across studies. Only 4 studies used ad hoc questionnaires [34,36,38,44]. The remaining 16 studies [32,33,35,37,39-43,45-51] used validated instruments, some with contextual adaptations (eg, cultural and language modifications and scenario-specific items).

Characteristics of Interventions

The simulation-based training interventions detailed in the included studies were heterogeneous, as detailed in Table 4. Interventions ranged from single-session workshops (eg, 3.5 h) to multisession programs integrated into the curriculum.

The modalities of simulation used included high-fidelity simulators (HFS; n=9) [32,34,39-41,43,45,47,48], SPs (n=8) [35-39,48,49,51], virtual reality (VR; n=4) [44-46,49], role play (n=2) [38,50], and board simulations (n=1) [33]. Several studies combined HFS with SP or VR, so the categories are not mutually exclusive. The transfer of communication using a structured methodology between the team uses different strategies, such as SBAR (Situation, Background, Assessment, Recommendation) and SBAR-R [32,34,37,47,50] handover tools and KidSIM-TPS [50] teamwork frameworks, while other less commonly used techniques include the Kalamazoo communication checklist [46]. Structured communication with the patient is guided by the SEGUE (Set the stage, Elicit information, Give information, Understand the patient's perspective, End the encounter) framework [36]. These structured tools were detailed in the instruments and notes of Table 3.

Table . Characteristics of interventions.

Author (year), country	Modalities and type of simulation	Security aspects covered	Direction of effect	Type of intervention in the study	Case
Breen et al [47] (2019), Ireland	HFS[a]-HF[b]	Communication between professionals	Favors competency-based simulation	All groups 15 min training on the ISBAR[c] tool. Group (E[d]): HF room. Group (E+S[e]) work in mixed discipline pairs: telephone calls on 4 standardized cases (3.5 h). Group (E+PBP[f]): same training as group E+S, reached competencies	4 standardized clinical cases of acute patient deterioration
Son and Kim [36] (2019), Korea	SP[g]-HF	Communication with the patient	Favors simulation	CG[h]: Prebriefing + pretest (50 min), simulation 60 min, debriefing+posttest (50 min) afterward, and SEGUE[i]-based communication (30 min). IG[j]: SEGUE communication before	Standardized pediatric scenario, with mothers of 5-year-old children admitted to the hospital for acute gastroenteritis with fever
Jeong and Kim [37] (2020), Korea	SP-HF	Falls and communication	Favors simulation	IG: 3 educational sessions on falls communication and SBAR[k] method (theory, practice, and discussion). CG: training according to guidelines on patient care and transfer of information	Standardized patient falling out of bed
Liaw et al [49] (2020), China	VR[l] (simulated environment with avatar use) and live simulation (SP)-HF	Interprofessional communication and teamwork	Noninferior (VR vs live)	All groups received 3 h of team training on nurse-physician communication. IG: virtual environment and avatar, CG: SP. Each scenario lasted approximately 15 - 20 min and was followed by a 30-min facilitator briefing	Sepsis and septic shock scenario
Sanko and McKay [33] (2020), United States	Board simulation (board game) to teach and develop systematic thinking-LF[m]	Notification of incidents and adverse effects. System failures	Favors simulation	CG: Simulation scenarios. IG: 2017 course included a tabletop simulation“ Friday Night in the ER.”	Emergency care
Lee and Kim [34] (2020), Korea	HFS (IAM[n])-HF	Interprofessional communication	Positive association	Before the scenario training on SBAR-R[o] communication and election of the leader of each team. Development of the scenario in 2 times: before a call to a fictitious doctor and performance of the task in a team after receiving instructions by phone	Acute myocardial infarction emergency care

Author (year), country	Modalities and type of simulation	Security aspects covered	Direction of effect	Type of intervention in the study	Case
Wai et al [48] (2021), Korea	HFS-HF	Teamwork	Both improved	IG: combined classroom+simulation. CG 1: online training on team-based learning, individual test and later in group, with those who would solve the simulation. CG 2: clinical case simulation. All groups are training on patient safety, human factors, and communication	Predetermined critical case scenarios: chest pain and weakness in MMII[p]
Musharyanti et al [38] (2021), Indonesia	Role play and simulated patients (actors)-LF	Medication administration	Favors simulation	IG: 18-h training sessions over 5 wk, overview and training activity with a 4C/ID[q] approach including presentation of real cases, small group discussion, reflection and simulation of oral and intramuscular drug administration. CG: 2 wk, overview, 2 lecture sessions and video playback, and posttesting	Oral and intramuscular drug administration
Du et al [39](2021), China	SP in high fidelity room-HF	PUP[r]	Favors simulation	CG: pressure ulcer training in the conventional classroom 90 min, IG: training through simulated clinical scenarios	Three clinical scenarios from admission, hospitalization and deterioration of the disease
Lee and Lim [32] (2021), Korea	HFS (respiratory)-HF	Communication in transfer	Favors simulation	Students were divided into groups of 3 to 4 for 120-min sessions consisting of 50 min of theoretical training and 70 min of simulation-based training	2 patients with respiratory problems with high-fidelity simulator
Craig et al [40] (2021), United States	HFS with computer package, electronic medical records (identification wristbands, carts, barcodes, and computerized records)	Medication administration	Favors simulation	4 wk of simulation. IG: 1. low-fidelity simulation on medication administration. 2. high-fidelity simulation focused on safe medication administration. 3. clinical rotation. 4. high-fidelity simulation+debriefing. CG: 1. standard training. 2 clinical rotation and 3 - 4 same as IG	Scenario for administration of oral and subcutaneous medication (insulin aspart)

Author (year), country	Modalities and type of simulation	Security aspects covered	Direction of effect	Type of intervention in the study	Case
Raurell-Torreda et al [50] (2021), Spain	Role-playing SBAR. -LF	Interprofessional communication	Favors simulation	IG: divided into subgroups of 20 students for 1-h role play session, learning objectives focused on basic professional health care skills, teamwork, use of SBAR worksheet and role distribution in respiratory tract management, nursing procedures and techniques, and use of documentation. Patient assessment and intervention in 3 nursing roles: procedures, assessment, and follow-up	Patient in shock in an emergency department setting (based on a clinical case from the National League for Nursing) to assess teamwork and nontechnical skills
Park and Kim [41] (2021), Korea	HFS (mannequin)-HF	Systemic and organizational factors. Diagnostic errors	Favors simulation	IG: The PDS-IB[s] and CG: simple PDS. The scenario theme for the simulations in both groups was patient deterioration. The simulations for both groups consisted of 1.5 h	Patient with chronic obstructive pulmonary disease was transferred from the emergency room to the inpatient ward (worsening)
Chen et al [51] (2022), Taiwan	SP-HF	Teamwork	Comparable gains	In group 1 (received IPE[t] training, followed by SPE[u]) and group 2 (received SPE training followed by IPE training). Simulation training was structured for 4 wk (3 h/wk) that incorporated a 2-wk IPE program during which medical and nursing students were trained together	Critically ill patients with AHA[v] guidelines for cardiopulmonary resuscitation and emergency cardiac care
Pol-Castañeda et al [42] (2022), Spain	SP (clinical case)-HF	Medications	Favors simulation	Briefing, simulation scenarios were conducted in 24 groups of 6 to 8 students, each playing a different role	3 scenarios: hypocalcemia due to gastrointestinal disease in the emergency department, respiratory infection, paracentesis
Goldsworthy et al [44] (2022), Canada, England, Scotland, and Australia	VR-HF	Patient deterioration	Favors virtual simulation	The treatment group completed 6 VR of medical surgical nursing case studies over 3 wk (2/wk). Two VR were completed each week that they could repeat	Acute deterioration care: angina and cardiac arrest; anaphylaxis; acute asthma exacerbation; COPD[w] and pneumothorax, pulmonary embolism; and blood transfusion reaction.
Li et al [43] (2023), China	HFS (standardized patient+mannequin)-HF	Patient safety, medication errors, and adverse effects	Favors combined training	All: online course-training adverse effects, types, effects, and communication and teamwork. IG: 2 simulation cases in addition to training. CG: online training only	Scenarios of care in respiratory infection (medication) and hemiplegia (basic care)

Author (year), country	Modalities and type of simulation	Security aspects covered	Direction of effect	Type of intervention in the study	Case
Haerling et al [45] (2023), United States	HFS mannequin and VR displays-HF	Safety risks. Interprofessional and patient communication Medication Administration	Manikin superior and equivalent	Clinical experience: 4 h of traditional clinical experience Mannequin simulation: simulation activities with mannequins in 2 scenarios VR was similar to that of the mannequin-based simulations. The groups varied according to the type of experiential learning activity they completed first	Postoperative discharge care and postoperative emergency room readmission
Chou et al [46] (2024), Taiwan	VR-HF	Communication	Favors VR simulation	IG received a VR training in nurse-patient communication skills 2 wk prior to practice. The program was delivered in 4 sessions for 30 min each time for 2 wk. CG received the 30-min nurse-patient communication teaching video that could be downloaded and viewed	Simulated hospital ward scenarios with 4 learning tasks: self-presentation, establishing a nurse-patient relationship, interaction, and medical history collection
Heier et al [35] (2024), Germany	SP-HF	Notification of medication errors	Favors simulation	Interprofessional communication skills training on acute care medical errors (IG) with a cohort that did not receive interprofessional training (CG)	3 scenarios reported in a critical incident reporting system focused on medication errors caused by a chain of errors. Chemotherapy, wrong antibiotic, and chemotherapy preparation with errors

[a]HFS: high-fidelity simulator.

[b]HF: high-fidelity.

[c]ISBAR: Identity-Situation-Background-Assessment-Recommendation.

[d]E: e-learning.

[e] E+S: e-learning plus standard simulation group.

[f] E+PBP: e-learning plus competency-based progression simulation group.

[g]SP: standardized patient.

[h]CG: control group.

[i]SEGUE: Set the stage, Elicit information, Give information, Understand patient perspective, End the encounter.

[j]IG: intervention group.

[k]SBAR: Situation, Background, Assessment, Recommendation.

[l]VR: virtual reality.

[m]LF: low fidelity.

[n]IAM: High Fidelity Simulator for Acute Myocardial Infarction.

[o]SBAR-R: SBAR with Readback and Response.

[p]MMII: Lower Limbs.

[q]4C/ID: Four Components Instructional Design.

[r]PUP: pressure ulcer prevention.

[s]PDS-IB: Patient Deterioration Simulation with Inattentional Blindness.

[t]IPE: Interprofessional Education.

[u]SPE: Single Profession Education.

[v]AHA: American Heart Association.

[w]COPD: chronic obstructive pulmonary disease.

Methodological Quality Results

The overall methodological quality of the studies was moderate to high. Using the JBI Critical Appraisal Tools, RCTs generally scored between 9 and 13 out of 13 possible criteria, quasi-experimental studies between 7 and 9 out of 9, and cross-sectional studies met 6 to 8 out of 8 criteria, assessed according to JBI methodological standards for evidence synthesis [29-31].

Common strengths included clear description of inclusion criteria, valid measurement of outcomes, and appropriate statistical analyses. The most frequent limitations were related to lack of blinding of participants or assessors, incomplete follow-up, and limited control of confounding factors.

A summary of the appraisal results is presented in Table 5, while full details of the assessment can be found in Tables S2, S3, and S4 in Multimedia Appendices 3-5.

Table . Summary of methodological quality results.

Study design	Number of studies	JBI[a] tool used	Mean criteria met (%)	Common strengths	Common limitations
Randomized controlled trials	8	JBI RCT[b] Checklist (13 items)	85 - 100 (9, 13/13)	Clear objectives, valid measurement tools, and appropriate statistical analysis	Lack of blinding (3), small samples
Quasi-experimental studies	11	JBI Quasi-Experimental Checklist (9 items)	78 - 100 (7, 9/9)	Clear cause-effect design and reliable outcome measures	Absence of control group in some cases (3), incomplete follow-up (2)
Cross-sectional studies	1	JBI Analytical Cross-Sectional Checklist (8 items)	75 (6/8)	Clear inclusion criteria, valid exposure, and outcome measures	Confounding not always controlled

[a]JBI: Joanna Briggs Institute.

[b]RCT: randomized controlled trial.

Topics

The topics they discussed were communication, both interprofessional [32,34,46,47,49,50] as communication with the patient [36], teamwork [48,51] aspects related to medication, such as its administration [38,40,42] and notification of errors or adverse effects [33,35,43], systemic and organizational factors [41], falls [37], pressure ulcer prevention [39], patient deterioration [44], and various security aspects a mix of the above [45].

Mixed groups, with nursing and medical students, address topics such as interprofessional communication and teamwork [48-51]; only one of them addresses the issue of medication [35].

Most simulations aimed at developing communication and teamwork skills used high-fidelity modalities, including SP and mannequins [32,34,36,47,48,51] and VR environments [46,49]. One study used role-playing as the primary simulation modality [50].

To develop skills in aspects of medication administration, HFS has been used [40], role play [38], and simulated patients [38,42]. In the case of notification of medication errors and adverse effects, the simulation scenarios have used SPs and mannequins [35,43] and a board game [33]. The rest of the safety aspects discussed have used simulated patients or mannequins, except the study on patient deterioration, which has used VR technology [44].

High-fidelity simulation through HFSs, VR, and SPs predominated across studies. However, low-fidelity approaches, such as role-playing, were also used, either alone or combined with other modalities, particularly in interprofessional communication [50], medication administration [38], and incident or system failure reporting [33].

Safety Outcomes

In general, almost all studies link training through simulation scenarios with an improvement in safety-related skills and knowledge [32-47,50]. One study directly compared live (face-to-face) simulation with immersive VR simulation in scenario-based training [49]. The comparator was therefore 2 different simulation modalities rather than simulation versus traditional teaching. No statistically significant differences were found between live and VR simulation in the development of teamwork and communication skills. These findings suggest that VR-based simulation may represent a comparable alternative to live simulation for fostering these competencies.

Simulation training complemented by other techniques (lectures, presentations, debates, and demonstrations) achieves better results than simulation training alone for improving patient safety competency among nursing students [43]. However, the effects of a blended classroom plus clinical simulation versus clinical simulation alone on teamwork attitudes did not further improve teamwork attitudes, perceptions, and performance in medical and nursing students compared with clinical simulation alone [48]. A quasi-experimental study comparing traditional clinical practice, manikin-based high-fidelity simulation, and screen-based virtual simulation (n=193) found no significant differences in cognitive outcomes between groups [45]. However, students in the manikin-based simulation group achieved significantly higher scores than those in the traditional clinical group in several competency domains measured by the Creighton Competency Evaluation Instrument, including communication (effect size=0.52; P=.04), although no significant differences were observed in the Patient Safety domain. These findings suggest that the type of simulation experience may influence specific clinical competency outcomes [45].

Only 2 studies followed up over time after training [46,49]. In one study, the results were better than before after 1 week of practice [46]. A RCT compared immersive VR simulation with conventional live simulation in 120 medical and nursing students. Both modalities significantly improved teamwork attitudes and interprofessional socialization immediately postintervention. At 2-month follow-up, only the VR group maintained a significant improvement in Interprofessional Socialization and Valuing Scale scores (*P*=.047), although no statistically significant differences were found between groups at any time point, suggesting comparable effectiveness [49].

Two studies evaluated competencies using Objective Structured Clinical Examination–based assessments. In one study, 47 second-year nursing students receiving simulation-based training achieved significantly higher scores in pressure ulcer risk assessment than those receiving standard instruction (mean 29.04, SD 6.00 vs mean 12.38, SD 4.15; *P*<.001) across 3 simulated scenarios using SPs [39]. In another randomized educational trial including 90 nursing and medical students, competency-based simulation combined with e-learning led to higher communication competence (60%) compared with e-learning alone (6.9%) and standard simulation (13%), using a clinical structured communication tool [47].

Discussion

Principal Findings

This systematic review aimed to evaluate the effect of simulation-based education on patient safety outcomes in undergraduate nursing students, to identify the patient safety domains addressed through simulation, and to describe the characteristics of simulation-based educational interventions. Overall, the findings suggest that simulation-based education is associated with improvements in several competencies related to patient safety, particularly communication, teamwork, medication safety, and the recognition and reporting of clinical incidents. High-fidelity simulation predominated among the included interventions, with 16 studies using this modality [32,34-43,45,47,48,50,51]. In addition, the incorporation of VR [35,37,40] expands the range of clinical scenarios that can be recreated in educational environments and may facilitate the development of knowledge and skills related to patient safety [43].

Among the patient safety domains addressed, communication and teamwork were the most frequently studied. Several studies reported improvements in these competencies following simulation-based training among nursing and medical students [38-42]. Simulation scenarios provide opportunities for students to practice interprofessional collaboration and structured information transfer in controlled learning environments. Structured communication tools, such as SBAR and its adaptations, were frequently incorporated into simulation scenarios and were associated with improved team coordination and information transfer [32,34,37,46,47,50]. Similarly, structured communication strategies have been shown to improve communication between students and patients [36]. Communication-focused simulations often involved interprofessional scenarios in which students practiced structured communication during clinical deterioration or emergencies, strengthening collaborative decision-making between professionals [47,49,50].

Medication safety was another frequently addressed domain. Three studies evaluated students’ ability to safely administer medications, identify potential errors, and follow appropriate safety procedures [38,40,42]. Simulation provides a controlled environment in which students can practice medication administration while recognizing potential safety risks without endangering real patients. In addition, simulation-based education was associated with improvements in the reporting of adverse events and medication-related incidents [40,42]. Other 3 studies also explored the development of systems thinking and incident reporting competencies through simulation scenarios focused on adverse event reporting or clinical error disclosure [33,35,43]. These activities encouraged students to recognize systemic factors contributing to patient safety incidents and to adopt a nonpunitive perspective toward error management.

This review also highlights the diversity of simulation modalities used to address patient safety competencies. SPs were commonly used to train communication with patients [36], reporting incidents such as falls or medication errors [35,37], pressure ulcer prevention [39], teamwork and interprofessional communication [49,51], and medication administration [38,42]. High-fidelity simulation using mannequins was the most frequently used modality [32,34,39-41,43,45,47,48]. VR simulations were also used, particularly in scenarios focused on communication and teamwork [35,46,49].

Although high-fidelity simulation was widely used, lower-technology simulation approaches also demonstrated positive learning outcomes. Role-playing, tabletop simulations, and screen-based virtual simulations improved competencies related to communication, systems thinking, and incident reporting [33,38,50]. These findings suggest that simulation-based education can be implemented across a variety of educational settings, including institutions with limited technological resources. In addition to simulation modality, the instructional design of the intervention influenced outcomes. One study reported greater improvements when simulation was integrated with complementary educational strategies such as lectures, structured feedback, or online modules [43].

Comparison With Previous Literature

The findings of this review are consistent with previous literature highlighting the educational value of simulation in health professions education [5252]. Improvements in communication and teamwork competencies observed in the included studies align with recent meta-analyses emphasizing the importance of interprofessional education for improving role understanding and collaborative practice among health care students [53,54]. Improvements in these competencies are particularly relevant to patient safety, as failures in communication and teamwork are frequently associated with preventable adverse events in clinical practice. Interprofessional simulation experiences have been shown to strengthen role clarity and collaborative practice, thereby promoting safety-oriented behaviors among future health professionals [54].

Similarly, the improvements observed in medication safety practices are consistent with previous reviews suggesting that simulation-based education can be an effective method for improving patient safety competencies [24]. Evidence from systematic reviews also indicates that the use of SPs may enhance communication skills, learning outcomes, and problem-solving abilities in health professions education [23]. Previous reviews have also reported improvements in knowledge, confidence, and clinical skills following simulation-based learning [21,22], although many of these studies did not specifically focus on patient safety outcomes. Compared with earlier literature, the present review provides a more focused synthesis of evidence regarding the use of simulation-based education to address patient safety competencies in undergraduate nursing students.

The findings of this review also suggest that the use of different simulation methods and varying levels of fidelity, as observed across the included studies, can be similarly effective for developing competencies related to patient safety. These results are consistent with previous literature, indicating that the effectiveness of simulation-based education does not depend solely on the level of technological fidelity. Studies comparing high-fidelity simulation with alternative teaching strategies, such as written case studies, have not demonstrated clear advantages of high-fidelity simulation alone for improving critical thinking skills in nursing students [55].

Sustainability of Training Effects

Despite the positive outcomes reported in most studies, the long-term sustainability of simulation-based training effects remains unclear. Only 2 studies included follow-up assessments after the intervention, with relatively short follow-up periods of 1 week and 2 months [46,49]. Consequently, it is difficult to determine whether the improvements observed are maintained over time or translate into sustained behavioral changes in clinical practice. This limitation is particularly relevant because previous research on medication safety suggests that safety-related competencies may decline if they are not reinforced through continued practice and training [56].

Practical Implications for Nursing Education

The findings of this systematic review have several important practical implications for undergraduate nursing education. Overall, the evidence indicates that simulation-based education is an effective strategy for developing key patient safety competencies, particularly in communication, teamwork, medication safety, and error recognition [32-47].

The results support the systematic integration of simulation-based learning into nursing curricula, rather than its use as an isolated or supplementary teaching activity. Simulation-based interventions embedded within educational programs improved students' patient safety competencies [40,42,43,45,46]. Simulation scenarios focused on real-world patient safety challenges enable students to apply theoretical knowledge in a safe and controlled environment [39,41,44].

The impact of structured communication tools, such as SBAR, ISBAR (Identification, Situation, Background, Assessment, Recommendation), and SEGUE, suggests that these frameworks should be explicitly incorporated into simulation-based training [32,34,36,37,47]. The use of these tools during simulation may reduce communication-related errors and enhance patient safety.

In terms of the characteristics of the simulation, the included studies used various methods, including manikin simulation, SPs, virtual simulation, role-playing, and tabletop simulation. The level of fidelity within these modalities varied between low, medium, and high, depending on the technological complexity and degree of clinical realism described by the authors. While experiences with a higher level of technological fidelity were common, several studies demonstrated that modalities with lower technological requirements, such as role-playing or tabletop simulation [33,38,50], as well as basic virtual environments [44-46,49], could also be effective in improving patient safety knowledge and skills. These findings suggest that meaningful educational outcomes can be achieved with modalities that have lower technological requirements, which is particularly relevant for institutions with limited resources.

Current Gaps in the Literature

Even with mounting evidence backing simulation-based training in nursing, this review identified several important gaps in existing literature. One of the most significant limitations is the lack of long-term follow-up. Only 2 of the studies included assessed outcomes beyond the immediate postintervention period, with follow-up periods of 1 week and 2 months, respectively [46,49].

Another gap relates to study design and methodological rigor. Although RCTs were included, 9 of studies used quasi-experimental designs with convenience sampling and relatively small sample sizes [24,25,29-31,33-36]. In addition, blinding of participants and assessors was rarely reported. Also, studies used a wide range of instruments to assess patient safety competencies, including self-developed questionnaires and modified scales [25,27,29,33,35].

Geographically, most studies were conducted in high-income countries [22-42], with limited representation from low- and middle-income settings, indicating a lack of global diversity in the evidence base.

Recommendations for Future Research

Future research should address the limitations identified in this review. Longitudinal studies are needed to assess retention and maintenance of competencies. The use of standardized tools and methodologically sound, multicenter clinical trials would improve external validity and avoid bias. On the other hand, studies comparing the efficiency and cost-effectiveness of different simulation modalities would help guide curricula and resource allocation. It would be necessary to include other educational contexts in low- and middle-income countries in order to apply the results and guide nursing training plans. The limited reporting of facilitator preparation across studies highlights the need for future research to examine the role of educator training in simulation-based patient safety education.

Limitations

It is important to consider the limitations of this study when interpreting the results. First, there is a considerable degree of heterogeneity between the studies, not only in terms of the type of intervention and duration, but also in terms of the training of the participants, experience, and origin. Additionally, the variability of measurement instruments, convenience samples, and the use of self-reported data may introduce bias. Furthermore, the restriction of the search to studies published in English, Spanish, and Portuguese may have resulted in the exclusion of some relevant studies. The criteria used to establish the cutoff point in the methodological quality assessment may have influenced the final selection of evidence included.

The search strategy was limited to the terms "patient safety" and "safety," which may have led to the exclusion of relevant studies addressing patient safety outcomes. Although additional manual screening of references was performed to identify potentially relevant studies, this restriction may have reduced the sensitivity of the search. Although a systematic approach to study selection ensures the quality of the evidence, it may result in the omission of relevant research that, although less rigorous, could offer valuable insights.

Conclusions

Despite considerable discrepancies between individual studies, simulation is an important tool that empowers nursing students to identify, mitigate, or eliminate potential risks to patient safety. The use of simulation methodology facilitates the acquisition of essential competencies, including communication skills, teamwork, medication administration, and error detection and adverse effect recognition. These skills are crucial for ensuring patient safety upon entering the professional workforce. The use of high-fidelity simulation enables the recreation of clinical scenarios, facilitating the integration of theoretical and practical training, and thus the development of skills and a more comprehensive integration of knowledge.

Simulation-based education improves nursing students' competence in key safety domains (communication, teamwork, medication safety, and error recognition), thus contributing to improved patient safety outcomes.

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Conflicts of Interest

None declared.

Multimedia Appendix 1
Characteristics of the studies.
[PDF File, 91 KB - nursing_v9i1e87898_app1.pdf]

Multimedia Appendix 2
Characteristics of the interventions.
[PDF File, 68 KB - nursing_v9i1e87898_app2.pdf]

Multimedia Appendix 3
Quality assessment 1.
[PDF File, 36 KB - nursing_v9i1e87898_app3.pdf]

Multimedia Appendix 4
Quality assessment 2.
[PDF File, 56 KB - nursing_v9i1e87898_app4.pdf]

Multimedia Appendix 5
Quality assessment 3.
[PDF File, 60 KB - nursing_v9i1e87898_app5.pdf]

Checklist 1

PRISMA checklist.
[PDF File, 82 KB - nursing_v9i1e87898_app6.pdf]

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Abbreviations

HFS: high-fidelity simulator
ISBAR: Identification, Situation, Background, Assessment, Recommendation
JBI: Joanna Briggs Institute
MeSH: Medical Subject Headings
PIO: Patient, Intervention, Outcome
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT: randomized controlled trial
SBAR: Situation, Background, Assessment, Recommendation
SEGUE: Set the stage, Elicit information, Give information, Understand the patient's perspective, End the encounter
SP: standardized patient
VR: virtual reality
WHO: World Health Organization

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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].

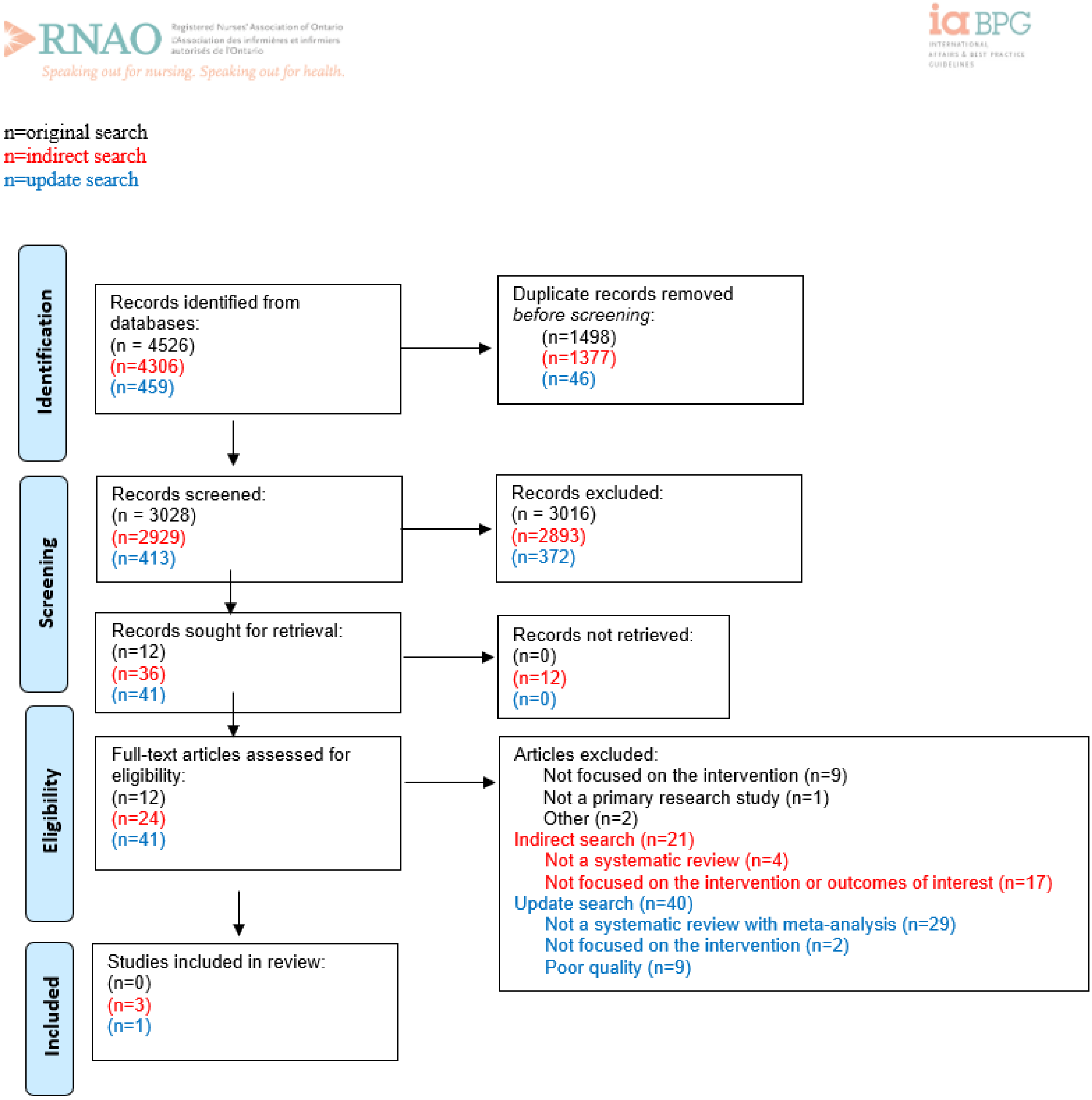

Figure 2. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for recommendation question 2: “Should education about relational care and interpersonal communication skills be recommended or not for nurses practicing in virtual care settings and in-person digital health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

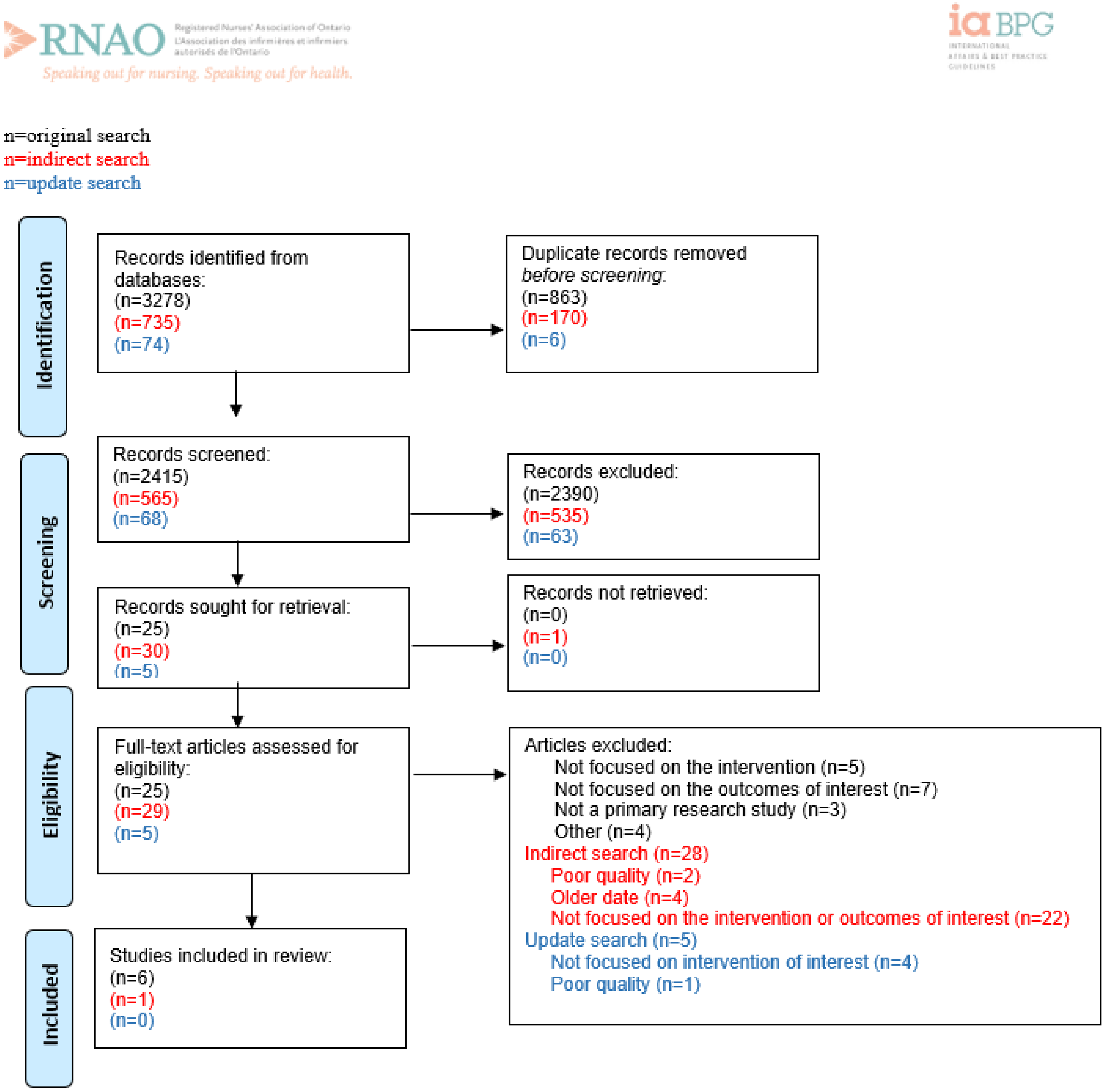

Figure 3. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for recommendation question 3: "Should the implementation of interdisciplinary peer champion models in health service organizations be recommended or not to facilitate education for health providers on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

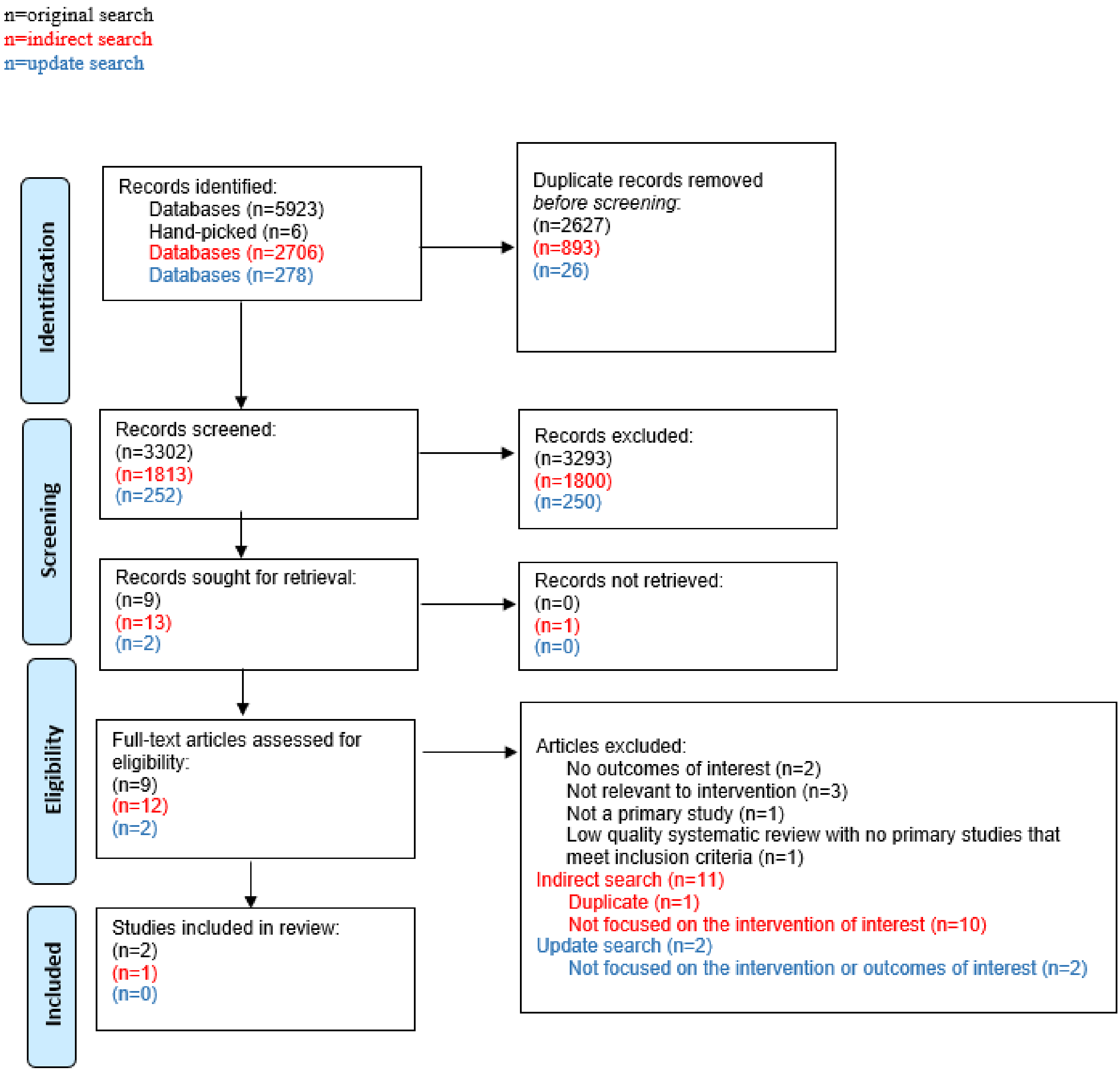

Figure 4. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for recommendation question 4: “Should the use of predictive analytics software or systems (eg, command centers and risk assessment software tools) for nurses providing care in all practice settings be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

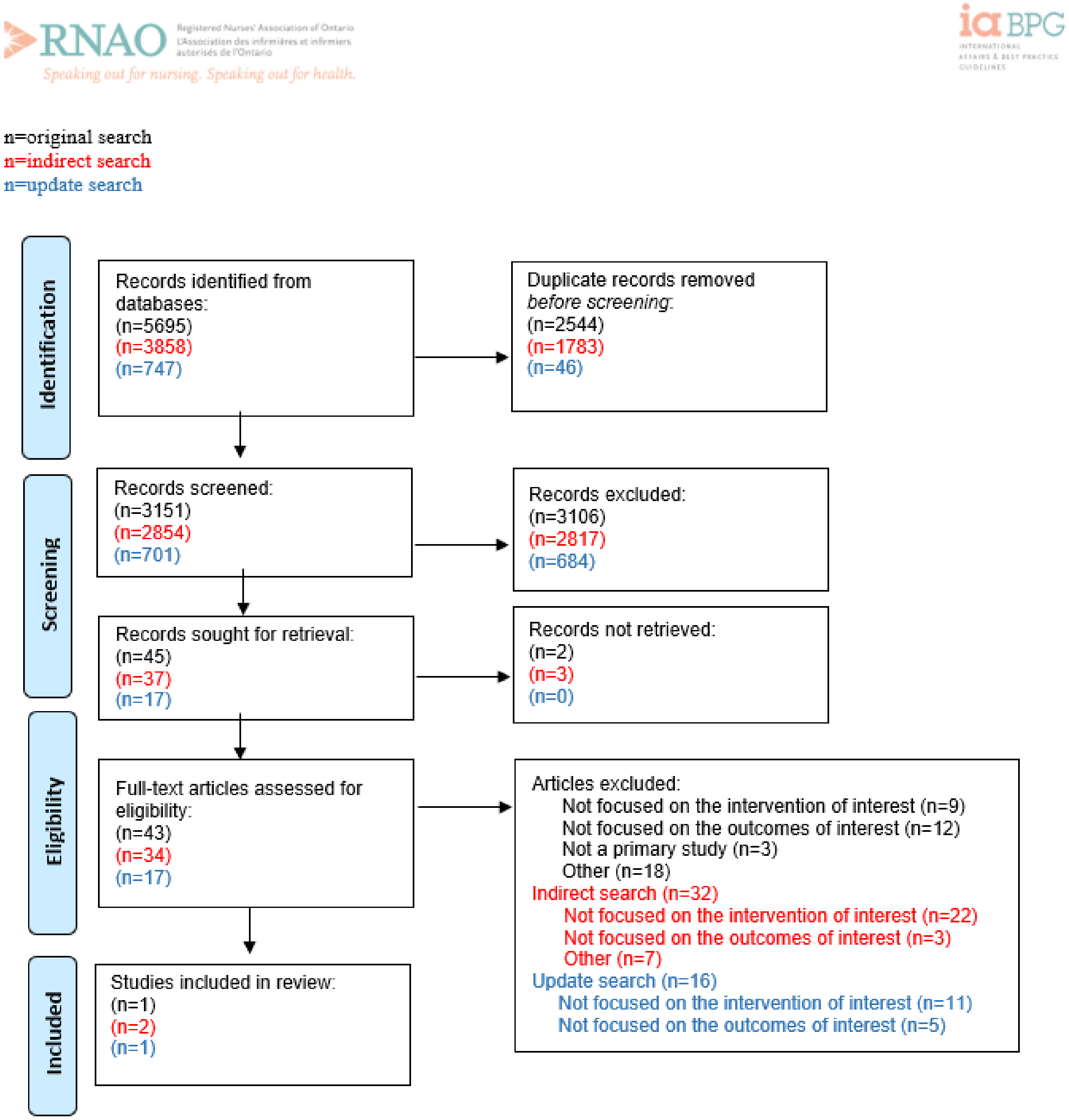

Figure 5. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for recommendation question 5: “Should a distributive model (vs no distributive model or any other type of change management model) be recommended to integrate digital health competencies into the professional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

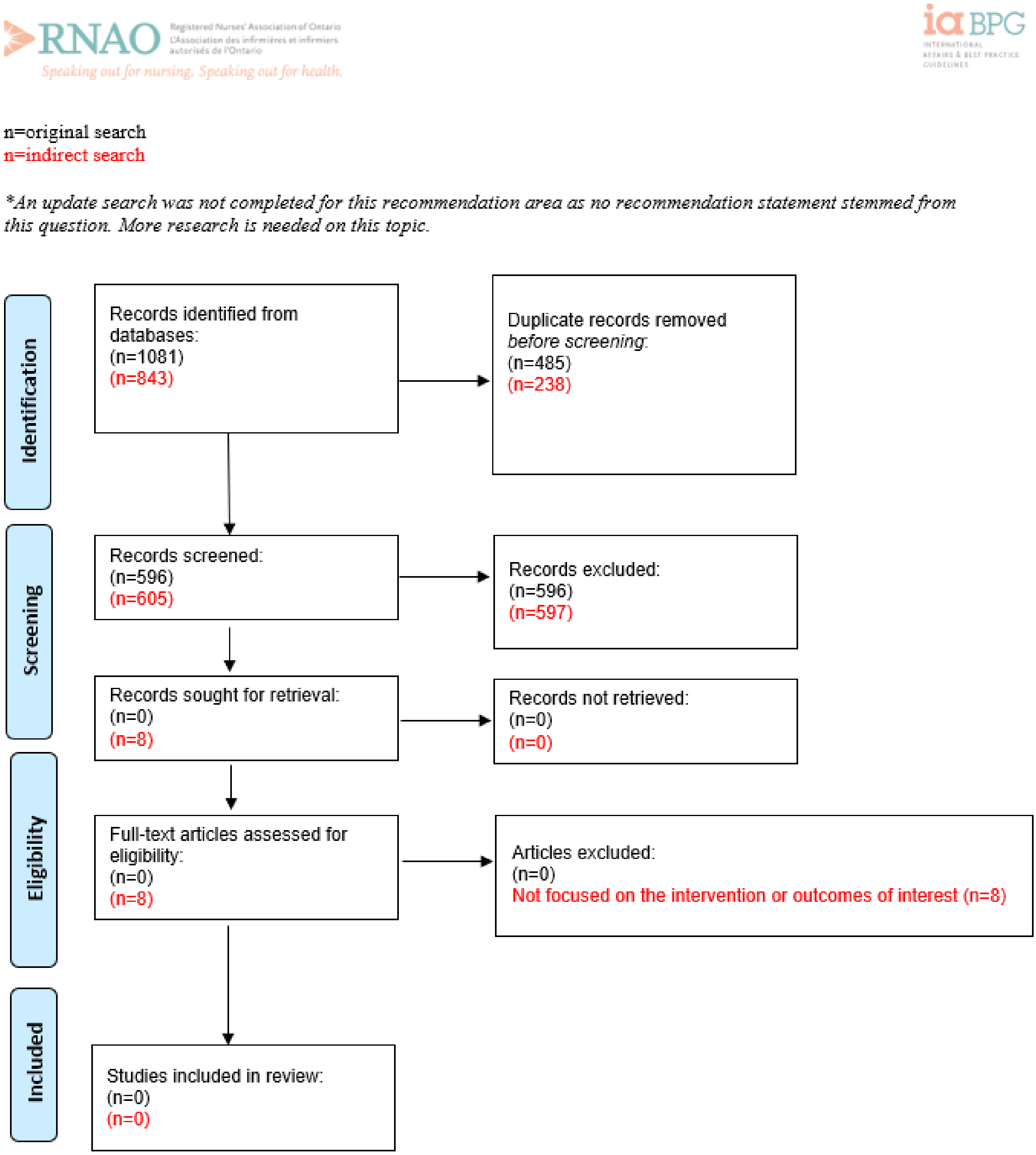

Table . Summary of recommendations in the best practice guideline.

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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Nurses' Experiences Using AI in Clinical Practice: Systematic Review

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Abstract

Background: Artificial intelligence (AI) tools are increasingly used in clinical settings, yet most syntheses focus on nurses' attitudes or readiness rather than experiences after direct use in practice.

Objective: This study aimed to synthesize registered nurses' experiences of using AI in clinical practice and to identify perceived benefits, barriers, and implementation implications.

Methods: We conducted a systematic literature review of empirical studies reporting nurses' experiences of AI use in clinical settings. Searches were performed in CINAHL, Embase, MEDLINE, PsycINFO, and PubMed (last search: September 13, 2023). Moreover, 2 reviewers (AJSS and QZ) independently screened titles, abstracts, and full texts and appraised included studies using the Mixed Methods Appraisal Tool. We used thematic synthesis with a primarily deductive framework based on the Technology Acceptance Model 2, with the addition of facilitating conditions from the unified theory of acceptance and use of technology.

Results: In total, 20 studies met the inclusion criteria. Perceived usefulness and facilitating conditions were most frequently reported; nurses described AI as supporting decision-making, workflow efficiency, and confidence when implementation included adequate training, interoperability, and technical infrastructure. Ease of use was closely tied to interface design and training. Job relevance and output quality were rated more positively when nurses described AI as aligning with nursing tasks and as producing interpretable, reliable outputs. Common barriers included usability issues, limited integration into workflows and electronic systems, privacy and trust concerns, and inconsistent or poorly contextualized outputs. Across studies, nurses often described adoption as conditional on organizational readiness and meaningful involvement of nurses in design and implementation.

Conclusions: Nurses' accounts suggest that AI may augment clinical work, but the perceived benefits reported in the included literature were contingent on workflow alignment, usable interfaces, training, and supportive infrastructure. These findings suggest potential value in involving nurses in the co-design and iterative refinement of AI tools, grounded in the consistent evidence that facilitating conditions, such as training, interoperability, and organizational readiness, are the primary determinants of whether AI is experienced positively. Prospective evaluation using nursing-relevant outcomes, such as usability, workflow integration, and trust, is needed to move beyond post hoc experiential accounts and establish what implementation conditions reliably produce benefit.

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KEYWORDS

artificial intelligence; nursing; clinical practice; user experience; decision support systems; technology acceptance model; implementation; systematic review; PRISMA

Introduction

The integration of artificial intelligence (AI) into health care has transformed clinical practice, significantly impacting the roles and responsibilities of registered nurses (RNs). As the largest group of health professionals, RNs are at the forefront of these technological shifts and have historically been an afterthought in technology development [1]. AI holds significant potential to enhance nursing practice in administration, clinical practice, policy, and research, but it remains an area of ongoing exploration [2]. For example, natural language processing systems are increasingly used to assist with clinical documentation, decision support algorithms enhance diagnostic reasoning, and in nursing administration, AI has been applied to workload prediction and staff scheduling, while in research, it supports pattern recognition in large datasets [3].

AI's emergence in health care has altered nursing roles, workflows, and the nurse-patient relationship [4,5]. Technologies like predictive analytics, virtual health care assistants, and robotics are influencing nursing practice in substantive ways: (1) predictive analytics supports early identification of deteriorating patients, enabling more proactive clinical intervention; (2) virtual health care assistants facilitate patient education and remote monitoring; and (3) robotic technologies are increasingly used for medication dispensing and patient mobility support, reshaping how physical tasks are distributed [6-8]. While these AI-driven technologies offer improvements in health care delivery, they also challenge the maintenance of person-centered, compassionate care [2]. AI already contributes significantly to decision-making support and skill augmentation within clinical practice [9]. Nurses must proactively ensure AI technologies align with nursing's core values, maintaining ethical and compassionate care [10].

The integration of AI into nursing practice is accelerating, and existing systematic reviews predominantly explore general perceptions and theoretical readiness or educational readiness among nurses [11,12]. These studies offer valuable insight into anticipated benefits and challenges, yet conclusions are derived from nurses who have not directly interacted with AI in clinical settings. For example, 1 recent review synthesized qualitative studies focused on nurses' perceptions without requiring previous AI use [12]. Several recent reviews have examined AI specifically within nursing education contexts; one explored AI use in nursing training [13], while another synthesized empirical evidence on AI implementation in hospital settings using a strengths, weaknesses, opportunities, and threats framework [14], and another mapped AI applications, such as generative tools and virtual patient simulators, in university-level nursing programs [15]. All 3 address AI as a pedagogical resource for nursing students and trainees, rather than clinical practice. There remains a lack of synthesis of studies capturing nurses' attitudes after engaging directly with AI tools.

Several theoretical frameworks can be used to understand individuals' acceptance and use of technology, such as AI. The Technology Acceptance Model 2 (TAM2) is among the most extensively validated, proposing that perceived usefulness, perceived ease of use, and social and cognitive influences shape technology adoption [16]. TAM2 was developed in general organizational technology contexts, and we acknowledge that it may underweight dimensions that are particularly salient in nursing, including professional judgment, the nurse-patient relationship, ethical responsibility, accountability for patient outcomes, and the emotional and moral dimensions of clinical work. We selected TAM2 nonetheless because our review question concerned nurses' acceptance-relevant experiences after direct AI use, where TAM2's validated constructs provide an established and transparent analytic vocabulary. To address TAM2's primary acknowledged limitation, its limited treatment of organizational and infrastructural context, we incorporated the Facilitating Conditions construct from the unified theory of acceptance and use of technology (UTAUT) [17], which captures the technical, training, and resource conditions that nurses' accounts suggested were central to their experiences. We did not adopt the full UTAUT to avoid construct duplication with TAM2 (the implications of this deductive choice for what the synthesis could and could not surface are discussed in the Limitations section). This review explores the experiences of RNs navigating modern health care complexities, with a focus on AI's impact on nursing roles, the challenges in adapting to AI technologies, and how these changes are perceived to influence patient care using TAM2 and UTAUT's Facilitating Conditions as the analytical framework.

The research question guiding this systematic review is "What are the experiences of nurses using AI in their clinical work?" The objectives are to (1) develop a better understanding of how nurses interact with AI in clinical practice, and (2) provide insights into nurses' perceptions of AI's impact on efficiency, satisfaction, and nurse-patient relationships.

Methods

Overview

The primary objective of this systematic review is to understand the experiences of nurses using AI in clinical practice.

A systematic review methodology was selected because the research question required a comprehensive, transparent, and reproducible synthesis of empirical evidence from multiple studies. This approach is appropriate for identifying and integrating findings across a body of literature to address a focused question about a specific population's experiences, and is consistent with established guidance for evidence synthesis in health professions research [18].

Protocol and Registration

The study protocol was registered with PROSPERO (CRD42022308051) [19]. The manuscript title has been refined from the registered title for clarity; the review question, eligibility criteria, and methods are consistent with the registered protocol.

Ethical Considerations

Ethics approval was not required because this study synthesizes data from previously published literature and did not involve collection of identifiable participant data.

Eligibility Criteria

Eligibility was determined using predefined inclusion and exclusion criteria (Textbox 1).

Textbox 1. Eligibility criteria.

Inclusion criteria

- Empirical research published in English: to ensure consistency and enable thorough analysis, only studies published in English were included.
- Peer-reviewed journal articles: studies published in peer-reviewed journals were prioritized for their methodological rigor and reliability.
- Studies where registered nurses describe their experiences of using artificial intelligence (AI) in clinical practice: the review focused on direct, real-world experiences of registered nurses with AI technologies. For inclusion, studies were required to report on nurses' experiences or perceptions arising from actual use of or interaction with an AI tool in a clinical setting. Studies reporting only on anticipated, hypothetical, or theoretical attitudes toward AI, without confirmed direct use, were excluded.
- Non–peer-reviewed sources (such as poster presentations and conference abstracts): these would have been considered only if they contained unique empirical data not yet published in a peer-reviewed format and demonstrated methodological rigor as assessed using the Mixed Methods Appraisal Tool (MMAT) criteria applied to all included studies.

Exclusion criteria

- Studies published in languages other than English: non-English language publications were excluded due to language barriers affecting interpretation.
- Studies reporting the experiences of nurses using technology not underpinned by AI: studies reporting on technologies that were not underpinned by AI were excluded.
- Studies reporting the experiences of nurses working in non-clinical settings: research focusing on administrative, academic, or educational settings outside of clinical practice were excluded.
- Studies related to health care professionals (eg, midwives and doctors): studies were excluded unless they specifically reported data related to registered nurses.
- Duplicate reports of the same study: the most comprehensive versions of duplicate studies were included.

Information Sources

A comprehensive literature search was conducted on September 13, 2023 across 5 electronic databases—PubMed, Embase, MEDLINE, CINAHL, and PsycInfo.

Search Strategy

A search strategy was developed and refined through repeated testing and adjustment, using both keywords and controlled vocabulary tailored to each database. Concept blocks, illustrated in Textbox 2, provided the structure for the search, with keywords and controlled vocabulary terms merged using Boolean logic (AND/OR) to ensure comprehensiveness. No date restrictions were applied, allowing for the inclusion of all eligible studies up to the date of the search. Searches were not restricted by language, but inclusion was limited to studies published in English. Reference lists of identified articles were also reviewed, but no additional studies met the inclusion criteria. Full search strategies are provided in Multimedia Appendix 1.

Textbox 2. Search strategy concept blocks.

Block 1: Nursing

- Keywords: Nurse* (Title or Abstract), "Nursing staff" (Title or Abstract), "Nursing professional*" (Title or Abstract), "Registered nurse*" (Title or Abstract)
- CINAHL Headings: Nurses, Nursing Staff

Block 2: Artificial intelligence

- Keywords: "Artificial Intelligence" (Title or Abstract), "Machine Learning" (Title or Abstract), "Neural Network*" (Title or Abstract), "Deep Learning" (Title or Abstract), "Computer Vision" (Title or Abstract), "Natural Language Processing" (Title or Abstract)
- CINAHL Headings: Artificial Intelligence, Machine Learning

Block 3: Experiences or perceptions

- Keywords: Experience* (Title or Abstract), Perception* (Title or Abstract), View* (Title or Abstract), Attitude* (Title or Abstract), Feedback (Title or Abstract), Opinion* (Title or Abstract)
- CINAHL Headings: Attitude, Perception

Study Selection

The review was conducted following the Joanna Briggs Institute (JBI) methodology for systematic reviews, using the "JBI Manual for Evidence Synthesis" [20] as the guiding framework. The reporting of this review adheres to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines [21]. Study management and screening were managed with Covidence software (Veritas Health Innovation Ltd). Furthermore, 2 reviewers (AJSS and QZ) independently screened titles, abstracts, and full texts, resolving discrepancies through discussion and consensus. In cases where multiple reports of the same study were identified, the most comprehensive version was prioritized, and duplicates were merged accordingly. The screening and selection process are presented in the PRISMA flow diagram in the Results section. The completed PRISMA 2020 checklist is also provided in Checklist 1.

Data Extraction

Data extraction followed the JBI mixed methods data extraction form following a convergent integrated approach [20]. Where studies included multidisciplinary samples, nurse-specific findings were extracted separately where the primary data permitted. In cases where profession-specific disaggregation was not possible, this was noted explicitly in the data extraction table (Multimedia Appendix 2).

Quality Appraisal

Study quality was assessed using the Mixed Methods Appraisal Tool (MMAT) [22] to accommodate the diversity of included study designs. This aligned with the convergent integrated approach used in this review [20]. Additionally, 2 reviewers (AJSS and QZ) independently assessed study quality, and any discrepancies were resolved through discussion to reach consensus. To capture the complexity of interpretive and critical understandings of AI use in nursing, an inclusive approach to study selection was maintained. As noted by Hannes and Lockwood [23], qualitative evidence can simultaneously illuminate both broad patterns and context-specific detail, and excluding studies entirely based on quality grounds risks narrowing this breadth. Including all studies regardless of MMAT scores allowed for a representative synthesis across diverse clinical contexts. Quality appraisal results were therefore used to inform the interpretation of findings, rather than as a basis for exclusion. Where lower-quality studies contributed to a construct, this is noted within the relevant Results section.

Synthesis Approach

Thematic analysis was conducted using a predefined deductive framework based on TAM2, supplemented by the single UTAUT construct of Facilitating Conditions. All included studies were read in full, and relevant text segments, including direct participant quotations, authors' qualitative summaries, and quantitative findings, were coded line-by-line into the framework constructs. Coding was undertaken by the first author (AJSS), with regular review and discussion of coding decisions with 2 supervising coauthors (BCB and DD) throughout the analysis period. These supervisory discussions served as a calibration mechanism for the application of the codebook; ambiguous extracts and decisions about construct boundaries were brought to these meetings, discussed against operational definitions, and resolved by consensus before being applied across the dataset. The codebook (Table 1) was iteratively refined through these discussions to clarify operational boundaries; construct categories themselves remained fixed throughout. Formal interrater agreement was not calculated, as only a single author (AJSS) coded the data; this is acknowledged as a limitation. Quantitative findings relevant to TAM2 constructs, such as survey results, were summarized and integrated narratively with the qualitative data under relevant headings. Where frequency of reporting is described, this refers to the number of included studies in which relevant data were coded to a given construct. Frequency counts indicate how commonly a construct appeared across the included studies and should not be interpreted as a measure of the depth or strength of any individual theme.

Table . Codebook adapted from TAM2[a]+UTAUT[b].

Construct	Definition (as applied in this review)
Perceived usefulness	• Excerpts where the AI[c] is seen as having an impact on job performance. • Statements indicating that the AI impacts the effectiveness of task completion or enables more task opportunities. • Examples of how AI is perceived to enhance patient care or nursing outcomes.
Perceived ease of use	• Descriptions of how the AI is straightforward and easy to use or interact with. • Quotes about the learning curves in relation to using AI in practice. • Facilitators or challenges related to technical aspects of interacting with the AI.
Subjective norms	• Comments about how the organization, management, or colleagues influence attitudes toward AI. • Encouragement or pressure from peers to use or not use AI. • The role of policy supporting or discouraging AI use.
Intention to use	• Nurses' statements related to plans or indications to use AI in the future. • Motivating or deterring factors relating to the intention to use AI in practice. • Conditional intentions (eg, willingness to use AI if specific supports or changes are implemented).
Usage behavior	• Discussions of actual use or engagement with AI in practice. • Context, duration, and frequency of AI use in practice. • Examples of tasks or procedures where AI is being implemented.
Facilitating conditions[d]	• Technical or organizational infrastructure supporting the use of AI. • Availability or lack of resources like support staff, training, and technical expertise. • Compatibility of the AI with existing systems and workflows.
Job relevance	• To what degree do nurses think AI is relevant to their job. • Specific responsibilities or tasks that are impacted by AI. • Changes in responsibilities or job roles as a result of AI integration.
Output quality	• Perceptions of quality of the results provided by AI systems. • AI's impact on the overall quality, timeliness, and accuracy of nursing care. • Consistency and reliability of AI outputs.
Result demonstrability	• Visibility and tangibility of results of using AI in nursing practice. • Examples of observable and clearly articulated benefits or drawbacks of AI use. • Stories demonstrating the impact of AI use on patient outcomes or nursing practice.

[a]TAM2: Technology Acceptance Model 2.

[b]UTAUT: unified theory of acceptance and use of technology.

[c]AI: artificial intelligence.

[d]Added from UTAUT.

Results

Study Selection

The PRISMA flow diagram (Figure 1) is presented to illustrate the screening and selection process. The initial searches yielded 952 records. After 424 duplicate or merged records were removed in Covidence, 528 articles were screened by title and abstract. Of these, 60 reports were sought for retrieval and assessed for eligibility, resulting in the exclusion of 40 reports for reasons such as the lack of AI experience (n=15), lack of experiential data (n=11), a focus on non-AI technology (n=6), and other contextual or methodological reasons as detailed in Multimedia Appendix 3. Ultimately, 20 studies [24-43] met the inclusion criteria and were included in the final synthesis.

Of the 20 included studies, 13 were appraised as high quality [31-43], 5 as medium [24-28], and 2 as low [29,30] (Multimedia Appendix 4). The 5 medium-rated studies were predominantly quantitative surveys with limitations relating to sampling representativeness and nonresponse bias [24-28]. The 2 low-rated studies had insufficient methodological reporting to fully assess rigor [29,30]. Job Relevance and Output Quality were supported exclusively or predominantly by high-rated studies. Perceived Usefulness was well-represented across quality levels but anchored by a majority of high-rated studies. Facilitating Conditions drew contributions from the broadest quality range, including both low-rated studies; findings for this construct are therefore interpreted with appropriate caution below.

Of the 20 included studies, the proportion of nurse participants varied substantially. Of the total, 9 studies reported that nurses comprised the majority of participants [24,25,29,31-36]. In the remaining studies, nurses participated alongside other professional groups, and in some cases were a small minority. While there was no requirement for studies to have a majority of nurse participants, this variability affects the extent to which findings directly reflect nursing perspectives. Where possible, data specific to nurses was extracted for synthesis. However, in several studies (eg, [26,34,37]) nursing data were supplementary or aggregated with other professions. A full summary of participant demographics and professional backgrounds is presented in Table 2.

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram of study selection.

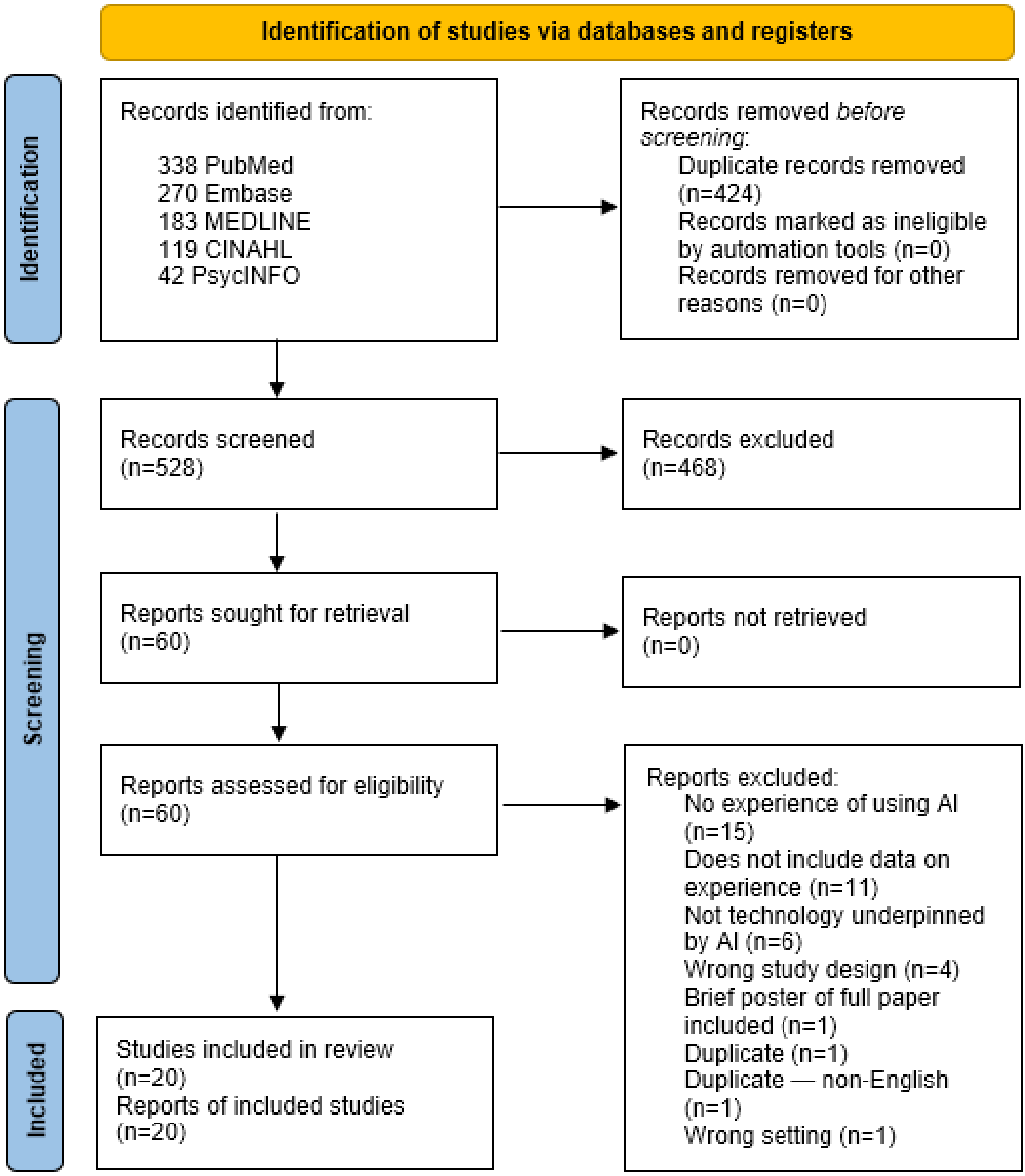


Table . Characteristics of included studies.

Study (year)	Country and setting	Study design	Participants	AI[a] and technology focus
Alanzi (2023) [31]	Saudi Arabia, health care sector (government hospitals)	Qualitative, focus group interviews	Total: 54 participants • Physicians: 11 • Nurses: 24 • Dieticians: 8 • Pharmacists: 6 • Physiotherapists: 5 • Sex: 33 females, 21 males • Majority have more than 6 years of experience • Professions: physicians, nurses, dieticians, pharmacists, and physiotherapists	• ChatGPT
Belmin et al (2022) [27]	France, multicenter trial with community-dwelling adults receiving home care	Quantitative, uncontrolled multicenter pragmatic trial	• 206 community-dwelling older adults • Mean age: 85 (SD 8) y • Gender: 78% women • Age eligibility: ≥75 years • Health status: community-dwelling older adults with mild or moderate dependency (GIR 3 or 4) • Receiving care from 109 home aides	• eHealth system with a machine learning algorithm for predicting ED[b] visits • Decision support for predicting and reducing emergency department visits among older adults, patient monitoring, and optimizing care pathways
Boggiss et al (2023) [38]	Aotearoa, New Zealand, pediatric diabetes clinics and online communities	Qualitative, online focus groups, and one-on-one interviews	Total: 30 • Adolescents: 19 (adolescents aged 12-16 y with type 1 diabetes) • 58% female, 68% Aotearoa New Zealand European, 11% Māori • Living in Aotearoa, New Zealand • Diagnosis of type 1 diabetes for more than 6 months • No serious developmental or psychiatric disorders • Diabetes health care professionals: 11 (health care professionals from various disciplines, such as diabetes nurse specialists, health psychologists, dieticians, and endocrinologists)	COMPASS Chatbot (Expert System) • Psychological support and self-management assistance for adolescents with type 1 diabetes
Castagno and Khalifa (2020) [37]	London, United Kingdom, Royal Free London NHS Foundation Trust hospitals	Qualitative, web-based survey	Total: 98 • Medical doctor: 34 • Nurse: 23 • Manager: 11 • Therapist: 7 • Other: 23 • No demographic information was collected	General AI applications in medicine.

Study (year)	Country and setting	Study design	Participants	AI[a] and technology focus
Catalina et al (2023) [28]	Central Catalonia, Spain, primary care settings	Quantitative, observational cross-sectional study using a validated survey	Total: 301 • Mean age: 46.0 (SD 11.0) year • Sex: female (81.1%), male (18.9%) • Occupation: Nursing (47.8%), Medicine (48.5%), Others (3.65%) • Years of experience: More than 10 years (62.5%)	AI as a health care tool, with a specific focus on its impact on PC radiology.
Gardner and Lundsgaarde (1994) [24]	United States, LDS Hospital	Quantitative, observational study using a questionnaire survey	Total: 1320 • Physicians: 360 (aged 27-82 y, mean age 45.5 y) • Nurses: 960 (aged 20 to 67 y, mean age 33.57 y) • Nurses average professional experience of 9.52 years, with 6.96 years at LDS Hospital	Health Evaluation through Logical Processing (HELP). Expert system • Decision support, patient monitoring, and documentation assistance.
Ginestra et al (2019) [29]	Philadelphia, United States, 782-bed academic hospital	Mixed methods, prospective observational study. Surveys were deployed to collect qualitative data on clinicians' perceptions, and quantitative analysis was performed on the survey results	Total: 287 • Nurses: 180 • Providers: 107	Early Warning Score tool (EWS 2.0). Machine Learning. Decision Support and patient monitoring for sepsis.
Gonçalves et al (2020) [32]	Brazil	Experience report, direct observation, and semistructured interviews	Not clearly mentioned	Robot Laura. Machine learning. Decision support for identification of sepsis.

Study (year)	Country and setting	Study design	Participants	AI[a] and technology focus
Haugsten et al (2023) [39]	Denmark	Qualitative, focus group interviews, and thematic analysis	Total: 14 • Doctor: 8 • Nurse: 6 • Regularly work in a pigmented lesions clinic	ATBM Master (FotoFinder), deep learning, assessment and diagnosis of skin lesions suspicious of melanoma through total body dermoscopy and estimation of malignancy probability.
Helman et al (2022) [33]	Pittsburgh, United States	Qualitative, focus group interviews	Total: 23 • Nurses: 14 • Nurse Practitioners: 4 • Physicians: 5 • Median age: approximately 35 years • Sex: 60% female • Median clinical experience: 8 years	Predictive algorithm for cardiorespiratory insufficiency (CRI) as part of an intelligent decision support system, machine learning, decision support, and patient monitoring.
Im and Chee (2006) [25]	United States	Mixed methods, prospective observational study, and questionnaires	Total: 122 nurses • Mean age: 40.26 years • Predominantly female (93%) • Majority White (75%) • 40% have graduate degrees • 49% Protestant • 59% married	Decision Support Computer Program (DCSP) for cancer pain management. Expert system.
Jauk et al (2021) [34]	Austria	Mixed methods. Convergent parallel design combining questionnaire-based assessments and expert group meetings.	Total: 47 • Nurses: 37 • Physicians: 10 • Sex: male (14), female (33) • Age: median 29 (IQR 26 - 42) years	Predictive algorithm for delirium management decision support. Machine learning.
Jordan et al (2023) [35]	United States	Qualitative, single-site. Small group and individual semistructured interviews and comparative analysis	Total: 13 • ED triage nurses • 72.7% female, 27.3% male • Age ranges: 45.5% aged 25 - 34 years, 27.3% aged 35 - 44 years, 18.2% aged 45 - 54 years, 9.1% aged 55 - 64 years • Highest educational degree in nursing: 9.1% nursing diploma, 36.4% associate, 45.5% bachelor, 9.1% master’s • Employment status: 9.1% per diem, 27.3% part-time, 63.6% full-time • Years of nursing experience: mean 11.5 (SD 10.5, range 1 - 35) years	KATE, decision support for emergency nursing triage to improve patient acuity determination. Machine learning.
Koech et al (2022) [40]	Kenya	Qualitative, cross-sectional descriptive, interviews, and focus groups		TraCer Device, gestational age assessment. Computer vision.

Study (year)	Country and setting	Study design	Participants	AI[a] and technology focus
			Total: 70 • Focus group discussions: 52 • In-depth interviews: 18 • Health care workers: diverse group of professionals from antenatal care (ANC) clinic, maternity, outpatient, and radiology departments • Community members: pregnant women, partners, and parents • Sex: health care workers—7 male, 11 female; Community members—15 male partners, 37 female (pregnant women and mothers) • Age groups: health care workers—<35 years (n=7), 35 - 44 years (n=6), 45+ years (n=5); Community members—<35 years (n=30), 35 - 44 years (n=8), 45+ years (n=14)	
LeBaron and Wang (2023) [41]	United States	Mixed methods, surveys	Total: 40 • Clinicians: 5 • Nursing students: 19 • Medical students: 16	CommSense, real-time feedback to clinicians on communication performance metrics such as medical jargon, interruptions, and speech dominance to improve patient-clinician communication and health care delivery. Natural language processing.
Lintz (2023) [26]	Texas, United States, Rural medical center	Quantitative, cross-sectional questionnaire	Total: 48 • Returned questionnaires: 36 • Majority younger than 39 years old • 70% physicians, 20% registered nurses, 10% other kinds of providers • Male: 58%, female: 42%	Hand hygiene monitoring system. Machine learning.
Petitgand et al (2020) [30]	Quebec	Qualitative. Semistructured interviews, informal conversations, nonparticipant observations, with thematic content analysis	Total: 20 • DSS developers: 5 • AHC managers: 5 • Emergency physicians: 7 • Nurses: 3	Decision support for diagnostic decision-making in emergency care. Deep learning.
Rui et al (2023) [42]	Massachusetts, United States	Mixed methods. Usability study including observations, think-aloud		DynaMed and Micromedex with Watson (DynaMedex). Decision support for clinicians related to drug and disease management. Natural language processing and machine learning.

Study (year)	Country and setting	Study design	Participants	AI[a] and technology focus
			Total: 43 • Physicians: 21 • Pharmacists: 14 • Registered nurses: 2 • Nurse practitioners: 1 • Physician's assistants: 5 • Specialties: internal medicine, neurology, cardiology, oncology or hematology, infectious diseases, endocrinology • Average years of practice: 10 years	
Sandhu et al (2020) [36]	Duke University Hospital, United States	Qualitative. Semistructured interviews, modified grounded theory approach	Total: 15 • ED Physicians: 7 • RRT Nurses: 8	Sepsis Watch. Decision support for early sepsis detection and monitoring in emergency departments. Machine learning.
Schwartz et al (2022) [43]	Massachusetts, United States	Qualitative. Semistructured interviews with content analysis	Total: 17 • Prescribing providers: 9 • Nurses: 8	CONCERN, predictive clinical decision support for in-hospital deterioration.

[a]AI: artificial intelligence.

[b]ED: emergency department.

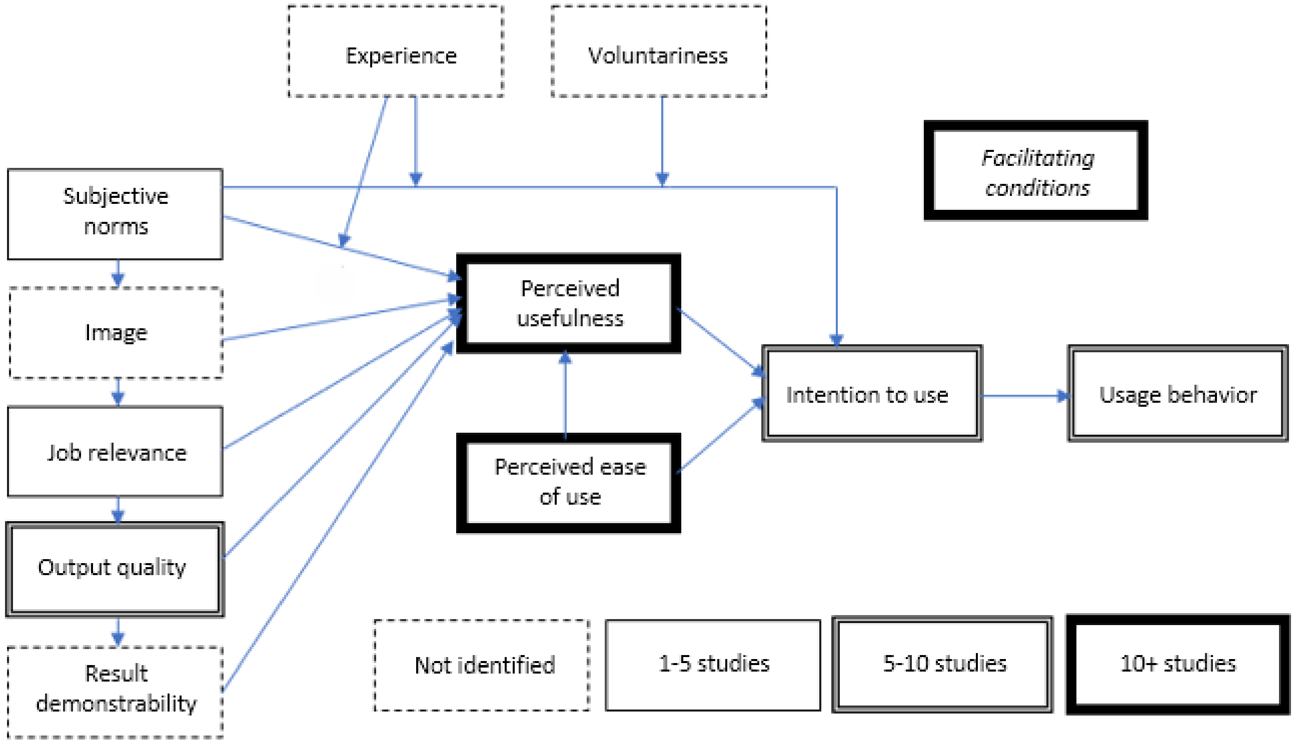
Quality Appraisal

Using the MMAT [22], adherence to quality criteria ranged from strong methodological coherence [31,33] to studies with notable limitations such as unclear sampling strategies [27], lack of representativeness [26], and insufficient reporting of nonresponse bias [24,25]. Common issues included limited discussion of divergences between qualitative and quantitative findings in mixed methods studies [29,34], and a reliance on single data sources [37]. Detailed MMAT findings for each study are presented in Table S1 in Multimedia Appendix 4.

Synthesis of Findings

Findings from the included studies, grouped by TAM2 constructs, are summarized below and presented in detail in Multimedia Appendix 2. Figure 2 illustrates a conceptual map of the TAM2 and UTAUT constructs weighted by frequency of them being identified in the included studies.

Figure 2. Conceptual map of constructs weighted by frequency.



Perceived Usefulness

A total of 17 studies reported nurses' perspectives of AI as enhancing the effectiveness and quality of their work [24-27,29,31,33-43]. Reported benefits included earlier detection of clinical deterioration, improved triage and decision-making [29,35,36], more structured and efficient documentation [24,43], and enhanced patient-clinician communication [41]. As 1 nurse explained,

> [ChatGPT can help me in learning new developments in the telenursing process, especially in relation to the standards of practices, treatment or monitoring procedures. This helps me to improve my skills and capabilities and be up-to-date with the developments in the telenursing sectors, and provide high quality care to the patients remotely.] [31]

In some cases, AI tools contributed to professional confidence and visibility [32,35], with nurses describing the technology as a "safety net" in relation to their decision-making [35]. Perceived usefulness was mixed where the tangible benefits to workflow were unclear or where implementation was limited [34,39]. Furthermore, 3 contributing studies [26,34,37] involved multidisciplinary samples from which nurse-specific data could not be disaggregated; these studies are highlighted in Multimedia Appendix 2, and the nurse-attributed findings above are therefore drawn predominantly from the remaining 14 studies.

Facilitating Conditions

In total, 16 studies reported on facilitating conditions [24-26,28-31,33,35-41,43]. Common themes included access to adequate training, system interoperability, hardware availability, data privacy, and sufficient time within workflows. Willingness to adopt AI was often expressed as being conditional on meeting these facilitating factors [26,28,40]. For example, 1 nurse noted that,

> *Training was yet another organizational matter… not all participants had taken part in these sessions.* [39]

Nurses also requested integrated feedback mechanisms, such as dashboards and trend data [33,41], which highlights the importance of embedding technical support and continuous learning into implementation strategies.

This construct drew contributions from the broadest quality range of any major theme, including both low-rated studies [29,30] and 4 medium-rated surveys. Petitgand et al [30] additionally only involved 3 nurse participants within a predominantly physician sample. While the consistency of facilitating conditions findings across a large number of high-quality studies lends the construct overall coherence, the specific findings from lower-quality studies should be treated as indicative rather than definitive, and the low-rated studies should be interpreted in the context of their methodological limitations as documented in Multimedia Appendix 4.

Perceived Ease of Use

A total of 11 studies addressed perceived ease of use [24-26,28,30,34,36,38,40,42,43]. Nurses valued clear, straightforward interfaces and outputs [36,42], with structured displays facilitating interpretation [24]. As 1 nurse commented,

> *The nurses commented that their computer-printed charts were readable and understandable.* [24]

Barriers included slow system responses, limited interoperability, and difficulty editing records [24,26], as well as challenges interpreting model outputs, with nurses questioning "what have you done to change our processes? What have you done to improve the medical history?" [30].

Several studies noted that ease of use was closely tied to training and resources [28,38,40], which suggests that structured exposure supports both usability and uptake. Moreover, 4 of the contributing studies were medium-rated quantitative surveys, and 1 was rated low [30]; meaning findings on ease of use from these studies are less methodologically robust than those drawn from the high-rated qualitative studies, which provide the primary evidential basis for this construct.

Intention to Use

In total, 9 studies described nurses' intentions to use AI tools [24,27,33,35,39-43]. Intentions were generally reported as positive, with participants expressing interest in continuing or expanding use of AI, particularly with tools that supported decision-making, communication, or workflow efficiency. However, this willingness to adopt was often conditional on receiving adequate training and support, reflecting the critical role of preparatory education in facilitating adoption. All 9 contributing studies reported nurse-specific findings on intention to use, providing a clear nurse-attributable evidence base for this construct; quality ratings of contributing studies were predominantly high (7 high and 2 medium).

Use Behavior

In total, 8 studies described nurses' actual AI system use [24,26,27,29,34-36,43]. Usage ranged from integration into usual practice [36] to limited uptake during pilot testing [34]. Where AI was used, nurses described making changes to patient management and blending system outputs with their own expertise and clinical judgment [27,29]. Lower usage was usually linked to technical limitations, time constraints, or incomplete integration with existing systems. Of the 8 contributing studies, 6 reported nurse-specific use patterns; in 2 studies [26,34], profession-specific use could not be disaggregated and findings reflect aggregated clinician use behavior.

Output Quality

A total of 8 studies addressed perceptions of output quality [26,27,31,32,34,35,38,43]. High-quality outputs were described as accurate, relevant, and timely, supporting decision-making and patient care [27,35]. In contrast, neutral or mixed views emerged when outputs were perceived as unclear, lacked contextualization, or when usability issues were present [26,34]. Of the 8 contributing studies, 2 [26,34] involved multidisciplinary samples in which nurses' perceptions of output quality could not be separated from those of other clinical groups; the findings on output quality therefore reflect a combination of nurse-specific and broader clinician views.

Job Relevance

Of the total, 4 studies talked about job relevance [31,32,35,38]. Nurses could see a clear alignment with some core professional tasks, such as maintaining up-to-date clinical knowledge [31], supporting patient self-management [38], aiding early identification of sepsis [32], and enhancing triage decisions without replacing professional nursing expertise [35]. AI systems that aligned with existing nursing responsibilities appeared to reinforce acceptance and perceived value. All 4 contributing studies [31,32,35,38] were appraised as high quality on the MMAT and reported job relevance findings specific to nurses, providing the most consistently nurse-attributable evidence base of any construct in this review, albeit drawn from a small number of studies.

Subjective Norms

Of all, 2 studies contained discussion of subjective norms [27,32]. Positive attitudes toward AI among peers and team leaders were associated with greater acceptance, while involvement in the development process contributed to professional satisfaction and perceived status. These findings highlight the influence of workplace culture and peer endorsement in shaping AI adoption. Given that this construct was evidenced by only 2 studies, 1 high-quality qualitative study [32] and 1 medium-quality quantitative study [27], the latter with participant sample limitations including a low response rate, and given the limited evidential base overall, these findings should be treated as preliminary, with low confidence, and interpreted with caution.

Across the included studies, perceived usefulness and facilitating conditions emerged most frequently, highlighting nurses' focus on whether AI tools tangibly improve patient care and whether the necessary infrastructure and education are in place to support their integration. Perceived ease of use was also a fairly common theme, closely tied to training and ongoing support, suggesting that structured exposure to AI systems is essential for successful adoption. Job relevance and output quality were less frequently discussed but were positive when present, which reinforces the importance of aligning AI applications with core nursing tasks, as well as the need for them to deliver accurate, contextually relevant outputs. In contrast, subjective norms were only sparsely reported, indicating limited exploration of how peer attitudes and organizational culture shape adoption.

Discussion

Overview

This systematic review synthesized findings from 20 studies reporting RNs' experiences of AI in clinical practice. Nurses described AI as having the potential to support decision-making, workflow efficiency, and clinical confidence, although these reported benefits were consistently contingent on implementation quality. Perceived usefulness and facilitating conditions emerged as the most frequently reported constructs, with ease of use, workflow alignment, and organizational support recurring as determinants of whether nurses experienced AI as a benefit or a burden. Findings most directly attributable to nurses come from studies with majority nurse samples (notably for Job Relevance and several studies contributing to Perceived Usefulness), whereas constructs such as Output Quality, Subjective Norms, and elements of Facilitating Conditions drew partially on multidisciplinary samples; these are interpreted with caution below. Confidence in each finding is therefore not uniform; Job Relevance and Output Quality are anchored by high-quality studies, Perceived Usefulness is supported by a mostly high-quality evidence base, Perceived Ease of Use and Facilitating Conditions draw on a wider range of methodological quality, and Subjective Norms rests on the smallest and most heterogeneous evidence base.

Principal Results

Across the 20 included studies, nurses generally viewed AI as having the potential to improve clinical workflows and to contribute positively to care delivery, although the breadth of these perceptions varied by AI type and clinical setting. However, challenges were also evident, such as training needs, workload concerns, interoperability issues, and ethical considerations. While constructs such as perceived usefulness and facilitating conditions were frequently discussed, subjective norms and job relevance were less often explored, suggesting underresearched areas with potential to influence adoption.

Comparison With Previous Work

Perceived Usefulness

Findings from this review align with the broader AI in health care literature, in which clinicians have expressed optimism about AI's perceived capacity to support clinical tasks, improve efficiency, and contribute to patient care [44-46]. Nurses in the included studies valued AI for specific applications where they perceived benefits as tangible, such as clinical decision support or rapid information retrieval. However, these perceptions were contingent upon the technology being implemented in a way that integrated meaningfully into existing workflows and practice.

Perceived Ease of Use

Consistent with previous research, user-friendly design was a key determinant of willingness to adopt AI in nursing practice [5,47]. Positive experiences were associated with technologies that nurses described as streamlining workflows and reducing burden [48,49]. Conversely, steep learning curves, significant training demands, and inadequate integration led to frustration and resistance [48,50]. Ethical and social concerns, including privacy, trust, and algorithmic bias, were additional barriers [51,52]. These findings suggest that even with positive initial intentions to use AI, without adequate support, integration, and training, this may not translate into long-term adoption.

Subjective Norms

Although less frequently addressed in the included studies, subjective norms play a recognized role in technology adoption across contexts [53-55]. Positive cultural attitudes, leadership endorsement, and peer support could foster AI uptake among nurses. Educational settings represent an opportunity to shape these norms early by embedding AI exposure into curricula, normalizing its use, and developing confidence before clinical deployment.

Facilitating Conditions

Facilitating conditions emerged as critical to successful implementation. Key barriers included interoperability, data sharing, algorithm transparency, and infrastructure readiness [44]. Education and training were consistently identified as enablers [48,56,57]. Academic institutions can play a pivotal role by equipping future nurses with AI competencies and fostering a culture of informed, confident use. Embedding AI in training environments may help bridge the gap between intention and practice.

Job Relevance

While discussed less frequently, job relevance is important for long-term adoption. Concerns included overreliance on AI potentially diminishing nursing roles and the need to ensure AI complements rather than replaces nursing judgment. A proactive approach, where nurses adopt a positive stance toward technological integration [58], may enhance perceived relevance and strengthen the profession's role in shaping AI use.

Implications

Policy and Practice

Findings from this review reinforce that nurses view AI as a tool to supplement rather than replace clinical decision-making, a perspective echoed in previous research [1,59]. Buchanan et al [59] further call for urgent curricular reform to prepare nurses for AI-enabled health care. Embedding AI into nursing education can demystify the technology, highlight its clinical benefits, and provide hands-on experience that builds confidence and competence.

At a policy level, priorities should include establishing clear interoperability standards, developing robust ethical guidance, and ensuring ongoing professional development for AI use in nursing. At a practice level, health care organizations should actively involve nurses in the design, testing, and evaluation of AI tools to ensure they meet usability and clinical relevance standards. Structured training programs can reduce resistance, improve confidence, and normalize AI use before nurses enter practice, which could help to translate positive perceptions into long-term adoption in real-world clinical settings.

Nursing Research

The findings of this review highlight several key areas for future nursing research. First, there is a need for studies exploring the optimal integration of AI systems into nursing workflows, focusing on usability, interoperability, and the impact on patient care outcomes. Research should investigate how AI can supplement clinical decision-making without replacing nursing judgment, which may go some way to addressing concerns about overreliance on technology. Second, given the critical role of education in fostering AI adoption, studies should examine effective strategies for incorporating AI education into nursing curricula and continuing professional development. This includes exploring the use of innovative educational tools to prepare nurses for the evolving health care landscape. Third, research is needed on the long-term effects of AI integration on nursing roles, job satisfaction, and patient-nurse relationships. Finally, studies should address the ethical implications of AI in nursing, including issues of data privacy, algorithmic bias, and the potential transformation of nursing practice. By focusing on these areas, future research can guide the development of AI technologies that enhance nursing practice while preserving the core values of compassionate, patient-centered care.

Limitations

A key strength of this review is its comprehensive synthesis across diverse AI applications and settings, supported by a transparent search strategy and appraisal process using the MMAT [22]. Another strength is the structured use of the TAM2 framework [16], which provided a consistent lens for analysis and allowed for thematic comparison across studies, although, as noted below, this carries trade-offs for inductive emergence.

There are 6 notable limitations. First, the included studies encompassed a heterogeneous range of AI technologies and contexts, from sepsis prediction tools to natural language processing documentation aids, which limits the generalizability of specific implementation recommendations. In particular, conclusions regarding workflow alignment and facilitating conditions are likely to be highly context-dependent and should not be applied uniformly across all AI tool types or care settings.

Second, many studies involved multidisciplinary participant samples in which nurses were not always the majority, and in several cases, nursing data were aggregated with data from other professions. Where studies included multidisciplinary samples, nurse-specific data were extracted separately where the primary data permitted, as documented in Multimedia Appendix 2. In a small number of studies where profession-specific disaggregation was not possible, findings may reflect broader health care professional perspectives rather than distinctly nursing experiences, and these cases are flagged explicitly in Multimedia Appendix 2.

Third, the deductive analytical framework carries an inherent trade-off. TAM2 was selected a priori and registered with PROSPERO, which ensures transparency and reduces post hoc analytical drift; however, coding line-by-line into prespecified constructs may have constrained the emergence of nursing-specific themes that did not map cleanly onto these categories. We did not encounter substantial extracts that fell entirely outside the framework, although themes relating to professional identity, relational care, or moral distress may be more likely to be visible under inductive analysis. Dimensions such as professional identity, relational care, ethical responsibility, and moral distress in AI-assisted practice may therefore be underrepresented in the synthesis not because they were absent from the primary literature, but because the framework did not create space for them. Inductive or hybrid reanalysis of this literature could potentially surface a complementary picture and is recommended as a priority for future qualitative synthesis.

Fourth, coding of the included studies was undertaken by a single reviewer (AJSS), with regular consultation and consensus discussion of coding decisions with 2 supervising coauthors (BCB and DD) but without independent double-coding of the data. While the consultative process was designed to support consistent application of the codebook, the absence of independent dual coding means that formal interrater agreement could not be calculated, and we cannot fully exclude the possibility of single-coder interpretative bias. This limitation is partially mitigated by the use of a transparent, preregistered framework and by the iterative supervisory review process, but readers should weigh the synthesis findings with this constraint in mind.

Fifth, although the search syntax was not restricted by language, inclusion criteria were limited to studies published in English. This decision was made on practical grounds of interpretive validity, but we acknowledge that it may have excluded relevant empirical work from non-English speaking health care contexts, which could have captured different cultural and organizational dimensions of nurses' AI experiences.

Finally, the rapid pace of AI development means that nurses' perceptions are likely to evolve over time, potentially affecting the long-term applicability of these findings.

Conclusions

This systematic review synthesizes nurses' experiences with AI in clinical practice, identifying both the opportunities and challenges associated with its integration. While nurses often view AI as a means to enhance workflows, support decision-making, and contribute to patient care, adoption is reported to be hindered by barriers such as usability issues, limited training, and concerns about trust and clinical relevance. It is important to note that this review captures nurses' reported perceptions and experiences, rather than direct evidence that AI improves patient outcomes, workflow efficiency, or clinical safety; such claims require prospective evaluation. Addressing these challenges requires aligning AI development with user needs and embedding robust education and training into both preregistration curricula and continuing professional development. The consistent findings that facilitating conditions are the primary determinant of positive experience suggest potential value in involving nurses meaningfully in the co-design and iterative refinement of AI tools; this inference is drawn from the weight of evidence on implementation prerequisites rather than direct evidence on participatory design processes, which were only sparsely reported in the included literature. Prospective evaluation using nursing-relevant outcomes, including usability, workflow integration, and trust calibration, is needed to establish which specific implementation conditions reliably produce benefit, and to test whether co-design approaches improve adoption in practice.

By closing these gaps, nursing can play a central role in shaping AI tools that enhance, rather than erode, the human elements of care. As AI capabilities evolve, the profession has an opportunity, and a responsibility, to lead their ethical, effective, and patient-centered implementation.

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Data Availability

Full search strategies and supporting materials are provided in Multimedia Appendices 1-4. Additional extracted data are available from the corresponding author on reasonable request.

Authors' Contributions

Conceptualization: AJSS
Formal analysis: AJSS, QZ, BCB, DD
Methodology: AJSS, BCB, DD
Supervision: BCB, DD
Writing - original draft: AJSS
Writing - review & editing: AJSS, QZ, JFP, BCB, DD

Conflicts of Interest

None declared.

Multimedia Appendix 1
Full search strategies.
[DOCX File, 13 KB - nursing_v9i1e91238_app1.docx]

Multimedia Appendix 2
Results summary table.
[XLSX File, 37 KB - nursing_v9i1e91238_app2.xlsx]

Multimedia Appendix 3
Excluded full-text articles and reasons for exclusion.
[DOCX File, 20 KB - nursing_v9i1e91238_app3.docx]

Multimedia Appendix 4
Quality assessment.
[DOCX File, 37 KB - nursing_v9i1e91238_app4.docx]

Checklist 1
PRISMA checklist.
[DOCX File, 277 KB - nursing_v9i1e91238_app5.docx]

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Abbreviations

AI: artificial intelligence
JBI: Joanna Briggs Institute
MMAT: Mixed Methods Appraisal Tool
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RN: registered nurse
TAM2: Technology Acceptance Model 2
UTAUT: unified theory of acceptance and use of technology

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Correction: Perceptions and Intentions of Nursing Students Regarding Digital Health: Cross-Sectional Study

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In "Perceptions and Intentions of Nursing Students Regarding Digital Health: Cross-Sectional Study" [1], the authors made one correction.

The file originally published as Multimedia Appendix 2 has been replaced with the correct questionnaire corresponding to this study, which is attached here as Multimedia Appendix 1.

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

Multimedia Appendix 1
Study questionnaire assessing nursing students' perceptions, experiences, and attitudes toward digital health technologies (revised Multimedia Appendix 2).
[DOCX File, 50 KB - nursing_v9i1e98552_app1.docx]

Reference

1. Castonguay A, Hegg-Deloye S, Paré G, Etindele Sosso FA. Perceptions and intentions of nursing students regarding digital health: cross-sectional study. JMIR Nurs 2026 Mar 5;9:e77051. [doi: 10.2196/77051] [Medline: 41813428]

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Nurses' Experiences of Interprofessional Collaboration in Digitally Supported Hospital Discharge Planning: Qualitative Study

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Abstract

Background: Effective interprofessional collaboration (IPC) in patient discharge planning is essential for ensuring continuity of care, improving patient outcomes, and strengthening coordination among health care professionals. Nurses often serve as primary coordinators due to their continuous engagement in patient care. However, the implementation of IPC continues to face barriers at the individual, team, and organizational levels. Many hospitals have adopted digital tools, such as integrated patient progress notes (IPPNs), to facilitate information sharing. Nevertheless, the use of these tools to support IPC remains suboptimal and has been insufficiently explored, particularly within the Indonesian digital health context.

Objective: This study aimed to explore how IPPNs support IPC during patient discharge planning, particularly from the nursing perspective.

Methods: A qualitative phenomenological study was conducted at a hospital in Bukittinggi, West Sumatra. Data were collected through in-depth interviews and a focus group discussion involving 9 purposively selected health care professionals. Thematic analysis was used to identify key patterns related to IPC practices and communication dynamics involving the use of IPPNs.

Results: The findings revealed 3 main themes: (1) individual understanding and motivation in IPC, encompassing motivation, role expectations, personality style, and professional strengths; (2) team dynamics, including leadership, management, communication, and social support; and (3) organizational support for IPC, comprising collaborative culture, institutional goals, organizational structures, and the organizational environment. Participants perceived IPC as essential yet inefficiently utilized for coordinating patient care across disciplines, with limitations in standardization, accessibility, and clarity of digital documentation hindering effective collaboration.

Conclusions: This study demonstrated that IPC practices were shaped by individual, team, and organizational factors, with digital communication holding a potentially transformative role in facilitating collaboration. These findings contribute to existing knowledge by highlighting context-specific challenges in Indonesian digital health settings, including digital literacy, system usability, and institutional support, which influence IPC and discharge planning outcomes. Integrating digital optimization within IPC frameworks may represent a valuable strategy for advancing digital health practices.

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KEYWORDS

digital health; digital communication; discharge planning; electronic health records; health information systems; interprofessional collaboration; integrated patient progress notes; qualitative study

Introduction

Patient discharge from hospital care represents a critical stage in the care continuum, particularly for individuals with chronic or complex conditions [1]. Effective discharge planning requires interprofessional collaboration (IPC) to ensure continuity of care and minimize adverse health outcomes [2]. Nurses play a central role as patient and family educators and function as key coordinators of interprofessional communication. However, IPC remains suboptimal in many health care systems, particularly in low- and middle-income countries (LMICs), contributing to prolonged hospital stays, medication errors, fragmented care, and reduced patient satisfaction [1,3].

Technological innovations have been identified as potential strategies for enhancing IPC. Web-based platforms, such as *Discharge Today*, have demonstrated improvements in team coordination without increasing workload, with most users perceiving the information as accurate and useful [3]. In situations with limited face-to-face interaction, such as shift handovers, these tools support continuity of information exchange among team members [4]. Virtual simulation–based interprofessional education (IPE) has also been shown to strengthen collaborative competencies among health care professionals, particularly nursing students [5]. However, the successful implementation of such interventions is highly dependent on health care professionals' digital readiness, motivation, and technological competence.

Barriers to effective IPC persist at both institutional and individual levels. Organizational constraints, including weak leadership and inadequate managerial support, hinder technology-enabled collaboration and contribute to poor communication and reduced team performance [6,7]. At the individual level, resistance to change, heavy workload, limited digital literacy, and unclear professional roles impede collaboration, particularly during discharge transitions [2,6].

Digital documentation tools, including electronic health records, shared care plans, and standardized discharge forms, are designed to support IPC by improving clarity and consistency of clinical information [3]. However, practical challenges, including documentation fatigue, limited training, and system incompatibility, often limit their optimal use in clinical practice [4].

In Indonesia, hospitals have adopted an integrated patient progress notes (IPPNs), locally known as *Catatan Perkembangan Pasien Terpadu*, as part of the national electronic health records system to support multidisciplinary documentation [8]. Although nurses are required to routinely document patient progress using this system, studies have reported implementation inconsistencies, including incomplete entries, lack of standardization, and suboptimal use during discharge planning [9], compounded by unclear protocols, administrative workload, and limited digital literacy training [10].

Similar implementation gaps are evident in a type B teaching referral hospital in West Sumatra that has adopted the IPPNs system as part of its digital health strategy. However, despite being policy-mandated, no formal evaluation has examined the use of IPPNs in supporting IPC during discharge planning, particularly from nurses' perspectives. Existing studies have primarily focused on technical or administrative aspects of documentation, with limited examination of IPPNs as a digital collaboration tool within clinical practice.

This hospital was selected as the study site because it functions as a regional referral center and teaching institution that actively implements national digital health integration and manages multidisciplinary, high-complexity cases requiring intensive interprofessional coordination. These characteristics make it representative of mid-level health care facilities transitioning toward integrated digital health systems. Therefore, this study aimed to explore how IPPNs are used as a digital collaboration tool to support IPC during patient discharge planning, with a particular focus on nurses' perspectives and interprofessional practice.

Methods

Study Design

This study used a qualitative phenomenological design to explore health care professionals' experiences of IPC in patient discharge planning supported by digital documentation in a hospital setting. The phenomenological approach was selected because it enables an in-depth exploration of participants' subjective experiences and the meanings they ascribe to the phenomenon under investigation [11-15].

Setting and Samples

This study was conducted between January and February 2025 at a type B teaching referral hospital in West Sumatra, Indonesia. The hospital has implemented IPPNs, locally known as *Catatan Perkembangan Pasien Terpadu*, as part of its digital service standards. The hospital was selected because it involves multiple health care professions in the collaborative process of patient discharge planning.

Participants were recruited using purposive sampling and comprised 9 participants: 3 physicians, 2 nurses, 2 pharmacists, and 2 nutritionists. This interprofessional composition was intended to reflect collaborative dynamics among health care team members. Data saturation was achieved, as no new themes emerged after the eighth interview, and the ninth interview confirmed thematic repetition. In phenomenological studies, data saturation is typically achieved with 6 to 10 participants who have direct experience with the phenomenon under investigation [12,13].

Although the study was nursing-oriented, 2 nurses were included because the primary focus was IPC in discharge planning rather than nursing practice alone. The selected nurses had direct clinical and coordinative experience in the discharge process, providing sufficiently rich insights to represent nursing perspectives. In phenomenological research, depth and richness of meaning are prioritized over sample size, making this sample appropriate for addressing the research objectives [13,14].

Participants were selected based on the following inclusion criteria: (1) Physicians must hold a valid practice license (Surat Izin Praktik, SIP) and a clinical competency certificate (Surat Keterangan Kewenangan Klinik, RKK), have at least 2 years of work experience at the hospital, and consent to participate; (2) Clinical nurses (level III) must possess an SIP and a signed RKK, have at least 2 years of work experience at the hospital, and consent to participate; (3) Pharmacists must hold an SIP and an RKK, have at least 2 years of work experience at the hospital, and consent to participate; and (4) Nutritionists must hold an SIP and an RKK, have at least 2 years of work experience at the hospital, and consent to participate.

All participants were anonymized and assigned codes to ensure confidentiality and protect personal information throughout the research process.

Data Collection Procedures

Data were collected through in-depth interviews and face-to-face focus group discussions (FGDs) conducted at the hospital. The interview guide was developed based on the World Health

Organization (WHO) IPC framework and King's Interpersonal System Theory, focusing on 4 main domains: (1) perceptions of IPC in discharge planning; (2) roles and responsibilities of each professional group within the team; (3) barriers and facilitating factors influencing IPC implementation in the hospital; and (4) utilization of the IPPNs as a digital communication tool for coordination among professionals.

The following are the example interview questions:

1. How do you perceive IPC in the discharge planning process?
2. What challenges have you encountered when using IPPNs to coordinate with other professionals?
3. In your view, what factors could strengthen interprofessional teamwork in this hospital?

Each interview lasted approximately 45 to 60 minutes, was audio-recorded with participants' consent, and was transcribed verbatim.

Following the individual interviews and initial thematic analysis, an FGD was conducted to validate and refine the themes that emerged from the interviews. The FGD served as a member-checking process to confirm the credibility of the findings and to provide cross-professional reflection on shared experiences. Importantly, the FGD was not intended to generate new themes but to enhance trustworthiness through data triangulation and ensure consistency of meaning across professional perspectives.

All participants received a clear explanation of the study objectives and procedures, and informed consent was obtained before data collection.

Data Analysis

Data collection and analysis were conducted in 2 stages. The first stage involved 9 in-depth interviews using a semistructured interview guide consisting of open-ended questions based on the WHO framework for IPC and the core IPC competencies as outlined by the Institute of Medicine in the expert panel report. The information obtained from these face-to-face interviews was recorded with consent and transcribed verbatim. As the interviews and FGD were conducted in Bahasa Indonesia, data analysis was performed in the original language. Quotations included in the manuscript were translated into English carefully to retain conceptual accuracy. Interview data were analyzed thematically following the approaches proposed by Braun and Clarke [12,13], including open coding, theme development, and interpretation. The coding and theme categorization process was supported by NVivo 15 software (Lumivero) to ensure analytic consistency and traceability.

The reporting of this study adhered to the COREQ (Consolidated Criteria for Reporting Qualitative Research) checklist to ensure transparency and methodological rigor. The coding process followed the 6 phases of thematic analysis proposed by Braun and Clarke, including data familiarization, generation of initial codes, searching for themes, reviewing, defining, and naming themes. A preliminary codebook was developed inductively from the data, then refined through iterative discussions among the research team to ensure conceptual clarity. Coding discrepancies were resolved through peer debriefing and consensus meetings to achieve analytic consistency.

The second stage of data collection was an FGD conducted only once, including 4 participants selected from the initial participants based on the richness and relevance of the information provided during the previous analysis. FGD data were analyzed using the same thematic method, and the results from both stages were integrated using triangulation.

Potential bias was addressed in the FGD by ensuring equal opportunities for all participants to speak and by avoiding dominant voices that overshadowed others. The discussion was guided neutrally, with questions designed to elicit further reflection rather than primary responses.

Trustworthiness and Rigor

To maintain the trustworthiness and rigor of qualitative data, the strategies outlined by Nowell et al [14,15] were applied as follows: credibility was ensured through data saturation, verbatim transcription, and triangulation of in-depth interviews and FGDs; transferability was supported by a detailed description of the study context, including participants' profiles and data collection procedures; dependability was ensured through detailed documentation of the data collection and analysis processes; and confirmability was established through triangulation and discussions with study team members to ensure consistent and objective interpretations [14,15].

Ethical Considerations

This study underwent ethical review and was approved by DR Drs M Hatta Brain Hospital, Bukittinggi, Indonesia (002555/KEP.RSOMH Bukittinggi/2024). Before data collection, participants were provided with a study information sheet explaining the purpose, benefits, methods, and participant rights. Participation was voluntary, and participants could withdraw at any time without consequences. Written consent was obtained from each participant after they read and understood the information provided. Confidentiality and anonymity were maintained by excluding individual identities from the report. Data were used solely for this study and stored securely in accordance with privacy policies. The research was conducted in accordance with the Helsinki Declaration. Participants did not receive any financial or material compensation for their participation in this study.

Results

Descriptive Results

Before presenting the main findings, an overview of participant characteristics is provided in Table 1, which summarizes the characteristics of 9 participants, all within the productive age range (25 - 64 y) as defined by the WHO. Most participants were female (n=7, 78%) and held a master's degree (n=7, 78%). The majority were married (n=7, 78%) and had more than 10 years of work experience (n=6, 66.7%).

Table . Participants’ characteristics.

Characteristics	Frequency, n (%)
Age (y)	
25 - 64: adult (productive age range) according to WHO[a]	9 (100)
Sex	
Male	2 (22)
Female	7 (78)
Education	
Bachelor's degree	2 (22)
Master's degree	7 (78)
Marital status	
Married	7 (78)
Not married	2 (22)
Profession	
Doctor	3 (33.3)
Nurse	2 (22.2)
Pharmacist	2 (22.2)
Nutritionist	2 (22.2)
Work period (y)	
<5	0 (0)
5 - 10	3 (33.3)
>10	6 (66.7)

[a]WHO: World Health Organization.

Participants represented 4 professional backgrounds: doctors, nurses, pharmacists, and nutritionists, reflecting multidisciplinary involvement in patient discharge planning.

Health Care Professionals’ Experiences in Implementing IPC in Hospital Settings

Overview of Emergent Themes

Three main themes and 12 subthemes emerged from the analysis, describing health care professionals’ experiences in implementing IPC during patient discharge planning. The main themes and subthemes are summarized in Table 2.

Table . Themes of health professionals’ experiences in IPC[a] practice at a type B teaching referral hospital in West Sumatra, Indonesia.

Code	Themes	Subthemes
1	Individual understanding and motivation in IPC	• Motivation • Role expectations • Professional power • Personality style
2	Team interaction dynamics in the discharge planning process	• Group leadership • Coping • Communication • Social support
3	Organizational support for IPC	• Organizational culture • Organizational goals • Organizational domain • The organizational environment

[a]IPC: interprofessional collaboration.

Further details of each theme, including supporting categories and illustrative participant quotations, are presented in Figures 1-3, which were generated using NVivo 15 to visualize the thematic structure, and described in the following sections.

Figure 1. Thematic analysis of theme 1: individual.

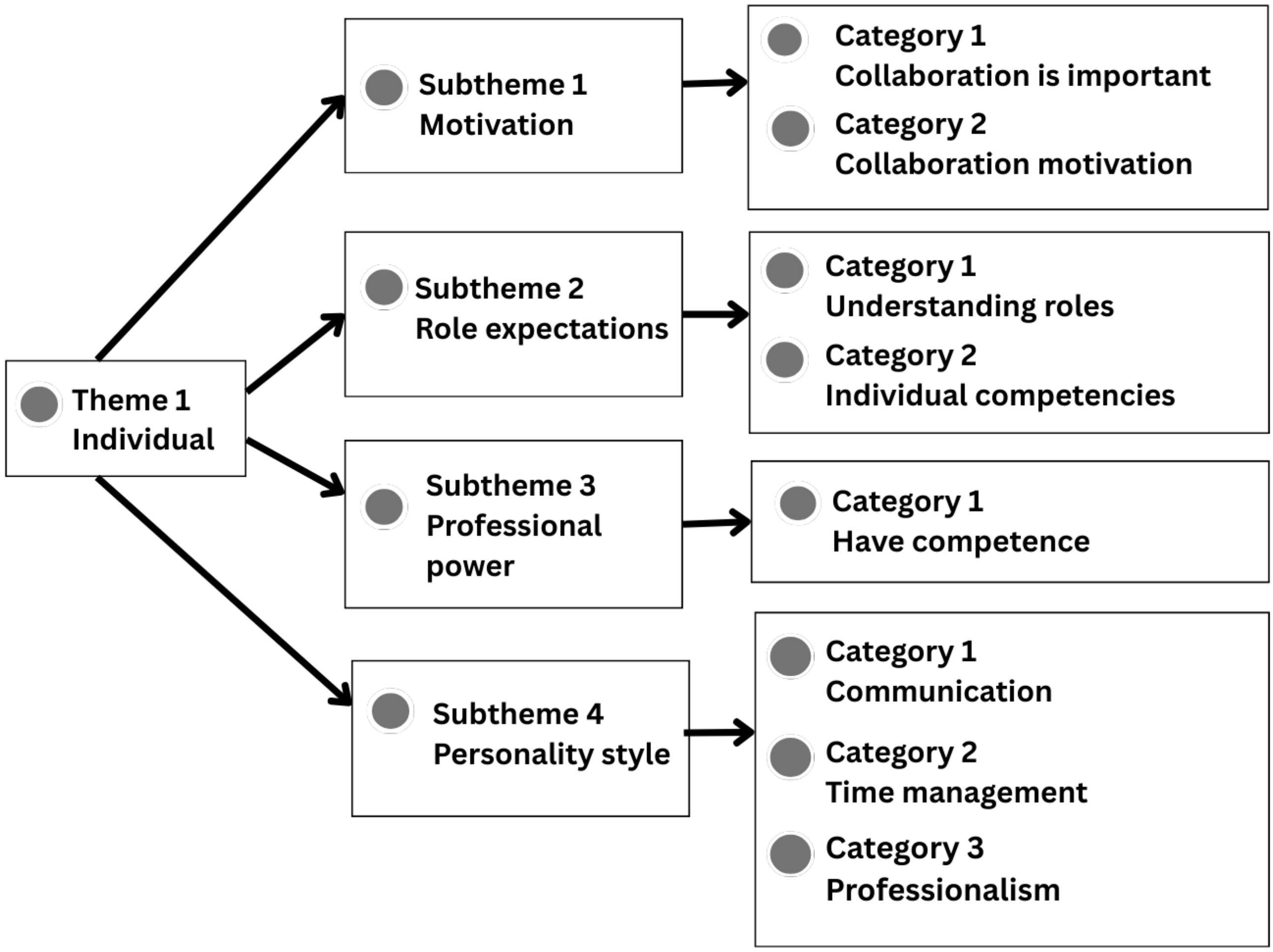


Figure 2. Thematic analysis of theme 2: team

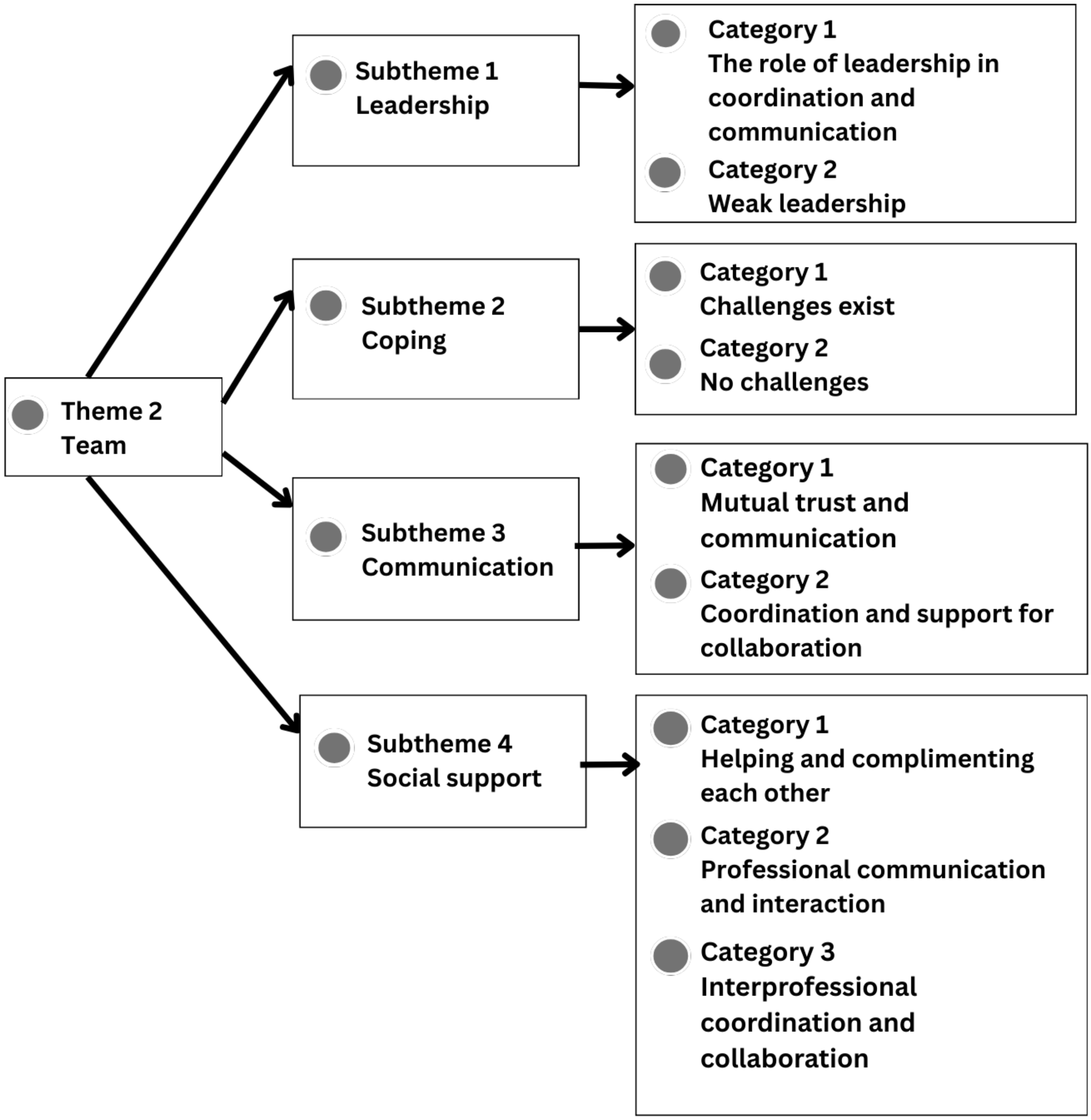
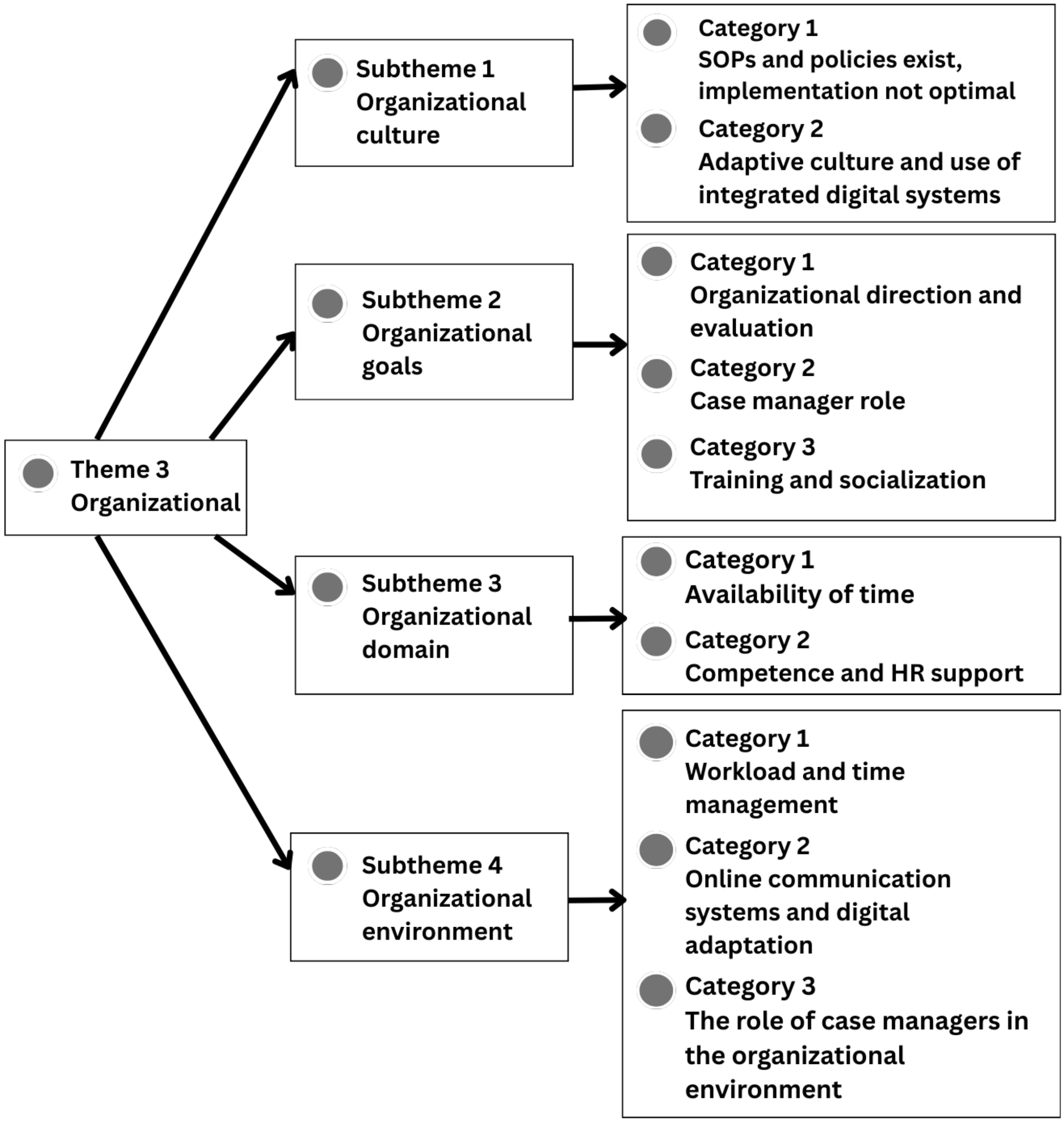


Figure 3. Thematic analysis of theme 3: organizational support. HR: human resource; SOP: standard operating procedure.



Theme 1: Individual Understanding and Motivation in IPC

Overview of Theme 1

Qualitative findings suggest that individual factors play a crucial role in the implementation of IPC, particularly in the context of patient discharge planning. This theme comprises 4 subthemes: motivation, role expectations, professional authority, and personality styles, as presented in Figure 1.

Figure 1 illustrates theme 1, "individual factors", which includes 4 subthemes with associated categories: (1) motivation, including the importance of collaboration and collaborative motivation; (2) role expectations, including understanding professional roles and individual competencies; (3) professional authority, including possession of professional competence; and (4) personality style, including communication, time management, and professionalism.

The following sections elaborate on each subtheme and present supporting quotations from the 9 participants.

Subtheme 1: Motivation

Internal motivation emerged as a key driver encouraging nurses to participate actively in collaborative discharge planning. Several participants recognized teamwork as essential to ensuring patient safety and continuity of care.

> *Collaboration is essential, especially in planning patient discharge to avoid mistakes.* [Participant 2]

Nurses also expressed motivation stemming from a desire to provide comprehensive patient education before discharge.

> *I'm driven to collaborate so patients receive the right information before going home.* [Participant 4]

This intrinsic drive was reinforced by shared professional goals and a sense of collective responsibility.

> *I feel more enthusiastic when working with a cross-professional team because we share the same goal—the patient's recovery.* [Participant 5.]

Some participants noted that motivation diminished when their contributions were not equally recognized.

Subtheme 2: Role Expectations

Role clarity influenced participation in discharge planning. Participants emphasized that understanding their professional responsibilities guided their involvement in team discussions.

> *I understand that as a nurse, my responsibility is to educate the patient before discharge.* [Participant 2]

Several participants identified interprofessional communication as part of their professional role.

> *I report the patient's condition to the team before they are discharged.* [Participant 3]

Some nurses reported frustration when their roles were perceived as limited to routine tasks.

> *Sometimes we're seen only as medication providers, but we also educate patients about side effects.* [Participant 9]

This perception gap between professions can act as both a facilitator and a barrier to collaboration, suggesting the need for clearer role delineation and mutual respect in team settings.

Subtheme 3: Professional Power

Professional hierarchy influenced collaborative dynamics. Some nurses expressed confidence in their clinical competence and independence.

> *As a nurse, I feel capable of carrying out discharge planning.* [Participant 3]

Others reported discomfort when expressing opinions in the presence of physicians.

> *Sometimes it's difficult to share opinions because we're seen as subordinates.* [Participant 5]

Training and institutional support were described as contributing to professional confidence.

> *After attending training, I felt more confident managing discharge planning.* [Participant 6]

Conversely, some participants reported that dominant attitudes from certain professionals affected collaboration.

> *Sometimes doctors act like they know everything, which makes it hard for others to express their views.* [Participant 7]

These findings illustrate the dual nature of professional power; it can empower individuals through competence and training or hinder collaboration through entrenched hierarchies.

Subtheme 4: Personality Styles

Interpersonal communication and personal traits influenced teamwork. Participants associated effective collaboration with openness, confidence, and adaptability.

> *I'm used to coordinating and listening to team members' input.*
>
> *[Participant 7]*
>
> *I prefer being open if there's a different view, I take it as constructive feedback.* [Participant 8]

Adaptability was identified as helpful when working with professionals from different disciplines.

> *I'm adaptable and used to working across different professions.* [Participant 9]

Nevertheless, communication gaps were occasionally reported, especially when individuals lacked confidence or were hesitant to speak up. This subtheme underscores that successful IPC depends not only on technical skills but also on interpersonal awareness and flexibility.

Summary of Theme 1

Individual factors influenced participation in IPC during discharge planning. Participants described motivation, role understanding, professional hierarchy, and personal communication styles as shaping their collaborative experiences.

Theme 2: Team Interaction Dynamics in the Discharge Planning Process

Overview of Theme 2

Team interaction dynamics played an important role in the discharge planning process and influenced the implementation of IPC. Participation and coordination among different professional groups were described as central to daily collaborative practice. Participants from various professions, including doctors, nurses, pharmacists, and nutritionists, described diverse interaction patterns that shaped how collaboration was formed, maintained, or hindered during discharge planning. These interaction dynamics encompassed leadership, communication, coordination, and social relationships within the health care team. The identified patterns illustrate how team members worked together to support patient discharge planning in routine practice. The structure of the themes, subthemes, and categories related to team interaction dynamics is presented in Figure 2.

Figure 2 presents Theme 2, "team interaction dynamics", which includes 4 subthemes with associated categories: (1) group leadership, including leadership roles in coordination and communication and weak leadership; (2) coping, including collectively managed challenges and absence of challenges; (3) communication, including mutual trust in team communication and coordination and support for collaboration; and (4) social support, including helping and complementing each other, professional communication and interaction, and interprofessional coordination and collaboration.

Subtheme 1: Leadership

Group leadership influenced the effectiveness of collaboration in discharge planning. Participants described leaders as facilitators who initiated meetings, allocated responsibilities, and guided discussions.

> *Our leader always starts the discharge planning meeting and divides the tasks.* [P1]

> *The team leader always guides the discharge planning discussion firmly but openly.* [P2]

Participants described leadership styles characterized by fairness and openness: “Our leader encourages all members to express their opinions” (P3), and “Our leader is wise and willing to listen to all input” (P5). Some participants highlighted emotional control and role modeling by leaders: “Our team leader can maintain harmony, not authoritarianism” (P6), and “Our leader sets an example and supports joint decisions” (P7). Collectively, these narratives underscore leadership that balances authority with inclusivity.

Subtheme 2: Coping/Handling

Participants described both the presence and absence of challenges in IPC. Reported barriers included inconsistent evaluation, limited family engagement, and uneven participation across professions: “The challenges exist, especially because there has been no proper evaluation” (P1); “Coordination is a challenge because not all professions are present during joint visits” (P5). Differences in patient contact among professionals were also noted (P3). Some participants reported minimal challenges due to clear standard operating procedures (SOPs) and defined roles: “There are no challenges because all professions already have clear SOPs” (P6).

Subtheme 3: Communication

Participants described communication as occurring primarily through digital platforms, particularly WhatsApp groups: “Communication is carried out via WA groups” (P2, P7, P8, P9). Verbal discussions and documentation were also used to share patient updates: “We routinely inform each other about patient progress” (P1); “I routinely report patient progress to the team via medical records” (P3). Some participants reported communication challenges among new staff unfamiliar with interprofessional communication practices: “There are minor challenges if there are new employees who do not yet understand the ethics or interprofessional communication” (P6). This indicates the need for structured orientation and communication training within multidisciplinary teams.

Subtheme 4: Social Support

Participants described social support as contributing to team cohesion. They reported mutual trust, respect, and shared responsibility. As participant 1 stated, “I feel supported by other team members, so I am more confident,” while participant 3 added, “We respect each other; no one feels more important.” Participants also described encouragement and practical support among team members: “My team members always give encouragement and moral support” (P4). Moreover, collective accountability was evident when colleagues substituted for absent members without complaint: “If someone is absent, the team still covers for each other without protesting” (P6); “If someone is absent, the others are ready to change shifts without any problems” (P8).

Summary of Theme 2

Team interaction dynamics influenced IPC during discharge planning. Participants described leadership, communication, coping with challenges, and social support as shaping their collaborative experiences.

Theme 3: Organizational Support for IPC

Overview of Theme 3

Organizational support influenced the implementation of IPC in patient discharge planning. Participants described the role of policies, management, resources, information systems, and work culture in shaping collaborative practice. The structure of the themes, subthemes, and categories for organizational support is presented in Figure 3.

Figure 3 presents Theme 3, “organizational support”, consisting of 4 subthemes with associated categories: (1) organizational culture, including existing SOPs and policies with suboptimal implementation and adaptive culture through integrated digital systems; (2) organizational goals, including organizational direction and evaluation, case manager roles, and training and socialization; (3) organizational structure, including availability of time and competence supported by human resources; and (4) organizational environment, including workload coverage, time management, online communication systems, and the role of case managers in supporting IPC.

Subtheme 1: Organizational Culture

Participants reported the presence of SOPs and policies supporting discharge planning. However, limited dissemination and inconsistent implementation were noted.

> *There are SOPs, but access is uneven across units, which can hinder implementation.* [Participant 4]

> *[A]lthough collaboration is mandated, the execution remains suboptimal.* [Participant 9]

Some participants described the integration of electronic medical records as supporting collaboration. For example, a participant shared, “The new H-1 discharge policy is linked to electronic medical records, making it more transparent” (Participants 3, 5).

Others noted that implementation at the unit level remained inconsistent: “Although management has established procedures, their execution at the ward level still needs improvement” (Participants 2, 5). A formal structure supporting IPC exists, while cultivating a shared culture that translates into consistent, collaborative behavior in daily clinical work remains a challenge.

Subtheme 2: Organizational Goals

Participants described management support for collaboration through direction, case management, training, and evaluation.

> *There are directions from management, but no overarching policy; however, patient satisfaction remains a central focus.* [Participant 2]

> [The presence of a case manager facilitates cross-professional decisions. Participant 6]

> *Periodic training and evaluation are carried out to adjust discharge planning practices.* [Participant 8]

Some participants highlighted the role of digital systems in monitoring collaboration:

> *The iKame system allows us to track multidisciplinary participation.* [Participant 7]

Subtheme 3: Organizational Structure

Participants reported that the availability of discharge planning teams and digital tools supported collaboration. Several participants described sufficient time allocation and improved efficiency through electronic systems. A participant shared, "Time is sufficient as long as roles are clear" (Participant 4), while another added, "Using the electronic system saves time compared to manual charting" (Participant 9). However, human resource limitations were also reported: "Time remains a challenge, but we hope things improve with more staff" (Participants 3, 5).

Facilities and digital access were described as adequate: "computers are available" and "nutrition leaflets and counseling are provided" (Participant 2). Participants also described the hospital's electronic system as structured and role-based: "the IT system supports collaboration" and "access is structured based on role and profession" (Participants 6, 7). In summary, structural elements such as time, facilities, and information systems play a critical role in enabling IPC, although workload distribution and continuity of IPE still require improvement.

Subtheme 4: Organizational Environment

Participants generally perceived the work environment as supportive of collaboration: "The work environment supports collaboration and discussion" (Participant 2). Scheduling and coordination challenges were commonly reported. For example, "lack of adherence to schedules affects plans like physiotherapy" and "conflicting rounds and outpatient duties disrupt communication" (Participant 6).

Some participants suggested integrated scheduling and dedicated interprofessional meetings. "More integrated scheduling and dedicated interprofessional meeting time" (Participant 8). While digital systems were viewed as helpful, some participants preferred direct communication: "IT helps, but direct coordination is still more effective" (Participant 7).

Participants also mentioned the need for regular evaluations: "There should be routine meetings and comprehensive evaluations beyond administrative aspects" (Participant 2). Importantly, individual commitment was stated: "Even with full organizational support, without individual commitment, collaboration won't work" (Participant 9).

Few participants consider IPC to be running optimally. However, the results suggest that organizational improvements, particularly in scheduling, evaluation, and communication, are still needed to sustain collaborative efforts.

Summary of Theme 3

Participants described organizational policies, digital systems, managerial support, training, case managers, and work environment as influencing IPC during discharge planning. They also reported challenges related to policy implementation, scheduling, workload, and communication.

Discussion

Principal Findings

The findings of this study indicate that the success of IPC in patient discharge planning is influenced by 3 main factors: individual factors, team dynamics, and organizational support. Individual factors include motivation, role understanding, professional competence, and personality styles; team dynamics involve leadership, communication, problem-solving abilities, and social support; and organizational support encompasses work culture, service goals, resource availability, and a supportive work environment. These findings underscore that IPC effectiveness depends on the interaction between personal capabilities, effective team processes, and organizational structures.

Before discussing the findings in detail, participant characteristics should be considered, as they influence experiences and perceptions of IPC. All participants (n=9) were within the productive age range of 25 to 64 years, reflecting readiness for IPC and adaptation to digital systems [16]. Most participants were female (78.0%), consistent with the gender distribution in nursing and public health professions, which may influence collaboration dynamics through communicative and empathetic approaches [17]. Most participants held a master's degree (78%), indicating strong academic capacity for understanding IPC concepts and applying digital communication in clinical practice [18,19]. The majority had more than 10 years of work experience (66.7%), contributing to professional maturity and confidence in interprofessional communication [17].

Although only 2 nurses participated, they were selected due to their strategic role as primary coordinators of discharge planning, making them representative of nursing competencies in IPC [16].

Exploring the Professional Experiences of Nursing Professionals

Theme 1: Individual Understanding and Motivation in IPC

Overview of Individual Factors Influencing IPC

The findings demonstrate the critical role of individual factors in IPC implementation during discharge planning. Motivation, role expectations, professional power, and personality traits shaped health care professionals' engagement and readiness. These findings align with international IPC literature, highlighting individual awareness and intrinsic motivation as foundational to effective collaboration.

Motivation

Motivation emerged as a strong internal driver rooted in responsibility for patient safety and care continuity. This aligns with Smith et al [5], who showed that interprofessional simulation strengthened motivation and collaborative readiness, and with Reinders et al [20], who emphasized intrinsic motivation in sustaining discharge coordination. In Indonesian settings, motivation is influenced by workload, resource constraints, and institutional incentives, indicating that it is both intrinsic and contextually shaped [20].

This study further shows that digital platforms such as IPPNs and WhatsApp function as external motivators by facilitating timely information exchange and shared accountability, consistent with global evidence on digital engagement in teamwork [16]. However, infrastructure limitations, technical barriers, and workload concerns remain as challenges [21]. Thus, technology-supported motivation requires organizational training, leadership, and incentives, particularly in LMIC contexts where motivation is more relational than structurally reinforced.

Role Expectations

Clear role understanding enhanced IPC participation, especially in patient education and communication. Conversely, undervalued or ambiguous roles—particularly among nurses—limited engagement. These findings support Tong et al [22], who found that role clarity improves collaboration and mutual respect. In Indonesia, hierarchical traditions and inconsistent policy enforcement continue to constrain role clarity [9,10]. Compared with high-income settings where roles are codified through standardized policies and digital protocols, local adaptation of IPC policies remains essential [16].

Professional Power

Professional hierarchy remained a persistent barrier. Despite clinical competence, some nurses hesitated to voice opinions due to perceived lower status. This mirrors Tan et al [23] and Nie et al [4], who reported that digital tools alone do not flatten hierarchies without inclusive leadership and policy support. In LMIC contexts, unequal authority and weak institutional enforcement limit the transformative impact of digitalization on power relations [4].

Personality Style

Personality traits such as openness, adaptability, and empathy facilitated IPC, consistent with prior studies linking emotional intelligence to effective handoffs and reduced information loss [10,24,25]. In the Indonesian context, strong family involvement added complexity to discharge planning, requiring sensitivity to sociocultural dynamics [26]. Comparable findings in high-income settings also highlight emotional intelligence as a key IPC enabler [27]. These results indicate that IPC effectiveness is shaped not only by systems but also by personal and interpersonal competencies [28].

Critical Reflection

These findings reinforce that IPC is shaped by individual attitudes and professional culture in addition to formal systems. Digital platforms can enhance coordination, but their effectiveness depends on leadership, organizational readiness, and equitable governance. Persistent hierarchies and uneven policy implementation in LMICs underscore the need for capacity building that integrates reflective leadership, interprofessional mentoring, and psychological safety.

Theme 2: Team Dynamics in IPC for Discharge Planning

Overview of Team Interaction Dynamics

Team dynamics revealed the importance of leadership, communication, coping strategies, and social support. While digital platforms facilitated coordination, collaboration quality ultimately depended on leadership consistency, institutional accountability, and cultural readiness.

Group Leadership and Participatory Team Culture

Inclusive leadership fostered trust, shared accountability, and psychological safety, consistent with Bornman and Louw [29] and Keniston et al [30]. Conversely, inconsistent leadership resulted in fragmented communication and unclear roles, reflecting uneven policy implementation and limited leadership development common in LMICs [5].

Coping and Operational Challenges in Coordination

Teams faced logistical challenges such as inconsistent participation and fragmented workflows, echoing findings by Nie et al [4]. Clear SOPs and predefined roles mitigated some challenges, aligning with Buljac-Samardzic et al [31]. Persistent hierarchies and uneven enforcement reflected deeper governance barriers, while family involvement occasionally delayed decision-making when authority was unclear [31].

Communication Infrastructure and Team Transparency

Hybrid communication using WhatsApp, face-to-face meetings, and documentation supported coordination, consistent with Keniston et al [30] and Teuwen et al [32]. However, message overload and unequal participation persisted without shared digital literacy and leadership oversight [21,33-35]. Compared with high-income settings, IPC in Indonesia remains dependent on interpersonal initiative rather than integrated systems [27,34]

Social Support and Emotional Climate

Mutual respect, encouragement, and role flexibility strengthened team resilience, consistent with Cadel et al [34]. These findings align with evidence from high-income contexts showing emotional cohesion as a universal driver of IPC effectiveness [35-42].

Critical Reflection

Digitalization facilitates coordination but does not eliminate hierarchies or policy inconsistencies. Compared with high-income settings, IPC success in Indonesia relies more heavily on interpersonal leadership and local initiative, highlighting the need for aligned policy, leadership development, and collaborative governance.

Theme 3: Organizational Support for IPC

Organizational-Level Support for IPC

Organizational support emerged as a prerequisite for sustainable IPC, encompassing culture, goals, structure, and work environment.

Organizational Culture

Although SOPs and policies exist, uneven dissemination and weak supervision limited consistent implementation. Hierarchical norms continued to shape communication despite digital tools. These findings align with Redzewsky et al [40] and Ishii et al [41], emphasizing that policy without localized integration fails to sustain IPC.

Organizational Goals

Leadership support through case managers, training, and evaluation facilitated IPC, although the absence of a comprehensive IPC policy remained a barrier. These findings align with Labrague et al [42], who linked supportive environments to improved safety outcomes.

Organizational Domain

Structural supports such as discharge teams, digital systems, and facilities enhanced IPC efficiency [43-46]. However, workload imbalance and limited IPE persisted [45]. Rawlinson et al [46] emphasized that the success of IPC was strongly influenced by team competencies, including effective communication, clearly defined roles, and consistent organizational support.

Adopting digital systems, such as electronic medical records and the iKame app, streamlines coordination and reduces time burden across professions. However, human resource shortages and compressed work schedules continue to present major barriers. Buljac-Samardzic et al [31] suggested that team structure optimization, including task clarity, adherence to SOPs, and structured time allocation, could alleviate operational barriers to IPC. Digital platforms such as IPPNs and WhatsApp improved responsiveness but remained informally governed, limiting institutional monitoring.

The Organizational Environment

The organizational environment plays a critical role in enabling effective IPC. Factors such as the availability of resources, dedicated time allocation, and structured workflows are essential for fostering a productive collaborative climate. Although digital technologies have been introduced to support interprofessional communication, several structural barriers persist, including noncompliance with schedules, overlapping clinical responsibilities, workload pressure, and a lack of integrated cross-professional scheduling systems. Ginting et al [47] emphasized that while digital tools could facilitate IPC, their effectiveness was limited in the absence of a supportive organizational culture and inclusive leadership.

Beyond systemic factors, individual commitment remains essential to ensure sustainable collaboration. A previous study found that interprofessional trust emerges from the quality and regularity of relationships, individual attitudes, and a supportive organizational culture, and that trust, in turn, enhances communication, coordination, teamwork, and ultimately collaborative outcomes [48]. Similarly, Reeves et al [49] showed that workplaces promoting team reflection and shared evaluation cultivated trust and accountability among professionals.

When compared to high-income settings, where IPC practices are often embedded in digitalized and standardized systems, hospitals in Indonesia face persistent challenges related to uneven digital infrastructure, informal communication channels, and resource limitations. Similar barriers have been observed in other low- and middle-income contexts such as Ethiopia and the Philippines, where digital and managerial gaps hinder consistent IPC outcomes. These contrasts highlight that while policy frameworks may be globally aligned, contextual and resource-based differences shape IPC implementation in diverse health systems [50-54].

These inconsistencies often stem from institutional hierarchies, variable managerial commitment, and uneven digital literacy among professionals, which prevent the full translation of collaborative policies into daily clinical practice [55].

Holistic Interdependence Between IPC and Organizational Support

Cadel et al [34] and Smith et al [56] reported that peer substitution and team solidarity were critical to sustaining IPC, particularly during workforce fluctuations. Interprofessional simulation-based learning was also shown to strengthen team relationships and preparedness for role substitution when necessary. These findings emphasize the importance of organizational support mechanisms, including structured training and adaptive team models that can withstand staffing dynamics.

Link to Regional Evidence

A systematic review found that satisfaction with organizational support and positive attitudes toward IPC were associated with collaboration effectiveness, although not often statistically significant [50]. This highlights the need for systemic approaches to improve working conditions, promote regular training, and implement inclusive interprofessional models in clinical practice.

Critical Reflection

Organizational support for IPC depends on alignment between structure, culture, and leadership. Policies and digital tools alone are insufficient without consistent supervision, organizational learning, and reflective practice. Strong leadership commitment and structured evaluation forums are essential to embed IPC as a sustainable norm.

Strengths and Limitations

This study's strengths include its qualitative phenomenological approach, inclusion of multiple professions, and focus on digital documentation (IPPNs) within a middle-income country context. Methodological rigor was ensured through triangulation and trustworthiness criteria, contributing to theory building in IPC within resource-constrained systems.

Limitations include the single-site setting and small sample size. The study did not fully examine system usability or interoperability, and cultural hierarchies may limit transferability. Future research should adopt multisite and mixed-method designs to explore system-level and leadership influences on IPC outcomes.

Conclusion

In conclusion, this study revealed the complex dynamics that underlie IPC in hospital discharge planning. A total of 3 interrelated themes emerged: individual understanding and motivation, team interaction dynamics, and organizational support for IPC. The findings demonstrated that intrinsic motivation and clear role expectations were fundamental in fostering individual readiness for collaboration. IPE played a significant role in strengthening professional identity and enhancing collaborative competence among nursing professionals.

Professional hierarchies and leadership styles influenced collaboration outcomes. Power imbalances hindered open communication and participation, whereas inclusive leadership fostered psychological safety and active engagement. Organizational support encompassing culture, structure, and systems proved essential, although challenges persisted in coordination, communication, and policy implementation.

Effective IPC in discharge planning requires a holistic approach that integrates individual preparedness, cohesive team dynamics, and strong organizational commitment. Actionable strategies, such as structured interprofessional orientation programs, regular digital literacy training, and consistent policy dissemination at the unit level, could strengthen collaborative practice and ensure its sustainability. These efforts can promote more integrated, patient-centered care and enhance continuity of care post discharge.

The findings provide implications for policymakers, hospital administrators, and nursing education institutions to incorporate IPC principles into professional development programs, digital health initiatives, and institutional governance frameworks, supporting collaboration as a sustained norm within health care systems.

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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

None declared.

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Abbreviations

COREQ: Consolidated Criteria for Reporting Qualitative Research
FGD: focus group discussion
IPC: interprofessional collaboration
IPE: interprofessional education
IPPN: integrated patient progress notes
RKK: Surat Keterangan Kewenangan Klinik
SIP: Surat Izin Praktik
SOP: standard operating procedure
WHO: World Health Organization

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Implications for Virtual Nursing Role Development in Acute Nursing Care: 24-Hour Time-and-Motion Study

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Abstract

Background: Understanding current nursing workflows is essential to informing future workforce redesign strategies, including virtual nursing roles. However, granular insights into current nursing workflows over a 24-hour period and across different staff grades are lacking.

Objective: This study aimed to (1) quantify how registered and enrolled nurses in the general acute medicine wards distribute their time across direct and indirect care tasks over a 24-hour period, (2) identify multitasking burdens and temporal distributions, and (3) identify opportunities for the development of a virtual nursing role.

Methods: Using time-and-motion methodology, we observed registered and enrolled nurses in 3 general medicine wards over a 24-hour period between April 2024 and June 2024. We observed 3 task categories (administrative, communication, and bedside tasks), with multiple individual tasks monitored under each category. Multitasking (ie, the occurrence of 2 or more tasks concurrently) was also tracked. The checklist was piloted and refined before data collection.

Results: We observed a total of 48 nursing shifts. During the daytime, registered nurses spent 70% (587/834 min) of their time on indirect care tasks compared with 54% (412/764 min) of the time for enrolled nurses. At night, the proportion of time spent on indirect care tasks decreased to 58% (410/705 min) for registered nurses and 39% (274/711 min) for enrolled nurses. During a 24-hour period, registered nurses spent 209 (SD 51.8) minutes multitasking in the day and 117 (SD 41.0) minutes at night, whereas enrolled nurses spent 152 (SD 54.7) minutes multitasking in the day and 110 (SD 75.9) minutes at night.

Conclusions: These findings highlight opportunities for virtual nursing roles, which, if thoughtfully designed, may help redistribute indirect care tasks, reduce multitasking burden, and enhance overall efficiency without compromising care quality.

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KEYWORDS

time and motion; nursing workflows; multitasking; inpatient; virtual nursing

Introduction

Background

Health systems are facing a myriad of workforce challenges. Populations are aging, increasing the demand for care and the complexity of the care required [1]. Simultaneously, the workforce is shrinking; by 2030, the World Health Organization projects an estimated shortfall of 11 million health workers [2]. Furthermore, high-income nations find it increasingly challenging to recruit and retain home talent, relying on foreign workers to fill staffing gaps [3]. Challenges in recruitment and retention are further exacerbated by the increasing levels of staff dissatisfaction and burnout reported in recent years [4]. Collectively, these challenges raise significant questions about the sustainability of health care if no change occurs.

To address workforce challenges, there is an urgent need for role redesign and the careful application of technology to streamline processes and automate tasks. At Alexandra Hospital in Singapore, a new approach is being pioneered—the integration of a virtual workforce enabled through technology. Supported by the Ministry of Health, the hospital is investing in the development of remote or “virtual” nurses. In this context, virtual nursing refers to an emerging model of practice in which qualified nurses provide support to clinical team members remotely through digital technologies, thereby complementing bedside nursing. For example, virtual nurses may remotely monitor vital signs and fall risk, act as virtual discharge coordinators, participate in rounding through teleconsultation, or provide remote patient and caregiver education and staff supervision [5-8]. Additionally, the introduction of new virtual roles will provide more flexible work options such as working from home, which can support staff retention efforts [9]. Thus, virtual nursing is a promising model for workforce redesign.

To develop the virtual nursing workforce, understanding the status quo is important. Nurses are responsible for a range of direct (ie, involving direct interaction with patients) and indirect (ie, performed away from the patient) patient care tasks, including administering medication, monitoring patient conditions, coordinating with other health care providers, and managing administrative duties [10]. It is also well known that nurses handle diverse and often conflicting tasks, often leading to overwork and suboptimal practice [11] (eg, the duality of direct and indirect patient care tasks competing for attention). Furthermore, it has been widely reported that nurses frequently multitask (ie, perform multiple tasks simultaneously) throughout the day, which can create inefficiencies, increase the risk of errors, and reduce overall quality of care [12].

At the same time, nursing practice is fundamentally grounded in caring science, where the therapeutic nurse-patient relationship and presence are central to promoting healing and well-being [13]. However, growing administrative burden, competing indirect care demands, and multitasking can displace the relational aspects of care that form the essence of nursing. Therefore, understanding how nurses currently spend their time is essential not only for efficiency but to safeguard opportunities for caring practices. Role redesign—including virtual nursing—must be guided by the principle that technology should preserve and enhance nurses’ ability to deliver person-centered, relational care.

Despite this, much of the existing evidence base is qualitative, and there remains a gap in quantitative measurement. Where quantitative data exist, there is limited data capture on nighttime activities, the occurrence and patterns of multitasking over a 24-hour period, and the tasks undertaken by different staff grades (eg, registered nurses, who are qualified to dispense medications and instruct junior nurses, and enrolled nurses, who primarily handle patient care, such as bathing, feeding, and toileting) [10,11,14,15]. This study addresses these gaps by systematically mapping real-world nursing activity over a 24-hour cycle, examining the distribution of direct and indirect care tasks, identifying when multitasking occurs, and comparing activity patterns across staff grades. By doing so, this study provides empirical evidence to inform the design, timing, and scope of virtual nursing roles, identifying activities suitable for remote support without compromising patient-facing care.

Aims

Our aims were as follows:

1. To quantify how registered and enrolled nurses in the general acute medicine wards distribute their time across direct and indirect care tasks over a 24-hour period
2. To identify multitasking burdens and temporal distributions
3. To identify opportunities for the development of a virtual nursing role

Methods

Overview

We used time-and-motion methodology to map and quantify the tasks and time spent on direct and indirect patient care in an inpatient setting. In brief, time and motion involves a period of continuous observation and timing of activities. This study is reported according to the Suggested Time and Motion Procedures checklist [16].

Participants

This study was conducted at Alexandra Hospital in 3 general acute medicine wards. Ward sizes range from 19 to 33 beds, and each has several isolation beds where additional infection control measures are in place (eg, methicillin-resistant *Staphylococcus aureus* precautions). The typical nurse-to-patient ratio is 1 nurse for every 4 or 5 patients, with nurses opting for various full-day (12-hour) shifts or partial day shifts. A typical ward comprises a team of registered nurses (who are qualified to dispense medications and instruct junior nurses), enrolled nurses (who primarily handle patient care, such as bathing, feeding, and toileting), and a nurse manager who oversees ward operations. Each nurse has access to the electronic medical record (EMR) system through desktop computers or mobile phones (ie, Epic Rover).

As the roles of registered nurses and enrolled nurses are distinct, we observed both profiles through convenience sampling during a 3-month period. Inclusion criteria were being a full-time staff member and having worked on the wards for at least 6 months. Exclusion criteria were basic care assistants, part-time workers, or those with less than 6 months of experience on the wards. The month before data collection commenced, briefing sessions were held with the nurse managers to introduce the research project and seek their approval. Observers (health service research staff) had no direct relationship with the nursing staff being observed.

Data Collection

The initial checklist of observation items was developed through consultation with the ward managers and comprised 3 overarching domains (administrative, communication, and bedside tasks), 8 task subcategories (activities of daily care, patient communication, clinical care, administrative tasks, staff communication, staff education, ward observation, and break time), and 27 individual task codes, mapped in Table 1. The checklist was piloted and refined during observations between November 29, 2023, and December 8, 2023, before the actual data collection commenced. A second pilot was conducted from April 9 to 12, 2024, to standardize the observation process and train the 10 observers. Tasks were observed and tracked concurrently to capture periods of multitasking (ie, when 2 or more tasks were performed at the same time). For example, a communication task could be timed at the same time as a bedside care task. In our study, transition periods (short intervals between the end of one task and the start of another) were recorded as part of the subsequent task whenever the transition was functionally inseparable from task initiation (eg, walking from a workstation to a patient's bedside to begin care).

Data collection consisted of continuous nurse observation over 1 complete work shift (8:30 AM-8 PM or 8 PM-8:30 AM). Observations were conducted between April 15, 2024, and June 24, 2024. A roster was created in Python (version 3.8; Python Software Foundation) randomly allocating observers across different days of the week and weekend slots across the 3 wards. We used the Time Capture Tool TimeCaT on an iPad (Apple Inc) to track activities. TimeCaT is a validated tool frequently used in observations of health care processes [17]. Tasks are entered into the app a priori, and observers select the appropriate task as it occurs, activating a timer. Observers can also add notes to specific data points. During data collection, we also captured bed occupancy, the number of patients discharged, and the number of bed days.

Table . Direct and indirect care tasks, subcategories, and individual task codes.

Task categories and subcategories	Task codes
Direct care tasks	
Supporting activities of daily living	• Ambulation • Bathing • Changing bedding • Diapering or assisting with toileting • Assisting with food and drink
Patient communication	• Nurse to patient • Meal ordering • Attending patients' call bell
Clinical care	• Vital sign taking • Laboratory samples (collection and sending) • Other assessments and procedures • Medication handling • Patient comfort • Patient transfer (diagnostics) • Waste disposal (clinical and nonclinical waste)
Indirect care tasks	
Administrative	• Electronic medical record entry • Record viewing (no data entry) • Nonclinical administrative tasks • Discharge or admission
Staff communication	• In-person staff member to staff member • Remote staff member to staff member • Remote staff member to caregiver • Handover • Team meetings
Staff education	• Staff education
Ward observation	• Observing patients
Break time	• Break

Ethical Considerations

This study was reviewed and approved by the National University of Singapore Ethical Review Board (NUS-IRB-2023-327). A waiver for consent was obtained from the National University of Singapore Institutional Review Board. Data were anonymous and analyzed at the aggregate level. Participants were not individually compensated.

Data Analysis

Before analysis, each observation data file was cleaned. TimeCaT includes a note function that allows observers to comment on specific data points. Each note was reviewed, and revisions were made to the data if required (eg, removal of tasks that were erroneously timed or relabeling of incorrect observations). We then mapped the observed tasks to direct and indirect care tasks, creating subcategories within each domain. Direct care tasks involved direct interaction with the patient (eg, bathing and procedures), and indirect care tasks were those that were performed away from the patient (eg, documentation and staff communication) but on behalf of the patient (Table 1).

Time-and-motion data were analyzed in multiple steps. To calculate the average time spent on each task, we summed the total time spent on each task across all observations, including instances in which the task was not performed (ie, zero time), and divided it by the total number of observations. This produced the average task load time for a typical day or night shift. We then calculated the total task load time for a shift by summing all average task times and used this value to determine the proportion of time spent on each task as a fraction of the total task load time. To analyze the data by hour, each observed task was assigned to a 1-hour "time bin." For example, a task performed from 9:01 AM to 9:20 AM was categorized under the 9 AM to 10 AM time bin and recorded as 19 minutes. If a task spanned multiple time bins, its duration was divided accordingly. This approach enabled accurate tracking of task distribution across the 24-hour period. We also measured multitasking by calculating the total time during which 2 or more tasks were performed simultaneously (eg, communication and administrative tasks). Periods of no activity were excluded from the analysis. All data processing and analyses were conducted using Python (version 3.8) and Stata (version 19; StataCorp LLC).

Validity and Reliability

The observation checklist was tested and optimized over 6 separate pilot observations (a total of 17.5 hours) between November 29, 2023, and December 8, 2023. Prior to the actual data collection, a training session was conducted (April 8, 2024) to introduce the team of observers to the process and address any initial questions. A set of training observations was then conducted in pairs from April 9 to 12, 2024, to familiarize the observers with the process, standardize coding of observed tasks, and ensure that the checklist was complete. The team met 4 times during this period to discuss coding alignment and resolve any questions. Interrater agreement was assessed during the pilot phase of the study [18]. As tasks across the 3 domains (administrative, communication, and bedside) could occur concurrently, the Cohen κ statistic and percentage of agreement were calculated separately for each domain. For each observer pair, a 30-minute observation period was analyzed. The observational data were divided into 30-second intervals, and agreement between coders was assessed based on the task assigned to each interval. κ values ranged from 0.62 to 0.69, indicating substantial agreement, whereas the percentage of agreement ranged from 78% to 84%, reflecting good consistency between coders. Formal data collection commenced on April 15, 2024.

Results

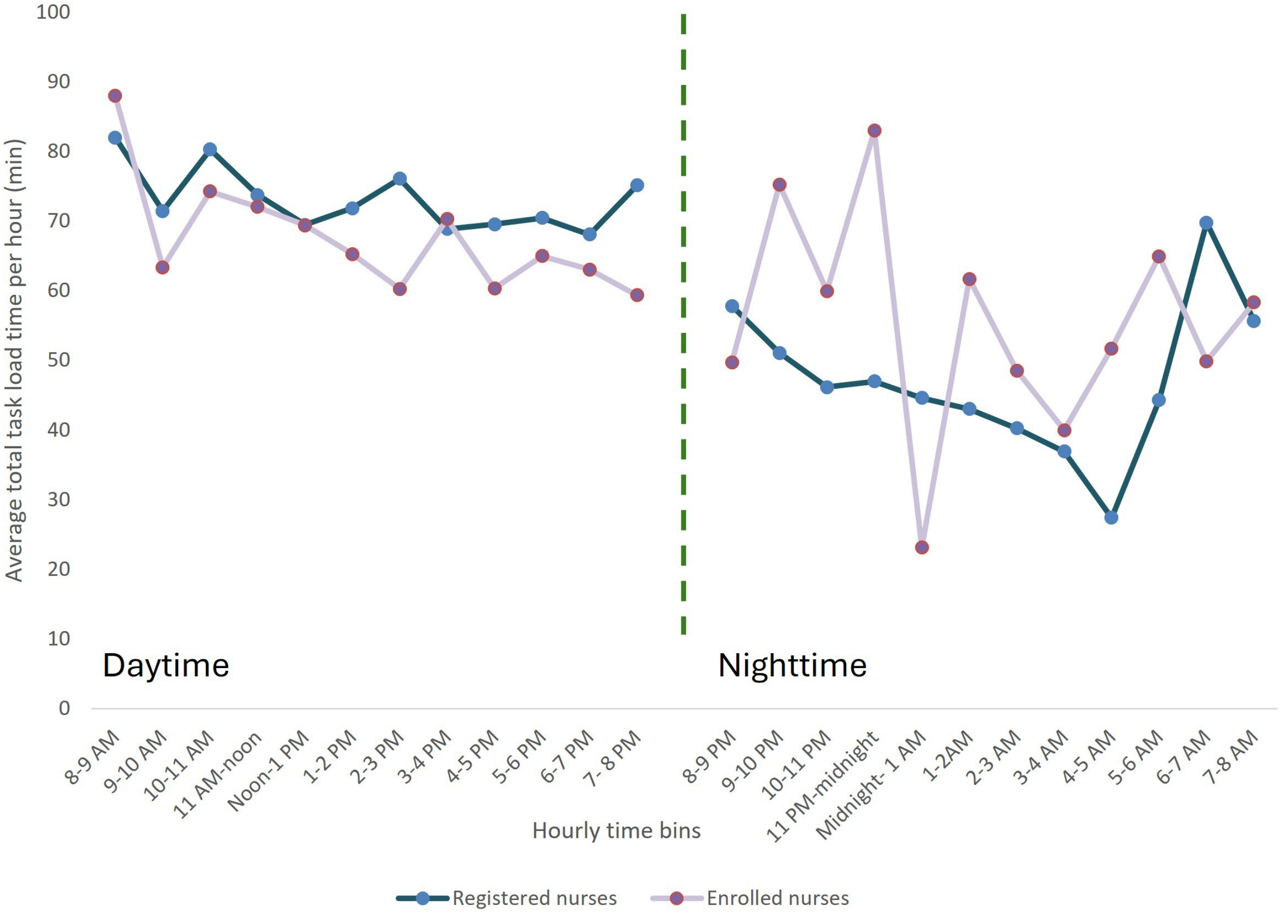
Overview

During the study period, we observed 48 shifts, including a total of 30 nurses during the day (8:30 AM-8 PM; n=22, 73.3% registered nurses and n=8, 26.7% enrolled nurses) and 18 nurses at night (8 PM-8:30 AM; n=14, 77.8% registered nurses and n=4, 22.2% enrolled nurses). The total active task observation time for registered nurses was 164 hours and 29 minutes, and for enrolled nurses, it was 47 hours and 22 minutes. During the observation period, bed occupancy ranged from 71% to 90%, and 1044 patients were discharged from the wards, representing 5559 bed days.

Task Load Over a 24-Hour Period

Task load varied over the course of 24 hours, with higher variability at night—particularly for enrolled nurses (Figure 1). During the day, the highest peak in task load for registered and enrolled nurses was between 8 AM and 9 AM, whereas the lowest task load was between 6 PM and 7 PM for registered nurses and between 7 PM and 8 PM for enrolled nurses. In the night shift, the highest task load peak was between 6 AM and 7 AM for registered nurses and between 11 PM and midnight for enrolled nurses. Conversely, the lowest task load was observed from 4 AM to 5 AM for registered nurses and midnight to 1 AM for enrolled nurses.

Figure 1. Total task load (minutes) by hour for a 24-hour period (task load by hour exceeds 60 minutes due to multitasking) for registered nurses (blue) and enrolled nurses (pink).

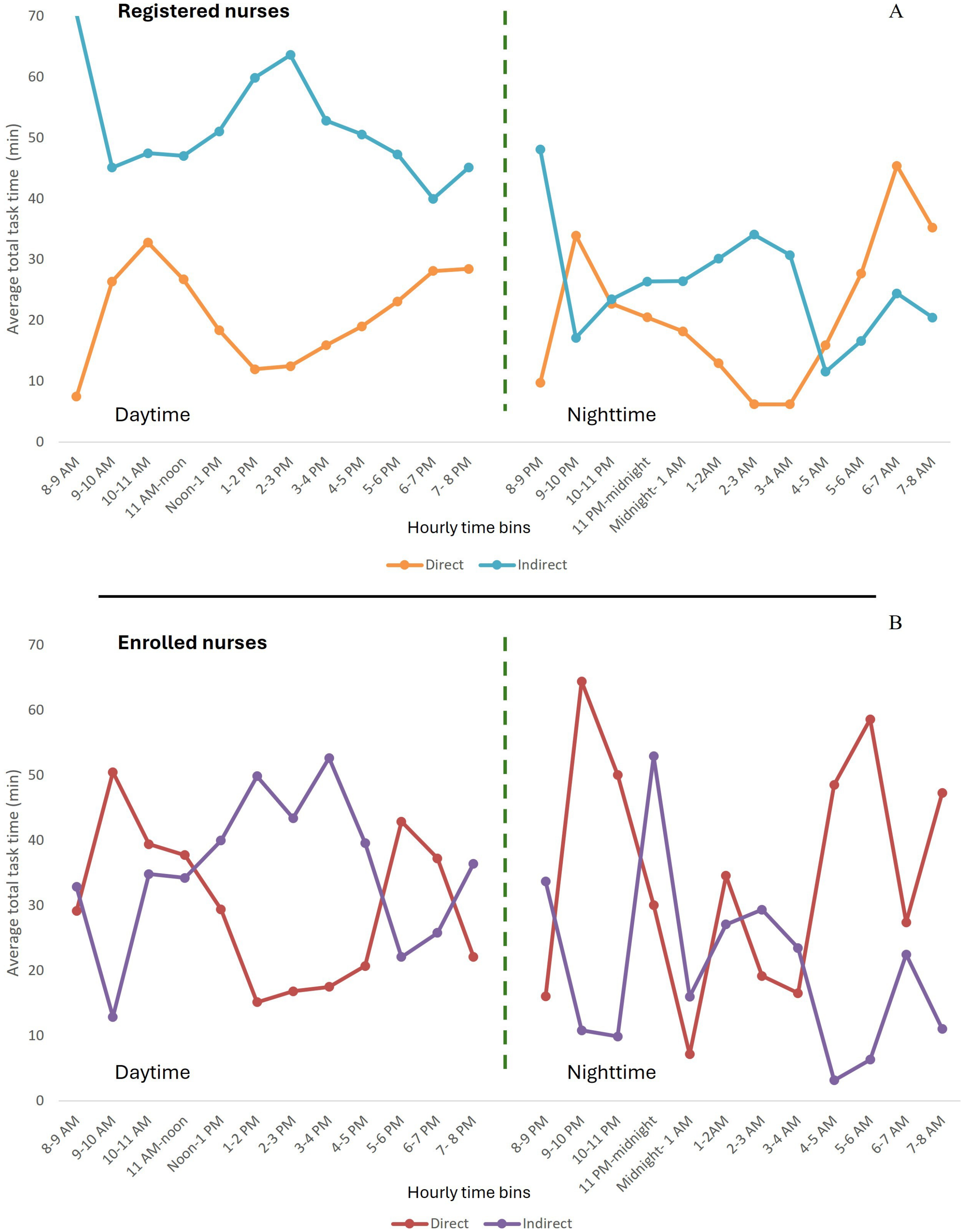


Task Type: Direct and Indirect Nursing Care Tasks

During the day, registered nurses spent an average of 30% (248 min; SD 74.6) of their time on direct clinical care and 70% (587 min; SD 98.9) of their time on indirect care tasks (Figure 2 and Table 2). Enrolled nurses, in contrast, spent an average of 46% (351 min; SD 52.5) of their time on direct care tasks and 54% (411 min; SD 73.2) of their time on indirect care tasks. At night, the proportion of time spent on direct care tasks increased for both groups: registered nurses spent an average of 42% (295 min; SD 78.9) of their time on direct care tasks, whereas enrolled nurses spent 61% (436 min; SD 98.5) of their time on direct care tasks, with the remainder dedicated to indirect care tasks (410 min, 58%; SD 67.2) for registered nurses, and 39% (275 min; SD 31.7) for enrolled nurses.

For registered nurses, indirect tasks dominated, with a consistently higher average total task load during the daytime (Figure 2). Direct task load typically remained at less than 30 minutes per hour, with a peak between 10 AM and noon and between 6 PM and 8 PM. At night, there was a noticeable drop in time spent on indirect tasks, and time spent on direct care tasks gradually decreased until 3 AM. From 3 AM onward, direct care tasks increased, peaking at 6 AM. For enrolled nurses, time spent on direct care tasks tended to dominate over time spent on indirect care tasks for much of the day, especially in the early morning and late afternoon, with a dip in the middle of the day. At night, there was considerable variability in both direct and indirect care tasks. There were notable spikes in direct care tasks (eg, around 11 PM-1 AM and 5 AM - 7 AM) and indirect care tasks (eg, 11 PM-midnight), suggesting time-specific care demands.

Figure 2. Direct and indirect total task load (minutes) by hour for (A) registered nurses and (B) enrolled nurses.



For registered nurses, medication handling (88/834 min, 10%), procedures (46/834 min, 5%), and patient communication (46/834 min, 5%) were the largest contributors to direct care task load during the day (percentage of total task time), with no change at night (Table 2). Staff communication (134/834 min, 16%), data entry into the medical record system (117/834 min, 14%), and record viewing (104/834 min, 12%) were the largest contributors to indirect care task load. At night, data entry and record viewing remained as the top tasks, but time spent on staff communication decreased, whereas handover time increased from 5% (38/834 min) during the day to 8% (59/705 min) at night.

For enrolled nurses, procedures (85/764 min, 11%), assisting with toileting or diaper changes (57/764 min, 8%), and patient communication (57/764 min, 8%) were the largest contributors to direct care task load during the day (percentage of total task time), with no change at night. In addition, the proportion of task time spent on vital sign taking increased from 4% (33/764 min) during the day to 12% (82/711 min) at night. Staff communication (107/764 min, 14%), data entry into the medical record system (90/764 min, 12%), and record viewing (60/764 min, 8%) were the largest contributors to indirect care task load during the day. At nighttime, data entry and record viewing remained high contributors to task time, but staff communication decreased to 2% (11/711 min), whereas observation of patients in the ward became the third largest contributor at 7% (52/711 min).

Table . Average time taken (minutes) on tasks during the day or night for registered nurses (RNs) or enrolled nurses (ENs).

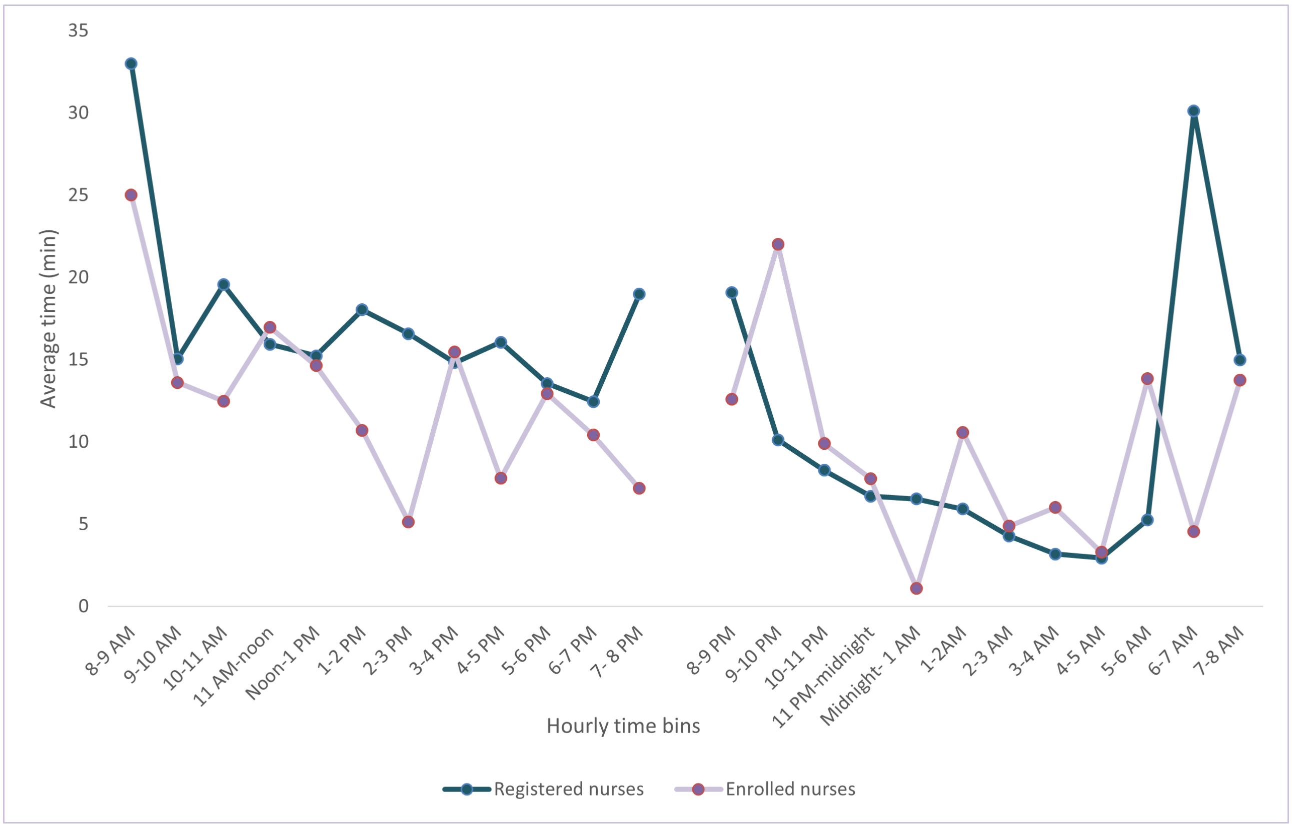
Task category, subcategory, and task codes	Time taken on tasks during a day shift (min), mean (SD)		Time taken on tasks during a night shift (min), mean (SD)	
	RN	EN	RN	EN
Direct care tasks				
Supporting activities of daily living				
Ambulation	2 (2.7)	10 (7.7)	3 (4.7)	7 (2.0
Bathing	13 (17.2)	30 (20.2)	2 (5.7)	7 (6.0)
Changing bedding	4 (5.2)	12 (7.7)	1 (1.8)	2 (1.5)
Diapering or assisting with toileting	12 (13.3)	57 (30.2)	33 (24.7)	103 (65.7)
Assisting with food and drink	9 (11.5)	19 (14.0)	3 (4.2)	18 (7.5)
Patient communication				
Nurse to patient	46 (22.6)	57 (26.7)	62 (41.4)	99 (112.2)
Meal ordering	0.4 (1.1)	4 (6.4)	1 (2.3)	2 (1.4)
Attending the patient call bell	1 (2.6)	2 (2.0)	2 (3.0)	4 (1.3)
Clinical care				
Vital sign taking	5 (6.4)	33 (12.4)	17 (12.9)	82 (23.2)
Laboratory samples	9 (13.1)	1 (2.1)	26 (20.1)	3 (5.8)
Other assessments and procedures	46 (24.7)	85 (25.6)	41 (22.8)	87 (16.5)
Medication handling	88 (44.3)	11 (13.3)	96 (34.7)	4 (3.3)
Patient comfort	4 (3.0)	14 (8.4)	5 (5.2)	4 (3.4)
Patient transfer (diagnostics)	5 (12.0)	8 (17.4)	0.3 (1.2)	5 (10.3)
Waste disposal (clinical and nonclinical waste)	3 (2.1)	9 (2.8)	3 (2.4)	10 (4.2)
Indirect care tasks				
Administrative				
Electronic medical record data entry	117 (37.2)	90 (38.6)	92 (32.3)	59 (23.1)
Record viewing (no data entry)	104 (41.9)	60 (43.8)	92 (39.3)	53 (14.2)
Nonclinical administrative tasks	24 (21.3)	17 (18.4)	9 (14.7)	7 (3.7)
Discharge or admission	19 (16.9)	4 (4.3)	8 (13.6)	3 (2.7)
Staff communication				
In-person staff member to staff member	134 (36.6)	107 (18.4)	46 (41.0)	11 (9.5)
Remote staff member to staff member	22 (11.2)	2 (1.4)	8 (6.6)	0 (0)
Remote staff member to caregiver	1 (1.8)	0 (0)	0.4 (1.0)	0 (0)
Handover	38 (30.5)	16 (15.1)	59 (23.9)	18 (21.4)
Team meetings	22 (14.6)	11 (16.4)	10 (7.1)	10 (14.7)
Staff education				
Staff education	36 (35.5)	4 (6.2)	3 (5.8)	0.4 (0.8)

Task category, subcategory, and task codes	Time taken on tasks during a day shift (min), mean (SD)		Time taken on tasks during a night shift (min), mean (SD)	
	RN	EN	RN	EN
Ward observation				
Observing patients	6 (8.3)	8 (5.3)	41 (70.9)	52 (69.7)
Break time				
Break	64 (32.2)	93 (22.4)	40 (27.3)	61 (3.2)

Multitasking Load

During a 24-hour period, registered nurses typically spent 209 (SD 51.8) minutes multitasking in the day and 117 (SD 41.0) minutes at night. For enrolled nurses, 152 (SD 54.7) minutes were spent multitasking in the day and 110 (SD 75.9) minutes at night. The frequency of occurrence varied over the course of the day (Figure 3). During the daytime, the period with the highest multitasking load was between 8 AM and 9 AM for registered nurses (33, SD 14.6 min) and enrolled nurses (25, SD 11.7 min), and the lowest multitasking load was observed between 6 PM and 7 PM for registered nurses and between 2 PM and 3 PM for enrolled nurses. At nighttime, the period with the highest level of multitasking was 6 AM to 7 AM for registered nurses (30, SD 33.1 min) and 9 PM to 10 PM for enrolled nurses (22, SD 16.3 min).

Figure 3. Average time (minutes) spent multitasking in each hour for a 24-hour period by registered nurses (blue) and enrolled nurses (pink).



Discussion

Principal Findings

To address ongoing workforce challenges, there is a pressing need for role redesign and the careful application of technology to support nursing practice. This study provided empirical insights into how nurses in general medicine wards spend their time across a 24-hour period, including the distribution of direct and indirect care activities and the occurrence of multitasking. This study is part of a wider program of work to inform how virtual nursing roles can be designed and integrated into ward workflows by identifying which tasks may be amenable to remote support and during which times support may be most beneficial.

Our findings show that nurses spent only 30% (247/834 min) to 46% (352/764 min) of their time on direct clinical care; the remainder was dedicated to indirect care tasks such as documentation and coordination. Task loads frequently exceeded 60 minutes of activity per hour, indicating significant multitasking and overlapping responsibilities. Such patterns reflect recognized inefficiencies in inpatient workflows, where competing demands require nurses to switch rapidly between tasks, increasing cognitive load and potential for error. We also observed predictable peaks in indirect care duties—particularly around early-morning and evening shift transitions—where administrative and communication tasks accumulated. In contrast, night shift patterns demonstrated marked variability, with periods of low activity followed by compressed workloads toward the end of the shift, when cumulative fatigue is likely to be highest. These specific patterns represent risk-prone periods within the nursing workday.

From a service design perspective, these findings suggest that virtual nursing support may be particularly beneficial when targeted to predictable high-risk periods, such as shift transitions and late-night hours, rather than implemented as a constant or uniformly distributed resource. Our data show that documentation and coordination activities cluster at these transition points, creating periods where clinical sensemaking and narrative continuity may be compressed or fragmented. While often treated as discrete tasks, documentation and handover are essential to a nurse's understanding of patient care and response over time. Thus, the design of virtual nursing roles should support clinical sensemaking by assisting with preparatory documentation, information synthesis, and record completion while preserving the primary nurse's responsibility for clinical interpretation, evaluation, and relational care. In this way, virtual nursing supports continuity of care rather than displacing the ground nurse's knowledge of the patient.

Our analysis showed that nurses frequently experienced task loads exceeding 1 hour of activity per observed hour, reflecting substantial multitasking and the fragmented nature of nursing work [10,11,14,15]. While some multitasking may improve efficiency, excessive cognitive load increases the likelihood of errors and reduces care quality, underscoring the need to reconsider how workload is organized [19,20]. By mapping when peaks in documentation, coordination, and multitasking occur, we highlight concrete opportunities for virtual nursing integration. For example, indirect care tasks that cluster around shift handover—such as preparing documentation, updating EMR entries, and coordinating care plans—could be supported by virtual nurses operating remotely. Importantly, the high degree of task concurrency observed suggests that virtual nursing should prioritize offloading cognitively competing tasks (eg, documentation and coordination) rather than introducing additional parallel interactions that could further fragment attention.

Night shifts exhibited greater variability, particularly for enrolled nurses, with pronounced peaks and a late-shift surge, when fatigue is likely to impair performance and elevate error risk [21,22]. Prior studies have raised similar concerns, noting that staffing levels during night shifts often fail to meet patient needs, leading to increased stress and task compression or even unresolved tasks [23-25]. Although interventions such as scheduled napping and optimized lighting can mitigate fatigue [26-28], they do not address the underlying workload imbalance. These patterns point to specific opportunities for virtual nursing support, such as documentation, discharge preparation, remote monitoring, and assisting junior staff, to relieve peak pressures and enhance workflow continuity [29-31]. Aligning virtual nursing activity with these high-pressure windows offers a targeted approach to smoothing workflow peaks, reducing multitasking burden, and supporting safer, more sustainable practice.

Analysis of the types of nursing activities revealed that a substantial proportion of time was spent on indirect care tasks, particularly EMR documentation, by both registered and enrolled nurses. This aligns with extensive literature showing that administrative workload, especially documentation, is a major contributor to reduced direct care time, job dissatisfaction, and burnout [10,14,20,32,33]. From the perspective of the theory of human caring by Watson [13], excessive administrative demands diminish nurses' capacity to engage in the relational, patient-centered interactions that underpin caring-healing practices, such as being fully present, developing trust, and supporting patients' emotional and existential needs. Our findings reinforce these concerns by showing that administrative peaks occur at predictable times, particularly during shift changes, thereby reducing opportunities for therapeutic engagement. Rather than treating documentation reduction as a generic goal, our findings indicate that documentation support is most critical during temporally concentrated peaks—particularly at shift transitions, where administrative demands can displace opportunities for patient-facing care. These patterns highlight clear opportunities for workflow redesign, including improved handover protocols, EMR-integrated automation tools, and shifting routine documentation to virtual care teams or dedicated virtual administrative assistants. Early evaluations of virtual nursing models show promise in reducing documentation burden, improving workflow efficiency, and enhancing staff satisfaction [34-37]. Our data help identify where such support would be most impactful, ultimately enabling bedside nurses to devote greater attention to the caring practices central to the nursing profession.

Taken together, these insights offer timely evidence to guide the development of virtual nursing roles within inpatient workflows. Virtual nurses, equipped with real-time access to EMRs, vital sign dashboards, secure messaging, and telepresence tools, could assume a range of indirect care tasks—documentation, discharge coordination, remote education delivery, and virtual rounding [29-31,35-38]. Importantly, we should tailor support by staff role: for registered nurses, reducing documentation and coordination workload allows for greater focus on complex clinical care, whereas for enrolled nurses, virtual teams could assist with supervisory or routine administrative tasks [29-31,35-38]. Over time, this infrastructure also provides a foundation for automating selected processes with artificial intelligence–enabled tools, contributing to more scalable and sustainable workforce models.

At the same time, it is essential that the ethical considerations of virtual nursing are taken into account. Redistributing nursing work to virtual roles raises important ethical considerations related to professional responsibility, accountability, and the nurse-patient relationship. While indirect care activities may be performed remotely, clinical judgment, evaluation of patient responses, and ownership of care outcomes must remain with the primary nurse responsible for the patient. Therefore, our findings highlight the importance of designing virtual nursing models that reduce cognitive and administrative burden without fragmenting accountability or distancing nurses from patient care, ensuring that virtual support enhances—rather than replaces—the ethical commitments embedded in bedside nursing practice.

Limitations

Our direct observations allowed us to gather unbiased data on nursing processes and report objectively on time use, overcoming the limitations of qualitative interview or survey data, which may be prone to bias. Our observation checklist was comprehensive, allowing for a fine-grained analysis of the task load. However, limitations must be acknowledged. We cannot ignore the Hawthorne effect, where staff may alter their behavior while being observed. We attempted to minimize this by briefing nursing teams and taking multiple sampling points over a 3-month period. There may also have been issues with observer variability. To minimize this risk, we conducted pilot work and training sessions with each observer to standardize the process. Observers were also encouraged to discuss issues and ask for clarifications during regular team meetings. Finally, our sampling took place during a 3-month period, which may not accurately reflect the average task load across the year.

Conclusions

This time-and-motion study documents the substantial and complex workload experienced by inpatient nursing staff over a 24-hour period across different nurse roles. The data reveal consistently high task demands, frequent multitasking, and pronounced peaks and troughs in workload throughout the day and night. These patterns suggest significant cognitive strain, with potential consequences for staff well-being and patient safety. These insights can inform the design of virtual nursing models or other technology-enabled workforce innovations. Future research should test and evaluate these models through staged implementation and outcome assessment, ensuring that virtual and hybrid care teams are safe, effective, and responsive to the realities of inpatient workflows.

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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: JS, EHHC, SYP, AWY
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Funding acquisition: AWY, EHHC
Investigation: JS, EHHC, SYP, JXXL, CK, AA, JMA, HWL, AB, EC, CY, EH, AWY
Methodology: JS, EHHC, SYP, JL, PC, AWY
Project administration: AWY, EHHC
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Conflicts of Interest

None declared.

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Abbreviations

EMR: electronic medical record

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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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Exploring the Impact of Electronic Medical Record–Enabled Versus Paper-Based Systems on the Quality of Nursing Handover: Comparative Case-Study

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Abstract

Background: Ineffective clinical handover has the potential to compromise patient safety and quality of care. Standardizing the handover process is a widely adopted improvement strategy intended to reduce failures of information transfer. By enabling real-time access to patient information, electronic medical records (EMRs) could address communication issues inherent to nursing handover.

Objective: This case study sought to compare the quality of nursing handover occurring at EMR-enabled sites with that occurring at paper-based sites, within a single Australian public health service.

Methods: A comparative case study design was used, using quantitative data collected from observational audits of 60 handovers and posthandover surveys conducted in EMR-enabled and paper-based ward environments. Handover quality was measured through compliance with the organization's Clinical Handover Standard and staff-reported perceptions, enabling comparison between cohorts.

Results: Compared with paper-based wards, EMR-enabled wards demonstrated more consistent communication of clinical alerts and risks and fewer interruptions, whereas paper-based wards showed higher rates of bedside handover and patient engagement.

Conclusions: EMR implementation alone does not ensure high-quality nursing handover. EMR interface design and functionality may act as a barrier to bedside handover and patient engagement, and contribute to continued reliance on paper-based artifacts. Targeted EMR design and nursing informatics-led optimization are required to better support nursing handover as a complex and cognitively challenging communication process.

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KEYWORDS

nursing handover; electronic medical record; electronic health record; health information systems; patient engagement

Introduction

Overview

Nurses play a vital role in determining the clinical outcomes of their patients, particularly in relation to ensuring patient safety and continuity of care [1]. Extensive research demonstrates that deficiencies in clinical communication processes represent a significant risk to patient safety [2] and are a common source of sentinel events [3]. When communication is incomplete, unclear, or inaccurate, patient safety may be compromised [1].

Clinical handover is a critical and complex health care communication process, serving as the primary mechanism for transferring responsibility and accountability between shifts [4]. Effective and high-quality nursing handover is a core patient safety mechanism, facilitating the timely, accurate, and efficient exchange of clinical information [5]. Consistent with the National Safety and Quality Health Service (NSQHS) Standards, effective handover requires information to be clear, comprehensive, and precise to support safe, appropriate, and continuous care [6].

Conversely, inadequate or poorly executed clinical handovers can adversely affect patient outcomes [5]. Ineffective communication during handover has been associated with inaccurate clinical assessments [7], delayed diagnoses [6], inappropriate treatments, and medication errors [5]. The impacts of these failures range from minor disruptions to care to severe and potentially catastrophic outcomes. As health care systems increasingly adopt electronic medical records (EMRs) to support clinical communication, understanding how these systems influence the quality and safety of nursing handover is essential.

Background

Efforts to structure and standardize nursing handover processes are often recognized as key improvement strategies for improving the quality and safety of clinical communication [8]. Standardized communication protocols and structured handover tools such as ISOBAR (Identification Situation Observations Background Assessment/Action Recommendation) [9] are "intended to prevent failures of information transfer" [10] by ensuring that information shared is relevant, concise, and focused [5]. Handover mnemonics like ISOBAR reduce the cognitive workload associated with performing handover [11,12] and were designed to overcome differences in communication styles, a factor contributing to communication errors [13]. By streamlining the handover process, these tools also enhance situational awareness within team-based environments, supporting the development of a shared mental model of a patient's clinical status [13,14]. Standardizing handover processes is therefore a frequent recommendation aimed at improving handover quality and patient outcomes.

In Australia, NSQHS Standards provide a quality assurance mechanism and "a nationally consistent statement about the standard of care consumers can expect from their health service organizations" [15]. NSQHS Standard 6, "Communicating for Safety includes the criterion for communication at clinical handover," encompassing structured clinical handover, defining minimum information content of handover, key principles of clinical handover, and engaging patients and caregivers in clinical handover processes [15].

Increasingly, bedside handover has been adopted as standard practice in Australian hospitals [1] and is promoted as a strategy to enhance patient engagement, transparency, and patient-centered care [16]. Best practice bedside handover requires nurses to communicate accurate, comprehensive, and contemporaneous clinical information in real time [5], often in the presence of the patient, their families, and caregivers. While this model of handover offers important benefits [1,16], it also increases the complexity of information exchange [17], requiring nurses to synthesize and communicate large volumes of clinical data efficiently [18] while maintaining patient engagement [16] and situational awareness [11,13]. These demands place heightened emphasis on the availability, accuracy, and usability of clinical information at the point of care, and on the systems through which that information is accessed and communicated during handover.

In this context, EMRs have been introduced internationally as a means of supporting complex clinical communication processes, including nursing handover. EMRs are clinical information systems that facilitate real-time access to patient data and provide structured system-level processes intended to support patient safety, quality improvement, and compliance with expected standards of practice [19,20]. Key patient safety mechanisms include electronic prescribing and medication administration, the use of alerts, checklists, and predictive tools and embedded evidence-based practices, supporting decision making at the point of care [19,21]. Beyond strengthening compliance, EMRs also enable continuous quality improvement by generating routinely collected data that can be used to monitor performance, identify variations in practice, and inform iterative improvement cycles [19].

With real-time access to up-to-date patient information, EMRs have been proposed as a means to address the communication challenges inherent to clinical nursing handover [9]. EMRs have the potential to support nursing handover through the use of structured EMR-based handover tools, thus aligning with the intent of NSQHS Standard 6, by supporting timely, accurate, and standardized communication of critical patient information [5].

The introduction of an EMR in itself does not guarantee improvements in clinical communication or patient safety. The literature remains equivocal regarding the extent to which EMRs improve efficiencies in health care, with some studies noting potential adverse effects on nursing handover, including increased work and decreased efficiencies [22,23]. Poorly planned or ineffective implementations of an EMR may disrupt established nursing workflows and may fail to provide the required cognitive support nurses require during handover [22,24]. Information fragmentation within EMRs and the need to navigate multiple screens or data sources may further increase nurses' cognitive workload during handover, introducing new risks for both patients and clinicians [25,26]. Understanding both the intended benefits and unintended consequences of EMR adoption is essential to assessing their value in practice [27,28].

While EMRs provide the technological infrastructure to support structured and standardized handover, the effective translation of EMR functionality into safe and high-quality nursing practice is underpinned by nursing informatics capability. Nursing informatics describes the knowledge and skills required by registered nurses to integrate nursing science with information and computer sciences to manage, communicate, and apply clinical data, information, and knowledge in practice [29].

The presence of digital technology alone is insufficient to improve clinical outcomes. Contemporary nursing practice requires nurses to navigate an increasingly complex digital environment, meaningfully engage with digital systems, adapt workflows, and effectively use information within the realities of clinical practice [30,31], including during time-critical activities such as nursing handover. Nursing Informatics, therefore, provides an interpretive and operational lens through which the impact of EMR-facilitated handover can be understood. Within this context, nurses play a critical role in shaping documentation practices, information use, and workflow integration [32,33] in ways that either support or undermine the safety and quality objectives of a structured, best-practice nursing handover, occurring at the patient's bedside.

While handover standardization alone has the potential to improve the effectiveness and efficiency of nursing handover and contribute to safer patient care [15], high-quality research linking the implementation of EMR-facilitated structured nursing handover to impacts on patient-related outcomes is still lacking. A knowledge gap therefore exists, as does an opportunity for further exploration of EMR-mediated solutions that may serve to support, standardize, and therefore enhance nursing handover.

Despite the widespread implementation of EMRs and increasing adoption of bedside handover, there remains limited empirical evidence examining how EMR-facilitated structured nursing handover translates into practice, particularly when compared with handover occurring in non-EMR environments within the same health service. Understanding how differences in information systems, workflow integration, and nursing informatics capability influence the quality of handover is essential to determining whether EMRs achieve their intended safety and quality objectives.

This gap is particularly salient for health services implementing EMRs in a staged or hybrid manner, where variations in digital maturity create a natural opportunity to examine the impact of EMR-enabled handover in context. It is within this organizational and digital landscape that the present case study was situated.

Context

Eastern Health is a large public health service situated in Victoria, Australia, serving a wide catchment across Melbourne's east. The organization spans 6 local government areas, covering 2816 square kilometers and comprising 21 health service locations. Eastern Health's 3 largest acute hospital sites are Box Hill Hospital, Maroondah Hospital, and Angliss Hospital.

A full EMR was implemented at Box Hill Hospital in October 2017. At Angliss Hospital, Electronic Medication Prescribing and Administration was implemented in November 2016; however, inpatient clinical documentation has remained predominantly paper-based. At the time of the study (conducted March to May 2023), implementation of the full EMR across inpatient wards at Maroondah Hospital (including Electronic Medication Prescribing and Administration) and completion of the full EMR deployment at Angliss were planned for late 2025 and early 2026, respectively. As a result, Eastern Health operated within a hybrid digital environment with varying levels of maturity across sites.

The introduction of full EMR at Box Hill Hospital fundamentally altered the interface through which nurses accessed, synthesized, and communicated clinical information during handover. In contrast, nurses at Maroondah and Angliss continued to rely primarily on paper-based documentation supported by other limited digital systems. These contrasting documentation environments, operating within the same organization, provided a structured basis for systematic comparison of EMR-enabled and predominantly paper-based nursing handover within a shared organizational context.

The sampling frame comprised nursing handovers conducted on all acute general medical and acute general surgical wards across Box Hill, Maroondah, and Angliss Hospitals. Each site has a 24-hour emergency department and intensive care unit, providing comparable patient cohorts within their respective acute medical and acute surgical wards. The selection of these was intended to promote homogeneity between the EMR-enabled and non-EMR sites, thereby minimizing the impact of variability in patient acuity on nursing expertise and handover practices. A total of 12 wards were identified as suitable for inclusion in the study. The target population comprised clinical nursing staff responsible for conducting routine shift-to-shift handovers.

Study Purpose

The purpose of this case study was to examine and compare the quality of nursing handover conducted in fully EMR-enabled wards at Box Hill Hospital with handover occurring in predominantly paper-based documentation environments at Maroondah and Angliss Hospitals. Handover quality was examined within routine clinical practice and assessed using two complementary measures: (1) the degree of compliance with the organization's Clinical Handover Standard, and (2) clinical nursing staff's self-reported perceptions of handover quality.

This purpose aligns with the study's focus on understanding how differences in documentation environments and information access may shape the conduct and perceived quality of bedside nursing handover within a shared organizational context.

Aims

The primary aim of this study was to compare the quality of nursing handover in fully EMR-enabled wards and predominantly paper-based wards within acute inpatient settings.

Specifically, the study sought to compare nursing handover practices in fully EMR-enabled wards with those occurring in predominantly paper-based environments, by examining whether EMR presence was associated with:

- Higher-quality nursing handover, as measured by compliance with the organization's Clinical Handover Standard (Multimedia Appendix 1).
- Differences in duration of nursing handover.
- Differences in the level of patient engagement in the handover process.
- Differences in staff-reported perceptions of handover quality.

Methods

Design

To address the study purpose and aims, nursing handover practices were examined across EMR-enabled and predominantly paper-based wards within the same health service. This study used a comparative quantitative case-study design using 2 complementary quantitative data sources.

Case study research is “a distinctive form of empirical enquiry” [34] that investigates a contemporary phenomenon within its real-life context [35]. This approach is well-suited to health care settings, where complex clinical processes can be examined using observational methods alongside other data sources, allowing meaningful characteristics of real-world practice to be retained [34], while generating opportunities for more comprehensive explanations [36].

As described within the context section of this case study, the staged implementation of the EMR across Eastern Health provided a naturalistic opportunity to apply a comparative case study design, enabling examination of nursing handover practices in wards supported by a fully implemented EMR alongside those operating in predominantly paper-based environments. Comparative evaluations of health information systems remain relatively uncommon, with much of the existing literature relying on descriptive or correlational approaches [27]. As such, this design offered the potential to generate contextually grounded insights relevant to both local system optimization and the broader evidence base on formative evaluations of digital health systems.

This case study used 2 quantitative data collection instruments. First, structured observational audits of routine shift-to-shift nursing handover were conducted to assess handover quality based on observed compliance with key principles of Eastern Health’s Clinical Handover Standard. Second, posthandover surveys were administered to capture clinical nursing staff’s perceptions of the quality of handover received, with responses quantified using Likert-scales, responses to closed yes/no questions, and counts of affirmative responses. For both data sources, comparisons were undertaken between handover occurring in the EMR-enabled wards and those in predominantly paper-based wards. This multi-source quantitative approach enabled direct observation of the phenomenon being studied alongside quantified staff perceptions of handover quality [34].

Consistent with guidance on health information system evaluation, the use of multiple data sources allowed complementary insights to be integrated, supporting a more comprehensive understanding of nursing handover within differing documentation environments [27]. EMR-supported handover was examined from a nursing informatics perspective, focusing on nurses’ use of available documentation systems and the clinical information exchanged during routine handover practice.

The data collected and analyzed in this case study form part of a broader program of research examining nursing handover processes within EMR-enabled clinical environments. Subsequent analyses will explore nurses’ interaction with, and use of, EMR functionality during handover in greater depth.

Participants

The study was conducted across acute general medical and acute general surgical inpatient wards within 3 hospital sites of a single public health service in Victoria, Australia. Participants in the observational audits and posthandover surveys were nurses conducting routine shift-to-shift nursing handovers on the 12 selected wards during the data collection period. The distribution of wards by site, documentation environment, and the number of handovers audited is presented in Table 1.

Table . Selected wards by site and number of handovers audited.

Site	Medical wards	Surgical wards	Medical record status	Total number of wards	Number of handovers audited
Box Hill	3	3	Full EMR[a]	6	30
Maroondah	2	2	Paper-based	4	20
Angliss	1	1	Paper-based	2	10
Total	6	6	—[b]	12	60

[a]EMR: electronic medical record.

[b]Not applicable.

For this comparative case study, the case was defined as the selected wards within the 3 hospitals of a single public health service. The unit of analysis was the individual shift-to-shift nursing handover. Data were collected between March and May 2023, across morning and afternoon shifts, encompassing both paper-based and EMR-enabled documentation environments.

Sampling

A convenience sampling approach was used, whereby nurses giving handover on the selected wards during scheduled data collection periods were invited to participate. To promote variation in observed practice, handovers were sampled sequentially across different days, shifts, and times within each ward to capture variation in routine practice. Five handovers per ward were targeted to ensure adequate representation of routine handover practices within each clinical context, while remaining feasible given the resource-intensive nature of direct observational auditing across multiple sites. Five nursing handovers were sampled per ward, resulting in a total of 60 observed handovers across the 12 wards.

Inclusion and Exclusion Criteria

Eligibility for participation was defined to ensure consistency across wards and sites.

Inclusion Criteria

Participants were eligible if they were registered nurses with current nursing registration, used by Eastern Health, and scheduled to participate in shift-to-shift nursing handover during the data collection period. All participants were required to provide informed consent.

Exclusion Criteria

Undergraduate nurses, assistants in nursing, agency nurses, and staff who declined to participate or did not consent to the collection of basic demographic information were excluded from the study.

Ethical Considerations

Ethics approval was obtained from Eastern Health's Human Research Ethics Committee, HREC number LR22-042-84698. Reciprocal ethics approval was obtained from La Trobe University. Written informed consent was obtained from all nurse participants involved in the observational audits and posthandover surveys, including nurses giving and receiving handovers. Patients whose handovers were observed were provided with written information about the observational audit in advance. Patients were informed that no personal identifiers or health information would be collected or recorded as part of the audit. Verbal consent to proceed with handover observation was obtained from patients immediately prior to handover commencement. Participants received no financial or other compensation for their participation.

Data Collection

Overview

A total of 60 observational audits and corresponding posthandover surveys were conducted between March and May 2023. Observational audits occurred during the morning-to-afternoon (AM to PM) shift-to-shift nursing handover. All observational audits were undertaken by a single auditor to ensure consistency. Both the observational audit tool and the posthandover survey were completed using paper-based instruments at the point of data collection. Immediately following each observed handover, the nurse receiving the handover completed a posthandover survey. All paper-based data were subsequently entered into REDCap by the same auditor later on the day of collection, following completion of data collection activities for that day.

Each nurse was observed delivering handover once; however, nurses may have received handover and completed the posthandover survey on more than one occasion, consistent with the sampling approach and routine practice, resulting in up to 120 participants.

For each participating ward, 5 observational audits and posthandover surveys were completed over a period of 1 to 2 days. The observational audits comprised 30 handovers in fully EMR-enabled wards and 30 handovers conducted and observed in predominantly paper-based documentation environments. As this study represented an observational comparative case study and an exploratory examination of nursing handover practices, formal sample size or power calculations were not undertaken.

Observational Audit

The observational audit was designed to quantify the quality of nursing handover by measuring compliance with the organization's Clinical Handover Standard (Multimedia Appendix 1). This Standard addresses 11 key principles underpinning best practice clinical handover and is aligned with the NSQHS Standard 6: Communicating for Safety. These principles are summarized in Table 2.

Table . Principles for best practice handover. Extracted from the Eastern Health Clinical Handover Standard, November 2022, available in Multimedia Appendix 1.

Number	Principle
1	Are undertaken using a consistent and structured process, “ISOBAR,”[a] which includes a minimum dataset.
2	Recognize that clinical handover requires effective communication between clinicians, including an opportunity to clarify information.
3	Maintain the patient’s right to confidentiality and privacy; sharing of information is based upon the relevance and impact to care and outcomes
4	Promote inclusion of patients and, where appropriate, their caregivers, while acknowledging that sensitivity is required where other patients or visitors may overhear patient information.
5	Consider the need to engage interpreters if patients have communication difficulties, such as cultural and linguistic diverse backgrounds or hearing impairments.
6	Occur prior to, or at the time when clinician/s transfer care and accountability, and acknowledge the transfer of accountability for some or all of the patient’s care.
7	Ensure adequate preparation prior to undertaking a clinical handover, making certain that the process is efficient and that all relevant information is transferred.
8	The clinician providing direct care leads the clinical handover, and where possible, handover occurs as face-to-face communication.
9	Respect the importance of handover, with minimal interruptions or distractions.
10	Within mental health settings, a team handover occurs prior to individual handover to ensure all staff are aware of the current milieu and risk issues present within the unit.
11	Documentation of the handover is recorded within the progress notes, or equivalent, in accordance with the Clinical Documentation Standard.

[a]ISOBAR: Identification Situation Observations Background Assessment/Action Recommendation.

Health service organizations are required to implement governance frameworks, systems, and processes that support effective clinical communication during handover. Locally contextualized clinical handover standards provide a mechanism through which NSQHS requirements are operationalized at the organizational level, thereby supporting patient safety and quality of care [15].

Audit Tool Development

The observational audit tool was developed to assess whether handovers complied with established principles of effective clinical communication. Tool development occurred in partnership with Eastern Health’s Communicating for Safety Clinical Risk Governance Committee (CFS CRGC) to ensure content validity and alignment with established clinical governance standards. Audit questions were aligned with those used in previous organization-wide Clinical Nursing and Midwifery Handover Audits, enabling comparison with existing organizational data and reinforcing alignment with established quality and safety processes.

In determining the final audit tool, several decisions were made:

- Two principles of the Clinical Handover Standard (Principles 10 and 11) were considered outside of the scope of this study and were therefore excluded.
- The location of handover was identified as a key variable of interest in the context of a newly introduced digital interface. Specified within the Standard is that “where possible, clinical handover will occur face to face and in the patient’s presence (bedside handover).” This element was therefore included as a distinct principle for auditing.
- Handover efficiency was measured through handover duration and whether handover commenced and concluded on time, with all required staff present.
- Respect for the handover process was quantified by recording the number of interruptions occurring during each handover episode.

Ten principles were therefore included in the final audit framework. A total of 28 audit questions were used to assess compliance with these principles. Each question required a yes or no response, with the exception of interruptions and handover duration, which were recorded as counts and time (minutes), respectively. The full list of audit questions and their alignment with each principle is presented in Table 3.

Table . Observational audit questions in relation to each principle.

Principle	Questions	Response	Interpretation and data analysis
Handover occurs at the bedside	• Did handover occur at the bedside?	Y/N	% compliance with the principle per ward/cohort/overall.
Handover follows ISOBAR[a]	• Identify: Was the person/team involved in the handover introduced to the patient? • Identify: Was a 3-point ID check completed? • Situation: Was the current clinical situation of the patient (ie, stable, improving, deteriorating, and discharge plan) discussed? • Observation: Were recent clinical observations discussed? • Background: Was the relevant patient background/history, evaluation, and management to date shared? • Assessment: Were relevant clinical assessments, any concerns from assessments, or outstanding assessments/actions discussed? • Assessment: Were clinical risks (ie, falls, pressure injuries, delirium, malnutrition, behavior of concern [BOC]) discussed? • Assessment: Were clinical alerts (ie, safety concerns such as aggression/harms to others, infection control) discussed? • Request/recommendation: Were actions required and recommendations for ongoing care discussed, including responsibility for actions and agreed transfer of responsibility?	Y/N	% compliance for each question and % compliance with the principle per ward/cohort/overall.
Communication is effective	• Did the nurse leading the handover provide an opportunity to ask questions? • Did the nurse receiving the handover ask any questions to clarify the information received? • Did the nurse receiving the handover ask any questions to seek information that was not offered?	Y/N	Principle deemed met if any 1 question answered in the affirmative and % compliance with the principle per ward/cohort/overall.
Patient's right to confidentiality is maintained	• Was all the information provided at the bedside clinically relevant, avoiding information pertaining to sensitive social or clinical conditions?	Y/N	—[b]

Principle	Questions	Response	Interpretation and data analysis
Inclusion of the patient, family, or caregiver is promoted	• Was the patient greeted during the handover process? • Was the handover process explained to the patient? • Was the patient and caregiver/family member present included in the handover? • Was the patient given an opportunity to ask questions or discuss goals or raise concerns?	Y/N	% compliance for each question and % compliance with the principle per ward/cohort/overall.
Interpreters are used where needed	• Is the patient's first language or native language a language other than English? • Is there a language barrier present that would prevent the patient from being included in the handover? • Was an interpreter used during handover? • Was the future planning or booking, or did an interpreter discuss?	Y/N	% compliance with the principle per ward/cohort/overall. Logic used: If N recorded for Q1 or Q2=N/A If Y recorded for Q1 & Q2 (interpreter deemed needed) AND Y recorded for either Q3 OR Q4 (interpreter is used or planned)=Y/N.
Transfer of care and accountability is acknowledged	• Was there an acknowledgment of a transfer of care or accountability? *SELECT ALL THAT APPLY: • Discussion of actions required and responsibility for actions occurred • Review of treatment and care plan, clinical risks, management, and recommendations occurred • Review of information and clarification sought by the recipient • Acknowledgment and agreement from the recipient of the plan of care	Y/N. Principle deemed met if any 1 question answered in the affirmative	% compliance with the principle per ward/cohort/overall.
The direct care clinician leads handover and, where possible, delivered face to face	• Did the clinician providing direct care lead the handover? • Was the handover delivered face to face?	Y/N	% compliance for each question and % compliance with the principle per ward/cohort/overall.
Respect for process – minimized interruptions and distractions	Was the handover interrupted?	Number of interruptions recorded	Number of interruptions recorded per ward/cohort/overall.
Handover is efficient	Time taken to deliver the handover	Duration of handover in minutes (rounded)	Duration of handover per ward/cohort/overall.
Handover is efficient	Handover started and finished on time, with all required staff present?	Y/N	% compliance for the question.

[a]ISOBAR: Identification Situation Observations Background Assessment/Action Recommendation.

[b]Not applicable.

Posthandover Survey

The posthandover survey was designed to complement the objective data captured in the observational audits by capturing the immediate assessment of handover quality from the perspective of the handover recipient. Survey items were developed to quantify staff perceptions of satisfaction, quality, efficacy, and efficiency associated with each handover episode. This approach is consistent with the literature, which emphasizes the importance of accurate and comprehensive communication during clinical handover to support patient safety [6].

The survey was developed collaboratively with the organization's CFS CRGC to ensure alignment with clinical handover principles and organizational standards, and comprised 11 items: 5 Likert-scale questions, 5 closed-ended (yes/no) questions, and 1 free text response. Likert-scale items were scored on a 5-point scale, with a composite score (out of 25) calculated for questions assessing satisfaction, quality, and perceived efficacy. Closed-ended items were analyzed using frequency counts and percentages. Free-text responses were reviewed descriptively; however, due to limited volume and specificity, they were not subjected to formal qualitative analysis. The full list of posthandover survey questions, response formats, and corresponding analytical approaches is provided in Table 4.

While formal psychometric analyses (eg, internal consistency) were not feasible due to the exploratory nature of the study, sample size, methodological triangulation with the observational audits supported interpretive validity.

Table . Posthandover survey questions.

Question	Construct	Response	Interpretation and data analysis
Are you satisfied with the handover you just received?	Satisfaction	Likert scale 1 - 5: 1=very dissatisfied 2=dissatisfied 3=neither satisfied nor dissatisfied 4=satisfied 5=very satisfied	Score (out of 5) for each question per ward/cohort/overall Composite score (out of 25) for questions 1 - 5 per ward/cohort/overall
Rate the overall quality of the handover received	Quality	Likert scale 1 - 5: 1=very poor 2=poor 3=average 4=good 5=excellent	Composite score (out of 25) for questions 1 - 5 per ward/cohort/overall
Did the handover follow the ISOBAR format?	Quality	Likert scale 1 - 5: 1=strongly disagree 2=disagree 3=neither agree nor disagree 4=agree 5=strongly agree	Composite score (out of 25) for questions 1 - 5 per ward/cohort/overall
Rate how accurate you believe the handover was?	Efficacy	Likert scale 1 - 5: 1=very poor 2=poor 3=average 4=good 5=excellent	Composite score (out of 25) for questions 1 - 5 per ward/cohort/overall
Rate how comprehensive you believe the handover was?	Efficacy	Likert scale 1 - 5: 1=very poor 2=poor 3=average 4=good 5=excellent	Composite score (out of 25) for questions 1 - 5 per ward/cohort/overall
Was the required content effectively communicated?	Efficacy	Y/N	% occurrence (count of yes) per ward/cohort/overall
Were you given the opportunity to clarify information?	Efficacy	Y/N	% occurrence (count of yes) per ward/cohort/overall
Was there any specific information you felt was missing?	Efficacy	Y/N	% occurrence (count of no) per ward/cohort/overall
If Y to Q8: In a few short words, briefly state what information you believe was missing	Efficacy	Free text	To be themed where possible
Was the duration of handover appropriate?	Efficiency	Y/ N - too short N - too long	% occurrence (count of yes) per ward/cohort/overall
Was the inclusion of the patient, family, or caregiver promoted?	Quality	Y/N	% occurrence (count of yes) per ward/cohort/overall

It should be noted that staff perceptions of patient engagement were higher than what was observed in audits, suggesting possible overestimation due to social desirability bias or limited understanding of effective patient inclusion during handover. This discrepancy highlights the importance of combining objective and self-reported measures when evaluating handover quality.

Data Analysis

Overview

Data were extracted from REDCap into Microsoft Excel by the research team and deidentified prior to analysis. All data handling and analysis complied with institutional governance, ethical, and privacy requirements.

Observational Audits

For each audit question, the frequency of affirmative responses was calculated. Compliance with each handover principle was determined by aggregating question-level responses and summarized at the ward level, by cohort (EMR-enabled vs paper-based), and for the overall sample. Descriptive statistics, including mean and median values where appropriate, were generated to enable comparison between cohorts. The detailed analytic approach, itemized by audit question, is presented in Table 3.

Nonparametric tests (Kruskal-Wallis rank-sum test) were used for intergroup comparisons due to nonnormal distribution of data. Handover duration and frequency of interruptions were analyzed descriptively.

Posthandover Surveys

Posthandover survey data were analyzed descriptively. Likert-scale responses were summarized using mean and median values at the ward level, by cohort, and overall. For closed-ended (yes/no) questions, frequencies and percentages of affirmative responses were calculated across the same groupings.

A composite score was derived from the 5 Likert-scale items assessing satisfaction, quality, and perceived efficacy to provide an overall measure of staff perceptions of handover quality. Comparative analysis was undertaken to examine alignment between staff-reported perceptions and observed handover quality as measured through compliance with the Clinical Handover Standard.

The posthandover survey also included a single free-text question inviting respondents to identify any information they believed was missing from handover. Responses were limited and lacked sufficient depth for qualitative analysis and were therefore not subjected to formal qualitative analysis or reported in this paper.

Given the exploratory nature of the study and the relatively small sample size, formal effect size estimation was not undertaken, and results were interpreted primarily descriptively.

Validity and Reliability

Overview

The observational audit and posthandover survey instruments were developed in collaboration with the organization's CFS CRGC, supporting content validity and ensuring alignment with established clinical governance standards. Audit items were mapped directly to the organization's Clinical Handover Standard and aligned with the NSQHS Standard 6: Communicating for Safety, ensuring construct relevance and consistency with best-practice frameworks.

To enhance the validity of the findings, objective measures of handover quality derived from observational audit compliance with the Clinical Handover Standard were compared with self-reported staff perceptions of the handover quality captured through the posthandover survey, providing methodological triangulation. Use of a single trained auditor and standardized data collection procedures further supported reliability and methodological rigor.

Observational Audits

Design of the observational audits was purposefully aligned with previous organization-wide Clinical Nursing and Midwifery Handover Audits. This alignment supported consistency in measurement and enabled comparison with existing audit data, strengthening confidence in the reliability of the observational audit approach.

Posthandover Survey

As the posthandover survey captured individual staff perceptions, inherent limitations relating to subjectivity and response bias are acknowledged. While the survey instrument had not been previously administered within the organization, its development was informed by established handover constructs and aligned with the observational audit framework, supporting interpretive validity.

Results

Observational Audits

Overview

Observational audit data were first analyzed to compare overall compliance with the Clinical Handover Standard between paper-based and EMR-enabled wards. Compliance with individual principles of the Standard was then examined to identify areas of variation between the 2 cohorts.

Overall Compliance With the Clinical Handover Standard

Overview

Overall compliance with the Clinical Handover Standard was assessed across 10 key principles. Eight of these principles were evaluated as either met or not met. Table 5 presents percentage compliance for each of these 8 principles, along with overall compliance by cohort, expressed using mean and median values. This composite measure, derived from compliance across the audited principles, indicated broadly comparable overall handover quality between EMR-enabled and paper-based wards.

Table . Overall compliance with the standard.

Principle	Paper-based[a]		EMR[b]-enabled[c]	
	Mean	Median	Mean	Median
Handover occurs at the bedside (%)	83	80	63	60
Handover follows ISOBAR[d] (%)	80	78	83	78
Communication is effective (%)	100	100	100	100
Patient's right to confidentiality is maintained (%)	100	100	100	100
Inclusion of the patient, family, or caregiver is promoted (%)	70	68	43	37
Interpreters are employed where needed	—[e]	—	—	—
Transfer of care and accountability is acknowledged (%)	100	100	100	100
The direct care clinician leads handover and, where possible, delivered face to face (%)	100	100	100	100
Overall compliance (first 8 principles) (%)	90	100	84	100
Handover is efficient (handover duration) (minutes)	3.87	4	4.13	3.5

[a]Respect for process: 7 interruptions.

[b]EMR: electronic medical record.

[c]Respect for process: 7 interruptions.

[d]ISOBAR: Identification Situation Observations Background Assessment/Action Recommendation

[e]Not applicable. The principle, "Interpreters are employed as needed,"demonstrated insufficient data for comparative analysis, with only 2 instances of interpreter need identified across the sample. This has been reported descriptively and excluded from composite compliance to avoid disproportionate influence on results.

Paper-based wards demonstrated slightly higher mean overall compliance with the Clinical Handover Standard (90%) than EMR-enabled wards (84%), although median compliance was equivalent across cohorts. This pattern suggests broadly comparable aggregate performance, with observed differences driven by variation across specific handover principles, rather than consistent divergence across all domains.

The 2 remaining principles, "Respect for Process" and "Handover is Efficient," were assessed using alternative metrics, quantified by the number of interruptions that occurred, and the duration of handover, respectively.

Interruptions During Handover

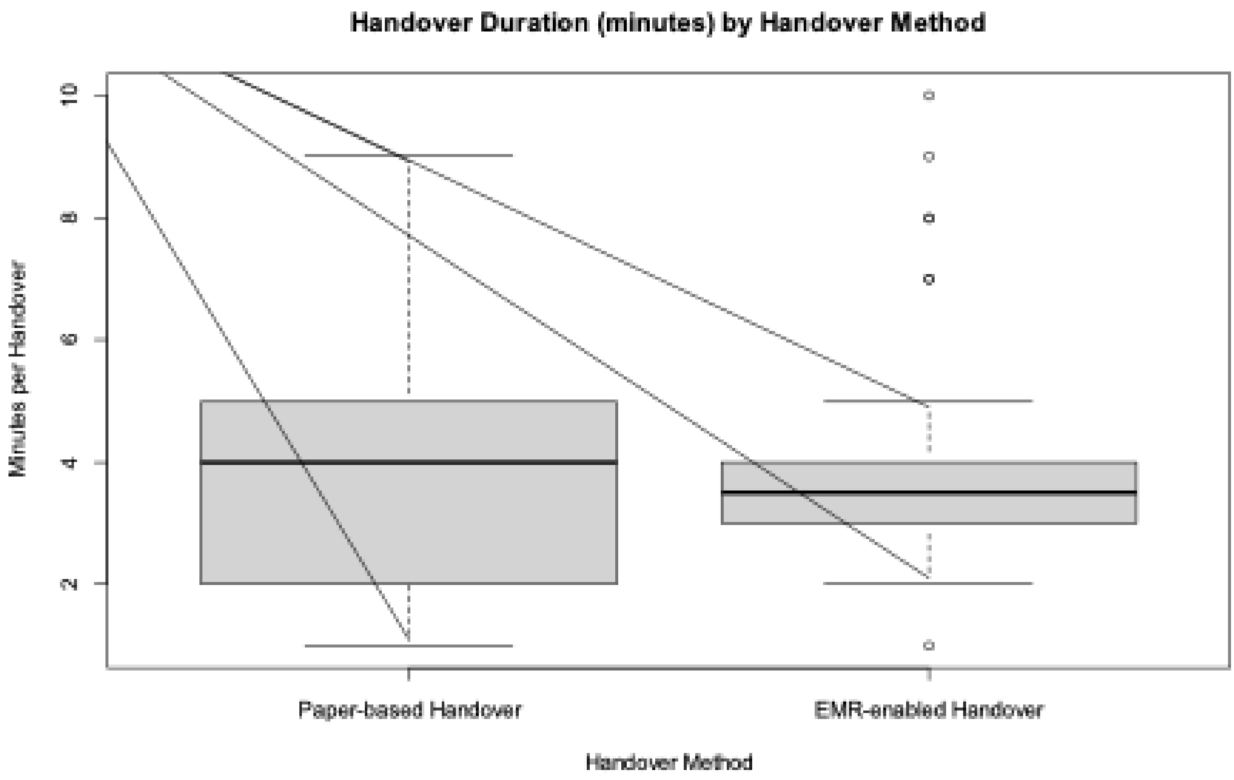
Across the 60 handovers observed, a total of 8 interruptions were recorded. Seven interruptions occurred in 2 paper-based wards, while only one interruption was observed in an EMR-enabled ward.

Handover Duration

Median handover duration was slightly longer in paper-based wards (4 min) compared with EMR-enabled wards (3.5 min). Initial analysis was considered using ANOVA; however, the data failed tests of normality (Shapiro–Wilk test for normality). Consequently, nonparametric methods, including the Kruskal–Wallis rank-sum test, were used. This analysis indicated no statistically significant differences between the paper-based and EMR-enabled wards, likely influenced by the small sample size.

As illustrated in Figure 1, the median handover duration was slightly longer for paper-based handover (4 min) compared with EMR-enabled handover (3.5 min), suggesting a marginally quicker handover in EMR settings. However, the IQR was wider for paper-based handovers (2.75 vs 1), indicating greater variability within the middle 50% of values, suggesting more consistent handover duration in EMR-enabled settings.

Figure 1. Handover duration by handover method.



Compliance Against Individual Principles of the Standard

Overview

Four principles demonstrated 100% compliance across all 12 wards:

- Communication is effective,
- Patient’s right to confidentiality is maintained,
- Transfer of care and accountability occur,
- Direct care clinician leads handover.

Analysis of the remaining principles revealed several areas of divergence between cohorts, as outlined below.

Compliance With ISOBAR

Compliance with all 9 ISOBAR elements was reviewed for both cohorts. Median compliance scores were equivalent between cohorts (0.778); however, EMR-enabled wards demonstrated a slightly higher mean compliance score (0.833) compared with paper-based wards (0.804). Paper-based wards exhibited greater variability, reflected by a wider IQR (0.194 vs 0.111). Both cohorts achieved the maximum possible compliance score of 1.0. These findings are illustrated in Figure 2.

Further examination of individual ISOBAR elements identified differences in the discussion of clinical risks and clinical alerts (Figure 3).

Figure 2. Compliance with ISOBAR by handover method. EMR: electronic medical record; ISOBAR: Identification, Situation, Observations, Background, Assessment/Action, Recommendation.

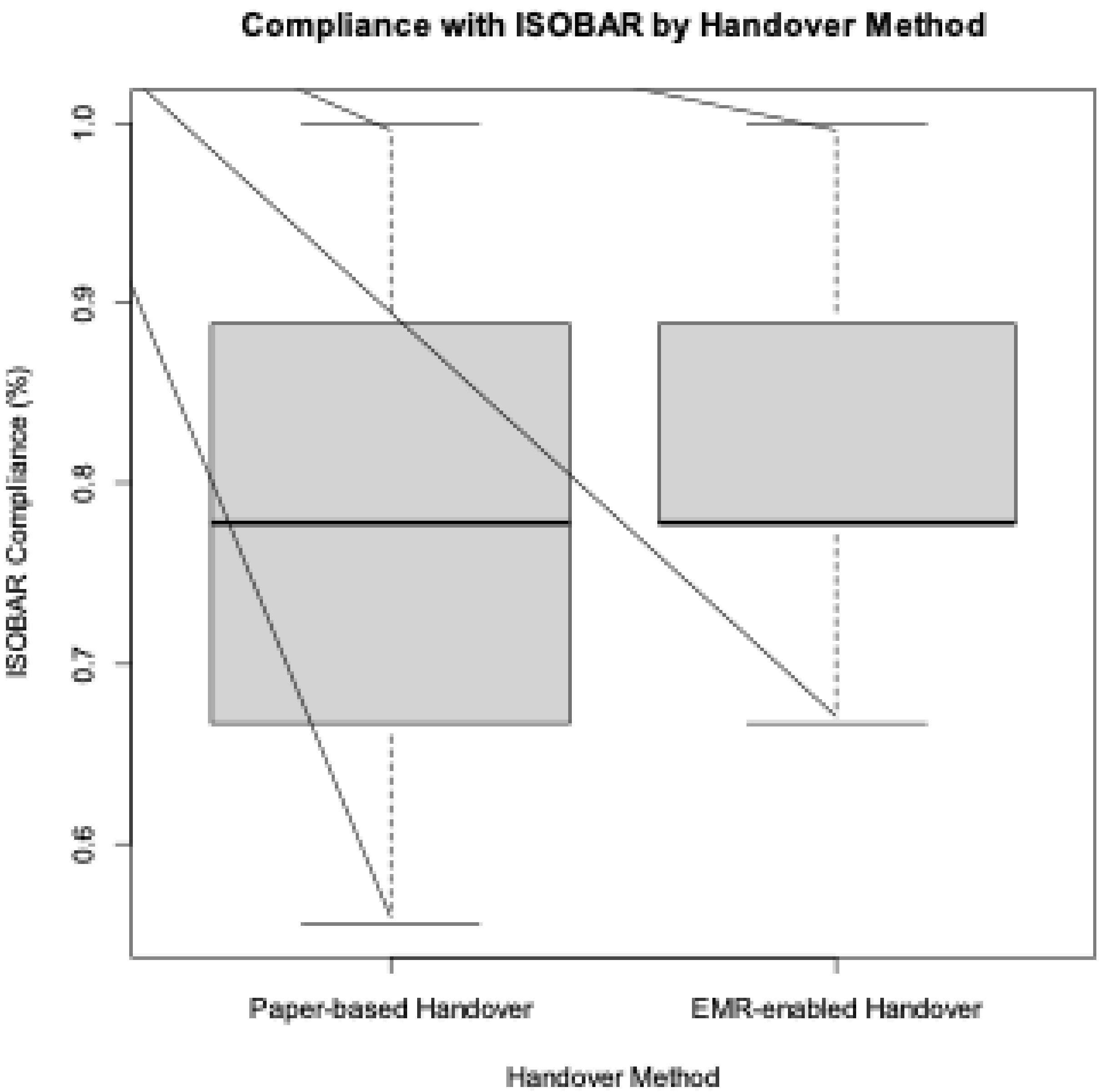
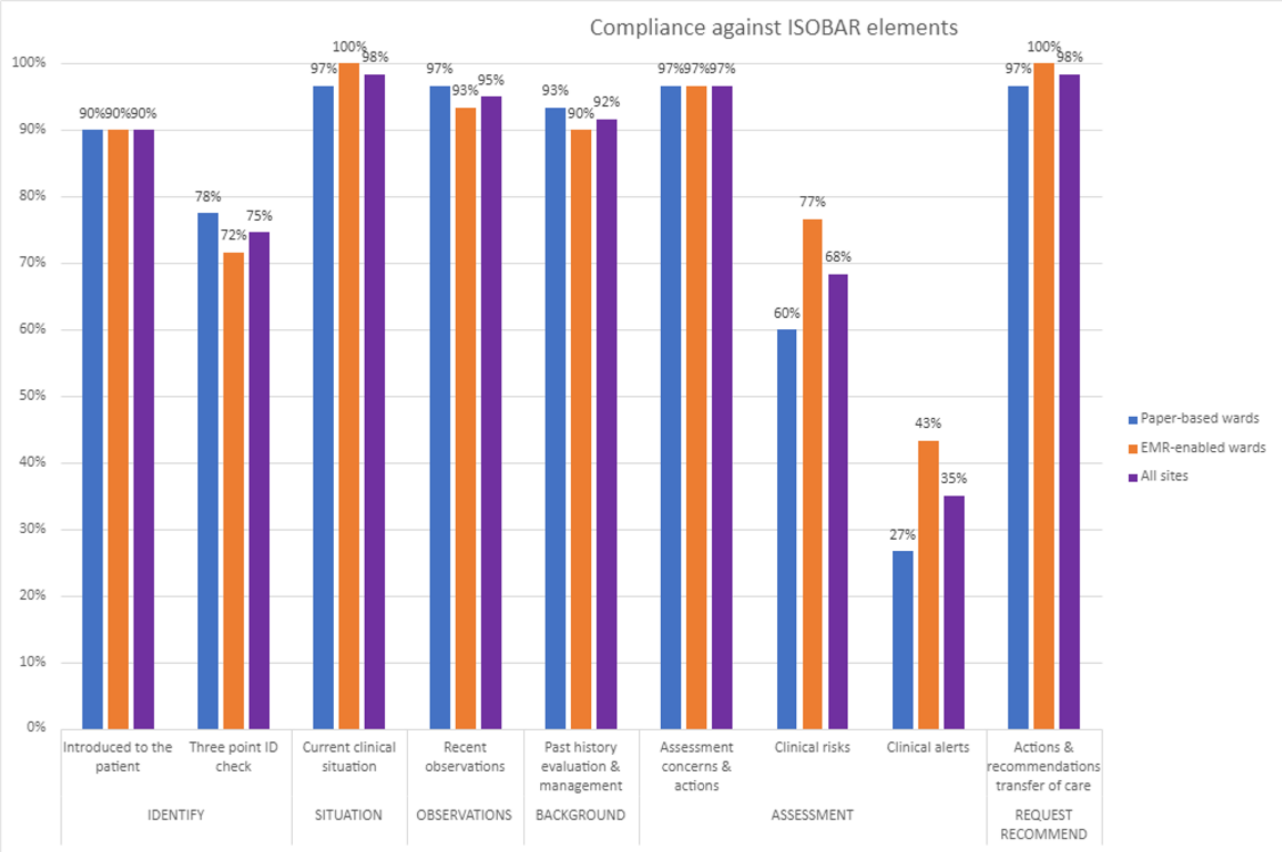


Figure 3. Compliance against ISOBAR elements. EMR: electronic medical record; ISOBAR: Identification, Situation, Observations, Background, Assessment/Action, Recommendation.



Clinical Risks and Clinical Alerts Were Discussed

Handover of clinical risks and clinical alerts occurred more frequently in EMR-enabled wards. Clinical risks were discussed in 77% of EMR-enabled handovers compared with 60% in paper-based wards, while clinical alerts were discussed in 43% of EMR-enabled handovers compared with only 27% in the paper-based wards.

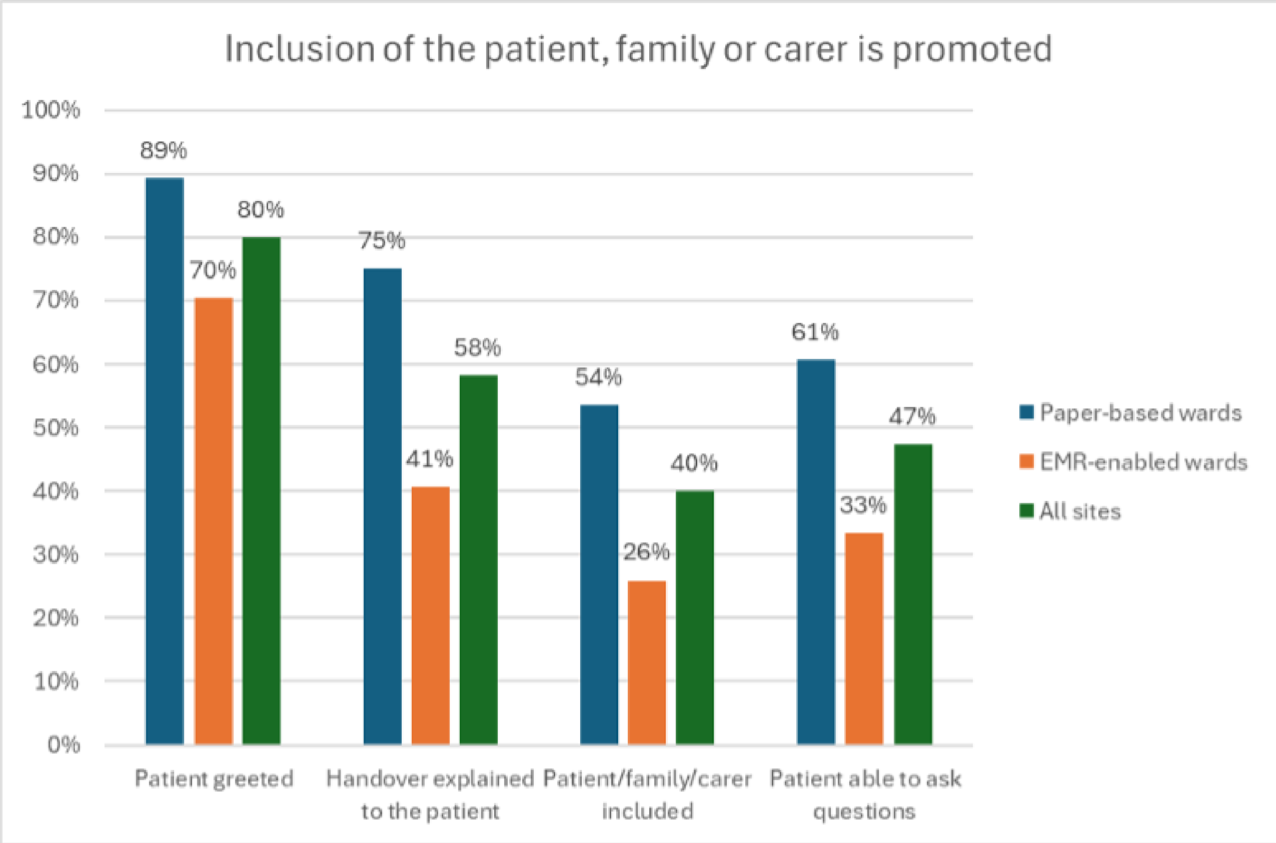
Bedside Handover

Handover occurred at the bedside more frequently in paper-based wards, with a mean compliance of 83%, compared with 63% in EMR-enabled wards.

Inclusion of the Patient, Family, or Caregiver

Promotion of patient, family, or caregiver inclusion occurred more frequently in paper-based wards. Compliance with all 4 patient inclusion indicators was observed in 70% of handovers in paper-based wards, compared with 43% in the EMR-enabled wards (Figure 4).

Figure 4. Inclusion of the patient, family, or caregiver is promoted. EMR: electronic medical record.



Comparison With Organization-Wide Handover Audits

Observational audit findings were compared with results from Eastern Health's Clinical Handover Nursing and Midwifery Audits conducted in 2022‐2023. Areas identified for improvement in the organization-wide audits aligned closely with findings in this case study, particularly in relation to bedside handover and patient and caregiver involvement.

Notably, overall performance relating to patient and caregiver inclusion was lower in this case study than in the organization-wide audits, suggesting potential variability in practice interpretation and reinforcing the need for further exploration of what constitutes effective patient inclusion and engagement in handover. Overall, these observational findings suggest that EMR availability was associated with variation in how handover was enacted across specific domains, rather than a uniform improvement or decline in overall handover quality.

Posthandover Surveys

Overview

Analysis of the posthandover survey data commenced with the calculation of a composite score derived from the 5 Likert-scale questions assessing staff satisfaction, perceived handover quality, adherence to ISOBAR, accuracy, and comprehensiveness of handover. A maximum composite score of 25 was possible. Results for individual items and composite scores by cohort are presented in Tables 6 and 7.

Table . Posthandover survey results (Likert scale questions). Overall score across all survey questions was 92% (median 97%) for paper-based and 91% (median 97%) for electronic medical record (EMR)-enabled handover.

Question	Paper-based mean (score)	Paper-based mean (%)	Paper-based median (score)	Paper-based median (%)	EMR-enabled mean (score)	EMR-enabled mean (%)	EMR-enabled median (score)	EMR-enabled median (%)
1. Are you satisfied with the handover you just received?	4.73	95	5	100	4.67	93	5	100
2. Rate the overall quality of the handover received	4.60	92	5	100	4.43	89	5	100
3. Did the handover follow the ISOBAR[a] format?	4.40	88	5	100	4.53	91	5	100
4. Rate how accurate you believe the handover was?	4.80	96	5	100	4.70	94	5	100
5. Rate how comprehensive you believe the handover was?	4.60	92	5	100	4.47	89	5	100
Composite score (Q1-Q5)	23.1	93	23	92	22.8	91	23	92

[a]ISOBAR: Identification Situation Observations Background Assessment/Action Recommendation.

Table . Posthandover survey results (Closed questions). Overall score across all survey questions was 92% (median 97%) for paper-based and 91% (median 97%) for electronic medical record (EMR)-enabled handover.

Closed questions (Y/N)	Paper-based mean (%)	Paper-based median (%)	EMR-enabled mean (%)	EMR-enabled median (%)
6. Was the required content effectively communicated?	100	100	100	100
7. Were you given the opportunity to clarify information?	100	100	97	100
8. Was there any specific information you felt was missing? (count of no)	93	100	90	100
10. Was the duration of handover appropriate?	93	100	100	100
11. Was the inclusion of the patient, family, or caregiver promoted?	70	70	70	70

Composite scores demonstrated minimal difference between cohorts, indicating similar levels of staff satisfaction and perceived handover quality. Across 10 of the 11 survey questions, responses were overwhelmingly positive, with no mean scores falling below 88% in either cohort.

Staff perception of the promotion of patient, family, or caregiver inclusion was the only survey item demonstrating a notable reduction in perceived performance.

Staff Perception - Promotion of Patient Inclusion

While observed patient engagement during the observational audits was limited, staff-reported perceptions indicated higher levels of patient involvement during handover. Promotion of patient inclusion was recorded as equivalent across cohorts, with both paper-based and EMR-enabled wards reporting 70% affirmative responses to this survey item.

Discussion

Principal Findings

This case study examined the impact of EMR implementation on both the process and perceived quality of nursing handover. Particular attention was given to how digital information systems shape nurses' access to, synthesis of, and communication about patient information. In this study, handover quality was operationalized using 2 complementary process-level measures: observed compliance with the organization's Clinical Handover Standard, and nurses' self-reported perceptions of handover quality following shift-to-shift handover exchange. Together, these measures provide insight into how EMR-mediated workflows influence handover behaviors, rather than downstream patient outcomes. Overall, EMR implementation did not uniformly improve handover quality; rather, its effects were heterogeneous across process domains, partially supporting the study objectives.

Quantitatively, overall compliance with the Clinical Handover Standard did not differ meaningfully between EMR-enabled and paper-based wards, nor did overall staff perceptions of handover quality. However, analysis of individual observational indicators revealed variation across specific domains. These included bedside location of handover, promotion of patient engagement, communication of clinical risks and alerts, handover duration, and frequency of interruptions. These findings suggest that while aggregate measures of handover quality appeared comparable, EMR implementation influenced *how* handover was enacted across specific components of the process.

Observational Audits

EMR-Facilitated Handover Creates a Barrier to Performing Bedside Handover

Observational audit data demonstrated a lower frequency of bedside handover in EMR-enabled wards compared with paper-based wards.

Bedside handover encourages direct and real-time engagement with the patient [1]. Active patient participation in the process can provide immediate information on the patient's condition [1]. Moreover, exchanging clinical information in the patient's presence can assist in identifying patient concerns, promoting continuity, quality of care, and improved patient satisfaction [1]. Implementing bedside handover is therefore key to promoting and supporting patient engagement and participation in care.

In this study, the presence of the EMR appeared to act as a barrier to nurses performing bedside handover. This finding points to challenges associated with EMR implementation that may, in turn, reduce the level of patient engagement during handover. The following factors may help explain this finding.

Limitations of the Physical Environment

In the EMR-enabled wards in this case study, nurses access the EMR on mobile workstations via computers mounted onto purpose-built trolleys, commonly referred to as Workstations on Wheels (WOWs). While ergonomic and adequately mobile, these WOWs are still relatively large. Often observed during the observational audit was one nurse from the AM shift giving handover to 2 nurses on the PM shift. Frequently, both nurses receiving handover would each be interacting with their own WOW. At times, the nurse giving handover would also be accessing the EMR on their own WOW, though this appeared to occur less frequently, with the nurse giving handover most commonly referring to their own printed handover sheet, inclusive of hand-written notes.

Despite the EMR-enabled wards being located in a relatively new and modern facility with spacious patient rooms, the available physical space at the bedside remained insufficient for 3 nurses and 2 WOWs. The devices are bulky and difficult to maneuver. As a result, staff appeared reluctant to take the WOWs fully into patient rooms and were frequently observed remaining in or just outside the doorway. The lead researcher was also made aware that in some patient rooms within the EMR-enabled cohort, Wi-Fi connectivity was reduced, resulting in poor or limited EMR functionality at the bedside.

Social Barriers to Using Technology at the Bedside

In addition to these identified physical limitations, a more nuanced barrier is a social one, where the presence of the EMR at the patient's bedside may be perceived as incongruous with a therapeutic environment. A positive and workable nurse-patient relationship develops when trust is established and maintained through an open exchange of information, supporting the delivery of interpersonal care [37,38]. In inpatient hospital settings, the nurse-patient relationship develops at the patient's bedside. Use of active listening techniques during nurse-patient interactions, such as making and maintaining appropriate eye contact, facing the patient, and minimizing distractions [37,38], further contributes to this therapeutic connection. Introducing digital technology into the therapeutic bedside space may be perceived by nurses as intrusive. It may disrupt active listening practices and interfere with the development of the therapeutic relationship. The patient may therefore perceive that the information being shared is not valued.

Duffy et al [38] similarly note that EMR documentation at the point of care can distract nurses' attention from the patient. This may reduce communication quality, appropriate eye contact, and overall meaningful interaction [38]. Misto [39] explored the impact of electronic documentation in the patient's presence on the nurse-patient relationship and noted that nursing staff perceptions of the EMR's influence on the therapeutic relationship were mixed [39]. Positive impacts included enhanced access to data at the patient's bedside and the ability to document contemporaneously and more efficiently, resulting in more time to spend with the patient [39]. Negative impacts centered on the recurring premise that using the EMR at the bedside is a distraction, resulting in both 'missed opportunities to connect with patients,' and an increased likelihood that subtle, nonverbal cues could be missed [39]. This was attributed to nurses being preoccupied with interacting with the EMR rather than being fully attentive to the patient [39]. Nurses in that study also reported that patients felt less valued when this occurred [39].

Gaudet [40] also explored the changes in nurse-patient interactions associated with the introduction of EMR documentation at the bedside, noting that this may create “an automatic, machine-like, task centered bedside environment” [40].

It is therefore possible that nurses feel that the insertion of a large and bulky, potentially distracting piece of digital technology into the space at the patient’s bedside may negatively impact the therapeutic relationship, serving only to make handover more impersonal rather than enhance it.

Cognitive Barriers to Performing EMR-Facilitated Handover at the Bedside

A recent review article exploring the impact of an EMR implementation on nursing handover determined that existing EMR interfaces are not currently meeting the needs of nurses during handover [22]. Navigating the EMR has been shown to impact cognitive workload due to the range of tasks required of users [26]. Combined with the way information is presented in the EMR, this results in fragmented or siloed data that must be skimmed through, sorted, and deciphered [18,24,25]. In this study, nurses were frequently required to navigate multiple EMR screens to locate alerts, risks, and clinical updates, reflecting well-recognized information fragmentation within EMR systems [25]. In this context, fragmentation shifts cognitive effort away from clinical reasoning and toward system navigation [25,41].

Handover is already a cognitively challenging task, requiring the nurse to be able to swiftly analyze and synthesize patient data across multiple information sources [24,42,43] and engage in complex knowledge-sharing processes [18]. The expectation that this demanding task also occurs at the bedside, involves the patient, and is mediated through an EMR that is often difficult to navigate, may further increase this burden. This raises an important question: Does this combination unintentionally work against the goal of improving handover quality and patient engagement? Is the presence of the patient themselves now an additional barrier to achieving the desired level of handover quality? Gaudet [40] explores this conundrum where ‘the complexity of the patients, the computerized prioritisations of tasks and the interruptions, limited the nurses’ ability to nurture and become familiar with their patients, thus creating “an environment that does not put the patients’ concerns at the center of care” [40].

From an informatics perspective, EMR-mediated handover requires nurses to simultaneously navigate, prioritize, and synthesize information. At the same time, they must maintain effective interpersonal communication with both colleagues and patients. Together, these demands increase cognitive workload during an already complex task. Given that a fully optimized EMR solution for nursing has not yet been realized [22], nurses may be reluctant to bring EMR-facilitated handover to the bedside. Doing so may be perceived as increasing complexity and potentially compromising handover quality.

Patient Engagement Was Better Promoted in Paper-Based Environments

Where a reduced frequency of bedside handover was observed in the EMR-enabled cohort, so too were lower levels of patient engagement and decreased promotion of patient, family, and caregiver inclusion in handover. Although the compliance gap for initially greeting the patient was smaller between the cohorts, meaningful patient inclusion cannot occur when handover takes place away from the bedside. This was demonstrated by the widening performance gaps for the remaining patient engagement indicators, ”Including the Patient in Handover” and “Providing the Patient an Opportunity to Ask Questions.”

Reduced frequency of bedside handover in the EMR-enabled wards was therefore identified as a stand-alone barrier to promoting patient engagement as measured by observational indicators of inclusion and the opportunity to ask questions.

Other Known Barriers to Bedside Handover and Patient Engagement

Despite the known benefits of bedside handover in improving patient engagement and supporting patient-centered care, studies continue to elucidate reluctance from nurses to perform handover at the bedside. Independent of EMR introduction, commonly cited barriers to bedside handover include concerns about patient privacy and confidentiality [44-46]. Nurses also report worries about being asked difficult questions or appearing unprofessional in front of patients [44,45]. Additional concerns relate to perceived prolongation of handover [47,48] and disruption to communication flow [46,47].

A pre-existing resistance to bedside handover for these myriad reasons must therefore be considered as a contributing factor to the gap in bedside handover implementation across both cohorts in this study. Where an existing baseline gap in practice may already be evident, the introduction of the EMR, and all the additional potential barriers it brings, has possibly further compounded this issue in the EMR-enabled wards, making bedside handover even less achievable.

Handover of Critical Information Occurred More Readily in EMR-Enabled Wards

In the hospital environment, EMRs are accessed by clinicians throughout the course of a patient’s treatment, replacing bulky paper-based medical records. In this case-study context, an EMR was introduced and mobile WOWs provided, providing up-to-date clinical information at the point of care and during handover. An EMR facilitates real-time sharing of patient data and has the potential to improve efficiency and care coordination [49]. The results of the observational audit support this, with improved handover of critical information such as clinical alerts and clinical risks evident in the EMR-enabled wards compared with the paper-based cohort.

This also aligns with marginally better performance observed for overall ISOBAR compliance in the EMR-enabled wards, where more consistent practice in using the mnemonic may have contributed to the improved handover of risks and alerts.

Reliance on Other Tools to Support Handover

In paper-based environments in this case study, nurses predominantly rely on printed handover sheets generated by bed management software known as Patient Flow Manager (PFM). PFM is not linked to the organization's EMR and clinical information stored within it, and it does not form part of the medical record.

To populate these handover sheets, clinical information is transcribed from the scanned patient history or EMR and manually entered into PFM. Nursing staff add and update clinical information in PFM throughout their shift, including the removal of any outdated information. It is not routinely used by medical or allied health staff in this way. Unfortunately, a reliance on duplication and manual data entry processes has the potential to result in transcription errors, decreasing the accuracy of the information contained on these handover sheets. Conversely, the EMR is considered the source of truth for clinical patient information, inclusive of clinical alerts and clinical risks, which have been configured to provide a visual alert to clinicians.

In the EMR-enabled wards, nurses also use PFM and are provided with PFM-generated printouts at the commencement of their shifts. In these wards, however, the EMR is always accessible during handover and is frequently used to check information, most notably by the handover recipients. This is consistent with recent studies, which predominantly described EMR use during handover as verifying or double-checking information [24,25,41] and keeping up to date with the latest developments [18].

In paper-based environments, nurses rely heavily on printed handover sheets. The information on these sheets may be outdated, incomplete, or inaccurate. Where critical changes in the patient's condition occur, it is imperative that nurses are immediately aware of changes to any clinical alerts and clinical risks. This will ensure that the most appropriate care, interventions, and safety precautions can be implemented to promote patient and staff safety.

Persistent reliance on PFM-generated paper handover sheets was observed in both cohorts, including the EMR-enabled wards. In this study, this pattern signaled a socio-technical misalignment between the EMR design and nursing handover workflows. Despite the EMR being the authoritative source of clinical information, nurses continued to depend on nonintegrated artifacts to support their cognitive load, information sequencing, and real-time note-taking during handover. This behavior suggests that existing EMR interfaces did not adequately support nurses' information needs during handover, reinforcing findings that poor task–technology fit drives workarounds and partial adoption of digital systems [22].

Handover Was More Efficient in the EMR-Enabled Wards

Observational audit data demonstrated reduced median handover duration in EMR-enabled wards compared with paper-based wards. Performance was also more consistent in the EMR-enabled environments, with more variability of duration noted in the paper-based wards.

Across a number of studies, accessing and navigating the EMR has been described as time-consuming [24,41], cumbersome [41], arduous [24], and not necessarily able to provide pertinent information quickly [43].

Despite these potentially negative connotations, studies reporting specific impacts of EMR implementation on handover duration offered mixed results. Hertzum and Simonsen [50] sought to understand the impact of a trial EMR implementation, finding that there was no significant difference in handover duration postintervention [50]. Correspondingly, Alghenami's [51] 2012 study exploring the role of EMRs in structuring handover communications found that nurses did not identify the EMR as a factor that would impact handover duration [51]. There is growing evidence, however, that use of specific EMR-structured handover tools or EMR-generated printouts can assist in making handover quicker and more efficient [52-54]. It is important to note, nonetheless, that positive outcomes are highly contingent on whether these tools are adequately aligned with the nature of the clinical work [55] and offer sufficient functionality to support the task [56]. Conversely, where an EMR interface does not adequately suit the task at hand, it fails the end user, which may result in incomplete adoption of the new technology and a continued reliance on paper-based tools [22]. Ultimately, when a gap in functionality or design is not readily addressed, or poor user experience persists, this has the potential to lead to user frustration and even boycott [56].

At Eastern Health, in the EMR-enabled wards, nurses were observed navigating various parts of the EMR during handover, yet they did not use any specific EMR-structured handover tools or EMR-generated printouts. Further to this, nurses across both cohorts were almost always observed consulting or making handwritten notes on paper handover sheets printed from PFM. Nurses in the EMR-enabled cohort demonstrated willingness to adopt EMR use during handover. However, the continued reliance on PFM-generated printouts suggests a gap in EMR design or functionality. While the PFM-generated printouts clearly provide support to nurses during handover, they remain problematic as they do not draw clinical information directly from the EMR. Ideally, an EMR-generated printout would replace those generated via PFM and thus provide the most up-to-date clinical information. Ultimately, these printouts must be purposefully designed by and for nurses in order that they fully support the task being performed.

Handover Occurring in EMR-Enabled Wards Experienced Fewer Interruptions

The paper-based cohort experienced more interruptions during handover, noting this may well be an anomaly given the very small sample size. Current research on the impact of interruptions during EMR use appears limited to those that occur via the EMR itself, such as automated alerts, reminders, and other clinical decision support mechanisms [57-59], or broader workflow interruptions associated with EMR implementations in general [60-62]. This case study sought to measure external interruptions caused by patients, phones, alarms, or other staff in the ward environment. The reason for fewer interruptions occurring in the EMR-enabled cohort is, therefore, entirely speculative.

A very well-researched field that could offer some useful comparisons is the frequency and impact of interruptions on medication administration workflows, which have the potential to result in medication errors. As a known high-risk activity, efforts to prevent and reduce interruptions that may lead to errors during medication rounds have also been thoroughly explored. Frequently used strategies to reduce and manage the risk of interruptions include the use of standardized checklists and protocols such as the 5 rights of medication administration, quiet zones for medication preparation, diversion strategies, and visual alerts such as wearable sashes and vests asking that others "Do Not Disturb" and "Do Not Interrupt" [63-65]. Nurses are therefore highly aware of this increased risk to patient safety, noting also that these types of interruptions are significant contributing factors to increasing mental workloads in hospital work environments [66]. One possible explanation is that engagement with the EMR may provide a visible cue to other staff that nurses are occupied with handover, potentially reducing external interruptions in a manner similar to visual "Do No Disturb" signals used during medication administration.

These findings should therefore be interpreted as indicative process trends rather than definitive performance improvements, and further investigation with larger samples or longitudinal designs may clarify their significance.

Staff Perception of Patient Engagement

Observational audit findings relating to patient engagement during nursing handover did not correlate with staff's self-reported perceptions of their own efforts to promote patient participation.

While bedside handover alone is insufficient to ensure meaningful patient engagement in the process [45], it remains a fundamental prerequisite in order for patient participation to occur. In this study, observational audits identified a compliance gap with bedside handover across both cohorts, with this gap more significant in the EMR-enabled wards. On this basis, lower observed rates of bedside handover in the EMR-enabled cohort would be expected to correspond with similarly reduced rates of self-reported promotion of patient engagement during handover. And yet the staff survey found that this was occurring in equal proportions across both cohorts, around 70% of the time.

The large mixed methodology study of Street et al [45] examining patient participation in handover may assist in explaining this, observing that whilst nurses do perceive the value in patient participation, 'the best way to effectively help patients be more involved in bedside nursing handover is poorly understood' [45]. The findings of this case study support this notion, suggesting that nurses, who may not understand how to effectively engage patients, may have limited insight into whether their handover practices genuinely facilitate patient engagement and participation.

This discrepancy may reflect an overestimation of patient engagement in staff self-reported data, potentially influenced by social desirability bias, whereby participants provide responses and report practices that are perceived as more acceptable [67]. In this instance, the self-reported practice aligned better with organizational expectations and the requirements of the Clinical Handover Standard, despite the decreased incidence of bedside handover necessary to facilitate the desired engagement.

Collectively, these findings highlight the value of using multiple measurement approaches when evaluating handover quality, as reliance on self-report alone may overestimate adherence to patient engagement principles.

Staff Satisfaction With Handover Quality

Despite the reduced occurrence of bedside handover, potential data fragmentation, workflow changes, and reliance on workarounds (including paper-based and nonintegrated artifacts) in EMR-enabled wards, staff satisfaction with overall handover quality remained high across both cohorts. Clinicians may report satisfaction with systems they have learned to cope with, even when those systems impose additional cognitive or workflow burdens [56]. These findings likely reflect nurses' ability to adapt to existing system constraints rather than optimal alignment between EMR design and nursing handover workflows.

Taken together, these findings suggest that staff satisfaction alone is an insufficient indicator of EMR effectiveness, reinforcing the need to examine how digital systems shape cognitive workload, workflow integration, and communication practices during nursing handover.

The contrast between consistently high staff satisfaction and observed variability in handover behaviors suggests adaptation and normalization of system constraints, reinforcing the importance of examining both objective and perceptual measures when evaluating digital clinical systems. Integrating observational and perceptual data strengthened interpretive validity and enabled identification of important differences between enacted and perceived practice that would not have been apparent using a single measurement approach.

Limitations

Several limitations should be considered when interpreting the findings of this study.

First, the relatively small sample size of 60 handovers limited the ability to detect statistically significant differences across all measures, particularly given the complexity and variability inherent in clinical handover practices. While sampling 5 handovers per ward enabled exposure to routine practice within each setting, the number of observations per cohort was insufficient to support more granular analyses or make more robust comparisons. As a result, findings should be interpreted as indicative of patterns of use and areas of variation rather than definitive estimates of practice prevalence. In addition, this study focused on process-level indicators of nursing handover quality, including observed compliance with the organization's Clinical Handover Standard and nurses' self-reported perceptions of handover quality. These measures provide important insights into how handover is conducted in different environments but do not directly assess patient outcomes or safety events. As such, findings should be interpreted as reflecting differences in handover processes only. Furthermore, as an exploratory case study conducted within a single health service, the findings have limited generalizability beyond similar organizational and hybrid EMR contexts. However, the design provides rich, practice-based insight into how nursing handover is shaped within real-world digital environments.

Second, the use of a single auditor introduces the potential for investigator bias. To mitigate this risk, the observational audit tool was designed to minimize subjectivity, with items structured wherever possible to limit reliance on auditor interpretation. Consistent use of a single trained auditor also supported standardization of data collection across sites.

Third, a degree of Hawthorne effect may have occurred, as participants were aware that they were being observed. This is particularly relevant for highly visible elements of the Clinical Handover Standard, such as conducting handover at the bedside and performing patient identification checks. While this may have influenced overall adherence to the Clinical Handover Standard, it is unlikely to have affected the comparative analysis between the 2 cohorts, as any observation effect would have been equally probable in both groups.

Finally, the study focused exclusively on shift-to-shift nursing handover within inpatient wards and did not include handovers occurring in other settings such as interdepartmental transfers and other transitions of care. Future research should consider observing and evaluating handovers across a broader range of clinical contexts, with particular attention to how EMRs are configured and used to facilitate and support nursing handover under varying workflow, environmental, and cognitive demands.

Conclusions

This case study demonstrates that EMR implementation has the potential to produce both beneficial and unintended effects on the quality of shift-to-shift nursing handovers. While EMR-enabled wards showed positive impacts in accessing and communicating up-to-date clinical information, particularly in relation to clinical alerts and risks, these benefits did not translate uniformly across all dimensions of handover quality.

Findings indicate that a pre-existing reluctance to perform bedside handover may be exacerbated in EMR-enabled environments, with negative implications for patient inclusion and engagement. Limitations related to the physical environment, EMR interface and design, social factors, and cognitive factors appear to impede nurses' ability to consistently promote patient participation during handover. These findings suggest that nurses may not have a clear or comprehensive understanding of the actions necessary to actively promote patient engagement, nor how to effectively assess these efforts, a challenge that appears more pronounced in digitally mediated handover contexts. This suggests a gap in informatics-enabled support for nursing practice, particularly in translating digital handover processes into patient-centered behaviors.

Positive impacts of EMR implementation included improved efficiency and reduced interruptions during handover, indicating a degree of user acceptance and adaptation. However, continued reliance on paper-based PFM-generated handover forms highlights persistent gaps in EMR functionality or design, and the need for workarounds to support cognitive and workflow demands during handover. While this study did not examine patient or safety outcomes directly, it provides important process-level evidence to inform the optimization of nursing handover within digitally enabled environments.

Collectively, these findings indicate that the presence of an EMR alone is insufficient to ensure high-quality nursing handover. Rather, the impact of EMR implementation on handover quality is mediated by nursing informatics capability and the degree to which digital systems are designed and aligned with nurses' cognitive processes and clinical workflows. Where EMR interfaces fragment information or fail to provide integrated, task-specific handover views, nurses compensate through workarounds that may limit the potential benefits of digital systems. Optimizing nursing handover in digitally enabled environments requires EMR designs that explicitly support handover as a complex, cognitively demanding, and safety-critical nursing activity, rather than assuming that quality improvements will occur through digitization alone.

Future Research

Future research should examine in greater depth how nurses interact with EMR systems during handover, including patterns of use, information navigation, and reliance on workarounds. Detailed analysis of user interaction with the EMR would assist in determining the degree to which the current technology suits the task being undertaken and which current digital tools are suited to the cognitive and workflow demands of nursing handover.

Qualitative exploration of nurses' perceived barriers and facilitators to EMR use during handover would further inform understanding of how EMR interface design, functionality, workflow integration, and device availability may influence handover practices. Such insights could support the identification of design flaws that contribute to the ongoing reliance on paper-based handover forms and other nonintegrated artifacts in EMR-enabled environments.

Future studies may benefit from the evaluation of discrete components of EMR implementation, including device footprint, software interface design, workflow integration, and overall user experience, to better understand each element's relative impact on the quality and effectiveness of nursing handover.

Comparative analyses across wards or sites with differing levels of digital maturity, including electronic prescribing and medication administration, may offer further clarification as to how specific EMR functionalities influence nursing handover processes and outcomes.

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Data Availability

The original contributions presented in this study are included in the article and Multimedia Appendix 1. Further inquiries can be directed to the corresponding author.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Eastern Health clinical handover standard.
[DOCX File, 374 KB - nursing_v9i1e85909_app1.docx]

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Abbreviations

CFS CRGC: Communicating for Safety Clinical Risk Governance Committee
EMR: electronic medical record
ISOBAR: Identification Situation Observations Background Assessment/Action Recommendation
NSQHS: National Safety and Quality Health Service
PFM: Patient Flow Manager
WOW: Workstations on Wheels

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Changes in Nurse-Patient Communication Through Health Technologies and Nursing Practices to Recognize and Support Limited Digital Health Literacy: Qualitative Study

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Abstract

Background: In the past decade, the use of health technologies, such as telemonitoring, video consultations, and patient portals, has increased. However, it remains unclear how these technologies have influenced nurse-patient communication. Additionally, little is known about the role nurses play in recognizing and supporting limited (digital) health literacy patients.

Objective: This study aimed to explore which health technologies are currently being used in a hospital context and how nurse-patient communication has changed as a result. Furthermore, we sought to identify the practices nurses use and the barriers they experience in recognizing and supporting patients with limited digital health literacy.

Methods: This is a qualitative descriptive study that used semistructured interviews with nurses working in a hospital (n=21). The interview guide was partly based on the 6-function model of medical communication by de Haes and Bensing. All interview transcripts were analyzed by 2 independent coders using a combination of deductive and inductive approaches.

Results: According to the nurses, health technologies have impacted all 6 functions of nurse-patient communication. They noted improvements in gathering information, providing information, enabling disease and treatment management, and responding to patients' emotions. In contrast, technology made fostering the relationship more difficult, and technologies were seldom used in shared decision-making. Nurses identified limited digital health literacy through intuition, observation of verbal and nonverbal cues, and direct questioning. To support patients with limited digital health literacy, nurses relied on building trust, involving the social network, tailoring communication, and offering additional support. High workload and limited knowledge were the main barriers to applying these practices.

Conclusions: Our findings show that health technologies have significantly influenced nurse-patient communication in the hospital setting. The results highlight the need for tailored training programs to strengthen nurses' competencies in identifying and supporting patients with limited digital health literacy. This is essential to ensure more comprehensible and accessible care and promote equitable patient engagement with health technologies.

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KEYWORDS

health literacy; digital health literacy; nurse-patient communication; hospitals; tailored communication; eHealth literacy; nursing; hospital

Introduction

One of the essential elements of nursing care is communication with patients and their relatives [1]. Communication between nurses and patients serves different functions. The 6-function model of de Haes and Bensing [2] distinguishes the following functions from the viewpoint of the care professional: (1) fostering the relationship, (2) gathering information, (3) providing information, (4) decision-making, (5) enabling disease and treatment-related behavior, and (6) responding to the emotions of patients. In practice, these functions overlap and interact during nurse-patient communication. Nevertheless, they are important for positive patient outcomes, including patient satisfaction, adequate diagnosis and treatment, treatment adherence, and even health [3,4].

Over the past decade, the rapid rise of the internet and digital health technologies has begun to reshape the context in which these communication functions take place. Nowadays, patients have access to health information via the internet and social media and to specific information about their own health status and treatment via the hospitals' patient portal. Apps exist for self-management, and the telemonitoring of vital functions may provide care professionals with continuous insight into bodily functions, which was formerly not possible. In addition, nursing consultations are increasingly being conducted digitally, via email, chat, or video conferencing, and health education is frequently supported by websites and videos.

These developments offer various benefits, such as improved patient insight into their health and reduced care costs and patient burden due to fewer hospital visits [5]. However, the benefits may not exist for all patients, and patients with limited health literacy may not experience the benefits from these health technologies. Patients with limited health literacy find it difficult to find, comprehend, or apply health information; they are not able to take responsibility for their health and find communication difficult [6]. The aforementioned digitalization of care requires even more skills of patients, such as the ability to operate devices and navigate on the web, understand and use health apps, and apply digitalized nursing consultations. These skills are called digital health literacy or eHealth literacy [7]. Digital health literacy is not only a technical skill set but the ability to engage with digital technologies in effective, safe, and helpful ways to achieve health goals [8]. It is influenced by sociodemographic factors, such as age, educational level, income, perception of the internet as a health source, and social support [9-11]. In the Dutch context, these inequalities are substantial: it is estimated that 1 in 3 people have a limited health literacy [12], and approximately 20% experience difficulties with digital skills [13]. It can be expected that, in a hospital setting, this number may even be higher because patients may experience tension. For example, in acute or critical care settings, patients may be sedated or intubated, limiting direct interaction, and nurses often need to communicate primarily with family members rather than the patients themselves.

Given these challenges, nurses could play an important role in the care of patients with limited (digital) health literacy, starting with their ability to recognize these patients. However, recognizing these patients is difficult, and studies have shown that nurses often overestimate the health literacy of their patients [14,15]. In addition, limited evidence exists regarding nurses' knowledge and awareness of patients' (digital) health literacy, and little is known about the practices nurses currently use to identify patients with limited (digital) health literacy in clinical practice. Once patients with limited (digital) health literacy have been identified, nurses need practices to support them. Although previous qualitative research has examined how nurses assess and support patients with limited health literacy, attention to the digital component is mostly lacking. In addition, concept descriptions of (digital) health literacy are available in the literature, and evaluations of nursing practices or interventions remain scarce. Given the increased use of health technologies, an understanding of recognizing and subsequently supporting patients with limited (digital) health literacy by nurses in hospitals is needed.

In conclusion, the increased availability of health technologies is likely to have changed nurse-patient communication. Yet, to date, only a few studies have examined how the rapid digitalization of health care specifically reshapes the 6 communication functions between nurses and patients in hospital settings. In addition, little is known about how nurses can recognize or support patients who experience difficulties in using these health technologies. Therefore, in this qualitative study, we aim (1) to explore which health technologies are used by nurses within a hospital context and how the 6 functions of nurse-patient communication have changed through the use of these technologies and (2) to examine nurses' current practices, as well as the barriers they experience, in recognizing and supporting patients with limited (digital) health literacy.

Methods

Design and Setting

A qualitative descriptive study was conducted, using thematic analysis of semistructured interviews. The interviews were conducted in Isala, a teaching hospital in Zwolle, and at Windesheim University of Applied Sciences in Zwolle, and a vocational education program at Drenthe College in Meppel, all in the Netherlands. This study is reported in concordance with the COREQ (Consolidated Criteria for Reporting Qualitative Research) guidelines [16].

Participants

Purposive sampling was used to obtain a heterogeneous sample of nurses, intentionally selecting participants with diverse specialisms and experiences. Inclusion criteria were current employment at Isala, a teaching hospital in Zwolle, the Netherlands, either as a registered nurse or a nurse in training; a minimum of 1 year of clinical experience or completion of at least 1 hospital-based internship; and currently using at least 1 health technology.

Procedures

Potential participants (17 registered nurses and 6 nurses in training) were invited via email, either directly by the researchers or through their supervisor about the study's aim, interview topics, and the implications of participation. Of those invited, 2 did not respond or were unable to participate due to time constraints, while the remaining individuals agreed to participate.

Interviews were conducted a few weeks after the invitations were sent, either face-to-face or via video call. Before each interview, participants provided written informed consent.

Interviews took place between November 2022 and January 2023 at the hospital and were conducted by 2 researchers (EMD and JW), both trained in qualitative research. One researcher was employed as a nurse researcher at the hospital, and the other was a lecturer at the University of Applied Sciences. A pilot interview was conducted to assess the clarity and structure of the interview guide, leading to minor adjustments in question sequencing.

A total of 21 interviews were conducted, with 17 held in person and 4 online. All interviews were audio-recorded with participants' permission and transcribed verbatim. During most interviews, a student assistant was present to help manage time and ensure all questions from the interview guide were addressed. Interviews lasted between 25 and 54 minutes.

Interview Guide

The interviews were conducted using an interview guide, including 3 main topics.

The Use of Health Technologies and Their Impact on the 6 Functions of Patient-Nurse Communication

The data were gathered using the 6-function model of communication (Table 1) [2].

First, nurses were asked how each function was part of the nurses' work and if any health technologies were used in performing this function. Health technology was defined as the application of organized knowledge and skills in the form of devices, medicines, vaccines, procedures, and systems developed to solve a health problem and improve quality of life [17]. An infographic with examples of health technologies (such as video calling, patient portals, and digital leaflets) used in nursing care was presented to stimulate discussions about their own experiences with these health technologies and experiences with other technologies they may have used. Furthermore, nurses were asked if and how these technologies have changed the specific function. Each participant was interviewed about at least 2 functions. If there was enough time, nurses were asked about more than 2 functions. These 2 functions were rotated between interviews so that all functions were addressed equally.

Table . The 6-function model of communication [2].

Six functions	Explanation
Fostering the relationship	Emphasizes the importance of mutual trust, understanding, and commitment, as well as agreement about each other's roles and expectations
Gathering information	Aims to ascertain a correct interpretation of symptoms and establish an adequate nursing diagnosis
Providing information	Aims to provide understandable, accurate, sufficient, and timely information in a manner appropriate to the patient
Decision-making	Aims to make sure decisions are being based on the information and preferences of patients
Enabling disease and treatment-related behavior	Aims to support patients in treatment adherence and a healthy lifestyle
Responding to emotions	Requires nurses to elicit patients' emotional distress, communicate an understanding of the patient's emotions, and respond with empathy and support

Current Practices in Recognizing and Supporting Patients With Limited (Digital) Health Literacy

The critical incident technique [18] was used to gain insight into current practices in recognizing and supporting patients with limited (digital) health literacy. Nurses were asked to describe a situation where the communication with a patient with limited (digital) health literacy failed, followed by several follow-up questions aimed at elaborating on the situation (eg, "What happened?," "What went wrong?," and "What did you do to fix it?"). Then, the opposite was asked to describe a situation wherein the communication was very effective. Again, nurses were encouraged with follow-up questions to elaborate on the situation. Furthermore, some additional questions were asked to gain insight into their current practices regarding recognition, such as, "Can you assess whether a patient you are seeing for the first time can work with that technology?," and support, such as, "How do you ensure that a patient with limited digital health literacy can work with this technology?"

Barriers to Recognizing and Supporting Patients With Limited (Digital) Health Literacy

Nurses were asked which barriers they experienced in recognizing and supporting patients with limited (digital) health literacy. For example, the following questions were asked: Which barriers do you experience in recognizing patients with limited digital health literacy? And how is this for supporting patients with limited digital health literacy?

Data Analysis

The data were analyzed using a thematic analysis [19] using Atlas.ti 22. Two researchers (EMD, JW) first independently read all transcripts to familiarize themselves with the data and identified relevant text fragments. Coding was conducted independently, and coders met after 3, 6, and 12 interviews to discuss their findings and refine the coding scheme. Any discrepancies were resolved through discussion, and a third researcher (CHCD) was consulted when necessary to reach consensus. After each round of discussion, the coding scheme was further refined. No formal intercoder reliability metrics were calculated, as this is not standard for thematic analysis, in which the focus is more on finding patterns of meaning rather than on numerical agreement. We combined deductive and inductive approaches: deductive coding was guided by the main research questions, while inductive coding allowed subcategories to emerge from the data. Text fragments were first sorted (deductively) into categories in line with the research questions: changes in the 6 functions of communication, practices to recognize limited (digital) health literacy, practices to support patients with limited (digital) health literacy, and experienced barriers in recognizing and supporting patients with limited (digital) health literacy. Within each category, subcategories were developed inductively, allowing themes to emerge from the data.

Data saturation was assessed following Hennink et al [20], who distinguish between code saturation, the point at which no new codes are identified, and meaning saturation, the point at which a richly textured understanding of the themes is achieved. In our study, no new codes or themes emerged after 16 interviews, indicating that code saturation had been reached. A total of 21 interviews were conducted, ensuring that all research questions were comprehensively addressed and meaning saturation was also achieved.

Ethical Considerations

The study was conducted following the ethical principles of the Declaration of Helsinki. The Medical Research Ethics Committees confirmed that the study (reference number 20221009) is not subject to the Medical Research Involving Human Subjects Act (WMO). Participants provided written informed consent prior to the interview. Participants were able to decline to answer any questions and withdraw from the study at any time up to the time of data analysis. All participant-related data were deidentified and kept by the researcher. Only research team members had access to the data. No compensation was provided, apart from reimbursement for the time participants spent participating in the interview.

Results

Characteristics of Participants

The characteristics of the participants (n=21) are presented in Table 2. One nurse worked at the virtual monitoring center, where patients at home are monitored remotely. A chief nursing information officer and 2 nurse information officers also participated; these roles aim to support the integration of health technologies into nursing practice. Additional specialized roles included an electronic medical record (EMR) key user, who acts as a mediator between EMR developers and clinical staff, and a digital health technology coach (“digicoach”) who supports nurses in using digital tools. No compensation was provided, apart from reimbursement for the time participants spent participating in the interview.

Table . Characteristics of participating nurses (n=21).

Characteristics	Participants, n
Age (y)	
20 - 29	10
30 - 39	5
40 - 49	5
≥50	1
Sex	
Male	4
Female	17
Working in	
Clinical wards	
Abdominal and vascular	2
Urology	1
Oncology	1
Dialysis	1
Intensive care	2
Cardiology	2
Nurses in training across various clinical wards	6
Outpatient specializations	
Pulmonary	1
Wound	1
Oncology	1
Ostomy	1
Virtual monitoring center	1
Other	
Chief nursing information officer	1

Health Technologies in Patient-Nurse Communication

Nurses indicated using various health technologies, both in the hospital and in the home environment. For example, at the hospital, nurses are using the EMR to report about the patient's condition, use videos to support their education for patients, and use a projector with images (eg, nature, animals, or cities) to calm patients. The mentioned health technologies were divided into 5 categories: e-interaction, e-monitoring, e-education, e-recording, and e-support (Table 3).

Table . Overview of health technologies used by the hospital nurses.

Category of health technologies	Health technology
E-interaction	Video consultation, e-coach, translator, email contact (including sending photos), phone call, and notifications for nurses via the app
E-monitoring	Distant monitoring of measurement directly transferred to EMR[a], online questionnaire about self-reported symptoms, monitoring exercise behavior, and camera surveillance
E-education	Images, digital leaflets, videos, webinars, and websites
E-recording	Electronic medical record, patient portal, and digital diary for family
E-support	Projector with calming images, virtual reality, music, online church services, and VR[b] cycling: stationary bike combined with a screen

[a]EMR: electronic medical record.

[b]VR: virtual reality.

Health Technology Influence on Patient-Nurse Communication

Overview

We analyzed nurses' responses regarding whether and how health technologies have affected the 6 functions of communication. According to the nurses, health technologies influenced all 6 functions of nurse-patient communication. They reported positive effects on gathering information, providing information, supporting disease and treatment management, and responding to patients' emotions. In contrast, technology was perceived as making the development of the nurse-patient relationship more challenging, and it was rarely used to support shared decision-making. The results are summarized in Table 4, with + indicating positive changes, – negative changes, and ± changes that were neither clearly positive nor negative, reflecting neutral effect.

Table . How health technologies have positive, negative, or neutral changed the 6 functions of communication.

Functions	Changes
Fostering the relationship	• Increases patients' sense of safety (eg, through camera surveillance) (+[a]) • Lack of eye contact or nonverbal communication (±[b]) • Creates more distance between patient and caregiver (eg, video consultations) (–[c]) • Requires more time to build a relationship (–) • Patients feel less listened to (–) • Less privacy for a patient (eg, through camera surveillance) (–)
Gathering information	• Data are more structured in EMR[d] (+) • Allows measurements to be recorded in the EMR with the patient present (+) • Increases safety through automatic transfer of vital signs into the EMR (+) • Quick and complete data collection via online questionnaires before or during admission (+) • Continuous data collection at home (+) • Reduces number of hospital visits through video consultations (+) • More insight into the home environment (+) • Email consultations offer the opportunity to respond whenever suitable (+) • Enables quick and adequate treatment in the home situation through, eg, sending photos of ostomy (+) • Missing "the clinical view" (±)
Providing information	• Increases patient insight into medical data through, for example, portal (+) • Provides relatives insight into patient well-being via "digital diary" (+) • Increases options for multimodal education, which enhance patient understanding (eg, videos) (+) • Can be sent in advance to enhance patient preparation (eg, digital leaflets) (+) • Check patient understanding in e-education (±) • Check patient understanding in e-education (±) • Some images are too complex and reduce clarity (–)
Decision-making	• Access to (personal) data can contribute to informed decision-making (+) • Retrieving information from EMR is simplified (+) • Online decision aid can contribute to shared decision-making (+)
Enabling disease and treatment-related behavior	• Exercise options to stimulate the patient to healthy behavior (+) • Requires patients to take a more active role through remote monitoring (±)
Responding to emotions	• Can contribute to distraction, for example, through VR[e] (which can reduce pain) (+) • Enables emotional expression via iPad emoticons (+) • Builds reassurance through better understanding of condition via e-education (+) • Enables nurses to inform their colleagues about patients' emotions fostering coordinated care (+) • Enhanced comfort in home situation (+) • Emotional support after admission through, for example, messages (+) • Requires attentive listening to the emotions expressed, as visual cues are not available (±) • Technology can create disruptions, for example, nurse paging systems (–)

[a]+: positive change.

[b]±: changes that were neither clearly positive nor negative.

[c]–: negative change

[d]EMR: electronic medical record.

[e]VR: virtual reality.

Fostering the Relationship

Building trust and fostering the relationship between nurse and patient constitutes the basis for successful nurse-patient communication. According to participants, this function has changed considerably with the increased use of health technologies, such as video consultation and notifications via patient portals and apps, and mostly in a negative way. It causes a lack of eye contact and nonverbal communication, creates more distance between patients and nurses, and requires more time to build a relationship. Some nurses mentioned that their patients feel less listened to because the nurse is typing during the conversation to add results into the EMR. Regarding e-monitoring, nurses thought that this would increase the patient's sense of safety. However, a negative consequence was also noted, namely that (camera) surveillance could compromise privacy. Finally, the nurses indicated that a good relationship could be established if it starts with a face-to-face interaction before the technology is being used, as is illustrated in the following quote:

> *It also does bring a bit of distance but I think you can reduce that distance if you have created trust during a [face-to-face] consultation at the outpatient clinic. And, if you have taken time for that.* [R10]

Gathering Information

The second function of nurse-patient interaction is gathering information: nurses need to gather information about symptoms and health status to reach an adequate diagnosis and treatment (care) plan. According to the nurses, this function has mostly positively changed with the availability of health technology. For example, e-recording provides more structured data of patients and allows a quick search for information, and the possibility to report the provided information into the EMR in the presence of the patient reduces the chances of mistakes. Automatic measurement and transfer of vital signals into the EMR increases safety and reduces workload for nurses. The use of online questionnaires allows for quick and complete gathering of data before or during hospital admission and continuous data collection also at home. The positive changes of e-interaction (eg, video consultations) included more insight into the home environment of the patient and that patients have to come less often to the hospital. In addition, nurses indicated that online consultations are less often interrupted, and email consultations or messages offer the opportunity to respond whenever suitable. For patients with ostomy or wounds, especially, the opportunity to send photos enables quick and adequate treatment in the home situation.

As a downside, nurses emphasized that by e-interaction, they sometimes miss "the clinical view." This makes listening skills particularly important, as is outlined in this quote:

> *It is very different to have a clinical view over the phone or email than live, where you can also watch someone. Yes, you have to listen very carefully and you have to start asking a lot more questions, so you don't just look at how someone is sitting, but you also ask, what did you just do when someone is out of breath? Because I didn't see all that. Where are you right now? Are you standing? So I have to start asking very specific questions about a measurement.* [R8]

Providing Information

The third function of nurse-patient interaction is information provision: nurses have to provide clear information tailored to the patient, for example, information about symptoms, diagnosis, disease, and treatment. Nurses felt that this function was mostly changed in a positive way. Regarding e-recording, the patient portal provides more insight for patients into their personal medical data, and a "digital diary on the ward" provides patients and their relatives insight into nurses' interpretation of patients' well-being and daily activities. Regarding e-education, websites, visualizations, and videos provide options for multimodal education and thereby enhance patients' understanding, as is illustrated in the following quotation:

> *A video with illustrations is a much better tool and easier than a leaflet, I think. Many leaflets that I hand out, turn out to be still unread at the bedside table by the end of the admission.* [R5]

Moreover, education via the internet can easily be sent in advance, enhancing patient preparation and improving personalized communication. On the other hand, one nurse indicated that some images are so difficult that they make the information less understandable. When oral education is replaced by e-education, for example, digital leaflets, it is important to check if the information is found and understood by the patient.

Decision-Making

Nurses play a pivotal role in facilitating shared decision-making by providing information and taking into account preferences. Currently, nurses use a limited number of health technologies in the decision-making process. Regarding e-recording, patient access to (personal) data can contribute to informed decision-making, and retrieving information by nurses from EMR is simplified. E-support, such as online decision aids, can contribute to shared decision-making. Although most interviewed nurses had not yet incorporated online patient decision aids into their daily practice, these technologies were recognized as potentially valuable additions for shared decision-making with patients. This potential valuable was described by one of the nurses as follows:

> *They exist [Patient decision aids], but are not used very often in practice. I was introduced to a digital colorectal cancer decision aid, explaining types of cancer and the advantages and disadvantages of different treatments, help patients choose what they want. I liked that, but in practice, it is hardly used.* [R11]

Enabling Disease and Treatment-Related Behavior

The fifth function includes enabling disease and treatment-related behavior, which involves supporting patients in treatment adherence and promoting a healthy lifestyle. Nurses described different changes in this function resulting from the increased use of health technologies. About e-support, the implementation of virtual cycling increases exercise options to stimulate the patient to healthy behavior.

Regarding e-interaction, the use of health technologies, such as apps and sending photos by email, facilitates a more active role of patients as they are required to make choices and take actions on their own. For example, patients have to make medication intake changes or have to make changes in the wound care treatment, such as stopping flushing the wound. This more active role is mostly regarded as positive but also requires extra effort and skills of the patient, as becomes clear from the following quote:

> *I always say [to patients]; care at a distance is good care, but it is care in which you are in charge, you have to take the steps yourself. But the patient also needs to understand those steps.* [R10]

Responding to Emotions

Patients often experience a range of emotions, such as anxiety, anger, and sadness, as a result of their disease. Nurses can play a crucial role in identifying and responding to these emotions, which can provide patients with a sense of support, but is also a basis for other functions, such as adequate information exchange, decision-making, and self-management. Nurses mentioned that health technologies mainly caused positive changes in this function. Technologies mentioned under e-support included music, virtual reality, video calling with relatives, and online church services that can provide distraction and support to patients. For example, one nurse explained how projected images could distract and calm patients:

> *For example, you find yourself in a forest that was really an experience, and you notice that patients are really happy with that, so in that way, yes, offering something with images and sound, brings distraction. Being in another world for a moment.* [R2; an image projector was used]

In a similar way, virtual reality can lower the experienced pain, for example, during wound treatment.

In addition, if patients are not able to talk, an app was used that allows them to digitally indicate emotions by selecting an emoticon on an iPad. This technology makes it possible to express emotions without using voice. E-education can establish reassurance because a better understanding of their condition or treatment can reduce emotional stress. Using e-interaction can contribute to enhanced comfort in the home situation and create the opportunity for emotional support after an admission. Additionally, as a result of new opportunities to communicate digitally with patients (such as via messages, phone consultations, and emails), nurses are required to attentively listen to the emotions expressed by patients as visual cues are not available. Finally, e-recording, such as the EMR, enables nurses to inform their colleagues about patients' emotions and feelings, fostering comprehensive and coordinated care. On a downside, nurses also admitted that interruptions caused by health technologies, such as nurse paging systems, can affect the emotional support provided by nurses.

Recognizing Patients With Limited Digital Health Literacy

In the interviews, nurses describe different practices to recognize a patient with limited digital health literacy, which could be divided into three categories: (1) intuition, (2) observation of verbal and nonverbal signals, and (3) explicitly ask and register in EMR (Table 5).

Table . Current practices in recognizing patients with limited (digital) health literacy.

Current practices and subthemes	Examples
Intuition	
Intuition	• Gut feeling, intuition
Observe verbal and nonverbal signals	
Patient characteristics	• Advanced age • Low educational level • Poor lifestyle • Comorbidities
Depending on network	• Social network • Care network
Behavior	• Non-compliant with advice • Not having a critical attitude • No motivation or not taking initiative • Asking less or irrelevant questions • Use of language: choice of words, writing style • Not understanding or not reading health information • Only using a few health technologies or difficulties with using them • Not willing to use health technologies • Excuses or avoiding information or do not want any information
Explicitly ask and register in EMR[a]	
Ask questions to identify limited digital health literacy	• Explicitly ask about digital skills and health literacy • Apply a validated assessment tool
Ask patients to demonstrate how they use health technologies	• Instructions are not carried out sufficiently • Ask the patient to demonstrate and observe difficulties
Register in the EMR	• Low literacy registered

[a]EMR: electronic medical record.

Intuition

One frequently used answer to the question on how nurses identify patients with limited (digital) health literacy was intuition. Twelve nurses mentioned that they use their gut feeling to assess if patients have limited or adequate (digital) health literacy. It was difficult for them to explain what this was based on, as is illustrated in the following quote: “You have a gut feeling that the patient is going to perform it properly, but on what do I base that ... I don’t know” (R3). Several nurses acknowledged that this nursing practice is quite uncertain and can lead to incorrect assessments.

Observe Verbal and Nonverbal Signals

Other nurses were more explicit about the cues they used for inferring limited literacy or digital literacy in their patients. Certain patient characteristics were mentioned, including advanced age, low educational level, multiple comorbidities, and an unhealthy lifestyle. Some of these characteristics were observed, such as being overweight, advanced age, smoking, and shabby clothing. Other characteristics were indirectly deduced, such as a low educational level and the presence of comorbidities.

Nurses also identify patients with limited digital health literacy based on the level of dependence on their social or care network. They either asked or observed during a hospital admission the extent to which patients rely on their family or acquaintances, for example, with reading or understanding health-related information or completing online questionnaires. Hospital nurses can collaborate with home care nurses or health care professionals from other departments to gather additional information of the patient.

Another nursing practice to identify patients with limited (digital) health literacy is by observing certain behaviors or verbal cues, such as lack of critical attitude, noncompliance with advice, asking irrelevant questions, and not being motivated. The following quote explains how a lack of a critical attitude is being used as a cue for limited (digital) health literacy:

> *I observe how critical a patient is, or whether he will let everything happen to him. For example, do they take their medication willingly, or do they ask me, what is it or what is it for? I take that into account in my assessment.* [R1]

Explicitly Ask and Register in EMR

Finally, nurses sometimes explicitly asked or assessed (digital) health literacy levels with questions or observed the patient while using the technology. An example of a question that was typically used by nurses to identify patients with limited health literacy was as follows: "Do you feel overwhelmed by the abundance of health information?"

Digital skills were mostly identified with straightforward questions about the patients' use of email, WhatsApp, or social media. Another nursing practice to identify limited digital literacy was to observe how a patient works with health technologies:

> *If we have the equipment on the ward to let them do it themselves and then I will observe them: How does the patient handle it, does the patient know how it works, what does someone do with the explanation? Does it then go right at once or does the patient need more frequent explanations? That does say something about the skills.* [R5]

Formal assessment tools to measure limited (digital) health literacy were never used, and most of the interviewed nurses did not know about the existence of such tools. During the interviews, it also became clear that low literacy is not or only scarcely registered in the EMR. Yet, several nurses indicated that it would be helpful to report about (digital) health literacy in the EMR to facilitate awareness and enable them to tailor care accordingly. Documentation in the EMR would also ensure that other involved health care providers would be informed so that the patient does not have to be repeatedly questioned about these skills.

Supporting Patients With Limited Digital Health Literacy

In daily practice, nurses use certain practices to support patients with limited (digital) health literacy in nursing care. Four main practices were identified: (1) create trust, (2) tailor communication, (3) provide additional support, and (4) use the patient network (Table 6).

Table . Current practices in supporting patients with limited (digital) health literacy.

Current practices	Subthemes
Create trust	• Create trust among patients in the health professional • Support the self-confidence of the patient • Normalize having limited (digital) health literacy
Tailor communication	• Repeat information • Limit the amount of information and use short explanations • Plain or easy language • Visualize • Use additional methods; write information down or use a whiteboard • Check if information given to the patient is understood (teach-back) • Step-by-step explanation • Clear instructions • Ask open questions • Develop tailored health technologies
Provide additional support	• More frequent contact (phone or face to face) • Provide a summary of the provided education and instructions • Create a place where patients can ask questions about the use of health technologies • Offer the nondigital method
Use the patient network	• Involving relatives to support the patient in using health technologies • Asking relatives to use health technology instead of the patient • When various relatives are receiving the information, relatives can also repeat it for the patient • If the patient does not understand the explanation, the nurse can use the patient's network • Relatives can help the patients formulate questions • If no relative is available, arrange home care • Consult and coordinate with other caregivers

Create Trust

To support patients with limited (digital) health literacy, 5 nurses indicated that it is important to create trust. This practice included addressing patients' distrust of health technologies, supporting and increasing patients' self-confidence, and also creating trust in health professionals. Nurses mentioned that these are important skills to support patients in understanding health information and support patients in using health technologies. It is crucial to normalize having limited (digital) health literacy and inform patients that many patients are experiencing difficulties in understanding and applying (digital) health information. This was explained by one of the nurses as follows:

> *Some patients ask me, why are you asking if I can't read? I always say, there are quite a lot of people in the Netherlands who cannot read at all. And if that is the case, we like to take that into account because then we can also show you information in a different way.* [R10]

Normalizing having limited (digital) health literacy hopefully contributes to less shame about having limited (digital) health literacy and makes it easier for the patient to ask questions or to indicate if something is not fully understood.

Tailor Communication

Different types of practices exist to tailor the communication to patients with limited (digital) health literacy. These include repeating information, using short explanations, using plain language, and visualizing information. Additional methods to support the patient's understanding of health information are to write down information or draw pictures and use a whiteboard in a hospital patient room. Certain nurses indicated using the teach-back method to ensure the patient's understanding. This method asks patients to state in their own words what they understood or remembered from the given health information [21]. Even though this method was mentioned, it was unclear whether all nurses performed it correctly, as several nurses subsequently indicated they were only asking if a patient still had any questions.

Provide Additional Support

Providing additional support is described as a useful nursing practice by the majority (n=16) of the nurses. An example was frequent telephone contact to establish more guidance and more opportunities to practice with health technology. Another suggestion was to create a support team who can be reached by phone, where patients can ask questions related to the use of health technologies.

In addition, nurses described that face-to-face communication instead of digital communication should remain possible, recognizing that not all patients may be capable of using health technologies even with extra support. Some nurses described that patients who were not willing or able to use health technologies were excluded from using health technologies. This means that these patients do not have the opportunity to participate and experience the positive effects of it. One nurse indicated that patients were never excluded from home dialysis, including the use of health technologies due to insufficient skills. Excluding none of the patients was a conscious decision, as long as the patient was willing to learn and try. Consequently, this requires nurses to invest time, patience, and creativity in guiding these patients.

Use the Patients' Network

The majority (n=15) of nurses reported that patients' social networks are also utilized to support patients with limited (digital) health literacy. For example, relatives can assist patients in working with health technologies and repeat important educational instructions: "But you can also check if the son, daughter, or grandchildren might know a little more about technology and could offer help" (R18). Besides, the health care network of a patient (eg, home care) can help if there are no relatives available. Consulting other caregivers about the care for the patient can lead to comprehensive care and appropriate support.

Barriers to Recognize and Support Patients With Limited (Digital) Health Literacy

Several barriers to recognize and support patients with limited (digital) health literacy exist. Regarding the work environment, one frequently mentioned barrier was the experienced workload. The continuous high workload often leaves limited time to identify patients with limited (digital) health literacy and provide tailored support. Moreover, nurses often see patients only for a very short time, which makes it particularly difficult to get to know the patient very well:

> *You don't know the patients when they enter the hospital and just being admitted. You have to get to know them first. That is sometimes difficult.* [R4]

Related to the patient, the nurse described that numerous patients feel ashamed about having limited (digital) health literacy and try to disguise this. This makes recognition more difficult. Another barrier is the family members who speak consistently on behalf of patients instead of giving the patient the opportunity to talk. This may make it difficult to gather the right information because it may be the opinion of the family rather than that of the patient. The last barrier is nurses' own lack of knowledge. Nurses indicate that they have little knowledge about recognizing and supporting these patients. As a result, they often rely on intuition.

Discussion

Principal Findings

The results of this study show that nurses in hospitals use a wide variety of health technologies, and this has affected the nurse-patient communication significantly, mainly in a positive way. Nurses mentioned intuition, observing verbal and nonverbal signals, and explicitly asking as nursing practices to identify patients with limited digital health literacy. Nursing practices to support patients with limited (digital) health literacy included building trust, tailoring communication, providing additional support, and engaging the patient's network. Several barriers were identified in recognizing and supporting patients with limited (digital) health literacy, including a high workload, lack of knowledge, and not knowing the patient.

Our results revealed that according to the nurses, health technologies affected all 6 functions of the de Haes and Bensing's communication model [2]. Positive consequences were seen in gathering and providing health information, enabling disease and treatment management, decision-making, and supporting patients to handle their emotions. These results are in line with previous research reporting benefits such as reduced unnecessary consultations, improved accessibility for patients, and the potential of messaging systems to facilitate nursing care [22. While our study primarily observed positive changes, we also identified certain challenges. These included, for example, verifying patients' understanding and addressing complex images or content that required additional explanation for patients. Similar challenges have been reported in other qualitative studies, including the additional workload associated with training patients [23]. These studies have further highlighted nurses' limited digital skills, as well as the rapid pace of technology implementation [24]. Although overall changes were largely positive, it was notable that our study identified predominantly negative changes within the function of fostering the nurse-patient relationship. Similar challenges were reported in a study using focus groups with primary health care nurses exploring their views on eHealth tools for patient self-management [24]. Nurses expressed concerns about losing personal contact, perceiving digitalization as a potential threat to the nurse-patient relationship [24]. To overcome this challenge, nurses in our study recommended always starting with a face-to-face meeting and switching to digital communication only after the relationship is built. The preference for initial face-to-face consultations, as well as for combining digital and in-person consultations, has also been noted previously [25]. Our findings suggest that task-oriented functions of the 6-function model, such as providing health information and supporting disease management, benefit from technology through increased efficiency, accessibility, and structure. In contrast, relational functions, such as fostering the nurse-patient relationship, are harder to support digitally, as they rely on nonverbal cues and trust-building [2].

To the best of our knowledge, this study is the first to examine the impact of health technologies on nurse-patient communication using the 6-function model of communication [2]. Although the 6-function model was not specifically designed for use in the nurse-patient communication context, it proved to be highly usable, and nurses could easily relate to the 6 identified functions. This is in line with a previous study in which the model was used to examine nurse-patient communication [26]. Although the model was also not developed to study the impact of health technologies, it turned out to be helpful in providing insight into their impact on the various functions of communication.

In nurse-patient communication, it is important to identify the patients who experience difficulties in using health technologies. Patients with limited health literacy are less likely to use health technologies or perceive them as difficult and useless [27], while these patients can actually benefit from them, for example, from the visualization of health education through videos. To reduce exclusion of patients with limited (digital) health literacy, nurses can play a pivotal role in recognizing and supporting these patients. Nurses in our study mentioned different practices to recognize patients with limited (digital) health literacy. These are intuition, observed verbal and nonverbal signals, and explicitly asking patients about their (digital) health literacy skills or asking them to demonstrate the use of the health technology. Previous studies also showed that nurses often use their intuition to estimate health literacy [28] and use verbal and nonverbal cues, such as patients' use of simple language, facial expressions, or level of interaction [29]. Unfortunately, "intuition" and "observing verbal and nonverbal signals" are very subjective. Relying only on intuitions may not be an appropriate practice, since it is known that nurses frequently overestimate the health literacy of their patients [30]. Some verbal and nonverbal signals, such as lower education, low self-management, less motivation, and low self-efficacy, are indeed associated with limited (digital) health literacy [31,32], but this does not apply to every individual patient and may be difficult to observe. Moreover, for some nonverbal signals, such as looking slobby, evidence is lacking. A potentially more reliable nursing practice is to explicitly ask patients about their (digital) health literacy skills or to demonstrate how they use technology. Although the importance of this was acknowledged by a few of the interviewed nurses, it was not common practice. A reason for being hesitant to ask patients about their health literacy is that many patients feel ashamed about having limited (digital) health literacy [33]. Our results highlight the importance of educating nurses on how to assess patients' (digital) health literacy in a neutral and nonoffensive manner, so as to avoid causing discomfort or feelings of shame.

Interestingly, our results showed that patients' levels of (digital) health literacy are only occasionally documented in the EMR, despite the availability of numerous questionnaires to assess digital health literacy [34]. The systematic documentation of this information could reduce the need for repeated assessment and could enhance continuity of care among health care professionals within hospital settings.

To support patients with limited (digital) health literacy, nurses used different practices: building trust, tailoring communication, providing additional support, and engaging the patient's network. To tailor communication, the "teach-back method," already proven to be effective [21], was often mentioned. Unfortunately, it appears that the teach-back method is not always performed correctly. A recent review including similar health literacy practices as in our study showed positive effects on patient support, including activation, patient comprehension, and engagement [35]. Strategies often included multimedia or technology-based approaches, simplification of written material, and facilitation of in-person sessions. More research is needed to examine if these practices are actually effective and how nurses can be motivated to use these in daily practice.

Our study revealed that many nurses are experiencing multiple important barriers while recognizing and supporting these patients. These include a high workload, lack of knowledge, and not knowing the patient. For some of these barriers, training could be helpful. Training, encompassing various educational programs and online resources, has been identified as an effective intervention that significantly contributes to improving digital health literacy [36]. Several studies have shown that offering training for nurses on how to recognize and support patients with limited health literacy shows positive effects on knowledge, attitude, confidence, and increased usage of strategies to recognize and support patients with limited health literacy [37-43]. Unfortunately, the digital component is often not included (yet) in these existing training. It is recommended that nursing education and existing training programs systematically integrate the digital component, with particular emphasis on enabling nurses to recognize and support patients with limited (digital) health literacy.

Strengths and Limitations

A strength of this study is that a heterogeneous group of nurses from different wards and various specializations was included. This contributed to more generalizable results regarding nurses working in hospitals. This study was conducted in the Dutch hospital context, where the implementation of health technologies is relatively advanced. However, it remains unclear how these findings translate to other countries, as differences in health care systems, digital developments, digital literacy of nurses, and organizational structures may influence the adoption and impact of health technologies. Further research in diverse international contexts is needed to explore their applicability beyond the Netherlands.

In this study, we selected participants who had at least some experience with health technologies to explore their perspectives based on actual use. As a result, our findings primarily reflect the experiences of nurses with some engagement in digital technologies. Future research including nurses with little or no prior experience could provide additional insights into potential barriers and challenges.

Future Research

Since this study primarily used self-reported data, it would be valuable to observe actual nursing behaviors in practice, for example, how frequently nurses use strategies to recognize and support patients with limited digital health literacy. Furthermore, gaining a deeper understanding of patients' perspectives is equally important. Patients with limited digital health literacy may experience challenges with health technologies that differ from or overlap with those faced by nurses. It is still unclear to what extent patients recognize potential disadvantages or barriers related to technology use. Therefore, future research should explore the specific difficulties patients encounter and the types of support they need to effectively engage with digital health tools.

Besides the patient perspective, future research may explore potential differences across hospital departments, as communication challenges may vary by clinical context. For example, nurses working in intensive care units may face distinct communication challenges, such as needing to communicate primarily with family members or navigating ethical considerations related to digital consent.

Providing training to nurses on how to support patients with limited (digital) health literacy could be beneficial. Such training may help nurses apply structured strategies rather than relying solely on intuition. When developing this training, it is important to cocreate its content with nurses from diverse clinical settings and with varying levels of experience, ensuring that the modules align with current practice. In addition, integrating these competencies into nursing education is essential so that future nurses also develop the necessary skills.

Moreover, involving nurses in the selection and implementation of health technologies is important. Their perspectives can guide the choice and adoption of new technologies, the design of training programs, and the development of user-friendly systems, such as EMRs. This approach helps ensure that digital health innovations are accessible, practical, and responsive to the needs of both nurses and patients. Ultimately, the impact of these technologies depends not only on the tools themselves but also on organizational and systemic factors, including staff readiness, training support, and supportive organizational structures [44-46].

Conclusions

This study shows that health technologies have strengthened nurse-patient communication and extended de Haes and Bensing's model [2] to the digital context. Yet, challenges persist, particularly in fostering relationships. It also reveals that systematic (digital) health literacy assessment remains lacking and that current practices to identify and support patients with limited (digital) health literacy may not always be effective. Once effective approaches are established, they should be integrated into nursing care plans and education.

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Data Availability

The datasets generated or analyzed during this study are not publicly available.

Authors' Contributions

Conceptualization: CHCD, CD, DE, EMD, JW
Data curation: ED, JW
Formal analysis: CHCD, ED, JW
Investigation: ED, JW
Methodology: CHCD, CD, ED, JW
Project administration: ED
Supervision: CD
Writing – original draft: CHCD, CD, DE, ED, JW

Conflicts of Interest

None declared.

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Abbreviations

COREQ: Consolidated Criteria for Reporting Qualitative Research
EMR: electronic medical record

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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

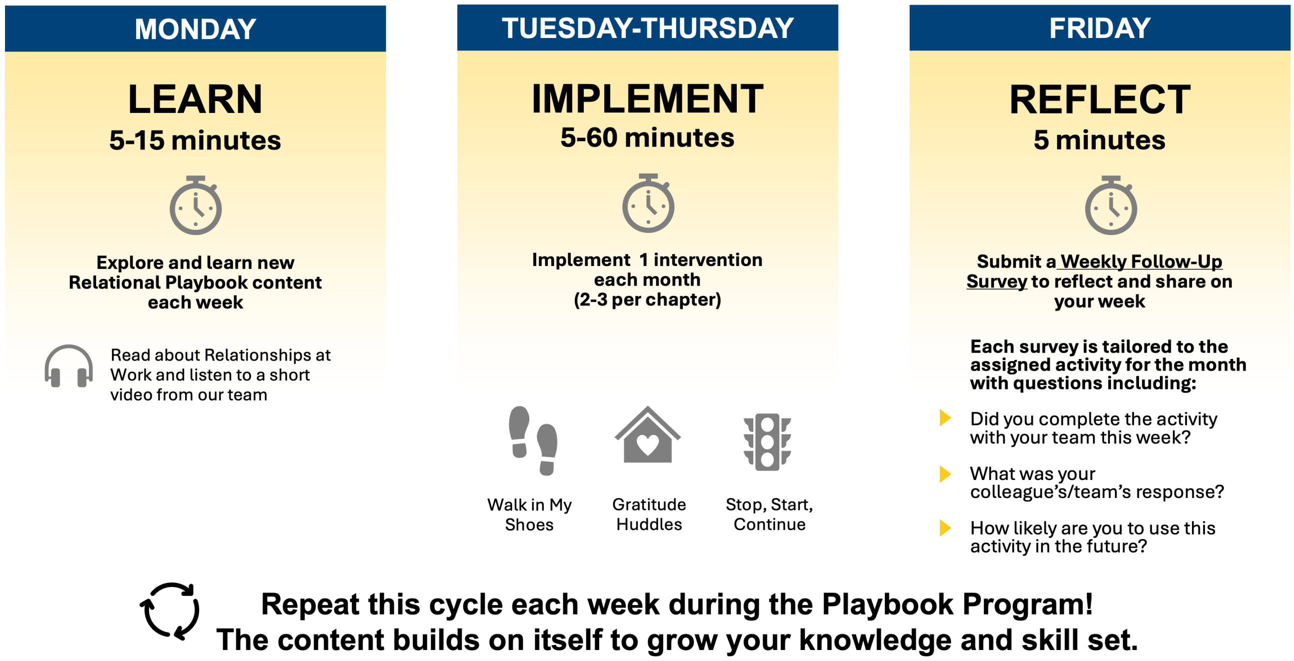
Overview

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:

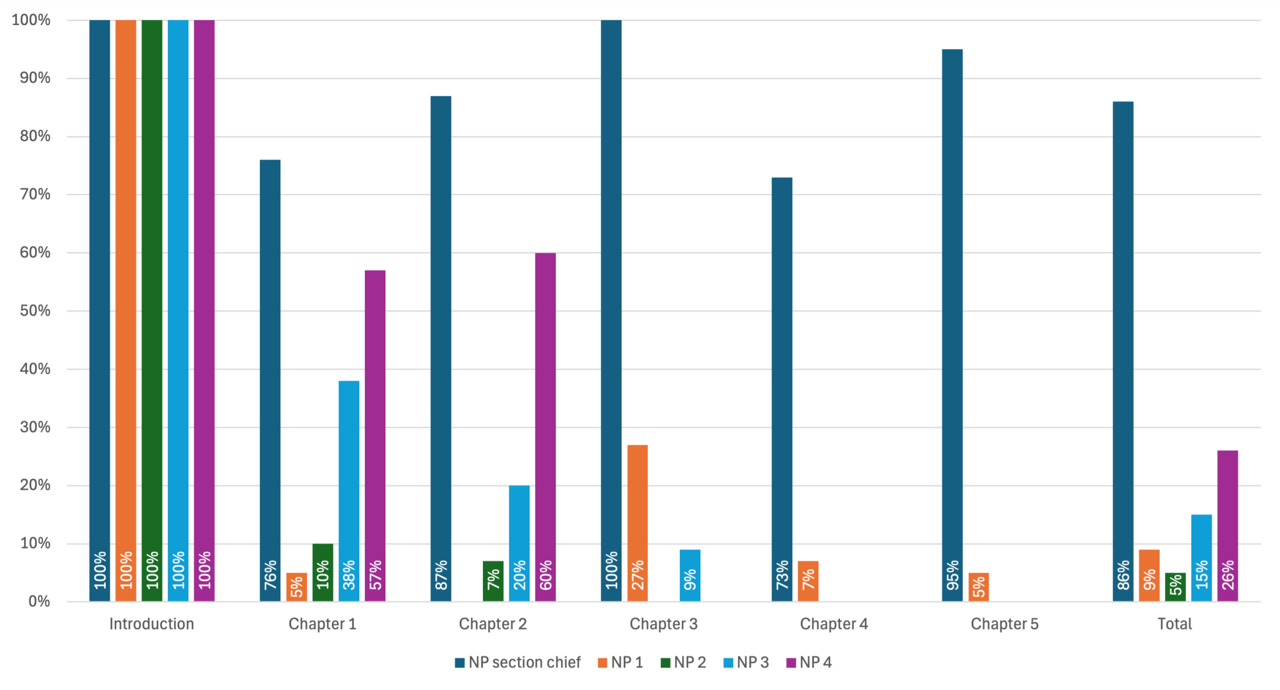
> *Worked well with a co-worker to solve a problem!*

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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Digital Leadership Scale for Clinical Nurses: Development and Validation of an Instrument

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Abstract

Background: The rapid advancement of digital technologies, combined with the evolving complexity of health care environments, has introduced a new paradigm in nursing practice. Clinical nurses are now required not only to deliver safe and effective patient care but also to demonstrate competencies in digital literacy and innovation. Among these emerging competencies, digital leadership has become a critical attribute—enabling nurses to lead digital transformation, ensure patient safety, enhance care quality, and support system-level change within health care organizations. Despite its increasing relevance, there is a notable absence of validated measurement tools tailored to assess digital leadership in clinical practice.

Objective: This study aimed to develop and psychometrically validate a Digital Leadership Scale for Clinical Nurses (DLS-CN) to systematically evaluate the digital leadership capabilities of nurses working in clinical settings.

Methods: The scale development process followed a rigorous multistep procedure. Initial items were derived from previous qualitative research involving a literature review and in-depth interviews, complemented by an additional literature review conducted in this study. The content validity of 38 preliminary items was evaluated by 9 experts over 2 rounds. A pilot test was conducted with 30 nurses, followed by cognitive interviews with 5 nurses to refine item clarity and relevance. The final set of items was administered to 446 clinical nurses across various health care institutions. Data were randomly split for exploratory factor analysis and confirmatory factor analysis. Additional analyses were conducted to evaluate item discrimination, convergent validity, and internal consistency using IBM SPSS 25.0 and AMOS 23.0.

Results: The finalized DLS-CN consists of 29 items grouped under four domains: (1) ability to use digital technology, (2) digital safety management, (3) digital collaboration mindset, and (4) organizational influence. These 4 factors explained 56.9% of the total variance. The scale showed strong internal consistency (Cronbach α=0.95). Convergent validity was demonstrated through strong positive correlations with the Nursing Informatics Competency Scale (Pearson correlation coefficient r=0.82; P<.001) and the Self-Leadership Scale (Pearson correlation coefficient r=0.83; P<.001).

Conclusions: The DLS-CN is a valid and reliable instrument for measuring digital leadership among clinical nurses. It offers a practical tool for educators, administrators, and researchers to assess and enhance digital leadership capabilities—ultimately supporting the digital transformation of health care systems.

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KEYWORDS

nurses; digital technology; leadership; digital health; factor analysis, statistical; nursing informatics; surveys and questionnaires

Introduction

The digital transformation era has accelerated the adoption of digital technologies in the health care sector, particularly after COVID-19, which catalyzed the integration of such technologies into clinical practice [1-3]. Clinical nurses are increasingly using digital tools to ensure safe care environments and to provide evidence-based nursing [4,5]. Common technologies used by nurses include wearable devices, electronic health records, and Barcode Medication Administration systems [6,7], all of which enhance patient safety and efficiency. The adoption of these digital tools in clinical settings has been shown to improve nursing efficiency and patient outcomes [8].

As health care environments become increasingly digitalized, nurses are expected not only to use digital technologies in practice but also to adapt to and support digital change in clinical settings. Nurses serve as coordinators, ensuring effective communication among patients, families, health care professionals, and nursing peers, which is directly related to patient safety [4,9]. In this context, digital leadership encompasses not only the technical ability to understand and apply digital tools [10] but also the capacity to introduce new communication systems and foster collaboration among team members [11]. Therefore, to successfully implement digitalization and health information technologies within hospital organizations, leadership from nurses who continuously enhance and manage their clinical competencies is essential [12,13]. The level of leadership demonstrated by nurses is closely linked to the quality of nursing services [14].

Digital leadership combines traditional nursing competencies with digital capabilities, thereby improving the quality and efficiency of care delivery [8]. In rapidly evolving health care environments, digital leadership is no longer a personal attribute of individual nurses but a comprehensive competency influencing teams and organizations [15]. Nurses must demonstrate adaptability to digital changes [2], solve problems arising during digital transitions [11,16], and support peer education and motivation [2,17]. Effective digital leadership also includes ethical considerations, such as the protection of patient information in the context of big data usage [18]. Existing tools for measuring digital leadership have primarily been developed for managers or employees in general corporate settings, focusing on behaviors and skills required in digital work environments, including vision sharing and resource support. These tools aim to assess general leadership attributes applicable in digital contexts [19,20]. However, they are limited in that they do not reflect the specific characteristics of nursing practice, which involves unique therapeutic relationships between nurses and patients [21], nor do they account for the evolving nature of contemporary clinical settings due to the introduction of new digital technologies [3]. While digital leadership among nurses—encompassing the ability to adapt to digital transformation and effectively integrate digital technologies with health data—is increasingly essential [2,22,23], there remains a lack of measurement tools that are specifically developed to reflect the unique roles and characteristics of clinical nurses.

The purpose of this study is to develop and validate the Digital Leadership Scale for Clinical Nurses (DLS-CN). This scale is intended to accurately assess the level of digital leadership among clinical nurses and provide a foundation for evaluating and enhancing their leadership capabilities in digital health care environments.

Methods

Study Design

This study is a quantitative methodological research conducted to develop and evaluate a measurement tool for assessing digital leadership among clinical nurses. The development of the DLS-CN was carried out in 2 phases, based on the tool development process proposed by DeVellis and Thorpe [24]. In the first phase, preliminary items were developed, followed by content validity testing, cognitive interviews, and a pilot survey. In the second phase, the tool was administered to clinical nurses to examine its reliability and validity.

Scale Development Process

Phase 1: Preliminary Item Development

Clarification of the Conceptual Definition

This study was based on the hybrid model of Schwartz-Barcott and Kim [25], applying theoretical, fieldwork, and final analytic phases. Based on a previous study analyzing the concept of digital leadership [15], a literature review was conducted, and concept attributes were integrated to establish a conceptual framework and identify core attributes. Through this process, 6 components of digital leadership were identified: digital problem-solving ability, digital ethical sensitivity, digital mindset, self-growth, digital collaboration, and organizational influence.

Item Generation

A total of 104 initial items were generated across 6 components of digital leadership for clinical nurses. Specifically, 21 items measured digital problem-solving ability, 19 items measured digital ethical sensitivity, 16 items measured digital mindset, 9 items measured self-growth, 17 items measured digital collaboration, and 22 items measured organizational influence.

Selection of Measurement Format

Since the items were designed to measure the level of agreement with statements regarding digital leadership among clinical nurses, the widely used Likert scale was deemed appropriate [24]. Therefore, a 5-point Likert scale was selected.

Expert Content Validity Assessment

To evaluate the content validity of the preliminary items, an expert panel of 9 members was formed: 2 clinical nurses with more than 5 years of experience; 2 nurse unit managers; 2 nursing professors; and 1 expert each in digital health care, leadership, and hospital management. After the researchers explained the concept of digital leadership for clinical nurses, the experts rated the appropriateness of the item content and components using a 4-point Likert scale. For item-level evaluation, the item-level content validity index was considered acceptable if it was 0.78 or higher. To assess overall content validity, the scale-level content validity index was calculated by averaging, with 0.90 or higher judged as acceptable [26]. Two rounds of expert validation were conducted. As a result of the first round, 71 items were selected. After the second round, the number was reduced to 46 items. During this process, sentence order and expressions were revised for better clarity and specificity, especially when abstract or ambiguous wording was identified.

Cognitive Interviews

Cognitive interviews were conducted with 5 clinical nurses who met the inclusion criteria of the main study. Each interview lasted 30 to 40 minutes and aimed to understand how participants interpreted and responded to the preliminary items. During the interviews, participants were asked to explain their thought processes while answering each item, including how they understood the wording, whether any terms were unclear, and whether the items were easy or difficult to answer. The interview data were analyzed by reviewing participants' explanations and feedback on item comprehension, wording, and response processes. Based on these findings, items were revised to improve clarity and reduce potential response errors. When similar or overlapping content was identified, the researchers rechecked whether the same concern was expressed by other interviewees before making revisions. The revised items were then reviewed again with the interviewees to confirm their appropriateness. Some participants questioned the appropriateness of the term “hospital information system,” but after reviewing related tools, literature, and expert texts, the term was retained to encompass systems such as electronic medical records and order communication systems. Regarding terms describing digital collaboration tools or systems, alternatives like “intranet” and “groupware” were suggested; however, “digital collaboration system” was found to be the most understandable and suitable. In response to feedback, the term “real-time” was added to better reflect the advantages of system usage. While some general staff nurses noted difficulty adopting new technologies and resources, replacing terms like “utilize” or “apply” was found to weaken alignment with intended attributes, so the original expressions were maintained. After revising the items, the modified 46 items were confirmed for appropriateness through follow-up review with the interviewees.

Pilot Study

To identify issues with the preliminary items, a pilot study was conducted with 30 clinical nurses who met the same criteria as those in the main study. This was conducted via an online survey identical in format to the main study. Respondents rated item comprehensibility on a 5-point scale (1=“very difficult” to 5=“very easy”), yielding an overall average of 4.14 (SD 0.24), indicating that the items were well understood. The time required to complete the survey ranged from 5 to 25 minutes, with an average of 11 (SD 1.84) minutes. Open-ended questions confirmed that item length, font size, and type were appropriate. Based on the pilot results, items with duplicate meanings or unclear wording were revised. Additionally, a new item was added to the organizational influence component, “I can help organizational members experiencing difficulties in digitalized work environments,” to complement the existing item, “I can ask organizational members for help when I face difficulties.” All items were revised through linguistic review to ensure correct spacing, terminology, and order. Ultimately, the preliminary item pool was finalized with 47 items across 6 components.

Phase 2: Instrument Evaluation—Reliability and Validity Testing

Participants

Participants were 446 clinical nurses working at tertiary or general hospitals in South Korea. Eligible participants were nurses who were directly involved in patient care and had at least 1 year of clinical experience. Nurses with less than 1 year of experience were excluded because they were considered to be in the novice stage of acquiring the knowledge and skills necessary for nursing practice [27,28]. Nurses in administrative, educational, or nondirect care roles were also excluded. A minimum sample size of 200 is generally recommended for factor analysis, and for confirmatory factor analysis (CFA), a commonly used rule of thumb is that the sample should be at least 10 times the number of estimated parameters [29,30]. Therefore, the total sample size of 446 was considered adequate. To examine the factor structure and cross-validate the model, the total sample was randomly divided into 2 equal groups, with 223 participants assigned to exploratory factor analysis (EFA) and 223 to CFA. This equal split was used to ensure independent and sufficiently large samples for both analyses.

Instruments

To evaluate convergent validity, 2 instruments were selected: the Nursing Informatics Competency Scale [31] and the Self-Leadership Scale [32]. The Nursing Informatics Competency Scale includes 20 items across 5 components: “Basic information and communication technology use” (3 items), “Utilization of nursing information” (5 items), “Professional responsibility and ethics” (5 items), “Use of information and communication technology in nursing” (4 items), and “Attitudes toward nursing informatics” (3 items). Each item is rated on a 4-point Likert scale. The reliability of the original scale was a Cronbach α of 0.91 [31], and in this study, internal consistency reliability was assessed using Cronbach α based on the responses of the study participants, with a Cronbach α coefficient of 0.91, indicating excellent internal consistency. The Self-Leadership Scale consists of 16 items across 4 components: “Collaborative self-dialog strategies” (4 items), “Physical vitality enhancement strategies” (4 items), “Goal-oriented self-training strategies” (4 items), and “Self-respect pursuit strategies” (4 items). This instrument uses a 5-point Likert scale. The original reliability was a Cronbach α of 0.86 [32], and in this study, the Cronbach α was also calculated using the current dataset, yielding a coefficient of 0.91, which indicated excellent internal consistency.

Data Collection

Data were collected from March 10, 2024, to March 30, 2024, through a self-administered online survey using a nonprobability convenience sampling method. Participants were able to complete the survey at their preferred time and location without direct contact with the researchers. To recruit nurses from diverse regions, recruitment notices containing the contact information of the researchers and the survey link (URL) or QR code were posted on online nursing community boards and workplace forums, allowing eligible participants to voluntarily access and complete the survey. All items were set as mandatory, preventing participants from proceeding without responding; consequently, no missing data were observed in the submitted questionnaires. Data collection continued until the predetermined sample size required for item analysis was reached, after which the survey was closed to prevent additional responses. Because the survey link was distributed through open online communities and workplace forums, the total number of individuals who viewed the recruitment notice could not be determined, and thus the response rate could not be calculated.

Data Analysis

Collected data were analyzed using IBM SPSS Statistics version 25.0 and AMOS version 23.0. First, participants’ general characteristics were analyzed using frequencies, percentages, means, and SDs. Second, for the item analysis, means, SDs, skewness, kurtosis, inter-item correlations, item-total correlations, and reliability (if an item was deleted) were calculated. Third, to test the suitability of EFA, the Kaiser-Meyer-Olkin (KMO) measure and the Bartlett test of sphericity were used. Fourth, principal component analysis with varimax rotation was performed to extract factors. Fifth, CFA was conducted to evaluate model fit and test convergent and discriminant validity. Sixth, convergent validity was also examined using the Pearson correlation coefficient. Finally, internal consistency reliability was tested using Cronbach α.

Ethical Considerations

This study was approved by the Institutional Review Board of Daegu Catholic Medical Center (CR-23-148). The online survey introduction clearly explained the study's purpose, informed consent, procedures, voluntary participation, confidentiality, potential benefits and risks, and stated that the data would be used only for research purposes. Participants received a small token of appreciation for their involvement. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki.

Results

General Characteristics of Participants

A total of 446 clinical nurses participated in the survey (Table 1). Among them, 223 participants were included in the EFA, with an average age of 30.71 (SD 5.45) years. Most participants were female (208, 93.3%). Regarding the type of hospital where they worked, 137 participants (61.4%) were employed at tertiary hospitals and 86 (38.6%) at general hospitals. The most common region was Seoul, the capital, with 106 participants (47.5%). The average length of clinical experience was 70.41 (SD 46.68) months. In terms of work departments, 137 participants (61.4%) worked in general wards, 52 (23.3%) in special units (eg, intensive care units, operating rooms, emergency rooms), 17 (7.6%) in outpatient clinics, and 17 (7.6%) in other departments. For the CFA, 223 participants were included, with an average age of 31.07 (SD 4.81) years. The majority were female participants (200, 89.7%). A total of 131 participants (58.7%) worked in tertiary hospitals and 92 (41.3%) in general hospitals. The highest number of participants was also from Seoul (99, 44.4%). The average length of clinical experience was 74.31 (SD 57) months. Regarding work departments, 147 participants (65.9%) worked in general wards, 38 (17.0%) in special units, 25 (11.2%) in outpatient clinics, and 13 (5.8%) in other departments.

Table . General characteristics of participants for factor analysis (N=446).

Characteristics and categories	EFA[a] (n=223)	CFA[b] (n=223)
Age (y), mean (SD)	30.71 (5.45)	31.07 (4.81)
Sex, n (%)		
Female	208 (93.3)	200 (89.7)
Male	15 (6.7)	23 (10.3)
Marital status, n (%)		
Married	161 (72.2)	163 (73.1)
Unmarried	62 (27.8)	60 (26.9)
Educational level, n (%)		
Associate’s degree	209 (93.8)	206 (92.4)
Bachelor’s degree	13 (5.8)	17 (7.6)
Master’s degree	1 (0.4)	0 (0.0)
Hospital type, n (%)		
Tertiary hospital	137 (61.4)	131 (58.7)
General hospital	86 (38.6)	92 (41.3)
Hospital location, n (%)		
	106 (47.5)	99 (44.4)
Capital		
Metropolitan	78 (35.0)	82 (36.8)
Province	39 (17.5)	42 (18.8)
Clinical career (y), mean (SD)	5.87 (3.89)	6.19 (4.75)
Working unit, n (%)		
General ward	137 (61.4)	147 (65.9)
Special department (ICU[c], OR[d], and ER[e])	52 (23.3)	38 (17.0)
OPD[f]	17 (7.6)	25 (11.2)
Other	17 (7.6)	13 (5.8)
Experience related to digital leadership education, n (%)		
Yes	13 (5.8)	7 (3.1)
No	210 (94.2)	216 (96.9)
Necessity of digital leadership education, mean (SD)	4.00 (0.89)	4.01 (0.82)

[a]EFA: exploratory factor analysis.
[b]CFA: confirmatory factor analysis.
[c]ICU: intensive care unit.
[d]OR: operating room.
[e]ER: emergency room.
[f]OPD: outpatient department.

Item Analysis

To examine the distribution of items in the 223 collected responses for factor analysis, the mean, SD, skewness, and kurtosis were calculated for each item. Since none of the items had an absolute skewness value greater than 3.0 or an absolute kurtosis value greater than 8.0, all items met the assumption of normality [33]. Item-total correlation coefficients were reviewed, and items with coefficients below 0.30 or above 0.80 were removed, as these values suggest low contribution to the scale or item redundancy [34]. Seventeen items were removed due to low internal consistency reliability and weak correlation between item pairs. Based on corrected item-total correlation and changes in reliability after item deletion [33], the corrected item-total correlations ranged from 0.43 to 0.72, and the reliability did not significantly change upon item deletion (Table 2). As a result, 30 items were retained for further analysis.

Table . Goodness-of-fit test for the measurement model (n=223).

Goodness-of-fit	*P* value	Chi-square (*df*)	χ^2/df[a]	CFI[b]	RMSEA[c]	SRMR[d]
Measurement model	<.001	661.64 (371)	1.78	0.91	0.06	0.5
Criteria	<.05	—[e]	<3	≥0.90	≤0.06	≤0.08

[a]χ^2/df: normed chi-square.

[b]CFI: comparative fit index.

[c]RMSEA: root mean square error of approximation.

[d]SRMR: standardized root mean squared residual.

[e]Not available.

Exploratory Factor Analysis

EFA using principal component analysis with varimax rotation was conducted on the 30 items of the DLS-CN. Prior to the factor analysis, data adequacy was assessed using the KMO measure and the Bartlett test of sphericity. The KMO value was 0.96, indicating excellent sampling adequacy, and the Bartlett test of sphericity was statistically significant [35], confirming the data's suitability for factor analysis. To determine the number of factors, eigenvalues greater than 1.0 and a cumulative variance explanation rate exceeding 60% were used based on Kaiser rule. Scree plot analysis and the interpretability of the factor structure were also considered. Items were retained based on communalities greater than 0.40, factor loadings above 0.40, and at least 3 items per factor [36]. One item with a factor loading below 0.40 was removed. The final analysis included 29 items, with a KMO of 0.95 and a statistically significant Bartlett test (χ^2_{820}=4799.3; *P*<.001), indicating the appropriateness of factor analysis. The EFA extracted 4 factors with eigenvalues greater than 1.0, explaining a cumulative variance of 56.9%. Communality values ranged from 0.52 to 0.64, and all factor loadings exceeded 0.40, indicating good model fit. The purpose of factor analysis is to understand the pattern of data and clarify the interpretability of factors [37]. The factor loadings and item contents were examined to ensure conceptual coherence. Cross-loading items that were theoretically essential were assigned to conceptually valid factors. The inter-item correlation coefficients within subfactors were as follows: factor 1: 0.43 to 0.64; factor 2: 0.35 to 0.57; factor 3: 0.35 to 0.51; and factor 4: 0.39 to 0.052, indicating that the model estimation was appropriate (Table 3).

Table . Communality and pattern matrix of the final exploratory factor analysis (n=223)[a].

Item number	Communality	Factor loading			
		F1[b]	F2[c]	F3[d]	F4[e]
1	0.58	0.63	0.29	0.30	0.12
46	0.64	0.63	0.05	0.25	0.42
39	0.60	0.62	0.17	0.30	0.31
8	0.61	0.61	0.44	0.16	0.12
9	0.54	0.60	0.32	0.21	0.17
2	0.62	0.60	0.34	0.35	0.18
40	0.63	0.59	0.14	0.24	0.45
45	0.52	0.52	0.33	0.25	0.25
4	0.57	0.49	0.43	0.33	0.21
22	0.66	0.24	0.68	0.20	0.31
14	0.60	0.29	0.68	0.21	0.13
16	0.60	0.31	0.66	0.13	0.24
26	0.58	0.16	0.65	0.29	0.22
30	0.52	0.10	0.55	0.33	0.31
36	0.52	0.30	0.48	0.45	0.06
31	0.62	0.03	0.29	0.62	0.39
33	0.53	0.31	0.20	0.61	0.17
37	0.53	0.40	0.11	0.58	0.14
34	0.54	0.29	0.22	0.58	0.27
20	0.54	0.32	0.34	0.56	0.05
21	0.56	0.20	0.28	0.54	0.39
25	0.54	0.35	0.25	0.49	0.33
19	0.58	0.15	0.27	0.27	0.64
12	0.56	0.26	0.29	0.15	0.63
41	0.59	0.27	0.06	0.42	0.58
18	0.57	0.22	0.46	0.18	0.53
27	0.53	0.20	0.44	0.18	0.52
42	0.52	0.44	0.12	0.28	0.48
38	0.54	0.44	0.36	0.00	0.47
Eigen value	—[f]	13.16	1.26	1.10	1.01
Variance (%)	—	16.31	14.80	13.23	12.60
Cumulative variance (%)	—	16.31	31.11	44.34	56.94

[a]Kaiser-Meyer-Olkin (KMO) value is 0.95, and the Bartlett test of sphericity was significant (χ^2_{406}=3492.66; *P*<.001).

[b]F1: ability to use digital technology.

[c]F2: digital safety management.

[d]F3: digital collaboration mindset.

[e]F4: organizational influence.

[f]Not applicable.

Confirmatory Factor Analysis

CFA was conducted to verify whether the 4 factors and 29 items extracted during the EFA appropriately reflected the constructs of digital leadership among clinical nurses. The model's goodness-of-fit was assessed to confirm the adequacy of the structure. To evaluate the model fit, the chi-square statistic was examined. A model was considered acceptable if the normed chi-square χ^2/df was less than 3, the comparative fit index was above 0.90, the root mean square error of approximation was below 0.06, and the standardized root mean squared residual was below 0.80 [38]. The results of the CFA indicated that the chi-square value was statistically significant, and the normed chi-square χ^2/df was 1.8, satisfying the criterion of being below 3. The comparative fit index was 0.91, exceeding the threshold of 0.90. The root mean square error of approximation was 0.06, which meets the criterion for a good model fit. The standardized root mean squared residual was 0.05, which is below the acceptable cutoff of 0.08, indicating that the model had a generally good fit (Table 2).

To verify the convergent validity of each factor, the standardized factor loading was required to be 0.5 or higher, the significance of the unstandardized regression coefficient (critical ratio) was required to exceed 1.97 (P<.05), the construct reliability had to be 0.7 or higher, and the average variance extracted (AVE) needed to be 0.5 or higher [39]. The results of the convergent validity test showed that the critical ratio values of the unstandardized regression coefficients ranged from 7.83 to 10.63, significantly exceeding the threshold [30], confirming that the measured items met the conditions necessary for validity testing. The standardized factor loadings for all factors met the criterion of 0.5 or higher. The AVE values for each factor ranged from 0.52 to 0.57, satisfying the minimum requirement of 0.50. The construct reliability values ranged from 0.85 to 0.90, all exceeding the minimum requirement of 0.70. Therefore, the DLS-CN demonstrated adequate convergent validity in terms of item construction. Through this, it was confirmed that 4 factors consistently measured the construct of "Digital Leadership Scale for Clinical Nurses," and that the 29 items consistently represented the corresponding factors. To assess discriminant validity, interconstruct correlation matrices were examined (Table 4). Discriminant validity was evaluated by checking whether the AVE of each factor was greater than the squared correlation coefficients between the factors [39]. In some cases, such as the ability to use digital technology–digital collaboration mindset, ability to use digital technology–organizational influence, digital safety management–digital collaboration mindset, and digital collaboration mindset–organizational influence, the squared correlations between factors exceeded the AVE of the individual constructs, indicating that discriminant validity was only partially satisfied.

Table . Correlations between variables and verification of construct validity (n=223).

Variables	Squared correlation (P value)				AVE[e]	CR[f]
	F1[a]	F2[b]	F3[c]	F4[d]		
F1	1	—[g]	—	—	0.57	0.91
F2	0.49 (<.001)	1	—	—	0.54	0.85
F3	0.66 (<.001)	0.53 (<.001)	1	—	0.52	0.90
F4	0.71 (<.001)	0.51 (<.001)	0.68 (<.001)	1	0.52	0.90

[a]F1: ability to use digital technology.
[b]F2: digital safety management.
[c]F3: digital collaboration mindset.
[d]F4: organizational influence.
[e]AVE: average variance extracted.
[f]CR: construct reliability.
[g]Not applicable.

Convergent Validity Testing

To verify convergent validity, the correlations with the Nursing Informatics Competency Measurement Tool [31] and the Self-Leadership Scale [32] were examined. The correlation with the Nursing Informatics Competency Scale was 0.82 (P<.001), and the correlation with the Self-Leadership Scale was 0.83 (P<.001). Since the correlation coefficients were all above 0.70, convergent validity was confirmed.

Reliability Testing

Reliability was tested using Cronbach α, with a criterion of 0.70 or higher [29,40]. Cronbach α for the 29 items measuring DLS-CN was 0.95.

By subfactor, Cronbach α was as follows: factor 1 (ability to use digital technology): 0.88; factor 2 (digital safety management): 0.78; factor 3 (digital collaboration mindset): 0.86; and factor 4 (organizational influence): 0.87.

Since Cronbach α for all subfactors and the overall tool exceeded 0.70, reliability was confirmed.

Final Items

In this study, the final version of the DLS-CN consisted of 29 items across 4 factors (Table 5).

By subfactor, the items were as follows: 8 items for the ability to use digital technology, 5 items for digital safety management, 8 items for a digital collaboration mindset, and 8 items for organizational influence.

Table . Final items of the convergence of Digital Leadership Scale for Clinical Nurses.

Factors and items	Item number
Ability to use digital technology	
I can provide patient-centered care by using digital technology.	1
I can explore ways to improve digital systems and processes for patient care and treatment.	46
I can explain the importance of actively using digital technology.	39
I can actively use new information obtained through digital technology to solve patients' health problems.	8
I can present new information obtained through digital technology to address issues in the nursing work environment.	9
I can systematically collect data on patients' health status and nursing needs using digital technology.	2
I can argue for the necessity of applicable resources (human, systems, equipment, etc) in the digitalizing clinical environment.	45
I understand the principles of digital technology necessary for nursing tasks and can apply them to patients.	4
Digital safety management	
I can learn methods for using and managing new digital technologies applicable to patient care.	22
I can maintain a secure environment for protecting patient privacy in the digitalizing clinical setting (eg, logging out of computers when changing locations).	14
I perform nursing tasks in accordance with organizational guidelines and procedures for managing personal information in the digital clinical environment.	16
I believe self-development is important for improving digital knowledge and technical skills related to nursing tasks.	26
I can request help from organizational members when encountering difficulties in the digital clinical environment.	30
Digital collaboration mindset	
I can assist organizational members who are struggling in the digital clinical environment.	31
I can logically express my opinions so that organizational members can understand them using digital collaboration systems (eg, EMR[a], PACS[b], in-hospital messenger, etc).	33
I feel comfortable exchanging real-time opinions through digital collaboration systems (eg, EMR, PACS, in-hospital messenger, etc).	37
I can understand organizational members' opinions easily when communicating via digital collaboration systems (eg, EMR, PACS, in-hospital messenger, etc).	34
I am not afraid of adapting to digital changes in the clinical setting.	20
If I do not know how to use a new digital technology, I can resolve the issue by using available resources.	21
I can proactively use digital technology to learn the latest nursing knowledge and skills.	25
I can accurately hand over information and nursing processes related to patients using digital collaboration systems (eg, EMR, PACS, in-hospital messenger, etc).	36
Organizational influence	
I am interested in new digital changes that benefit patient care.	19
I reflect on my values and norms that may affect patient privacy in the digital clinical environment.	12
I can encourage organizational members who attempt change by learning new digital technologies.	41
I understand the importance of using new digital technologies for advancing the nursing field.	18
I feel a sense of accomplishment when I effectively perform nursing tasks using newly acquired digital technology.	27
I can help improve organizational members' digital competencies for better work performance.	42
I strive to achieve organizational goals by introducing new digital technologies and resources.	38

Factors and items	Item number
I can present a vision (organizational future image) for performing nursing tasks using digital technology.	40

[a]EMR: electronic medical record.

[b]PCA: principal component analysis.

Discussion

Principal Findings

This study was conducted to develop a tool to measure digital leadership among clinical nurses, based on the instrument development steps proposed by DeVellis and Thorpe [24]. The research was carried out in 2 phases: the development of preliminary items and the evaluation of the instrument's validity and reliability.

During the item development phase, a conceptual framework was established by integrating the components of digital leadership identified in previous concept analyses and literature reviews on digital leadership in clinical nursing. Preliminary items were selected from the initial items through a content validity assessment by experts, followed by cognitive interviews and a pilot survey, which were used to derive the final set of preliminary items. Throughout this process, expert feedback and identified issues were systematically reviewed and refined.

In the instrument evaluation phase, data were collected from 446 clinical nurses through an online survey. A random sample of 223 responses was used for EFA, and another 223 responses were used for CFA. Construct validity was tested through these analyses, and convergent validity was assessed by examining the correlation with instruments measuring nursing informatics competency and self-leadership. Internal consistency reliability was confirmed with a Cronbach α of 0.95.

The final tool developed through this study consists of 29 items across 4 factors: 8 items for the ability to use digital technology, 5 items for digital safety management, 8 items for a digital collaboration mindset, and 8 items for organizational influence. The tool uses a 5-point Likert scale for self-report surveys, with a total score range from 29 to 145 points. Higher scores indicate a higher level of digital leadership among clinical nurses. Overall, the developed scale demonstrated strong reliability and validity for assessing digital leadership in clinical nursing practice. However, the tool did not fully satisfy the criteria for discriminant validity. Even when variables are used as conceptually independent constructs, correlations between related factors are common in practice [29]. This is consistent with findings from a study on the development of an integrated nursing leadership scale for Korean nurses [41], which also reported overlaps among constructs such as data management and communication technologies. In particular, relatively high correlations were observed between the ability to use digital technology and organizational influence, as well as between digital collaboration mindset and organizational influence. These results suggest that while the factors are conceptually distinct, they may be closely related in actual clinical settings where digital competencies are integrated with leadership behaviors. Although some aspects of discriminant validity were supported, these findings indicate that the boundaries between certain factors were not clearly distinguished. Despite these limitations, this tool has the advantage of including items that measure competencies needed to adapt to rapidly changing digital health care environments, such as work performance, learning, and adaptability [42]. Accordingly, future research is needed to more clearly distinguish the unique conceptual domains measured by each factor. Furthermore, the "digital safety management" factor included fewer items compared to other factors. Given the importance of patient safety and information security in digital health care environments, future research should consider expanding and refining items in this domain to enhance the comprehensiveness of the scale.

Given that leadership competencies required in digitally transforming health care environments are increasingly complex and diverse [13], this DLS-CN reflects the unique characteristics of Korean clinical settings and is the first scale of its kind to undergo statistical validation. Nevertheless, because data collection was conducted via an online survey using convenience sampling, caution is needed when interpreting the results. Additionally, the scale was developed for general clinical nurses and excluded nurses with less than 1 year of experience, nurse managers not involved in direct care, and those in administrative or educational roles, thereby limiting its generalizability. Moreover, the study did not include test-retest reliability, which represents another limitation.

Based on these findings, several implications can be drawn. In particular, the developed digital leadership scale should be applied to nurses from diverse countries and cultural backgrounds, as well as to nurses in various roles and settings, such as hospitals, community health centers, and educational institutions. Repeated studies are recommended to verify the reliability and validity of the instrument in diverse environments.

Future research should use this tool to assess digital leadership levels and develop tailored educational or intervention programs that enhance digital leadership according to workplace and contextual characteristics.

In addition, as this scale may be applicable not only to health care professionals but also to professionals in management, public administration, and related fields, further research should explore its broader applicability across disciplines.

Conclusions

The DLS-CN, developed through this study, is a systematic tool designed to measure and evaluate digital leadership among nurses in clinical practice settings. The DLS-CN consists of 4 core domains: ability to use digital technology, digital safety management, digital collaboration mindset, and organizational influence. It proposes a new standard for nursing leadership in health care environments driven by digital technologies.

In particular, the tool is useful for developing various educational programs aimed at identifying emerging nurse leaders and enhancing the digital leadership of clinical nurses in hospital environments where frequent changes in digital health care systems, technologies, and organizational structures occur. Furthermore, the development of this tool confirms that digital leadership extends beyond the mere acquisition of digital skills, encompassing the competence of clinical nurses to actively engage in and lead change. This is a meaningful contribution to the study.

Since this tool was developed based on data collected from clinical nurses in South Korea, and the items were created accordingly, further validation studies are needed in diverse health care settings and across cultural contexts. In the rapidly evolving digital health care environment, this tool can serve both as a foundational resource and a structured instrument for strengthening clinical nurses' digital leadership.

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Conflicts of Interest

None declared.

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Abbreviations

AVE: average variance extracted
CFA: confirmatory factor analysis
DLS-CN: Digital Leadership Scale for Clinical Nurses
EFA: exploratory factor analysis
KMO: Kaiser-Meyer-Olkin

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Assessing Digital Literacy Among Nursing Faculty Under the Artificial Intelligence–Enhanced Technological Pedagogical Content Knowledge Framework: Cross-Sectional Survey Analysis

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Abstract

Background: Digital literacy has become a core competence for nursing faculty to adapt to the digital transformation of education, improve teaching quality, and cultivate innovative nursing talents.

Objective: This study aimed to investigate the digital literacy status and influencing factors among nursing faculty in colleges and universities in Fujian province, China.

Methods: A cross-sectional survey analysis was conducted among 339 participants from July 2023 to June 2024 by selecting nursing faculty from 3 medical universities and 5 colleges in Fujian province. A general information questionnaire and a teacher digital literacy questionnaire (designed based on the artificial intelligence–enhanced technological pedagogical content knowledge theoretical model) were used to conduct the survey. The questionnaires included the following dimensions: an intelligent integration ethics layer (digital social responsibility), attention to the moral boundaries of applying technology; an awareness layer (digital awareness), the willingness to actively adapt to technological changes; a knowledge layer (digital technology knowledge and skills), mastery of the integration point of intelligent tools and subject teaching; an ability layer (digital application), the ability to design intelligent teaching plans; and a thinking layer (professional development; innovative thinking for the critical integration of technology). Statistical analysis included descriptive statistics, a 1-way ANOVA, Pearson correlation analysis, and multiple linear regression (using SPSS 28.0 software).

Results: The overall digital literacy of the nursing faculty was at a medium level (mean score 101.92, SD 16.47), with the highest score in digital awareness (mean 20.21, SD 9.43) and the lowest score in digital technology knowledge and skills (mean 9.68, SD 2.92). For the dimension of digital technology knowledge and skills, both age (β=−.142; *P*=.009) and years of teaching (β=−.147; *P*=.006) were significant negative predictors. Regarding digital application, age was found to be a significant negative predictor (β=−0.124; *P*=.02) but teaching experience was a positive predictor (β=0.123, *P*=.02). Similarly, age also had a significant negative impact on the professional development dimension (β=−.153; *P*=.005) and the overall digital literacy level (β=−.136; *P*=.01).

Conclusions: The digital literacy of nursing faculty is at a medium level, with especially low scores in technical knowledge. Age and teaching experience are key influencing factors. Recommendations to promote balanced development of awareness and skills include providing targeted training for senior faculty, integrating courses with clinical practice, optimizing the allocation of digital resources, promoting interdisciplinary cooperation, and strengthening ethical and safety training.

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KEYWORDS

digital literacy; nursing faculty; higher education; influencing factors; professional development

Introduction

Background

With the rapid advancement of the digital age, the education sector is experiencing a profound digital transformation. In this context, the digital literacy of faculty members has emerged as a central topic in the digital transformation of education. Currently, the international community has established a relatively comprehensive development system for faculty digital literacy. Through policy frameworks, standard setting, resource support, and assessment mechanisms, this system has integrated faculty digital literacy into the faculty education system, thereby promoting the digital transformation of education [1-3]. The Chinese government has actively advanced educational modernization through initiatives such as the "China's Education Modernization 2035" blueprint [4], the World Digital Education Conference [5], and the national smart education public service platform. These endeavors indicate a global transition in education systems from information infrastructure to digital empowerment and intelligent innovation, representing a systematic breakthrough in the digital transformation of education [6].

Although digital technology has been preliminarily implemented in medical education, there are still significant gaps in its application to nursing education. In particular, research on how nursing faculty can effectively use digital technologies to enhance processes in nursing education and optimize practical training outcomes remains insufficiently studied. During the digital transformation of nursing education, the development of digital literacy among college nursing faculty has emerged as a crucial factor in ensuring the effectiveness of pedagogical digitization [7]. While most nursing faculty recognize the necessity of integrating digital technology into teaching practices, they also report facing significant challenges in achieving the effective integration of technological tools in teaching due to inadequate digital literacy levels [8] and imbalanced resource allocation [9,10]. Faculty members also demonstrate significant deficiencies in the design, implementation, and evaluation of digital teaching and learning processes [11,12]. Moreover, the existing digital education model has not yet achieved the expected results in stimulating students' learning motivation [13,14]. Previous studies have also confirmed [15,16] that digital technologies play a key role in clinical scenarios, simulation skills training, and distance learning. Their use enhances students' learning experiences and enables faculty to effectively explain complex operations and nursing concepts [17,18].

Technological pedagogical and content knowledge (TPACK) is a comprehensive framework that identifies well-defined types of knowledge required for effective teaching of subject knowledge enhanced by technology adaptation [19]. The AI-TPACK (artificial intelligence–technological pedagogical content knowledge) framework offers a vital analytical tool, with its 5-layer model (encompassing ethical, awareness, knowledge, competency, and cognitive dimensions) providing a systematic approach to assessing educators' digital literacy [20]. This model emphasizes the integration of technology, pedagogy, and ethical considerations.

However, existing research predominantly focuses on general disciplines, neglecting nursing-specific contexts, and often prioritizes technical operational skills over ethical and pedagogical integration. The results of a recently published cross-sectional study showed that the digital literacy of academic nurse educators was at a moderate level and revealed relevant influencing factors [21]. Although existing studies have initially revealed the value of digital literacy in nursing education, there are still research shortcomings in investigating the digital literacy level at nursing faculty institutions and analyzing the influencing factors.

Objective

This study exhibited a broader sample coverage during the selection of research participants. The research group encompassed both clinical teaching faculty and college nursing faculty, thereby representing an instructional design that fully aligned with the core characteristics of the dual faculty within the AI-TPACK theoretical framework of the nursing program. Through standardized data collection, the system of influencing factors and empirical findings that have been identified significantly augment the comprehensiveness and objectivity of the research results. Furthermore, in response to the pressing requirement for the integration of nursing professional development and digital teaching, this study aimed to analyze the digital literacy status of nursing faculty in colleges and universities and examine their influencing factors through a cross-sectional survey, thereby providing a robust foundation for the formulation of precise and effective competency development strategies and the enhancement of digital teaching quality.

Methods

Ethical Considerations

This study was approved by the Bioethics Review Committee of Fujian Medical University (FJMU174) and conducted in strict compliance with the Declaration of Helsinki. All participants provided written informed consent after receiving detailed explanations regarding the research objectives, procedures, and potential risks. Participants received the appropriate compensation for their time and effort upon completion of the study. To ensure data confidentiality, personal information was anonymized and stored securely using encrypted storage methods.

Instrument Design

A cross-sectional survey was conducted from July 2023 to June 2024. This study was designed to comprehensively capture the current state of digital literacy among nursing faculty at 5 clinical colleges and 3 medical universities in Fujian province, China, thereby facilitating an effective assessment of the current situation and its associated influencing factors without the need for a long-term follow-up study. The inclusion criteria for this study were as follows: (1) nursing faculty in undergraduate colleges and universities or those involved in clinical nursing teaching; (2) ≥1 year of nursing teaching experience; and (3) provision of informed consent to participate in this study. The exclusion criteria included faculty who were not on duty due to sick leave, personal leave, maternity leave, or further studies. Our sample size was computed using the Soper online sample size calculator, with an expected effect size of 0.15, a statistical power of 0.85, a probability level of 0.05, and a minimum sample size of 140. In total, 339 participants were included in this study, thereby meeting the requirements of statistical efficacy.

Data Measurements

The questionnaire for this study contained 2 parts and took approximately 15 to 20 minutes to complete. As a core research instrument, it effectively enables standardized data collection from nursing faculty in universities in Fujian province. In addition, the tool assessed multiple dimensions of digital literacy and digital technology participation in a structured and easily analyzed format. The tool is aligned with China's digital literacy agenda and thus demonstrates appropriateness and reliability at both the cultural and semantic levels.

Section A: General Information

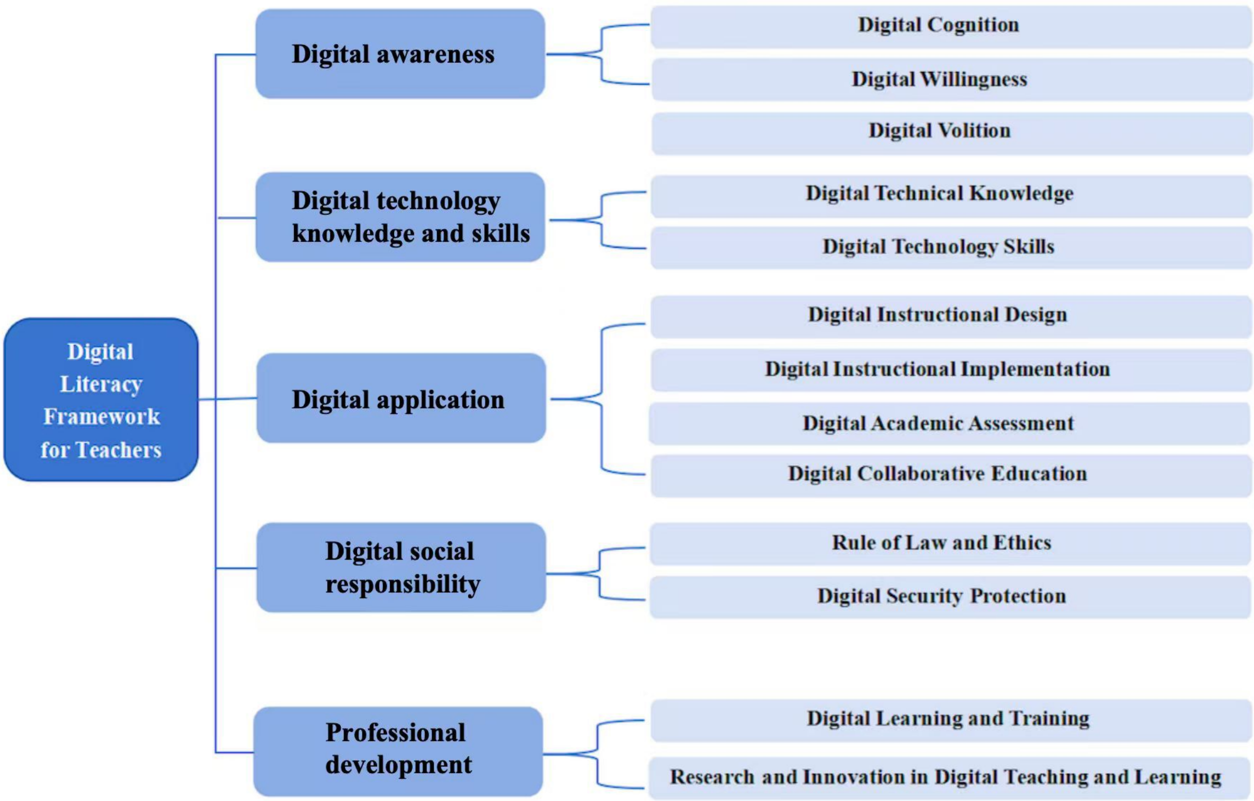
The general information questionnaire investigated the basic demographic characteristics of nursing faculty in colleges and universities. It included gender, age, education level, type of teaching, years of teaching experience, and professional title.

Section B: Nursing Faculty Digital Literacy Questionnaire

We adopted the Teacher Digital Literacy Industry Standard (2022) [6] and adjusted the questionnaire based on the AI-TPACK theoretical framework to align with our research objectives. It included the intelligent integration ethics layer (digital social responsibility), attention to the moral boundaries of technology application; the awareness layer (digital awareness), the willingness to actively adapt to technological changes; the knowledge layer (digital technology knowledge and skills), mastery of the integration point of intelligent tools and subject teaching; the ability layer (digital application), the ability to design intelligent teaching plans; and the thinking layer (professional development), the innovative thinking for the critical integration of technology. The questionnaire included 5 first-level dimensions, 13 second-level dimensions, and 28 third-level dimensions, mainly investigating the level of digital literacy among nursing faculty in colleges and universities. A 5-point Likert scale was used, with scores ranging from 1 for "strongly disagree" to 5 for "strongly agree," and total scores ranging from 28 to 140, with higher scores indicating higher levels of digital literacy among university nursing faculty.

Following iterative discussions among the research team that culminated in the development of the preliminary questionnaire, a rigorous expert validation process was conducted. The selection criteria mandated the inclusion of senior professionals holding associate professor or higher academic ranks with a minimum of 10 years of professional experience in relevant disciplines. The expert panel was strategically composed to encompass cohorts of both nursing education specialists and educational technology experts, ensuring comprehensive domain coverage. Considering the discipline-specific characteristics of nursing and the practice-oriented nature of instructional scenarios, this study systematically refined 28 core dimensions from the educational industry standards through a 2-round Delphi expert consultation process (Figure 1).

Figure 1. Digital literacy framework for nursing faculty.



The reliability of the questionnaire was assessed by pilot testing among 80 college nursing faculty. The Cronbach α of the faculty digital literacy questionnaire was tested to be 0.931, and the Kaiser-Meyer-Olkin value was 0.837, indicating a good level of reliability and validity and fully supporting the questionnaire's scientific rigor in terms of cultural adaptation and semantic validity.

Data collection for this study was officially initiated after ethics approval by the relevant institutional review board, and the questionnaires were collected from July 2023 to June 2024. The research team used the Questionnaire Star platform to administer the electronic questionnaire, which was sent to the nursing faculty in the form of a QR code after obtaining administrative approval from the participating organizations (including academic institutions and hospital nursing departments). Standardized procedures were strictly followed during survey implementation: a uniformly prepared informed consent form and standardized instructions were used, and anonymized data collection was performed after obtaining written informed consent from the study participants. Two master's degree nursing students independently verified the data through the platform's backend, eliminating questionnaires with logical errors and regular responses to ensure the validity of the datasets. Finally, the raw data were stored in an encrypted laptop, and only the researchers in the project team had access to the data.

Data Analysis

Statistical analysis was conducted using SPSS (version 28.0; IBM Corp). Normally distributed continuous variables, including dimension scores, were expressed as mean (SD). Categorical variables such as gender and professional titles were described using frequencies and percentages. Bivariate correlations between variables were examined using Pearson correlation analysis, and multiple linear regression analysis was conducted to identify the predictors of digital literacy dimensions. Before interpreting the regression coefficients, collinearity diagnostics were performed to ensure the stability of the model. An α level of .05 was considered statistically significant.

Results

Sample Characteristics

The study population comprised 339 nursing faculty members from higher education institutions. In total, 343 questionnaires were distributed, yielding a response rate of 98.83% (n=339). Among the respondents, 302 (89.1%) identified as female and 37 (10.9%) as male. Age distribution showed a predominant concentration in the ≤45-years age group (n=326, 96.2%). The vast majority (n=336, 99.2%) held bachelor's degrees or higher educational qualifications. Teaching experience was primarily within the 0- to 10-year range for 218 participants (64.3%). Additionally, 328 (96.6%) participants held intermediate-level academic titles or higher. Further demographic characteristics are detailed in Table 1.

Table . Comparison of digital literacy scores of nursing faculty in higher education institutions with different characteristics (N=339).

Variables	Digital awareness	Digital technology knowledge and skills	Digital application	Digital social responsibility	Professional development
Gender, mean (SD)					
Male (n=37)	4.04 (0.88)	3.25 (0.72)	3.34 (0.94)	3.71 (0.71)	3.95 (0.91)
Female (n=302)	4.04 (0.88)	3.22 (0.79)	3.32 (0.87)	3.72 (0.87)	3.97 (0.84)
t test (*df*)	−0.025 (337)	0.214 (337)	0.133 (337)	−0.076 (337)	−0.173 (337)
P value	.98	.83	.90	.94	.86
Age (y), mean (SD)					
≤35 (n=217)	4.04 (0.87)	3.27 (0.78)	3.40 (0.86)	3.74 (0.85)	4.03 (0.83)
36-45 (n=109)	4.11 (0.86)	3.22 (0.74)	3.21 (0.90)	3.69 (0.84)	3.96 (0.85)
≥46 (n=13)	3.57 (0.90)	2.51 (0.87)	2.91 (0.84)	3.67 (0.92)	3.06 (0.54)
F test (*df*)	2.250 (2, 336)	5.958 (2, 336)	3.163 (2, 336)	0.149 (2, 336)	8.323 (2, 336)
P value	.11	.003[b]	.04[a]	.86	<.001
Education level (y), mean (SD)					
≤12 (n=3)	4.13 (0.12)	4.11 (0.38)	3.78 (0.59)	4.44 (0.42)	3.80 (0.92)
13-15 (n=234)	4.01 (0.90)	3.21 (0.77)	3.30 (0.89)	3.69 (0.83)	3.94 (0.87)
15-16 (n=63)	4.11 (0.82)	3.24 (0.80)	3.27 (0.83)	3.84 (0.89)	4.06 (0.83)
≥17 (n=39)	4.13 (0.86)	3.21 (0.82)	3.48 (0.86)	3.67 (0.94)	4.01 (0.76)
F test (*df*)	0.413 (3,335)	1.307 (3,335)	0.824 (3,335)	1.257 (3,335)	0.397 (3,335)
P value	.74	.27	.48	.29	.76
Teaching experience (y), mean (SD)					
≤5 (n=218)	4.07 (0.83)	3.29 (0.73)	3.22 (0.90)	3.75 (0.80)	4.00 (0.84)
6-10 (n=89)	4.01 (0.97)	3.19 (0.79)	3.49 (0.86)	3.63 (0.96)	3.93 (0.88)
≥11 (n=32)	3.98 (0.94)	2.89 (1.03)	3.47 (0.69)	3.78 (0.87)	3.89 (0.79)
F test (*df*)	0.241 (2,336)	3.862 (2,336)	3.573 (2,336)	0.675 (2,336)	0.363 (2,336)
P value	.79	.02[a]	.03[a]	.51	.70
Professional title, mean (SD)					
Primary (n=11)	3.93 (1.04)	3.27 (0.61)	3.25 (0.73)	3.62 (0.65)	4.13 (0.72)
Intermediate (n=289)	4.04 (0.86)	3.24 (0.79)	3.29 (0.89)	3.73 (0.86)	3.96 (0.86)
Senior (n=39)	4.05 (0.96)	3.09 (0.82)	3.53 (0.81)	3.72 (0.82)	4.02 (0.82)
F test (*df*)	0.097 (2,336)	0.633 (2,336)	1.332 (2,336)	0.079 (2,336)	0.282 (2,336)
P value	.91	.53	.26	.92	.75

[a]*P*<.05.

[b]*P*<.01.

Digital Literacy Score Among Nursing Faculty

The study revealed that nursing faculty exhibited a moderate level of overall digital literacy (mean 3.64, SD 0.59). Among the 3 dimensions assessed, digital awareness demonstrated the highest proficiency (mean 4.04, SD 0.88), whereas digital technology knowledge and skills had the lowest score (mean 3.23, SD 0.78). Digital application (mean 3.32, SD 0.88), digital social responsibility (mean 3.72, SD 0.85), and professional development (mean 3.97, SD 0.85) were also demonstrated at a moderate level. Further details are shown in Table 2.

Table . Faculty scores on digital literacy level 1 dimensions (N=339).

Dimension	Items, n (%)	Score, mean (SD)	Score per item, mean (SD)
Digital awareness	5	20.21 (9.43)	4.04 (0.88)
Digital technology knowledge and skills	3	9.68 (2.92)	3.23 (0.78)
Digital application	9	29.86 (10.30)	3.32 (0.88)
Digital social responsibility	6	22.33 (6.44)	3.72 (0.85)
Professional development	5	19.84 (5.13)	3.97 (0.85)

Comparison of Digital Literacy Scores of Nursing Faculty With Different Characteristics

The results showed statistically significant differences among faculty members across different age groups in the dimensions of digital technology knowledge and skills (P=.003), digital application (P=.04), and professional development (P<.001). Significant differences were also observed among faculty members with different years of teaching experience in the dimensions of digital technology knowledge and skills (P=.02) and digital application (P=.03).

Factors Influencing the Dimensions of Faculty Digital Literacy

Variables with statistically significant differences in each dimension of digital literacy of nursing faculty in colleges and universities with different characteristics (age and years of teaching experience) were selected as independent variables, and each dimension was analyzed using multiple linear regression models as the dependent variable. The variance inflation factor for all independent variables was close to 1 (ranging from 1.003 to 1.007), which is well below the threshold of 5, indicating no multicollinearity issues in the model.

The results of the regression analysis are presented in Table 3. The result showed that age and years of teaching experience were significant predictors of specific dimensions of digital literacy, while sex, education level, and professional titles did not show statistically significant effects. Specifically, for the dimension of digital technology knowledge and skills, both age (β=−.142; P=.009) and years of teaching (β=−.147; P=.006) were significant negative predictors. Regarding digital application, age was found to be a significant negative predictor (β=−.124; P=.02), but teaching experiences show a positive predictor (β=.123; P=.02), suggesting that teaching experience may play a positive role in promoting teachers' digital application capabilities, possibly due to accumulated practical experience in integrating digital tools into teaching over time, whereas age might be associated with differences in adaptability to new digital application scenarios. Similarly, age also had a significant negative impact on the professional development dimension (β=−.153; P=.005) and the total digital literacy level (β=−.136; P=.01).

Table . Standardized coefficients (β) for factors influencing digital literacy among nursing faculty (N=339)[a].

Variables	Digital consciousness	Digital technology knowledge and skills	Digital application	Digital social responsibility	Professional development
Gender	0.007	−0.01	−0.002	0.006	0.015
Age (y)	−0.03	−0.142[b]	−0.124[c]	−0.03	-0.153[b]
Education level	0.058	0.0003	0.046	0.017	0.046
Teaching experiences	−0.04	−0.147[b]	0.123[c]	−0.023	−0.054
Professional title	0.013	−0.067	0.075	0.009	−0.008

[a]All variance inflation factor values were close to 1 and below the threshold of 5, indicating that there was no issue of multicollinearity among the variables.

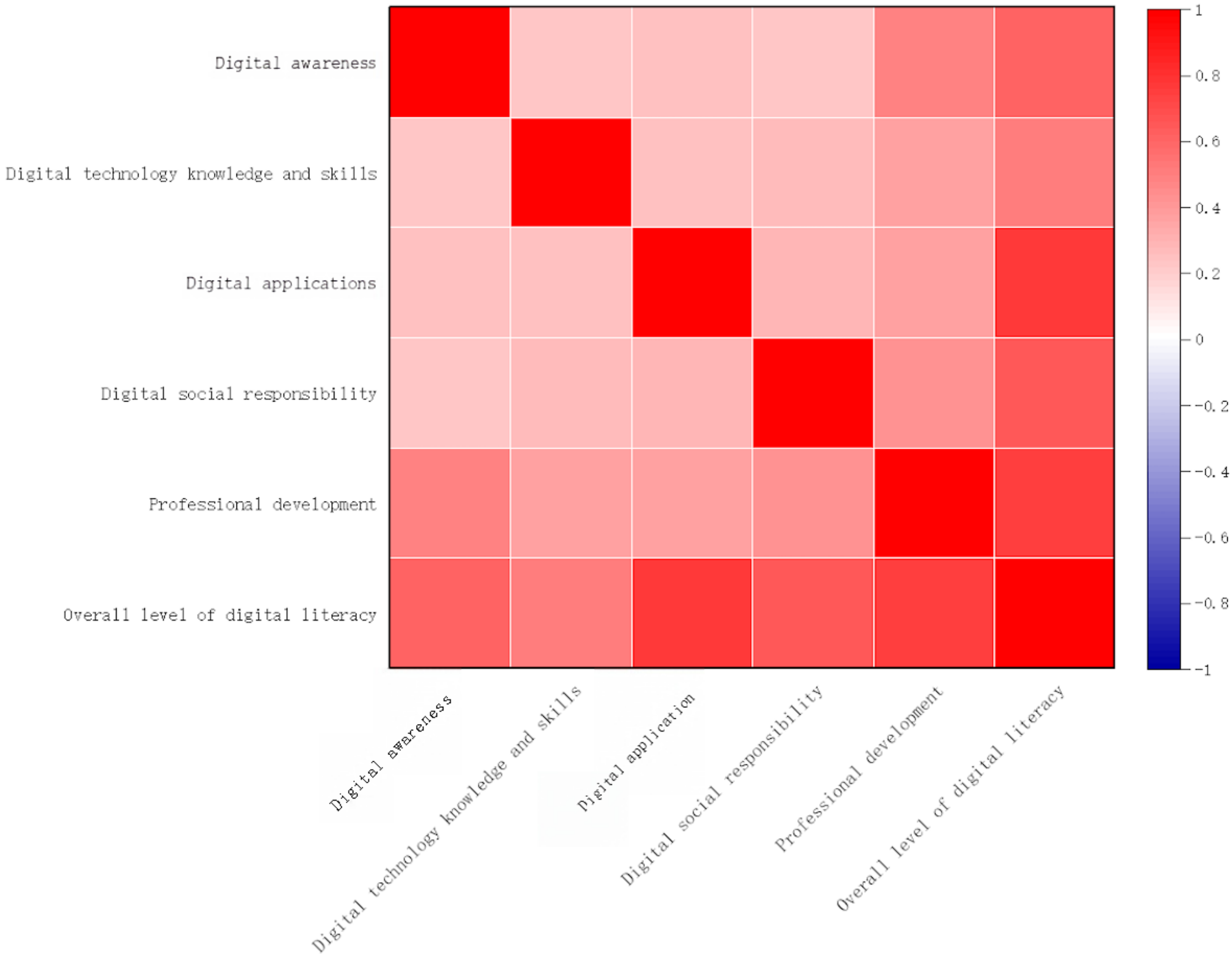
[b]P<.01.

[c]P<.05.

Correlation Analysis of the Dimensions of Digital Literacy Competence of Nursing Faculty

Correlation analysis showed that the overall digital literacy level of nursing faculty in colleges and universities was significantly and positively correlated with all dimensions (P<.001). In addition, the dimensions were positively interrelated, indicating mutual reinforcement among them. Details are presented in Figure 2.

Figure 2. Correlation coefficients between digital literacy and dimensions of nursing faculty.



Discussion

Principal Findings

Our study's findings on nursing faculty's digital literacy scores reveal a nuanced landscape of technological competence, with significant implications for nursing education and practice. The moderate overall digital literacy score (mean 3.64, SD 0.59) suggests that while nursing faculty possess a foundational understanding of digital tools, there remains considerable room for enhancement, particularly in the realm of digital technology knowledge and skills (mean 3.23, SD 0.78), which emerged as the weakest area. This finding is consistent with another study on intergenerational differences in digital competence among faculty [22].

This deficit may hinder faculty's ability to fully leverage advanced technologies in clinical training and patient care, potentially limiting the integration of innovative educational methods such as virtual simulations or AI-driven learning platforms.

The higher proficiency in digital awareness (mean 4.04, SD 0.88) indicates that nursing faculty are generally cognizant of the importance and ethical considerations surrounding digital technology use. This awareness is crucial for maintaining patient confidentiality and navigating the digital health care environment responsibly [23,24]. However, the average scores in digital applications (mean 3.32, SD 0.88), digital social responsibility (mean 3.72, SD 0.85), and professional development (mean 3.97, SD 0.85) suggest a gap between theoretical understanding and practical application. Although faculty may recognize the value of digital tools in education, their limited skills in digital technology knowledge and skills may prevent them from effectively implementing these tools in real-world scenarios [25,26].

The statistically significant differences in digital literacy scores across age groups and years of teaching experience highlight the dynamic nature of technological competence in nursing education. Older faculty members and those with longer teaching experience exhibited lower scores in digital technology knowledge and skills and digital applications, likely due to generational differences in technology exposure and the rapid evolution of digital tools in health care [27,28]. To address this gap, medical schools should develop tailored digital training curricula specifically designed for senior faculty. These programs should be structured to accommodate their unique learning needs and pace, ensuring gradual proficiency in basic digital technology knowledge and skills [29,30].

Furthermore, the findings reveal that faculty members' years of teaching experience also exert a certain influence on their digital literacy levels, which is reflected in a negative correlation with the dimension of digital technology knowledge and skills, and a positive correlation with the dimension of digital application. Pairwise comparative analysis focusing on the digital technology knowledge and skills dimensions indicated that faculty with more than 11 years of teaching experience exhibited lower willingness to learn digital technology knowledge and skills than those with <5 years of experience. Consequently, this reduced willingness translated to lower levels of mastery of relevant technological knowledge and skills, consistent with the results of previous studies [31]. This phenomenon may be attributed to the dual professional obligations of collegiate nursing faculty, who must concurrently fulfill clinical responsibilities and pedagogical duties [32]. Empirical investigations have demonstrated a statistically significant positive correlation between teaching tenure and burnout prevalence, particularly among faculty with more than a decade of pedagogical experience. Additionally, although experienced faculty possess rich pedagogical expertise accumulated through prolonged teaching practice, they often exhibit diminished motivation for ongoing professional development in emerging digital technologies. Such practitioners' technological knowledge is frequently confined to foundational competencies acquired during initial training phases, resulting in a growing disconnect with rapidly evolving digital innovations [33,34]. This stagnation impedes the systematic advancement of faculty digital technological knowledge and pedagogical skills, thereby constraining their ability to align with contemporary educational transformation requirements and ultimately hindering their capacity to cultivate digital literacy commensurate with the demands of modern education digital paradigm shift.

Additionally, the study showed that faculty members' years of teaching experience were positively correlated with the digital application dimension. This seems to contradict the finding that age was negatively correlated with the digital application dimension; however, we should analyze the effect of years of teaching experience on the level of faculty' digital literacy, all other influences being equal. This phenomenon may be attributed to some interrelated factors. Nursing faculty who have been teaching for a long time usually show significant advantages in the application of digital technology by virtue of their rich accumulation of teaching experience [35]. Research has shown that they are able to systematically screen high-quality digital educational resources (eg, innovative teaching tools such as virtual simulation experiment platforms) that meet the teaching objectives based on the laws of students' cognitive development, rather than unilaterally pursuing technological novelty to gain short-term attention [36]. Empirical research has shown that experienced faculty members are more adept at realizing the organic integration of traditional teaching methods with digital resources, such as visual case analysis method and multimodal narrative teaching method, among other innovative practices [37]. This model of digital application based on teaching a needs-driven approach has led to a significant professional advantage in the dimension of technology application.

The regression analysis provided nuanced insights into the factors shaping nursing faculty's digital literacy, with age and years of teaching emerging as the most robust predictors, while demographic variables such as gender, education level, and professional title showed no statistically significant effects. First, the consistent negative associations between age and multiple dimensions of digital literacy—including digital technology knowledge and skills, digital application, professional development, and overall digital literacy—align with prior research on generational differences in digital competency [38]. This pattern likely stems from a combination of cognitive, attitudinal, and structural factors: older faculty may face age-related declines in technological learning efficiency, experience anxiety or avoidance toward emerging digital tools due to past unsuccessful attempts, and prioritize traditional pedagogical approaches honed through decades of practice over innovative digital methods. Compounding these challenges, institutional resource allocation often prioritizes younger faculty for digital training, leaving senior educators with limited opportunities to update their skills amid heavy administrative and research responsibilities [39,40]. The significant negative relationship between years of teaching and digital technology knowledge and skills further underscores the impact of professional tenure on digital adaptation. While experienced faculty may develop sophisticated digital application strategies rooted in pedagogical expertise, their motivation to acquire new technical knowledge tends to wane over time. This stagnation can be attributed to factors such as burnout from long-term dual clinical and teaching responsibilities [41], as well as a reliance on foundational technological skills acquired during initial training, which may become increasingly outdated in the face of rapid digital evolution [42].

Notably, the absence of significant effects for gender, education level, and professional title suggests that digital literacy disparities in this context are primarily driven by generational and career-stage factors rather than demographic or hierarchical differences. This finding challenges assumptions that higher academic credentials or professional status correlate with greater digital proficiency, highlighting the need for targeted interventions that transcend traditional institutional hierarchies. The low variance inflation factor values (1.003 - 1.007) confirm the absence of multicollinearity, ensuring the reliability of the regression model. This strengthens confidence in the observed relationships between age, teaching tenure, and digital literacy outcomes.

Limitations

Despite the insightful findings, this study is not without limitations that warrant consideration. First, the data were exclusively collected from nursing faculty in universities and clinical colleges located in Fujian province. While the sample provides valuable regional insights, its geographic focus restricts the generalizability of the results, particularly beyond southern China. Future research would benefit from expanding the sampling frame to include diverse geographic regions, institutional types, and health care settings to enhance the external validity of conclusions. Second, the cross-sectional research design used in this study allows for the examination of correlations between variables at a single time point but cannot establish definitive causal relationships. A longitudinal research design, which tracks changes in digital literacy over time alongside potential influencing factors, would be necessary to disentangle these causal pathways. Finally, the reliance on self-reported questionnaires may introduce response bias, as participants might overestimate their digital skills due to social desirability or lack objective awareness of their competency gaps. Subjective perceptions of digital literacy could thus compromise the accuracy and authenticity of the data. To mitigate this limitation, future studies should integrate objective assessment tools.

Conclusions

This study highlights the critical importance of cultivating digital literacy among nursing educators, whose overall proficiency remains at a moderate level. Gaps persist in the dimensions of digital technology knowledge and skills, necessitating efforts to bridge theory and practice while enhancing applied operational capabilities. Age significantly influences nursing faculty's digital literacy, with younger instructors demonstrating greater advantages in digital teaching, underscoring the necessity for continuous professional development. The impact of teaching experience proves more complex, which further emphasizes the urgent need for medical schools to develop differentiated strategies to enhance digital literacy. Against this backdrop, strengthening digital technology training, implementing systematic instruction on digital ethics and information security, and cultivating educators' digital social responsibility are key to enhancing nursing education quality. For senior faculty, tailored training programs should prioritize gradual, context-specific skill-building that aligns with their learning pace and pedagogical needs, while addressing attitudinal barriers through peer mentoring and success case sharing. For midcareer faculty, interventions should focus on bridging the gap between existing pedagogical expertise and emerging digital tools, fostering innovative integration rather than technical replacement. By addressing age-related and tenure-related disparities, institutions can cultivate a more inclusive digitally competent nursing faculty workforce, better positioned to meet the demands of modern health care education. Future research should examine regional and institutional variations in nursing educators' digital literacy to explore personalized training strategies for targeted improvement.

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Data Availability

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

Authors' Contributions

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Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence
AI-TPACK: artificial intelligence–technological pedagogical content knowledge

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Informatics Competency and Technology Self-Efficacy Levels Among Undergraduate Nursing Students: Cross-Sectional Study

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Abstract

Background: The Saudi Arabian health care sector is transforming under Vision 2030 with the goal of digitizing its services. This necessitates a digitally prepared nursing workforce; however, there is evidence suggesting that nursing students have limited informatics competency and that these skills are minimally covered in their training programs.

Objective: This study measured the baseline informatics competency and technology self-efficacy of undergraduate nursing students at the University of Hail, Saudi Arabia.

Methods: Using a descriptive cross-sectional design, data were collected from 243 undergraduate nursing students at the University of Hail through an online survey. The survey measured demographics, informatics competency (Canadian Nurse Informatics Competency Assessment Scale), and digital technology self-efficacy. Data analysis used descriptive statistics, 2-tailed *t* tests, ANOVA, and hierarchical regression analysis.

Results: Students reported a moderate level of informatics competency, with a mean Canadian Nurse Informatics Competency Assessment Scale item score of 2.57 (SD 0.84) on a scale from 1 to 4. They also showed moderate to high self-efficacy for digital technology, with a mean item score of 2.7 (SD 0.56) out of 4. Informatics competency scores were substantially higher in students with prior informatics training and frequent electronic health record exposure. In the underpowered exploratory hierarchical regression model, self-efficacy for digital technology showed a small positive association with informatics competency that approached statistical significance; however, the overall model was not statistically significant and explained only a limited proportion of the variance.

Conclusions: This single-site study of undergraduate nursing students at the University of Hail found moderate self-reported informatics competency despite higher digital technology self-efficacy, indicating a need for strengthened informatics education to support the Saudi Vision 2030. While underpowered, exploratory analyses and self-report data mean that these institution-specific findings should be interpreted cautiously and used primarily to guide future multisite and mixed methods research.

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KEYWORDS

informatics competency; digital health; nursing education; self-efficacy; electronic health records

Introduction

The digital health revolution continues to transform health care delivery and organizational structures. Advances in artificial intelligence (AI), telemedicine, and electronic health records (EHRs) now support safer, more efficient, and data-driven care [1,2]. Consequently, preparing a globally competent health informatics workforce is essential for implementing these innovations and enhancing clinical outcomes [3,4].

Nurses comprise the largest portion of the health care workforce and are in a pivotal position to integrate technology into direct patient care. Informatics competency, the integration of computers to manage and communicate data [3], is a key skill that nurses must develop. Equally important is technology self-efficacy, or nurses' confidence in using digital tools in clinical and educational settings [5]. Despite the wide recognition of their importance, the inclusion of nursing informatics in undergraduate curricula varies considerably worldwide. Studies from North America, Europe, Africa, and the Asia-Pacific region have shown significant differences in course content, learning opportunities, and assessment methods used to measure informatics competency among nursing students [6-8].

International initiatives such as Technology Informatics Guiding Education Reform and the Canadian Nurse Informatics Competency Assessment Scale (C-NICAS) promote the formal integration of informatics into nursing education. However, their adoption varies widely across different programs and countries. This study used the C-NICAS as an assessment tool and conceptual framework to identify key informatics competency domains among undergraduate nursing students. Despite the global use of such frameworks, empirical studies have shown that students and new graduates consistently self-report only basic to intermediate proficiency, often lacking hands-on experience with clinical information systems. This highlights the persistent gap between curriculum design and real-world practice [4].

As part of Vision 2030, Saudi Arabia has launched a nationwide digital health initiative to modernize health care using digital tools, telemedicine, and AI [9-11]. Initiatives such as the Healthcare Sector Transformation Program aim to transform service delivery, improve accessibility, and enhance the quality and efficiency of care, reflecting a national focus on developing a data-driven, patient-centered workforce. However, studies have shown that Saudi nursing students and practicing registered nurses have lower informatics competency than their international counterparts, particularly those in countries with more advanced digital technologies and infrastructure [12-15]. Despite significant reform efforts, the integration of informatics into Saudi nursing education has not yet reached the level observed in many other high-income countries, indicating the need for targeted policy and curriculum intervention.

Although many global models advocate for the integration of informatics into nursing education, very little research has addressed this topic in Saudi Arabia. Few studies have investigated how prepared nursing students are for digital health roles or how their informatics competency relates to their confidence with technology, both of which are important factors for successfully joining today's digital health care workforce. These research gaps need to be filled so that evidence can guide faculty training and improve nursing curricula, especially given the Vision 2030 focus on digital health. This study measured the baseline informatics competency and digital readiness of nursing students at the University of Hail, Saudi Arabia. The goal was to provide local data that address a known gap in preparing Saudi Arabia's future nurses to work in digitally transformed health care settings.

Methods

Study Design

This study adopted a descriptive cross-sectional design to assess perceived informatics competency and digital technology self-efficacy among undergraduate nursing students using an online self-assessment survey.

Study Population and Sampling

Voluntary participation in an electronic survey allowed for data collection from undergraduate nursing students at a university in Hail, covering students from the first to fourth years (levels 1 - 4) of the Bachelor of Nursing program. The target population was all undergraduate nursing students enrolled in the Bachelor of Nursing program at the University of Hail during the 2024 - 2025 academic year (levels 1 - 4 and interns). The source population comprised all students with an active institutional email address on the official program mailing list at the time of data collection. Therefore, the accessible sampling frame consisted of this official mailing list of currently enrolled undergraduate nursing students, which was used to distribute a single open invitation to participate in the study.

Students were eligible if they (1) were currently enrolled as undergraduate nursing students in levels 1 to 4 at the University of Hail, (2) were able to read and understand English (the language of instruction), and (3) had an active institutional email account. Students on academic suspension, on long-term leave, or who had withdrawn from the program at the time of data collection were excluded from the study.

A convenience sampling approach was used in which all eligible students from the source population were invited to participate. This strategy was practical, cost-effective, and enabled the coverage of the broadest possible segment of the accessible student population. In this context, convenience sampling reflects all students who chose to respond to the open email invitation rather than a preselected subgroup. All invitations were distributed via the official undergraduate nursing program's email list. Because the list is updated dynamically, the exact number of invitations sent could not be confirmed, but it approximately matched the total number of eligible students. The survey was conducted using Google Forms. A total of 260 students started the survey, of whom 93.5% (243/260) completed it and were included in the analysis. In total, 6.5% (n=17) of the responses were excluded due to substantial missing data (more than 20% of the items were unanswered). Because the total number of active student email accounts at the time of the survey could not be verified, the exact response rate could not be calculated. However, program records indicated that the mailing list approximately matched the total number of enrolled and eligible students.

For inferential analyses involving year level, only students in levels 1 to 4 were included, excluding interns because their internship year is structurally distinct from the numbered academic levels. To reduce potential selection bias, all eligible undergraduate nursing students on the institutional mailing list were invited to participate using the recruitment protocol described in the Data Collection section.

Study Size

A priori power analysis indicated that at least 315 respondents were required to achieve 80% power at a 95% confidence level for medium effects in ANOVA, 2-tailed *t* tests, and regression analyses. Therefore, the final analytic sample of 243 respondents was underpowered for confirmatory inferential analyses but was considered adequate for descriptive and exploratory correlational analyses.

Instrument

The questionnaire was divided into 3 sections to capture comprehensive participant information. The first section collected general demographic data, including age, sex, academic year, prior experience with electronic medical records, and self-assessed computer proficiency. These variables provided a contextual background for interpreting the findings in the subsequent sections.

The second section assessed participants' informatics competency using the 21-item C-NICAS version 2 with permission from Kleib and Nagle [3]. This student-focused instrument has been adapted and validated for undergraduate nursing students across multiple international contexts, supporting its suitability for this population and enabling cross-study comparison. Originally developed and psychometrically validated among registered nurses in Alberta, Canada, the scale has also undergone cross-cultural validation, supporting its use in international benchmarking.

The C-NICAS includes 4 subscales: foundational information and communications technology (ICT) skills, information and knowledge management, professional responsibility and accountability, and use of ICTs in the delivery of care. These domains align with the core competencies relevant to the digital health ecosystem in Saudi Arabia. The instrument was administered in English, consistent with the language of instruction at the study site. Participants self-reported their competency using a 4-point Likert scale ranging from 1 ("not competent") to 4 ("very competent"). The total scores ranged from 21 to 84 and were categorized into 4 levels: not competent (21-41), somewhat competent (42-62), competent (63-83), and very competent (84). The scale demonstrated strong internal consistency (Cronbach α=0.93 overall and 0.74 - 0.89 for the subscales).

The final section measured digital technology self-efficacy using a revised 17-item version of the questionnaire by Hughes [16]. This scale complements the C-NICAS by assessing students' confidence in their ability to use digital technology. Responses were recorded on a 4-point Likert scale ranging from 1 ("strongly disagree") to 4 ("strongly agree"). In total, 12 items were reverse coded, and 5 items (1, 7, 8, 11, and 16) were positively coded. The mean scores ranged from 1 to 4, with higher scores indicating greater self-efficacy. The scale demonstrated strong reliability, with the Cronbach α exceeding 0.90 in both the original study and the sample in this study.

Both informatics competency and digital technology self-efficacy were assessed using self-report measures. Although both instruments have strong psychometric properties, self-reported data may be subject to bias and inaccurate self-assessment, potentially leading to over- or underestimation of actual competency and confidence levels.

Data Collection

An ethical recruitment plan was developed. Nursing students were invited through email, which contained an invitation letter, a survey link, an information sheet, and a consent statement. The invitation highlighted the purpose of the research, the importance of the study, and the possible implications of the study for nursing informatics research.

Reminder emails using a predetermined protocol were sent to encourage response; the first reminder was sent 24 to 48 hours after the initial email, followed by another one 3 to 7 days later, with a total of 3 to 5 reminders sent throughout the data collection period. Google Forms was used for the survey because of its accessibility and reasonable data storage capacity.

Statistical Analysis

Data analysis was performed using SPSS (version 29.0; IBM Corp) and the Python software (Python Software Foundation). Item-level missing data were minimal (<5% for all variables). Continuous items with less than 5% of missing data were imputed using item-specific means and categorical variables using the mode. Given the low proportion of missing data, this approach was unlikely to bias the descriptive estimates, although it may have slightly attenuated the variance in the inferential analyses.

Statistical assumptions were assessed prior to the inferential analyses. Descriptive statistics, including measures of central tendency (mean, median, and mode) and variability (SD), were calculated for key variables, such as C-NICAS and digital technology self-efficacy scores. Inferential analyses included Pearson correlation to examine relationships among variables, independent-sample *t* tests, and one-way ANOVA to assess group differences.

Hierarchical multiple regression was conducted using 4 models to identify the predictors of informatics competency. Potential confounders (age, sex, academic level, prior informatics training, and previous EHR exposure) were included; however, given the underpowered sample and limited variables, residual and unmeasured confounding (eg, informal IT training or personal interest in technology) cannot be excluded.

The significance level was set at an α value of .05. Effect sizes were interpreted using the Cohen standards for correlations (small=0.10; medium=0.30; large=0.50), and *F* change statistics were used to assess changes in R^2 values across regression models. As the final sample was below the a priori target (N=243 vs 315), all inferential analyses should be considered exploratory and hypothesis generating rather than confirmatory.

Ethical Considerations

Institutional review board approval from the University of Hail (H-2024-437) was obtained prior to data collection. Participation was entirely voluntary and no financial compensation was provided to the participants. All procedures were conducted in accordance with the ethical standards of the Research Ethics Committee and the 1964 Declaration of Helsinki and its subsequent amendments.

Informed consent was obtained from all students prior to accessing the online survey and questionnaire. Participation was entirely voluntary, and students had the right to withdraw at any time without adverse academic consequences. To preserve participants' anonymity, no personal identifiers (such as names or email addresses) were collected through Google Forms, and the researchers did not link any responses to individual participants. The dataset was stored on a secure, password-protected server, and access was limited to the research team members.

This study posed an extremely low risk as it involved noninvasive procedures and presented no more than minimal risk to the participants. The participants' normal coursework was not affected, and it was clearly stated that their decision to participate or not would have no impact on their academic status or their relationship with faculty members.

Results

Table 1 presents the study's 243 undergraduate nursing student participants from Saudi Arabia, with most being young adults aged 21 to 25 years (n=116, 47.7%) and only 7% (n=17) aged 26 years and above. The sample was predominantly female (n=159, 65.4%). Students were distributed across academic levels, with interns accounting for the largest group (n=63, 25.9%) and year level 8 students representing the smallest group (n=13, 5.3%). The participants were nearly equally divided between those with informatics training (n=124, 51%) and those without (n=119, 49%). Comfort with digital technology varied, with 41.2% (n=100) expressing discomfort and 22.2% (n=54) remaining neutral on the subject. EHR experience ranged from 40.3% (n=98) having occasional exposure to 29.6% (n=72) having no prior experience with EHRs. Most participants demonstrated good technology accessibility, with 82.3% (n=200) using technology daily for educational purposes and 65% (n=158) reporting excellent home internet access. Regarding career intentions, most (n=130, 53.5%) planned to pursue clinical care, whereas 13.6% (n=33) remained undecided about their future nursing career paths. A comparison between respondents and nonrespondents was not possible because identifiable sampling frame data were unavailable; therefore, some nonresponse bias cannot be excluded.

Table . Demographic characteristics (N=243).

Category	Values, n (%)
Age (years)	
≤20	110 (45.3)
21-25	116 (47.7)
≥26	17 (7)
Sex	
Male	84 (34.6)
Female	159 (65.4)
Year level	
First	69 (28.4)
Second	72 (29.6)
Third	39 (16)
Fourth	63 (25.9)
Have you previously completed any informatics-related training or coursework?	
No	119 (49)
Yes	124 (51)
Rate your comfort level with digital technology (eg, computers, smartphones, and EHRs[a])	
Very uncomfortable	47 (19.3)
Uncomfortable	53 (21.8)
Neutral	54 (22.2)
Comfortable	89 (36.6)
Previous exposure to EHRs	
No experience	72 (29.6)
Yes, occasionally (monthly or less)	98 (40.3)
Yes, frequently (weekly or daily)	73 (30)
Do you own or regularly have access to a personal computer or laptop?	
No	49 (20.2)
Yes	194 (79.8)
How often do you use technology (smartphones, tablets, or computers) for educational purposes?	
Monthly	11 (4.5)
Weekly	32 (13.2)
Daily	200 (82.3)
Internet accessibility at home	
Fair	19 (7.8)
Good	66 (27.2)
Excellent	158 (65)
Intended future nursing career area	
Undecided	33 (13.6)
Administration or leadership role	14 (5.8)
Academic or teaching role	35 (14.4)
Nursing informatics	14 (5.8)
Public health or community nursing	17 (7)
Clinical care (hospital or clinical setting)	130 (53.5)

[a]EHR: electronic health record.

Table 2 presents the self-reported C-NICAS item scores from the 243 undergraduate nursing students (mean 2.57, SD 0.84 on a scale from 1-4); the median was 2.50 (2.00-3.00). Regarding the total number of C-NICAS scores, the largest percentage of students (n=116, 47.7%) achieved a score of “somewhat competent”; 21.4% (n=52), or nearly 1 in 5, achieved a score of “not competent”; 23.9% (n=58) achieved a score of “competent”; and only 7% (n=17) achieved a score of “very competent.” When reviewing the subscales, the “foundational ICT skills” subscale had the highest average C-NICAS item score (2.62, SD 0.93), followed by the “use of ICT in the delivery of patient care” (2.60, SD 0.85) and “professional and regulatory accountability” (2.56, SD 0.88) subscales, whereas the “information and knowledge management” subscale had the lowest average C-NICAS item score (2.51, SD 0.86). Most students reported that they rated themselves as somewhat competent on 3 out of the 4 subscales (n=75, 30.9% ‐ n=106, 43.6%), and most students who evaluated themselves as not competent did so on the “foundational ICT skills” subscale (n=58, 23.9%) and least frequently in the “use of ICT in the delivery of patient care” subscale (n=43, 17.7%). Overall, students self-reported moderate levels of informatics competency; however, many rated themselves as only somewhat competent in practically all areas of informatics competency.

Table . Nursing students’ perceptions of informatics competency (Canadian Nurse Informatics Competency Assessment Scale [C-NICAS] mean item scores; N=243).

Scale and subscale	Item score (1-4), mean (SD)	Item score (1-4), median (IQR)	Range	Not competent, n (%)	Somewhat competent, n (%)	Competent, n (%)	Very competent, n (%)
NI[a] competency (overall C-NICAS)	2.57 (0.84)	2.50 (2.01–3.10)	1-4	52 (21.4)	116 (47.7)	58 (23.9)	17 (7)
Foundational ICT[b] skills	2.62 (0.93)	2.66 (2.00–3.33)	1-4	58 (23.9)	75 (30.9)	78 (32.1)	32 (13.2)
Information and technology management	2.51 (0.86)	2.50 (2.00–3.00)	1-4	57 (23.5)	103 (42.4)	57 (23.5)	26(10.7)
Professional and regulatory accountability	2.56 (0.88)	2.50 (2.00–3.17)	1-4	52 (21.4)	102 (42)	58 (23.9)	31 (12.8)
Use of ICT in the delivery of patient care	2.60 (0.85)	2.66 (2.00–3.17)	1-4	43 (17.7)	106 (43.6)	65 (26.7)	29 (11.9)

[a]NI: nursing informatics

[b]ICT: information and communications technology.

The mean self-efficacy score for the use of digital technologies was 2.7 (SD 0.56) on a scale from 1 to 4. This indicates that, as a group, the nursing students reported a moderate to high level of confidence in using digital technologies. Because the mean score of 2.7 is above the scale midpoint, the students’ digital technology self-efficacy can be considered strong.

Table 3 presents the data on informatics competency and digital technology self-efficacy among Saudi nursing students. There were no statistically significant differences in the C-NICAS total scores by year level for students in levels 3 to 8 (P=.48) or in the digital technology self-efficacy mean item scores (P=.87). The mean C-NICAS total scores ranged from 48.3 (SD 15.6) in level 3 to 55.4 (SD 17.9) in level 7, whereas the digital technology self-efficacy mean item scores ranged from 2.5 (SD 0.5) to 2.7 (SD 0.2) on a scale from 1 to 4. Exploratory *t* test analysis showed that students with prior informatics training had higher mean C-NICAS total scores (55.0, SD 15.8) than those without such training (50.6, SD 15.2; P=.005), whereas their mean digital technology self-efficacy item scores were similar (2.6, SD 0.4 vs 2.5, SD 0.5; P=.53). Exploratory ANOVA further indicated that students with no EHR experience had the lowest mean C-NICAS total scores (48.4, SD 16.1) compared with higher scores among those with occasional (53.4, SD 17.2) or frequent (54.9, SD 13.4) EHR use (P=.002); in contrast, digital technology self-efficacy mean item scores remained relatively stable across groups with EHR use (2.5, SD 0.4 to 2.6, SD 0.4; P=.40).

Table . Overall competency and self-efficacy levels by year level, prior informatics training, and routine electronic health record (EHR) use.

Variable	C-NICAS[a] total score (21-84), mean (SD)	*P* value	DT-SE[b] item score (1-4), mean (SD)	*P* value
Year level		.48		.87
3	48.3 (15.6)		2.6 (0.4)	
4	53.1 (16.2)		2.6 (0.4)	
5	53.5 (16.7)		2.5 (0.5)	
6	53.2 (14.3)		2.6 (0.5)	
7	55.4 (17.9)		2.7 (0.2)	
8	53.7 (15.7)		2.6 (0.4)	
Informatics training		.005		.53
Yes	55.0 (15.8)		2.6 (0.4)	
No	50.6 (15.2)		2.5 (0.5)	
EHR use		.002		.40
No experience	48.4 (16.1)		2.6 (0.4)	
Occasional	53.4 (17.2)		2.5 (0.4)	
Frequent	54.9 (13.4)		2.6 (0.4)	

[a]C-NICAS: Canadian Nurse Informatics Competency Assessment Scale.

[b]DT-SE: digital technology self-efficacy.

Table 4 illustrates the preliminary correlational findings showing a positive association between digital technology self-efficacy and 3 of the informatics competency subscales. The strongest correlation was with foundational ICT skills (r=0.181; P=.002), followed by professional responsibility and accountability (r=0.157; P=.002) and use of ICT in care delivery (r=0.113; P=.02). However, the strongest correlations were between the competency subscales themselves, indicating a good level of internal connection. Specifically, the strongest correlation was between professional accountability and use of ICT in care (r=0.794; P=.001), followed closely by the correlation between foundational ICT skills and professional accountability (r=0.769; P=.001) and between foundational ICT skills and use of ICT in care (r=0.765; P=.001).

Table . Correlation between competency and self-efficacy.

	DT-SE[a]	Foundational ICT[b] skills	Professional and regulatory accountability	Use of ICT in the delivery of patient care
DT-SE				
r	1	0.181	0.157	0.113
P value	—[c]	.002	.002	.02
Foundational ICT skills				
r	0.181	1	0.769	0.765
P value	.002	—	.001	.001
Professional and regulatory accountability				
r	0.157	0.769	1	0.794
P value	.002	.001	—	.001
Use of ICT in the delivery of patient care				
r	0.113	0.765	0.794	1
P value	.02	.001	.001	—

[a]DT-SE: digital technology self-efficacy.

[b]ICT: information and communications technology.

[c]Not applicable.

Table 5 presents the outcomes of an exploratory hierarchical multiple regression analysis examining potential predictors of informatics competency measured using the C-NICAS score. In model 1, age and sex were entered, yielding an R value of

0.013 and an adjusted R^2 value of 0.005 ($F_{2,243}$=1.611; P=.20), with no significant predictors. In model 2, year level (fourth-eighth) and internship status were added, resulting in an R value of 0.031 and an adjusted R^2 value of −0.002 ($F_{8,237}$=0.950; P=.48), and again, no significant predictors emerged. In model 3, prior EHR experience and informatics training were added, yielding an R value of 0.054 and an adjusted R^2 value of 0.013 ($F_{10,235}$=1.330; P=.22), with no variables reaching statistical significance. In the final model (model 4), the mean digital technology self-efficacy score was included, resulting in an R value of 0.069 and an adjusted R^2 value of 0.022 ($F_{11,234}$=1.577; P=.11). Digital technology self-efficacy showed at most a weak, borderline association with informatics competency (B=4.34; P=.05), accounting for only a negligible proportion of the variance; thus, it cannot be considered a robust predictor in this sample. Given the modest effect size, nonsignificant overall model, and sample size (N=243) falling below the a priori target (N=315), these regression results should be interpreted with caution and viewed as exploratory and hypothesis generating rather than confirmatory. Overall, the hierarchical models explained only a small proportion of the variance in informatics competency scores.

Table . Hierarchical multiple regression models predicting informatics competency[a].

Model	Variables entered	R^2	Adjusted R^2	*F* test (*df*)	*P* value	Significant predictors (final model)
1	Age and sex	0.013	0.005	1.611 (2, 243)	.20	None
2	+ year level (fourth-eighth) and internship	0.031	−0.002	0.950 (8, 237)	.48	None
3	+ EHR[b] exposure and informatics training	0.054	0.013	1.330 (10, 235)	.22	None
4	+ mean digital technology self-efficacy score	0.069	0.022	1.577 (11, 234)	.11	Digital technology self-efficacy (B=4.34; P=.05)

[a]None of the hierarchical regression models reached conventional statistical significance for the overall F test, and the explained variance was small (maximum adjusted R^2=0.022); therefore, these findings, including the trend-level association for digital technology self-efficacy, should be interpreted as exploratory and preliminary.

[b]EHR: electronic health record.

Discussion

Principal Findings

Overview

This study assessed the baseline informatics competency of undergraduate nursing students at a single institution in Hail, Saudi Arabia, based on self-reported informatics competency scores and revealed a moderate level of competency. Most students rated themselves as somewhat competent. These results suggest that current competency levels may be insufficient to fully support the digital health priorities articulated in the Saudi Vision 2030, indicating the need to further strengthen informatics education and experiential exposure to digital health systems. In addition, this study found that students with previous informatics education had notably higher C-NICAS scores than those without.

Informatics Competency Levels

A moderate level of informatics competency, particularly lower scores in the "information and knowledge management" and "professional responsibility and accountability" subscales, suggests that students may have basic ICT and documentation abilities but lack proficiency in the critical appraisal and interpretation of digital health data, application of ethical and regulatory standards, and more advanced use of information to support clinical decision-making. These deficits are likely related to limited systematically integrated informatics content within undergraduate curricula and restricted, structured exposure to digital health systems, particularly EHRs.

Several studies in Saudi Arabia have reported that nursing students possess basic informatics knowledge but do not consistently achieve high competency [17,18]. The reported deficits are greatest in clinical informatics and applied computer skills, highlighting the gap between knowledge and practice [17,18]. Students proficient in everyday digital technologies often struggle to transfer these abilities to clinical settings that require specific informatics skills [18].

Other studies have reinforced the distinction between digital literacy and informatics competency [19,20]. Nursing students may report moderate or high digital health literacy; however, literacy alone does not ensure competency in critical appraisal, data interpretation, or safe clinical application [19]. Although there have been initiatives to integrate digital skills into the curriculum, the lack of rich experiential learning limits students' progression to competent or advanced informatics levels [20]. Considering these findings and the C-NICAS results in our study, Saudi nursing programs should substantially expand informatics content across all years of study. The lowest mean scores in the "information and knowledge management" subscale underscore the need for modules that teach students to manage, retrieve, and critically appraise health information from electronic databases. These competencies can be addressed through dedicated courses and by embedding informatics objectives into existing theory and clinical units, consistent with recent international recommendations [21].

Experiential learning should include structured, practice-focused engagement with digital health systems, particularly EHRs, as students with previous EHR exposure in this study demonstrated higher competency. This aligns with evidence that greater EHR integration is associated with improved informatics knowledge and skills [22,23]. Targeted faculty development is also needed so that educators can confidently model and assess informatics competency in both classroom and clinical settings.

Academic-practice partnerships that provide students with supervised access to real-time informatics environments can help bridge the gap between classroom learning and clinical practice. Aligning these curricular changes with the Saudi Vision 2030 health strategy is essential for building a digitally competent nursing workforce capable of supporting high-quality, safe care across the kingdom [9,23,24].

Digital Technology Self-Efficacy

The moderately high digital technology self-efficacy found in this study likely stems from students' heavy use of digital tools, widespread internet access, and regular use of online resources. Although digital technology self-efficacy showed a small positive correlation with informatics competency, the hierarchical regression model was not statistically significant, explaining only 2% of the variance. Consequently, digital technology self-efficacy was not a strong predictor of informatics competency in this study. These results should be viewed as hypothesis generating, suggesting a weak association that requires confirmation in larger samples. Instead of making causal claims, the focus remained on robust descriptive and bivariate findings such as differences related to prior informatics training and EHR exposure.

A trend toward increased willingness to use digital technologies for educational and clinical purposes is evident among frequent users, consistent with the findings of another study [25]. Recent studies indicate that nursing students generally show acceptable preparedness for AI-based health care and a positive disposition toward digital health tools [14,25,26]. In Saudi Arabia, nursing students typically view e-learning favorably and are proficient in technology-rich environments, particularly in blended learning contexts [14]. Prior experience and digital literacy remain key indicators of self-efficacy and preparedness in undergraduate nursing education [26].

Nevertheless, digital technology self-efficacy varies considerably [14,27]. Many students remain uncomfortable with digital technologies, especially when transitioning to clinical settings [27]. Furthermore, some are dissatisfied with e-learning due to a lack of in-person interaction and support [14]. Technical difficulties, inconsistent design, and inadequate training can also decrease confidence and satisfaction [14].

These findings suggest that access and exposure are insufficient. Students face obstacles in applying personal technological knowledge to professional contexts and require more support [14,26]. Digital technology self-efficacy can be strengthened by providing consistent hands-on digital literacy education, individualized assistance, and cooperative blended learning environments. Nursing programs should also build strong technological foundations and systematically collect student feedback to improve these environments [14,26]. This approach will help students develop the confidence and skills necessary to use digital tools effectively in both study and practice.

Role of EHR Experience

Early experience with EHRs significantly influences nursing students' informatics competency. There was a positive relationship between EHR experience and informatics competency: students who reported frequent or occasional hands-on use had higher competency scores than those with little or no experience. Practicing informatics in real time enhances the translation of abstract knowledge into practical applications, and providing students with authentic EHR experiences contributes to their clinical preparation [28]. Exposure to educational EHR platforms requires technical proficiency and has broader implications for student learning.

Institutions emphasizing EHR use can expect improved student performance in informatics assessments and application skills, resulting in graduates who are better prepared for practice [22]. Structured exposure to EHR systems may also enhance students' documentation skills, clinical reasoning, and compliance with professional and regulatory requirements. As the demand for advanced informatics skills increases, all students will need structured and equitable access to educational EHR systems [28].

Digital literacy and informatics competency gaps are most apparent when students transition from classrooms to clinical settings. Many students who do not receive instruction on EHR use feel unprepared to document clinical data or perform other informatics tasks [28]. Furthermore, obstacles during clinical rotations are multifaceted, including limited EHR access, unclear learning expectations, and variable guidance from preceptors [28].

Similar concerns exist in the Saudi context, where inequitable student access to EHRs at clinical sites has been identified [15]. Nursing programs should provide comprehensive longitudinal training programs that address EHR use. Furthermore, programs should incorporate simulated or laboratory-based experiences that replicate authentic informatics tasks such as data retrieval, clinical decision-making, and regulatory documentation [21].

Finally, partnering with health care organizations can ensure that students have supervised EHR access and clear learning objectives during clinical rotations [28]. These strategies help bridge the gap between basic digital literacy and professional informatics competency, enhancing readiness for real-world practice, increasing patient safety, and creating long-term career opportunities in the digital health care field.

Implications

These results have significant implications for nursing education and policy in Saudi Arabia. Considering the moderate level of informatics competency, curricular reform is needed to align nursing students with the digital elements of Vision 2030. This can be achieved not only by viewing faculty as presenters of subject matter but also by emphasizing authentic learning experiences. This could be further aided by incorporating a specific informatics module or student engagement activities that rely on EHRs and digital health technologies, which have demonstrated successful clinical experiences in American and Canadian programs. Finally, it is of utmost importance to formalize partnerships between universities and practice settings to ensure that students have authentic experience with real-time informatics in practice settings. These initiatives could yield a digitally competent workforce that can use technology in patient care and contribute to health initiatives in the future.

Conclusions

This single-site survey found that undergraduate nursing students at the University of Hail showed noticeable gaps in informatics competency even though many reported moderate to high confidence in using digital technologies. This highlights the need to revisit the current curriculum considering Saudi Vision 2030 and its emphasis on digital health. The findings also suggest that being comfortable with everyday technology does not necessarily mean that students are prepared with the informatics skills required in clinical settings.

Students with prior exposure to informatics content or experience with EHRs generally demonstrated better competency levels. However, the study sample was smaller than originally planned, and the statistical analyses were not sufficiently powered. Therefore, any observed relationship, including the weak link between digital technology self-efficacy and informatics competency, should be interpreted with caution and considered exploratory.

It is also important to note that this study relied on a single-site convenience sample and self-reported data, both of which limit the generalizability of the findings. These factors may also lead to an overestimation of the actual competency levels. Therefore, the results are best understood as specific to this context rather than reflective of all nursing students in Saudi Arabia. Nevertheless, this study offers useful baseline information that can support local curriculum improvements and inform future research, particularly larger multisite or mixed methods studies aimed at strengthening nursing informatics education in the country.

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Data Availability

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

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence
C-NICAS: Canadian Nurse Informatics Competency Assessment Scale
EHR: electronic health record
ICT: information and communications technology

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Application of the Technology Acceptance Model to Predict Nursing Students' Intention to Use Informatics: Cross-Sectional Study

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Abstract

Background: Nursing informatics is essential for digital health transformation; however, the technology acceptance of undergraduate nursing students in Saudi Arabia remains underexplored.

Objective: This study examined factors influencing nursing students' intention to use informatics technologies using the technology acceptance model.

Methods: A cross-sectional survey was conducted with 132 undergraduate nursing students. Data were analyzed using descriptive, correlational, and hierarchical regression analyses.

Results: Perceived usefulness (mean 3.68, SD 1.22) and perceived ease of use (mean 3.64, SD 1.32) were the strongest predictors of acceptance, together explaining 87% of the variance (R^2=0.87; β=0.323 for usefulness, *P*<.001; β=0.195 for ease of use, *P*=.032). Only 25.8% (n=34) of the students often used electronic health records, while 31.8% (n=42) had no electronic health record experience, indicating a clear gap in practical informatics exposure.

Conclusions: Nursing students' acceptance of informatics is primarily driven by its perceived usefulness and perceived ease of use. These findings highlight the urgent need to integrate practical, user-centered informatics training and clinical simulation into undergraduate nursing curricula to better prepare students for technology-based practice.

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KEYWORDS

nursing informatics; technology acceptance model; TAM; digital health; nursing students; informatics

Introduction

The integration of nursing informatics has emerged as a key issue in improving health care delivery, particularly in rapidly changing contexts [1,2], such as Saudi Arabia. Nursing informatics, which serves to bridge information science, computer science, and nursing, can make substantial advances in nursing practice and management through advanced technology usage [3-5]. The effective adoption of systems such as electronic health records (EHRs), clinical decision support tools, and computerized physician order entry is vital for reducing medical errors [6], enhancing patient safety [7], improving care coordination [8], and directly supporting national quality goals. Considering the ambitious objectives of Saudi Arabia's Vision 2030 to digitize and transform its health care industry [9], the practicality of technologies used by the next generation of practitioners is important and perhaps even imperative. Despite the emerging national need, the acceptance and ability of undergraduate nursing students to engage in nursing informatics for implementation are quite concerning and warrant further research [8,10-12].

Recent studies have highlighted issues related to informatics education in Saudi Arabia. In general, nursing students are aware of the importance of nursing informatics; however, their practical acceptance and use are limited in scope for several related reasons, such as a lack of curricular content, limited clinical experience with informatics, and a lack of consistent faculty support [10,13]. In these attempts, there is a definite disconnect between the theory taught and the actual informatics competencies students need in the clinical environment. This highlights the need for the reform of education due to its limited examples of hands-on training and the development of curricular content that aligns more closely with the current informatics standards in health care delivery [14-17]. Thus, the primary research problem addressed by this study was the lack of empirical understanding of the factors that specifically predict the adoption and use of nursing informatics among undergraduate nursing students in Saudi Arabia, which is a necessary step before effective educational interventions can be designed.

To provide an empirical investigation of this gap, this study uses the established technology acceptance model (TAM) and aims to precisely investigate how undergraduate nursing students' personal perceptions—namely, perceived usefulness (PU) and perceived ease of use (PEOU) of informatics systems—predict their behavioral intention to use those technologies. This study provides a link between identified gaps in the curriculum, experiences, and measurable psychological factors.

A compelling theoretical framework is required to determine the gaps in this study. TAM, developed by Davis [18], is one of the most important and widely used models for studying users' willingness to adopt new technologies. This framework helps us study their main perceptions, PU, and PEOU of nursing informatics systems. The current literature helps to report these general barriers, but a quantitative study using the published and validated TAM framework that focuses on and measures acceptance of these general perceptions of nursing informatics by Saudi Arabian nursing students is nonexistent.

This study extends the core TAM by incorporating contextual factors relevant to nursing informatics education. Social influence was conceptualized in line with TAM2 [19], reflecting perceived expectations from peers, faculty, and clinical environments. Engagement and Sustainability were included as contextual constructs, capturing students' interactions with informatics technologies and their perceptions of their long-term relevance in clinical practice. These variables were examined as supplementary variables rather than primary predictors of acceptance. Although more recent models, such as TAM3 and the unified theory of acceptance and use of technology, incorporate additional contextual and organizational factors, the original TAM was selected for its parsimony and proven applicability in educational and early-stage technology adoption contexts.

As such, this study used the TAM framework in a quantitative study on nursing students' acceptance of nursing informatics in Saudi Arabia. Using the TAM framework, this study is a cross-sectional survey focused on how PU and PEOU affect students' behavioral intention to adopt informatics and provides empirical research and direction for educational policy and curriculum development in alignment with Vision 2030. Despite the recognized importance of nursing informatics in supporting digital health transformation, undergraduate nursing students in Saudi Arabia continue to have limited practical exposure to and variable acceptance of informatics technologies. The factors influencing the intention to adopt and use these technologies remain insufficiently understood, particularly within a theory-driven framework.

Therefore, this study aimed to identify factors that predict undergraduate nursing students' acceptance of nursing informatics technologies using the TAM. The following research questions guided this study: What are undergraduate nursing students' perceptions of nursing informatics in terms of PU, ease of use, and acceptance? What relationships exist between the core TAM constructs and nursing students' acceptance of informatics technologies? Which TAM-related factors significantly predict undergraduate nursing students' acceptance of nursing informatics technologies?

Methods

Research Design

This study used a quantitative, cross-sectional survey to investigate the factors affecting the intention to use informatics technologies, using the TAM as a framework. A cross-sectional survey design was selected for its practicality and feasibility in capturing undergraduate nursing students' perceptions and acceptance of informatics technologies at a single point in time. This design is appropriate for examining the relationships among TAM constructs and identifying key predictors of acceptance without the resource demands associated with longitudinal data collection. This study is reported in accordance with the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) statement guidelines (Checklist 1) [20].

Population and Sampling

This study involved third- and fourth-year undergraduate nursing students from the University of Hail in the Hail Region, Saudi Arabia, from October 2025 to December 2025. Participants were recruited using convenience sampling from students who had successfully completed a nursing informatics course and had relevant clinical experience. All qualified students were contacted via a university communication system. This sampling strategy may limit the generalizability of the results; however, it also facilitates the recruitment of students with proper knowledge and clinical experience. Eligible participants were third- and fourth-year undergraduate nursing students who had successfully completed the nursing informatics and core clinical nursing courses, including supervised clinical training as part of the undergraduate curriculum. Completion of these courses ensured that participants had foundational theoretical knowledge of nursing informatics and prior exposure to clinical practice environments in which health information technologies were used.

A priori power analysis was conducted using G*Power software (Mac and Windows, University of Düsseldorf) for hierarchical multiple regression. The analysis assumed an α level of .05, statistical power of 0.80, and a medium effect size (f^2=0.15). The analysis indicated a minimum sample size of 118 participants. A total of 150 students were invited, of whom 132 completed the survey, yielding a response rate of 88%.

Instrument

This study is comprised of 2 main parts. The first part explored the demographic and technology profiles of undergraduate nursing students participating in the study. The variables of interest included age, sex, year of study, comfort level with digital technology, previous experience using EHRs, computing access, frequency of technology use for educational purposes, Internet access at home, and planned area of nursing work.

The second part used the TAM questionnaire, modified from Davis [18], to measure students' perceptions and behavioral intentions regarding their use of health informatics technologies. The instrument measured 3 core constructs: PU, PEOU, and behavioral intention (BI). Items that further explored issues such as subjective norms (SNs; social influence), sustainability, engagement, and willingness to learn new technologies were also assessed. The TAM items were adapted from a study by Davis [18] and expanded to include domains relevant to contemporary digital health education, namely sustainability, engagement, and willingness to learn new technologies. The final instrument consisted of 31 items distributed across 7 constructs: PU (6 items), PEOU (6 items), SNs (2 items), sustainability (4 items), engagement (7 items), and learning new technologies (6 items). Participants rated their responses on a 5-point Likert scale (from 1="Strongly Disagree" to 5="Strongly Agree"), and the total scores ranged from 12 to 60. Higher ratings indicated that nursing students had more positive opinions about the usability of artificial intelligence in health care. The questionnaire was administered in English, which is the official language of instruction in the nursing program, and all participants were proficient in English. Therefore, no translation or back-translation procedure was required.

Minor wording adjustments were made solely to contextualize the items to nursing informatics and EHR use (eg, replacing generic references to "technology" with "nursing informatics systems"), without changing the meaning or theoretical intent of any item. The underlying structure and theoretical integrity of the original TAM instrument were maintained.

Prior to the main data collection, the instrument was pilot-tested with 20 second-year undergraduate nursing students to assess its clarity, reliability, and internal consistency. These students were excluded from the final sample. Feedback from the pilot test resulted in minor wording refinements to improve item clarity, while the overall structure of the instrument remained unchanged. Internal consistency demonstrated good-to-excellent reliability across constructs in the pilot test, with Cronbach α values of PU=0.953, PE=0.900, SN=0.929, sustainability=0.917, engagement=0.932, and learning new technologies=0.911, indicating satisfactory psychometric properties of the instrument.

Ethical Considerations

After obtaining institutional review board approval from the University of Hail (H-2024 - 437 on September 16, 2024), an ethical recruitment method was established. The purpose of the study was shared with the nursing students in the classroom, and the students were invited to participate. A link to the survey tool was distributed to the students via WhatsApp numbers and university email addresses. Data were collected electronically using Google Forms. Informed consent was obtained electronically through Google Forms. The anonymity and confidentiality of the participants were maintained throughout the study. Moreover, participants were informed that there were no incentives or compensations for participating in this study. Google Forms was chosen for its ease of access and reliable data storage capabilities, providing an efficient process for collecting information on undergraduate nursing students' informatics competencies.

The survey began with an introductory page outlining the purpose of the study, assurances of anonymity, and details of voluntary participation. Participation was voluntary, and the students were informed that they could withdraw at any time without penalty or impact on their academic standing. Data were collected anonymously using Google Forms, and no identifying information was obtained. Access to the data was restricted to authorized members of the research team to ensure confidentiality and data security. The study involved minimal risk and adhered to ethical principles throughout the recruitment and data-collection processes.

Two reminders (1 email and 1 in-class announcement) were used to increase the response rates.

Statistical Analysis

The data were analyzed using IBM SPSS Statistics (version 27). Descriptive statistics were used to summarize participants' demographic characteristics and study variables. Pearson correlation coefficients were calculated to examine the relationships among the TAM constructs. Hierarchical multiple regression analysis was conducted to identify the predictors of nursing students' acceptance of informatics technologies. In model 1, demographic and technology-related control variables (age, gender, year level, prior informatics training, exposure to EHRs, comfort with technology, frequency of technology use, internet accessibility, and intended future nursing career) were entered. In model 2, the core TAM variables—PU and PEOU—were added. Model 3 included extended TAM-related variables (SN, sustainability, engagement, and willingness to learn new technologies).

Before the analysis, the assumptions of multiple regression were examined. The normality of residuals and linearity were assessed through visual inspection of the residual plots. Multicollinearity was evaluated using variance inflation factor values, all of which were within acceptable limits. Statistical significance was set at $P<.05$ for all analyses.

Results

Most participants were female (n=113, 85.6%) and aged 21 to 25 years (n=96, 72.7%). Although access to technology was high, 76.5% (n=101) reported access to a personal computer, and 79.5% (n=105) used technology daily for educational purposes. Comfort with digital technology varied, and clinical informatics exposure remained limited. Only 25.8% (n=34) of the students reported frequent use of EHRs, while 31.8% (n=42) had no prior EHR experience. Clinical care was the most common career pathway (n=80, 60.6%; Table 1).

Table . Demographic and technological profile (N=132).

Category and subcategory	Value, n (%)
Age (y)	
≤20	31 (23.5)
21-25	96 (72.7)
≥26	5 (3.8)
Sex	
Male	19 (14.4)
Female	113 (85.6)
Year level	
Third year	55 (41.7)
Fourth year	77 (58.3)
Rate your comfort level with digital technology (eg, computers, smartphones, and EHRs[a])	
Very uncomfortable	18 (13.6)
Uncomfortable	33 (25)
Neutral	36 (27.3)
Comfortable	45 (34.1)
Previous exposure to EHRs	
No experience	42 (31.8)
Yes, occasionally (monthly or less)	56 (42.4)
Yes, frequently (weekly or daily)	34 (25.8)
Do you own or regularly have access to a personal computer or laptop?	
No	31 (23.5)
Yes	101 (76.5)
How often do you use technology (smartphones, tablets, and computers) for educational purposes?	
Monthly	8 (6.1)
Weekly	19 (14.4)
Daily	105 (79.5)
Internet accessibility at home	
Fair	7 (5.3)
Good	36 (27.3)
Excellent	89 (67.4)
Intended future nursing career area	
Undecided	19 (14.4)
Administration or leadership role	7 (5.3)
Academic or teaching role	11 (8.3)
Nursing informatics	8 (6.1)
Public health or community nursing	7 (5.3)
Clinical care (hospital or clinical setting)	80 (60.6)

[a]EHR: electronic health record.

The descriptive statistics for the study variables are presented in Table 2. Among the TAM constructs, PU (mean 3.68, SD 1.22) and PEOU (mean 3.64, SD 1.32) had the highest mean scores, indicating generally positive perceptions of nursing informatics. Learning new technologies (mean 3.61, SD 1.13) and overall acceptance (mean 3.60, SD 1.24) were also rated positively. In contrast, SN had the lowest mean score (3.21, SD

1.22), suggesting that social influence played a less prominent role in students' perceptions than individual cognitive factors.

Table . Descriptive statistics of study variables.

Variable	Value, mean (SD)
Acceptance	3.60 (1.24)
Perceived usefulness	3.68 (1.22)
Perceived ease of use	3.64 (1.32)
SN[a]	3.21 (1.22)
Sustainability	3.50 (1.20)
Engagement	3.35 (1.15)
Learning new technologies	3.61 (1.13)

[a]SN: subjective norm.

As illustrated in Table 3, the acceptance of nursing informatics demonstrated strong positive correlations with PU (r=0.83; P<.01), PEOU (r=0.81; P<.01), and learning new technologies (r=0.83; P<.01). Additionally, PU and PEOU were highly interrelated (r=0.82; P<.01), supporting the theoretical assumptions of TAM. SNs showed weaker, though still significant, correlations with acceptance (r=0.45; P<.01), reinforcing the comparatively limited role of social influence in this sample. Despite these strong correlations, multicollinearity diagnostics remained within acceptable limits (variance inflation factor<6), suggesting that the predictors could be reliably included in the regression models.

Table . Intercorrelations between study variables.

Variable	Acceptance	PU[a]	PEOU[b]	SN[c]	Sustainability	Engagement	LN[d]
Acceptance	—[e]	.83	.81	.45	.79	.69	.83
PU	.83[f]	—	.82	.43	.75	.60	.78
PEOU	.81[f]	.82[f]	—	.43	.77	.61	.78
SN	.45[f]	.43[f]	.43[f]	—	.50	.56	.47
Sustainability	.79[f]	.75[f]	.77[f]	.50[f]	—	.77	.84
Engagement	.69[f]	.60[f]	.61[f]	.56[f]	.77[f]	—	.77
Learning new technologies	.83[f]	.78[f]	.78[f]	.47[f]	.84[f]	.77[f]	—

[a]PU: perceived usefulness.

[b]PEOU: perceived ease of use.

[c]SN: subjective norm.

[d]LN: learning new technologies.

[e]Not applicable.

[f]P<.01 (2-tailed).

The hierarchical regression for predicting the acceptance of nursing informatics (Table 4) revealed that, in model 1, only comfort with technology was a significant predictor with a negative effect (β=−0.363; P=.05). Model 2 included PU and PEOU, and both variables were significant positive predictors (β=0.379; P<.001). The final model indicated that PU (β=0.323; P<.001), PEOU (β=0.195; P=.03), and learning new technologies (β=0.260; P=.008) were significant positive predictors.

Table . Hierarchical regression predicting acceptance with 95% CIs.

Predictor	B	SE	β	*t* test (*df*)	*P* value	95% CI	VIF[a]
Model 1							
Age (y)	−0.136	0.217	−0.053	−0.626 (122)	.53	−0.566 to 0.294	1.11
Gender	−0.080	0.295	−0.023	−0.270 (122)	.79	−0.663 to 0.504	1.07
Informatics training	−0.019	0.213	−0.008	−0.089 (122)	.93	−0.441 to 0.403	1.13
Exposure to EHRs[b]	0.199	0.135	0.122	1.472 (122)	.14	−0.069 to 0.467	1.05
Year level	0.387	0.219	0.154	1.766 (122)	.08	−0.047 to 0.820	1.16
Comfort with technology	−0.427	0.099	−0.363	−4.324 (122)	<.001[c]	−0.623 to −0.232	1.08
Often using technology	−0.250	0.183	−0.113	−1.366 (122)	.18	−0.611 to 0.110	1.13
Internet accessibility	0.145	0.208	0.065	0.695 (122)	.49	−0.267 to 0.557	1.18
Future nursing career	0.032	0.087	0.026	0.365 (122)	.72	−0.140 to 0.203	1.07
Model 2							
PU[d]	0.357	0.077	0.379	4.632 (120)	<.001[c]	0.205 to 0.510	3.16
PEOU[e]	0.347	0.077	0.379	4.632 (120)	<.001[c]	0.205 to 0.510	3.16
Model 3							
PU	0.330	0.083	0.323	3.980 (116)	<.001[c]	0.166 to 0.494	3.94
PEOU	0.207	0.084	0.195	2.481 (116)	.03[f]	0.018 to 0.395	3.99
SN[g]	−0.006	0.054	−0.007	−0.131 (116)	.89	−0.113 to 0.101	1.61
Sustainability	0.092	0.071	0.113	1.294 (116)	.20	−0.048 to 0.233	4.12
Engagement	0.192	0.085	0.185	1.094 (116)	.28	−0.155 to 0.276	3.62
Learning new technologies	0.286	0.105	0.260	2.721 (116)	.008[c]	0.078 to 0.493	5.46

[a]VIF: variance inflation factor.

[b]EHR: electronic health record.

[c]***P*<.01.

[d]PU: perceived usefulness.

[e]PEOU: perceived ease of use.

[f]**P*<.05.

[g]SN: subjective norm.

Table 5 summarizes the proportion of variance in the acceptance of nursing informatics explained by predictors across each step of the hierarchical regression model. In model 1, the demographic and technology-related control variables explained 45% of the variance (R^2=0.45), with an adjusted R^2 of 0.20. In model 2, when PU and PEOU were entered, the model explained 87% of the variance (R^2=0.87), with an adjusted R^2 of 0.75. In model 3, when SN, sustainability, engagement, and learning new technologies were added, the final model explained 90% of the variance (R^2=0.90), with an adjusted R^2 of 0.80. The increase in R^2 from model 1 (0.45) to model 2 (0.87) is striking; therefore, PU and PEOU are the primary predictors, and the final model has a very good overall fit.

Table . Hierarchical multiple regression.

Model	R^2	Adjusted R^2
1	0.45	0.20
2	0.87	0.75
3	0.90	0.80

Table 6 displays hierarchical regression, revealing that all models predicting acceptance of nursing informatics were statistically significant. In model 1, which included demographic and technological controls, the regression was significant ($F_{9,122}$=3.503; P<.001), accounting for a small amount of variance in acceptance. Model 2, which included the core TAM constructs (PU and PEOU), showed a substantial increase in the variance explained ($F_{11,120}$=32.442; P<.001), confirming the primary role of these 2 constructs in acceptance behavior. Model 3 also showed a strong statistically significant outcome ($F_{15,116}$=32.024; P<.001), as it included all 7 study variables and accounted for the largest amount of variance explained. The increasing values of the F test and the consistent statistical significance across the models indicate that the contextual variables and TAM constructs work in succession to predict students' acceptance of nursing informatics.

Table . ANOVA summary for hierarchical regression predicting acceptance[a].

Model	Sum of squares (regression)	Sum of squares (residual)	Mean square (regression)	Mean square (residual)	F test (df)	P value
1	41.527	160.702	4.614	1.317	3.503 (9, 122)	<.001[b]
2	151.339	50.890	13.758	0.424	32.442 (11, 120)	<.001[b]
3	162.893	39.336	10.860	0.339	32.024 (15, 116)	<.001[b]

[a]Analyses were performed using IBM SPSS Statistics (version 27; IBM Corp).

[b]P<.01.

Discussion

Perceptions and Acceptance of Nursing Informatics

Nursing students have a strong, positive perception of nursing informatics, recognizing these technological tools as practical resources that contribute to the quality and safety of patient care, which supports national modernization strategies for digital health in the sector. Consistent with the present findings, Al-Olaimat et al [21] reported that perceived usefulness is a strong predictor of nursing students' acceptance of health information technologies, underscoring the importance of clinical relevance. Similarly, Alnajjar et al [22] found that perceived ease of use significantly influenced technology adoption among nursing students, aligning with our results that usability remained central to informatics acceptance.

However, positive perspectives on nursing informatics and the use of technology are not universal and have exposed serious challenges to implementation. Studies have shown negative or mixed perspectives on nursing informatics and technology use, especially among students who have received little or no training. Given this gap between positive and negative experiences, nursing curricula should incorporate core informatics competencies across all training levels.

Correlation Between TAM Domains

The high positive correlations found between factors influencing nursing students' acceptance of informatics technologies and their perceptions of usefulness, ease of use, and learning opportunities indicate that these personal factors are the primary drivers of adoption. This is not surprising, as students are inherently drawn to technologies that optimize their work, are easy to navigate, and directly advance the acquisition of important professional skills; these direct personal advantages ultimately fulfill their pragmatic and professional needs.

Conversely, the study results indicate that external social norms or pressures have significantly less influence. In other words, students rely on their own attitudes and experiences rather than peer or institutional pressure when making adoption decisions.

This finding is consistent with other studies showing that personal direct advantages are significant predictors of technology acceptance by nursing students and clinicians. In a 2025 cross-sectional study by Jallad et al [23], which used TAM as a research framework, students' personal factors (usefulness, ease of use, human, and technology) were highly positively correlated with informatics adoption. Moreover, their findings suggest that personal advantages still matter even in the presence of institutional support. Similarly, Aldosari et al [24] found a highly positive correlation between PU and PEOU, which led to positive acceptance of health information technologies by nurses. Nguyen et al [25] likewise found that, especially for clinicians, PU and PEOU had an exceptionally influential effect on information and communication technologies acceptance, typically outweighing social influence.

Although these data likely emphasize personal factors, other studies indicate the opposite premise, where external social influence is stronger, at least comparable to, or even better than personal benefits, indicating that context affects the degree of influence. For example, Warshawski [26] found that social influence, performance expectancy, and facilitating conditions were important variables that positively contributed to nursing students' use of technology in Israel. Furthermore, Garavand et al's [27] systematic review made similar assertions regarding the importance of social impacts (eg, peer and institutional support), noting that they were not always weighted as heavily as personal factors.

Factors Influencing the Acceptance of Nursing Informatics

This study explored the factors influencing the prospective acceptance of nursing informatics by Saudi undergraduate nursing students. Overall, the findings highlight individuals' central and predominant personal perceptions as predictors of technology acceptance in this population, which is congruent with the underlying theoretical principles of the TAM. The input of cognitive and social variables provides institutions with practical recommendations to support the integration of informatics into the nursing education curriculum, which is pertinent, as the Saudi health care system continues to progress through digital changes.

The final structural model provided solid empirical support for the fundamental TAM constructs, highlighting that PU, PEOU, and students' ability and willingness to learn new skills are statistically significant positive predictors of perceived technology acceptance. The findings demonstrated that PU and PEOU were related to a positive and significant degree of perceived acceptance and were consistent with the fundamental TAM assumptions and an extensive array of empirical literature in health care. PU and PEOU were strongly and positively correlated with perceived acceptance. This is consistent with the fundamental premise of TAM, which posits that students who perceive informatics systems to be useful in their education and future desired clinical experience (PU) and easy to understand (PEOU) will act to adopt the technology. The existing literature, including studies on Saudi nursing students and practicing nurses [24,28-30], suggests that of all the elements explored, only 2 personal cognitive constructs, PEOU and PU, are consistently shown to have the greatest significance. The literature also describes how PEOU and PU are often interrelated, thereby bolstering their interconnected predictive ability [31], which may have contributed to the predictive ability of the present model.

In contrast, the endogenous variables of SN, sustainability, and engagement were not statistically significant, suggesting that these were even less important than personal experience with PEOU and PU. This suggests that social influence (SN), long-term environmental sustainability, and active engagement with technology (sustainability and engagement) did not influence the initiation of acceptance in this student population. While SN being nonsignificant is consistent with some uses of TAM, where personal interest overcomes the social element, sustainability and engagement are not significant and inconsistent with an emerging corpus of published research in the e-learning and health informatics space that has identified that user engagement, perceived enjoyment, and organizational support (variables conceptually associated with sustainability and engagement) could become predictive, particularly if the use was measured in a temporally posterior fashion [32,33].

The initial observation that PU and PEOU are key drivers of technology acceptance, whereas SN, sustainability, and engagement are not statistically significant, has important context. This finding indicates that, for initial adoption, personal internal motivation (use and ease) is more important than social pressure. Similarly, SN, sustainability, and engagement not being significant were probably affected by students' exposure to informatics systems (eg, EHRs) not being large-scale, and dimensions regarding long-term and organizational support do not have enough influence on study acceptance at the beginning of use.

This is consistent with TAM in the health care sector. Reviews have always supported PU and PEOU as dominant predictors and found that SN and its related constructs were nonsignificant [31]. Health care studies have shown that internal cognitive processes outweigh social influences on clinicians and students in novice settings [24,25,29]. The lack of predictive ability for sustainability and engagement constructs also aligns with the results in the context of a lack of practical experience [34,35].

However, this inverse result was also demonstrated. Research in learning technology or mobile health usually reports engagement or sustainability properties (such as enjoyment or organizational support) as significant [32,33] when examined in a technology-rich or long-term context.

Thus, the differential results highlight an important caveat. Although PU and PEOU drive acceptance for this undergraduate sample, the lack of importance of the other constructs may be a contextual (temporal and situational) feature of the participants' inexperience when using the systems in their educational (and possibly first) experiences with such systems. Consequently, participants may regard SN, engagement, and sustainability as collectively gaining importance as predictors later (ie, when adults have graduated and worked for a while in actual practice with longitudinal interactions with complex systems). Organizational support and peer influence have a greater impact in an institutional environment and lay the groundwork for future longitudinal studies.

The nonsignificant effects of social influence, engagement, and sustainability may reflect students' limited and largely theoretical exposure to informatics technologies. At this early stage, acceptance appears to be driven primarily by PU and PEOU, whereas contextual and organizational factors may become more influential during prolonged or mandatory system use in clinical practice. Overall, our findings support the classic TAM perspective that usability and use dominate early acceptance decisions, whereas social factors may play a greater role in long-term use or in highly structured environments.

Incremental Value of TAM Predictors

The hierarchical regression analysis demonstrated the incremental value of TAM predictors in explaining nursing students' acceptance of informatics technologies. While demographic and background variables accounted for a moderate proportion of the variance, their explanatory power was substantially enhanced by the inclusion of PU and PEOU, which emerged as the dominant predictors. This finding underscores that acceptance among undergraduate nursing students is driven primarily by individual cognitive evaluations rather than contextual or social factors.

The role of demographic characteristics, ecosystem characteristics, and other common predictors of adoption, such as social influence, is negligible in comparison, further lending credence to the notion that a strategy focused on usability and functionality will best advance informatics acceptance. This pattern is expected, as a substantial amount of evidence has emerged that supports the TAM as the reigning model in health care, consistently identifying usability and PEOU as the primary predictors for nurses' and other health professionals' adoption of health records and myriad other systems [24,36,37].

While the first 2 key TAM predictors are statistically reliable, the literature is not homogeneous. However, caution should be exercised when interpreting the extent to which the other variables of technology acceptance are equally or more robust. Some studies, especially those that have combined the unified theory of acceptance and use of technology model or the information system success model as a foundation, offer examples where social influence, engagement, organizational factors, and education are the strongest predictors of technology use, such as in mobile learning [38]. Moreover, reviews have reported that facilitating conditions, technostress, system quality, and satisfaction could be as impactful as, or more impactful than the primary TAM variables, especially in social, mandated, or organizational pressure contexts [35,38,39]. This suggests that PEOU may not always be a direct predictor, as its impact may be mediated by organizational culture, trust, or policy. Additionally, the direct impacts of TAM variables can be diminished or eliminated during periods of strong compliance or external pressure [35,39]. Future research should explore additional factors that may shape nursing informatics acceptance, including technostress, system quality, and organizational support, particularly in clinical settings where informatics systems are mandatory. Longitudinal and multi-institutional studies may help clarify how these variables interact with core TAM constructs over time and across different stages of professional development.

Limitations of the Study

This study had several limitations. First, the cross-sectional design limits causal inference; longitudinal studies are needed to examine changes in informatics acceptance over time. Second, the data were collected from a single nursing program within one university in Saudi Arabia, which may limit the generalizability of the findings to other institutions or countries. Third, the use of self-reported data may introduce response and social desirability biases, and potential nonresponse bias cannot be ruled out. Finally, participants' limited prior exposure to EHRs may have influenced their perceptions of informatics acceptance.

Implication

The results indicate that PU and PEOU are key predictors of the initial acceptance of nursing informatics, reflecting students' early cognitive evaluations rather than experiential judgment. Given the limited practical exposure to informatics systems among the participants, factors related to sustained use, such as social influence, engagement, and sustainability, were not significant. These findings suggest that while usability and perceived value drive early acceptance, continued use is more likely to depend on prolonged clinical exposure, institutional support, and repeated system interaction, underscoring the need for longitudinal practice-based informatics training in nursing education. Informatics competencies should be explicitly embedded into course learning outcomes to align education with digital health practice requirements. In addition, faculty development programs are needed to prepare educators as informatics "super users" who can effectively support students in technology-rich learning environments. Beyond education, the results are relevant to policymakers and hospital administrators who play a critical role in supporting digital transformation. Investment in standardized training platforms, collaboration between academic institutions and health care organizations, and the provision of supportive clinical informatics infrastructure can facilitate smoother transitions of nursing graduates into digitally enabled health care systems.

Conclusion

This study demonstrates that undergraduate nursing students' acceptance of nursing informatics is primarily driven by perceptions of its usefulness and ease of use, despite generally positive attitudes and high access to technology. These findings highlight a persistent gap between theoretical exposure and practical informatics experience, particularly in relation to EHR use. By prioritizing user-friendly, clinically relevant informatics education and simulation, nursing programs can prepare graduates to participate effectively in Saudi Arabia's ongoing digital health transformation.

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Data Availability

Upon request, the corresponding author will provide the data.

Authors' Contributions

Conceptualization: HA
Data curation: NA, RJM
Formal analysis: RJM
Investigation: HA, NA
Methodology: HA, RJM
Validation: HA
Visualization: HA
Writing – original draft: HA
Writing – review and editing: HA, NA, RJM
After reading and revising, each author approved the final draft of the manuscript for publication.

Conflicts of Interest

None declared.

Checklist 1
STROBE checklist.
[DOCX File, 33 KB - nursing_v9i1e85385_app1.docx]

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Abbreviations

EHR: electronic health record
PEOU: perceived ease of use
PU: perceived usefulness
SN: subjective norm
STROBE: Strengthening the Reporting of Observational Studies in Epidemiology
TAM: technology acceptance model

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Digital Health Literacy and Attitudes Toward Telehealth Use in Practice Among Nursing Students in Saudi Arabia: Cross-Sectional Study

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Abstract

Background: Nursing students are the future workforce, and their readiness to use digital health tools is important. Previous studies have focused on knowledge and attitudes; however, they have not examined the wide range of digital health literacy levels that may influence nursing students' attitudes toward using telehealth in clinical settings.

Objective: This study aimed to determine the relationship between nursing students' digital health literacy and their attitudes toward telehealth use in practice.

Methods: A cross-sectional design was used. The sample consisted of undergraduate nursing students enrolled in a Bachelor of Nursing program at a selected Saudi Arabian university. The online survey used 2 scales: the Digital Health Care Literacy Scale and the Nurses' Attitudes Toward Use of a Telehealth Scale.

Results: A total of 273 students participated (mean age 21.3, SD 1.9 years). Most of the nursing students demonstrated a high digital health literacy level (n=184, 67.4%; mean Digital Health Care Literacy Scale score 11.9 out of 15, SD 3.1). Digital health literacy was a significant predictor of positive attitudes toward telehealth use in practice (adjusted odds ratio 1.48, 95% CI 1.28-1.71; P<.001). Male students were significantly less likely to report positive attitudes than female students (adjusted odds ratio 0.62, 95% CI 0.39-0.97; P=.03). However, academic year, telehealth workshops, and informatics courses were not significantly associated with positive attitudes toward telehealth use in practice.

Conclusions: Higher levels of literacy appear to correlate with more positive attitudes toward telehealth use in practice. However, current formal education and workshops had no apparent influence on digital health literacy. This suggests a potential need for strengthening digital training and development in nursing education. This may enhance telehealth readiness and support future digital health care delivery.

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KEYWORDS

attitude; digital literacy; nursing education; nursing students; practice; telehealth; telemedicine

Introduction

The World Health Organization defines telehealth as the provision of health care services to individuals at a distance through information and communication technologies. It enables care to be delivered when the provider and the patient are in different physical locations [1]. Telehealth uses communication technologies for diagnosing and treating diseases, supporting research and assessment, and providing continuous professional education [1]. The rapid expansion of telehealth has transformed the health care system nationally and internationally. This expansion has increased the demand for professional competencies in digital health technologies.

Digital health literacy refers to the ability to access, analyze, and apply health information via electronic means to address health-related issues [2,3]. It also includes the ability to apply telehealth services and maintain electronic communication with health care professionals [2,3]. As telehealth becomes increasingly integrated into health care systems, digital health literacy has become an important competency for nursing students and future health care professionals. Students with stronger digital competencies may engage more effectively with telehealth technologies and adapt more easily to digital health care environments [2,4].

Previous studies have reported moderate to high levels of digital health literacy among nursing students internationally. A study among Indonesian nursing students found that participants possessed fundamental digital health skills. These skills were influenced by factors including higher self-perceived internet skills and more frequent use of the internet for health-related purposes [5]. Similarly, a study from Turkey reported good digital health literacy among nursing students, with higher scores observed among older students and those who reported greater internet use [6]. In contrast, a study of nursing students in Ethiopia found that students had lower digital health literacy levels, particularly among first-year students and those from rural areas [7]. These findings suggest that digital health literacy may vary according to educational exposure, demographic factors, and access to digital technologies [5-7].

Studies conducted in Saudi Arabia have also revealed positive attitudes and moderate knowledge and awareness of telehealth among nursing students [8,9]. This highlights the need for educational programs that strengthen students' digital health competencies [9]. Similar findings were reported in Egypt, where nursing students show positive attitudes toward telehealth despite limited formal training [10,11]. In South Korea, nursing students also had limited direct exposure to telehealth education and clinical telehealth experiences [12]. Nevertheless, telehealth education and self-efficacy were associated with more positive attitudes toward telehealth use in practice [12].

Telehealth has undergone rapid expansion and transformation in Saudi Arabia. In alignment with Vision 2030, the Ministry of Health has launched the E-Health Initiative in Digital Transformation to improve the health care system's effectiveness and efficiency through information technology and digital transformation [13]. According to the Technology Acceptance Model, individual adoption of new technologies is influenced by perceived usefulness and ease of use [14,15]. In the context of telehealth, digital health literacy may contribute to these perceptions by improving individuals' confidence and ability to use digital technologies effectively [2-4].

Although previous studies have investigated nursing students' knowledge and attitudes regarding telehealth, digital health literacy and digital health knowledge are conceptually different and often used interchangeably. Digital health knowledge refers to an individual's understanding of what digital health is; when it is used; and the benefits, limitations, and associated ethical or legal considerations [1,16,17]. Digital health literacy, however, goes beyond awareness to encompass the practical ability to access, use, and assess telehealth services effectively in actual practice [2-4]. Whereas knowledge appears primarily cognitive and content-based, literacy is skill-based and reflects the capacity to apply that knowledge in real-world telehealth interactions [2,3]. Thus, a person may possess knowledge about telehealth without necessarily having the literacy required to use it competently.

Despite increasing integration of telehealth into health care education and practice, there is a lack of evidence regarding the relationship between nursing students' digital health literacy and their attitudes toward telehealth use in practice. Therefore, this study aimed to examine the relationship between digital health literacy and attitudes toward telehealth use in practice among undergraduate nursing students in Saudi Arabia. The study also explored demographic and educational factors associated with positive attitudes toward telehealth use in practice.

Methods

Design

A cross-sectional study was conducted to capture undergraduate nursing students' digital health literacy and attitudes toward telehealth use in practice at a single point in time. This study was reported according to the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) statement guidelines (Checklist 1).

Participants and Setting

This study focused on students enrolled in a Bachelor of Nursing program within a selected university in western Saudi Arabia. In this selected program, telehealth was introduced theoretically to nursing students in many courses; however, limited practical opportunities were available in clinical settings. A convenience sampling method was applied to recruit the participants, which included distribution of invites through social media platforms, emails, and announcements sent through the university's learning management system. To prevent duplicate responses, only 1 submission per device was allowed.

The inclusion criteria for the study were current nursing students in their second year to internship year. First-year students were excluded because they had not yet progressed into the specialized nursing curriculum and had limited exposure to clinical courses, nursing informatics, or telehealth-related learning experiences. Therefore, only second-year, third-year, fourth-year, and internship students were included to ensure that participants had sufficient academic and clinical exposure to meaningfully evaluate digital health literacy and attitudes toward telehealth use in practice. Licensed or registered nurses enrolled in bridging or postlicensure programs were excluded because prior professional experience may influence digital health literacy and attitudes toward telehealth use in practice independently of undergraduate nursing education.

The data were collected from November 2025 to January 2026. During this research period, 440 female and 223 male nursing students were enrolled in the Bachelor of Nursing program. The targeted sample size was 244, which met the required sample size, with a 95% CI and 5% margin of error.

Data Collection Instrument

The survey consisted of 3 sections: part 1 asked about demographic data, while the second and third parts used 2 scales adopted from previously published and publicly accessible studies [18,19]. The first part of the survey collected demographic data such as sex, age, and academic year (second, third, fourth, or internship). Four questions inquired whether students had attended workshops or lectures related to telehealth, had taken nursing informatics courses, understood the definition of telehealth, and had applied telehealth in clinical placements.

The second part of the survey assessed digital health literacy using the Digital Health Care Literacy Scale (DHLS), with 3 items adopted from a previously published and publicly accessible study [18]. The scale exploratory factor analysis demonstrated good psychometric properties, with Cronbach α of 0.90 and 78% explained variance, supporting the scale's validity and reliability [18]. The responses were measured using a 5-point Likert scale ranging from strongly disagree to strongly agree.

The third part of the survey assessed the students' attitudes toward telehealth in practice using the 19-item Nurses' Attitudes Toward Use of a Telehealth Scale (NATUTS), which was obtained from a previously published and publicly accessible study [19]. NATUTS measured 3 factors: satisfaction, rejection, and development. The instrument demonstrated strong psychometric properties, with Cronbach α values ranging from 0.86 to 0.93 and a total explained variance of 64.4%, supporting its validity and reliability for assessing attitudes toward telehealth [19]. For descriptive interpretations purposes, the items were conceptually grouped under 4 domains, namely perceived benefits, professional integration and reliability, negative emotions and resistance, and engagement and self-development. Responses were recorded using a 5-point Likert scale ranging from strongly disagree to strongly agree.

The survey was administered in English because English is the language of nursing instruction at the study institution, and translation was therefore not needed. The survey was checked for face and content validity to assess its clarity and relevancy to the study objective before distribution. It was sent to 3 experts in nursing education and digital health for feedback. A pilot test was conducted with 10 nursing students to evaluate clarity, readability, and completion time. No modifications were required based on their feedback. Pilot participants were excluded from the final analysis.

The 3 DHLS items were adopted to assess the level of digital health literacy of the students. Each item was rated using the 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The 3 items were rated accordingly, and the total DHLS scores ranged from 3 to 15. The digital health literacy score was classified accordingly: 3 to 7 (low), 8 to 11 (moderate), and 12 to 15 (high). The total NATUTS score was calculated by adding up all 19 items after negatively worded items were reverse-coded to investigate predictors of positive attitudes toward telehealth. The total NATUTS scores ranged from 19 to 95. Higher scores indicated more positive attitudes toward telehealth use in practice. The sample mean score was used as a cutoff to dichotomize the overall attitude score. Mean score dichotomization has been used to facilitate interpretation of logistic regression outcomes when no established cutoff exists. Values below the mean were classified as negative attitudes, and scores equal to or above the mean were classified as positive attitudes. The multivariable logistic regression model was then fitted with the dichotomized variable.

Data Analysis

SPSS (version 28; IBM Corp) was used to perform all statistical analyses. Descriptive statistics were adopted to classify the nursing students' educational background, level of digital health literacy, sociodemographic attributes, and attitude toward telehealth use in practice. Frequencies and percentages denote the categorical variables, and means and SDs denote the continuous variables.

To examine factors associated with positive attitudes toward telehealth use in practice, multivariable logistic regression analysis was performed. Digital health literacy score, age, sex, academic year, exposure to telehealth education, completion of a nursing informatics course, and telehealth use during clinical placement were entered as independent variables in the model. Adjusted odds ratios (AORs) with 95% CIs were calculated. A *P* value of <.05 was considered statistically significant.

Ethical Considerations

The study adhered to ethical research standards and received approval by a relevant institutional review board of Umm Al-Qura University (receipt number HAPO-02-K-021-2025-5-2785). A statement at the beginning of the survey informed participants of the study's objectives, processes, possible benefits, and any related risks. It explained that participants' identities would remain anonymized and protected.

Participants provided consent by completing and submitting the survey anonymously. There were no significant risks, and the only cost to the participants was the time taken to complete the survey. Participation was voluntary, and responses were collected anonymously. No financial compensation or incentives were provided to participants for taking part in the study.

Results

Table 1 presents the sociodemographic and academic characteristics of the participating nursing students (N=273). Most students were aged 21 and 22 years (160/273, 58.6%), followed by 19 and 20 years (82/273, 30%), with a mean age of 21.3 (SD 1.9) years. Most participants were female (209/273, 76.6%). Regarding academic level, most students were in their third year (101/273, 37%), followed by fourth-year students (95/273, 34.8%), nursing interns (45/273, 16.5%), and second-year students (32/273, 11.7%). A high proportion of students reported having attended a telehealth workshop or lecture (198/273, 72.5%) and completing a nursing informatics course (194/273, 71.1%). The vast majority reported knowing the meaning of telehealth (244/273, 89.4%), and more than half reported using telehealth during their clinical placement (148/273, 54.2%).

Table . Sociodemographic and academic characteristics of nursing students (N=273).

Variables	Nursing students
Age (years), n (%)	
19 - 20	82 (30)
21 - 22	160 (58.6)
>23	31 (11.4)
Age (years), mean (SD)	21.3 (1.9)
Sex, n (%)	
Male	64 (23.4)
Female	209 (76.6)
Academic year, n (%)	
Second year	32 (11.7)
Third year	101 (37)
Fourth year	95 (34.8)
Nursing intern	45 (16.5)
Have you attended a workshop or lecture about telehealth?, n (%)	
Yes	198 (72.5)
No	75 (27.5)
Have you taken a nursing informatics course?, n (%)	
Yes	194 (71.1)
No	79 (28.9)
Do you know the meaning of telehealth?, n (%)	
Yes	244 (89.4)
No	29 (10.6)
During your clinical placement, do you use telehealth?, n (%)	
Yes	148 (54.2)
No	125 (45.8)

Table 2 illustrates the distribution of nursing students' responses to the 3-item DHLS. More than half (140/273, 51.3%) strongly agreed that they could use applications or programs such as Zoom independently, while 77 (N=273, 28.2%) agreed. Similarly, 130 (N=273, 47.6%) students strongly agreed and 75 (27.5%) agreed that they could set up video chats without assistance. Regarding problem-solving skills, 91 (N=273, 33.3%) students agreed and 80 (29.3%) strongly agreed that they could resolve basic technical issues on their own, while a smaller proportion (65/273, 23.8%) remained neutral. The overall DHLS score ranged from 3 to 15, with a mean of 11.9 (SD 3.1) out of 15.

Table . Distribution of nursing students' responses to the Digital Health Care Literacy Scale items (N=273).

Digital Health Care Literacy Scale items[a]	Strongly disagree, n (%)	Disagree, n (%)	Neutral, n (%)	Agree, n (%)	Strongly agree, n (%)
I can use applications or programs (such as Zoom) on my cell phone, computer, or another electronic device on my own (without asking for help from someone else).	16 (5.9)	13 (4.8)	27 (9.9)	77 (28.2)	140 (51.3)
I can set up a video chat using my cell phone, computer, or another electronic device on my own (without asking for help from someone else).	15 (5.5)	20 (7.3)	33 (12.1)	75 (27.5)	130 (47.6)
I can solve or figure out how to solve basic technical issues on my own (without asking for help from someone else).	12 (4.4)	25 (9.2)	65 (23.8)	91 (33.3)	80 (29.3)

[a]Range 3-15; mean 11.9, SD 3.1.

The overall distribution of nursing students' digital health literacy levels. Most participants had a high level of digital health literacy (184/273, 67.4%). Exactly 61 (22.3%) students had a moderate level, and a smaller proportion of students (28/273, 10.3%) showed a poor level of digital health literacy.

Table 3 presents the distribution of nursing students' attitudes toward telehealth use in practice. Overall, the findings show a predominantly positive attitude. In the perceived benefits of telehealth domain, most agreed or strongly agreed that telehealth reduces nurses' workload (211/273, 77.3%), is an important part of nursing services (218/273, 79.9%), is essential in nursing (204/273, 74.7%), improves individuals' quality of life (232/273, 85%), simplifies patient-nurse communication (210/273, 76.9%), enables nursing services to be carried out more effectively (209/273, 76.6%), gives professional advantage (202/273, 74%), and eases nurses' workloads (221/273, 80.9%). In the professional integration and reliability domain, 216 (N=273, 79.1%) students agreed or strongly agreed that they would like to include telehealth in professional practice, 173 (63.3%) considered it reliable, and 209 (76.5%) viewed it as essential in nursing services. In the negative emotions and resistance domain, agreement was much lower, indicating limited reluctance: only 61 (22.4%) reported disliking telehealth, 69 (25.3%) felt nervous using it, 67 (24.5%) experienced conflict with its use, 100 (36.7%) used it because they had to, and 71 (26%) would not recommend it to colleagues. Regarding the engagement and self-development domain, over half agreed or strongly agreed that they follow current telehealth developments (135/273, 49.5%), improve themselves regarding telehealth (167/273, 61.2%), and research telehealth (129/273, 47.3%). The overall NATUTS score ranged from 19 to 95, with a mean of 70.93 (SD 11.52) out of 95.

Table . Distribution of nursing students' attitudes toward telehealth use in practice (N=273).

Statements[a]	Strongly disagree and disagree, n (%)	Neutral, n (%)	Strongly agree and agree, n (%)
1. Perceived benefits of telehealth			
I believe that telehealth reduces nurses' workloads.	28 (10.3)	34 (12.5)	211 (77.3)
I believe telehealth is an important part of nursing services.	21 (7.7)	34 (12.5)	218 (79.9)
Telehealth is an essential part of nursing.	27 (9.9)	42 (15.4)	204 (74.7)
I believe that telehealth is effective in improving individuals' quality of life.	19 (7)	22 (8.1)	232 (85)
Telehealth simplifies patient-nurse communication.	22 (8)	41 (15)	210 (76.9)
Telehealth enables nursing services to be carried out more effectively.	23 (8.4)	41 (15)	209 (76.6)
Telehealth gives me an advantage in my profession.	24 (8.8)	47 (17.2)	202 (74)
I believe telehealth eases nurses' workloads.	23 (8.4)	29 (10.6)	221 (81)
2. Professional integration and reliability			
I would like to include telehealth in professional practices.	26 (9.5)	31 (11.4)	216 (79.1)
Telehealth is reliable.	24 (8.8)	76 (27.8)	173 (63.4)
Telehealth is essential in nursing services.	27 (9.9)	37 (13.6)	209 (76.6)
3. Negative emotions and resistance			
I don't like using telehealth.	157 (57.5)	55 (20.1)	61 (22.3)
I get nervous when using telehealth.	138 (50.5)	66 (24.2)	69 (25.3)
I have a conflict with using telehealth.	146 (53.4)	60 (22)	67 (24.5)
I use telehealth because I have to.	78 (28.6)	95 (34.8)	100 (36.6)
I would not recommend telehealth to my colleagues.	156 (57.1)	46 (16.8)	71 (26)
4. Engagement and self-development			
I follow current developments regarding telehealth.	49 (17.9)	89 (32.6)	135 (49.5)
I research telehealth.	57 (20.9)	87 (31.9)	129 (47.3)
I improve myself regarding telehealth.	32 (11.7)	74 (27.1)	167 (61.2)

[a]Mean 70.93, SD 11.52; range 19-95.

Multivariable logistic regression analysis was conducted to determine whether digital health literacy predicted positive attitudes toward telehealth use in practice after controlling for demographic and educational variables. Digital health literacy was a significant predictor of positive attitudes toward telehealth use in practice (AOR 1.48, 95% CI 1.28-1.71; *P*<.001). Male students were significantly less likely to report positive attitudes compared with female students (AOR 0.62, 95% CI 0.39-0.97; *P*=.03). No significant associations were observed for age, academic year, telehealth workshops, informatics courses, or telehealth use during clinical placement (Table 4).

Table . Multivariable logistic regression predicting positive attitudes toward telehealth use in practice (N=273).

Variables	AOR[a] (95% CI)	*P* value[b]
Digital health literacy score	1.48 (1.28 - 1.71)	<.001
Male (vs female)	0.62 (0.39 - 0.97)	.03
Age (years)		
21 and 22 (vs 19 and 20)	0.91 (0.63 - 1.32)	.62
≥23 (vs 19 and 20)	0.74 (0.40 - 1.36)	.33
Academic year		
Third year (vs second year)	1.18 (0.64 - 2.19)	.60
Fourth year (vs second year)	1.32 (0.70 - 2.50)	.39
Intern (vs second year)	1.01 (0.52 - 1.95)	.98
Telehealth workshop (yes vs no)	1.05 (0.66 - 1.67)	.84
Informatics course (yes vs no)	1.12 (0.71 - 1.78)	.62
Telehealth use in clinical placement (yes vs no)	1.09 (0.70 - 1.69)	.69

[a]AOR: adjusted odds ratio.

[b]Significance level: $P<.05$.

Discussion

Principal Findings

The purpose of this study was to examine the relationship between digital health literacy and attitudes toward telehealth use in practice among nursing students. The findings demonstrated that high digital health literacy was significantly associated with positive attitudes toward telehealth use in practice. Students with higher digital health literacy were significantly more likely to perceive telehealth as beneficial, reliable, and relevant for nursing practice.

Most of the nursing students demonstrated a high level of digital health literacy. This result aligns with previous studies that found moderate to high digital health literacy among nursing and health sciences students [20,21]. However, the findings should be interpreted with caution. Although students may possess the ability to access and use digital health information, this does not necessarily indicate preparedness to apply telehealth in complex clinical situations. Previous studies have shown that nursing students often experience difficulties in critically evaluating online health information and in applying digital knowledge in clinical decision-making [20,21]. Thus, possessing digital health literacy skills alone may be insufficient without practical telehealth training and supervised clinical application.

Most of the students stated that telehealth decreases workload, improves the quality of life of patients, and plays a critical role in nursing practice. These results are consistent with those of previous studies demonstrating that nursing students perceive telehealth as beneficial to health care accessibility, efficacy, and communication [19,22]. Positive attitudes toward telehealth use in practice may reflect nursing students' increasing exposure to digital technologies in both educational and health care settings. These attitudes may also be influenced by the rapid expansion of telehealth services following the COVID-19 pandemic [6,20]. Thus, students may perceive telehealth as consistent with contemporary nursing roles which require digital communication and remote patient monitoring [4,22].

Despite the reported positive attitudes, some students exhibited negative feelings such as reluctance and nervousness. These findings are important because they show that positive attitudes can sometimes coexist with discomfort, limited confidence, or perceived external pressure to use digital technologies. This may indicate that some students accept telehealth while still lacking confidence in their practical ability to use it efficiently and effectively. Such findings align with those of previous research, where the nursing students were hesitant due to reliability concerns and insufficient practical exposure [12,23]. These findings suggest that telehealth education should include hands-on simulation and supervised practice experiences to improve confidence and reduce resistance.

The presence of negative emotions toward telehealth use in practice may reflect limitations of current nursing education strategies. Although many students attended telehealth workshops or completed informatics-related courses, these experiences did not lead to more positive attitudes toward telehealth use in practice. This finding suggests that current educational strategies may emphasize theoretical knowledge more than practical competency. Short workshops or isolated informatics courses may increase awareness of telehealth without sufficiently improving students' confidence, communication skills, or ability to integrate telehealth into patient care [23]. Subsequently, students may recognize the importance of telehealth while experiencing anxiety or resistance to its practical implementation.

Digital health literacy independently predicted students' attitudes toward telehealth use in practice even after controlling for demographic and educational variables. This finding suggests that digital health literacy is not only a technical skill but also a determinant of technology acceptance in health care settings.

Students who are confident in using digital tools may perceive telehealth systems as easier to use and thus more useful in clinical care. These results align with the Technology Acceptance Model, which suggests that individuals with higher perceived competence in technology are more likely to adopt digital innovations in practice [14,15]. However, students with lower literacy levels may experience uncertainty and resistance due to difficulties navigating digital health care environments. These findings suggest that digital competencies play a critical role in shaping students' readiness to adopt telehealth technologies in future clinical practice. As telehealth becomes increasingly integrated into health care systems globally, digital health literacy may represent an essential professional competency for future nurses [4]. Therefore, improving digital health literacy may help not only to develop technical competence but also to reduce anxiety and strengthen professional acceptance of telehealth technologies.

The study statistically found that male students were less likely to report positive attitudes toward telehealth use in practice than female students. Although evidence regarding sex differences in attitudes toward telehealth among nursing students remains limited, this result may be related to communication preferences, engagement with patient-centered care, or attitudes toward health care technologies. However, this result should be interpreted cautiously given the lack of literature available and the potential influence of cultural and educational factors. Additional research is needed to better understand the reasons underlying these differences.

Overall, the results imply that telehealth education in nursing programs needs to be further enhanced beyond theoretical instruction. While students generally demonstrated positive attitudes and high digital health literacy, the persistence of nervousness, reluctance, and feelings of obligation indicates gaps between knowledge and practical readiness. Nursing curricula may benefit from integrating experiential telehealth learning activities such as simulations, virtual consultations, case-based learning, and supervised clinical telehealth experiences. These approaches may help students develop greater confidence, reduce resistance, and improve their ability to apply telehealth competently in real health care settings.

To summarize, digital health knowledge reflects understanding, whereas digital health literacy reflects the capacity to apply that understanding in practice. This study contributes to existing evidence that digital health literacy plays an important role in technical competence and is positively associated with students' attitudes toward telehealth use in practice. Nursing education courses need to strengthen digital competencies to reduce resistance and promote more positive perceptions of telehealth within nursing. As telehealth becomes integrated into health care systems worldwide, preparing digitally competent nursing graduates is critical to future workforce readiness.

Limitations

The cross-sectional design and single-educational setting of this study make it difficult to draw conclusions about the causal relationships between students' attitudes toward telehealth use in practice and their level of digital health literacy. It was not possible to ascertain whether exposure to telehealth education results in long-lasting changes in attitudes or abilities because the data were gathered all at once. Additionally, the results are less applicable to other nursing programs with distinct curricula, resources, or student characteristics when the study is limited to a single institution. Consequently, findings should be interpreted cautiously, as they might not be generalizable to the broader population of undergraduate nursing students because of potential self-reported bias.

Conclusions

The findings of this study demonstrate that nursing students have high levels of digital health literacy. In addition, most of the students exhibit positive attitudes toward telehealth use in practice, particularly pertaining to patient care delivery, decreasing workload, and professional integration. The significant finding was the association between higher digital health literacy levels and positive attitudes toward telehealth use in practice. These findings suggest a potential need to strengthen digital health content within nursing curricula to strengthen nurses' digital skills through formal training and continuous professional development.

Educators and clinical leaders can modify training strategies to meet the needs of specific groups. This targeted approach may reduce disparities in digital health and telehealth competencies across the clinical workforce. Offering workshops or informal learning experiences does not guarantee improved competency, so such clinical training should include skills that support telehealth use. Integrating structured, evidence-based digital health literacy curricula into clinical training may ensure that future health care providers develop their competency as technologies evolve.

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Data Availability

The research data will be available upon request from the corresponding author.

Conflicts of Interest

None declared.

Checklist 1
STROBE checklist.
[PDF File, 167 KB - nursing_v9i1e94722_app1.pdf]

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Abbreviations

AOR: adjusted odds ratio
DHLS: Digital Health Care Literacy Scale
NATUTS: Nurses' Attitudes Toward Use of a Telehealth Scale
STROBE: Strengthening the Reporting of Observational Studies in Epidemiology

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Psychometric Evaluation of the Canadian Nurse Informatics Competency Assessment Scale and the Digital-Technology Self-Efficacy Scale Among Saudi Nursing Students: Cross-Sectional Study

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Abstract

Background: The integration of digital health technologies into nursing education in Saudi Arabia requires reliable tools to assess nursing informatics competency and digital technology self-efficacy among students.

Objective: This study aimed to evaluate the reliability and validity of the Canadian Nursing Informatics Competency Assessment Scale (C-NICAS) and Digital Technology Self-Efficacy (DT-SE) scale among undergraduate nursing students at a Saudi university.

Methods: A descriptive cross-sectional survey of 243 undergraduate nursing students at the University of Ha'il was conducted using the C-NICAS and DT-SE. Internal consistency was examined using Cronbach α, and construct validity was assessed using exploratory and confirmatory factor analyses.

Results: A total of 243 students participated (mean C-NICAS score 54.0, SD 16.9; mean DT-SE score 2.7, SD 0.56). Both scales showed good internal consistency (C-NICAS total α=0.90; DT-SE α=0.80). C-NICAS demonstrated a multidimensional factor structure with an acceptable model fit (comparative fit index=1.00; root mean square error of approximation=0.081), whereas DT-SE showed a 3-factor structure with a suboptimal confirmatory model fit (comparative fit index=0.76, root mean square error of approximation=0.146).

Conclusions: The C-NICAS and the DT-SE are suitable for assessing informatics competency and digital self-efficacy among undergraduate nursing students at this institution, although further refinement of the DT-SE may improve model fit. These validated tools can inform curriculum reform at this and similar institutions in Saudi Arabia and support the digital health goals of Saudi Vision 2030.

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KEYWORDS

nursing informatics competency; digital self-efficacy; nursing students; Saudi Vision 2030; health care digital transformation

Introduction

Health care providers worldwide are urgently challenged to integrate digital health technologies into their practices, requiring them to acquire new competencies, especially nurses, the largest single profession in health care systems [1,2]. Electronic health records (EHRs), decision support systems, and mobile health apps are increasingly used to provide safe, efficient, and patient-centered care [3]. Informatics competencies are essential professional requirements for all practicing nurses today and have been established through international initiatives, including the Technology Informatics Guiding Education Reform (TIGER) initiative. TIGER seeks to prepare new nursing graduates to be digitally literate to enhance evidence-based practice and collaboration among health care disciplines [4]. Additionally, the International Medical Informatics Association (IMIA) has published global educational recommendations that define core biomedical and health informatics competencies and provide a framework for designing and accrediting health and nursing informatics curricula across different professional roles and levels of specialization [5,6]. In parallel, the World Health Organization's *Global Strategy on Digital Health 2020–2025* [7] emphasizes that strengthening the digital competencies of the health workforce, including nurses, through pre-service and in-service education is a key component of achieving safe, effective, and equitable digital health implementation. The World Health Organization guidance on digital education further highlights that integrating digital health content and e-learning into health professional curricula is essential for building workforce capacity and supporting lifelong learning in rapidly evolving digital health systems [8].

Saudi Vision 2030 represents Saudi Arabia's national vision for economic development and social reform, with a focus on digital transformation and the adoption of eHealth as a mechanism to cultivate a modernized and technologically prepared workforce to address future digital challenges in health care [9]. Investments in national EHR and health information systems demonstrate this commitment to digital transformation [10]. Although significant progress has been made toward achieving the digital transformation of health care services in Saudi Arabia, barriers continue to exist among nursing students; newly graduated nurses from Saudi Arabia continue to indicate that they possess modest levels of informatics competency and low confidence in their ability to apply digital technology in both academic and clinical settings [2,11]. The results of these studies clearly illustrate an important disconnect between the national goal of a fully developed digital health care system and the preparedness of the future nursing workforce to deliver services in this system [12].

Several international studies support the use of the Canadian Nursing Informatics Competency Assessment Scale (C-NICAS) in both high- and low-income countries. Internationally, studies validating the tool have provided evidence for its reliability and validity across multiple nursing populations in Canada [13,14] and have demonstrated high levels of reliability during adaptation efforts in Australia [15]. The Digital Technology Self-Efficacy (DT-SE) scale, which measures self-efficacy in relation to digital technology, has been used in Europe, Asia, and the Arab world. These studies have demonstrated consistent reliability across regions [16,17]. Systematic review results show that when these tools are transferred to other countries, they do not always perform similarly in terms of psychometric properties. Therefore, it is essential to conduct local validation to account for variations in nursing education and practice settings.

However, no prior study has rigorously validated the C-NICAS and DT-SE scales for Saudi undergraduate nursing students, which represents a significant gap in the field. The lack of culturally adapted and psychometrically sound measures for assessing digital competency in undergraduate nursing students in Saudi Arabia does not allow educators to reliably measure baseline digital competency, assess the effectiveness of their curricula, or make evidence-based decisions for reform, as required by the digital health priorities of Saudi Vision 2030.

Therefore, this study aimed to evaluate the reliability and validity of the C-NICAS and DT-SE scales among undergraduate nursing students in Saudi Arabia to provide robust, locally validated measures of informatics competency and digital technology self-efficacy.

This study also enables a reliable measurement of students' digital readiness, which bridges the gap between knowledge and practice, supports the design of educational interventions, and provides benchmarks for educational institutions. Finally, it offers practical insights into developing a digitally competent nursing workforce and advancing cross-cultural scholarship in nursing informatics for nurse educators, curriculum developers, and policymakers. The validation of the C-NICAS and DT-SE tools in Saudi Arabia will further facilitate the ongoing evaluation of curriculum changes in digital health education through repeated assessments and targeted integration of simulation learning and hands-on experience using electronic medical records while supporting investment in digital resources and informing workforce modernization strategies for national health care transformation.

Methods

Study Design

This descriptive cross-sectional study evaluated the psychometric properties of the C-NICAS and DT-SE scale among Saudi undergraduate nursing students.

Setting, Participants, and Sampling

Students attending the College of Nursing at the University of Ha'il were recruited between February and June 2025 for the study. A priori power calculation was conducted to identify how many participants would be needed to support a one-way ANOVA, using G*Power software (version 3.1.9.7) [18] with a small-to-medium effect size (f=0.25), an α level of .05, and a statistical power of 0.80. Two hundred students were required to achieve these parameters.

The most practical and efficient method for recruiting a sample within the confines of the project timeline and budget was convenience sampling. This sampling strategy allowed for the recruitment of students across multiple academic years/levels and facilitated a broader representation of student participation. However, the use of convenience sampling also introduced a risk of selection bias, in that students who were more readily available and/or engaged may have been overrepresented. Additionally, limiting recruitment to a single institution restricted the generalizability of the findings, as they may not have accurately reflected the larger population of Saudi nursing students in the country. Therefore, future studies should use multi-institutional or probability-based sampling designs to increase the representativeness and external validity of their findings.

The inclusion criteria were as follows: active students in the nursing program who were aged 18 years or older, were fluent in English, and provided informed consent. Students in their preparatory year, non-nursing majors, students on leave, those who withdrew, and visiting students not affiliated with the college were excluded. An additional 20% of the originally calculated number of participants was included to allow for attrition and missing data in participant responses.

Rationale for Instrument Versions

Two valid instruments were used in this study. The first was C-NICAS version 2, the most recent peer-reviewed version of an instrument that represents the current informatics standards accepted throughout international competency frameworks. Research has supported the reliability and relevance of the domains of this instrument for measuring nursing informatics competency worldwide; therefore, it was determined to be appropriate for establishing benchmarks in nursing informatics competencies for undergraduate nursing education in Saudi Arabia. The second instrument was the DT-SE scale [19], which has been shown to have high psychometric properties (α>.90) and has been successfully adapted in several cultures. This scale can measure and compare self-efficacy for digital health tasks among nursing students with some degree of reliability and comparability. Both instruments provided evidence-based and internationally comparable assessments while providing locally validated measures for use within the Saudi context.

Survey Instrument

The survey tool was divided into two components: part 1 contained demographic questions regarding age, gender, level of education, prior experience with EHRs, and individual self-perception of digital readiness. Part 2 contained the C-NICAS version 2 (4 subscales with 26 items), a tool designed to measure competency in 4 areas: foundational computer skills, information and knowledge management, professional and regulatory accountability, and use of computers in patient care. The DT-SE (17 items) measures individual self-efficacy for completing digital health tasks (Likert scale: 1="strongly disagree" to 4="strongly agree"; some items were reverse scored); higher scores represent greater digital self-efficacy.

Data Collection

Data were collected from the participants using anonymous online surveys administered through a secure web-based platform. Withdrawal from the study was permissible at any time . All items were completed in a self-report format, and the participants submitted their responses electronically upon completing the survey.

Data Analysis

Following data collection, all responses were exported to SPSS Statistics for Windows (version 29; IBM Corp) for data cleaning and analysis. Descriptive statistics (mean, median, SD, and frequency distribution) were computed to summarize the sociodemographic characteristics and overall scores on the C-NICAS and DT-SE. Reliability analyses were conducted to estimate the internal consistency coefficients for each scale and subscale, and exploratory and confirmatory factor analyses were performed to evaluate the underlying factor structures and model fit of the C-NICAS and DT-SE. Mean imputation was applied to address missing values for continuous variables, whereas mode imputation was used for missing categorical variables. Python was used to generate supplementary data visualizations to support the interpretation and presentation of the findings.

Ethical Considerations

This study was approved by the Institutional Review Board of the University of Ha'il (approval H-2024‑437). Online informed consent was obtained from each participant before the survey was initiated. The responses were anonymous and stored in a secure location on a password-protected server that only the research team could access. Participation in the study was voluntary and did not result in any penalties. No incentives were provided for participation.

Results

The demographic information of the 243 Saudi nursing undergraduates is presented in Table 1. Of the 243 participants, 110 (45.5%) were aged 20 years or less, 116 (47.7%) were aged between 21 and 25 years, and 17 (7%) were aged 26 years or more. The majority of participants were women (159/243, 65.4%) and a minority were men (84/243, 34.6%). There were 69 (28.4%) first-year students, 72 (29.6%) second-year students, 39 (16%) third-year students, and 63 (25.9%) fourth-year students. Of the 243 participants, 124 (51%) reported that they had completed some type of informatics-related education prior to participating in this study, and 119 (49%) stated that they had not completed any type of education related to informatics.

Table . Sociodemographic characteristics and experience/attitudes regarding technology among respondents (N=243).

		Participants, n (%)
Age		
	≤20 years	110 (45.5)
	21 - 25 years	116 (47.7)
	≥26 years	17 (7.0)
Gender		
	Male	84 (34.6)
	Female	159 (65.4)
Year		
	First year	69 (28.4)
	Second year	72 (29.6)
	Third year	39 (16.0)
	Fourth year	63 (25.9)
Informatics training		
	No	119 (49.0)
	Yes	124 (51.0)
Comfort with digital technology		
	Very uncomfortable	47 (19.3)
	Uncomfortable	53 (21.8)
	Neutral	54 (22.2)
	Comfortable	89 (36.6)
Electronic health record exposure		
	No experience	72 (29.6)
	Occasional	98 (40.3)
	Frequent	73 (30.0)
PC/laptop access		
	No	49 (20.2)
	Yes	194 (79.8)
Technology for education		
	Monthly	11 (4.5)
	Weekly	32 (13.2)
	Daily	200 (82.3)
Home internet		
	Fair	19 (8.7)
	Good	66 (27.2)
	Excellent	158 (65.0)
Career area		
	Clinical care	130 (53.5)
	Academic/teaching	35 (14.4)
	Public health/community	17 (7.0)
	Administration/leadership	14 (5.8)
	Informatics	14 (5.8)
	Undecided	33 (13.6)

Of the 243 participants, 47 (19.3%) stated that they felt very uncomfortable using digital technology, 53 (21.8%) felt uncomfortable, 54 (22.2%) felt neutral about using digital technology, and 89 (36.6%) felt comfortable. Of the participants, 72 (29.6%) stated that they had never seen an EHR before, 98 (40.3%) reported seeing EHRs monthly or less, and 73 (30%) reported using EHRs every week or more.

A large proportion of participants (194/243, 79.8%) either owned their own computers/laptops or had regular access to them. However, 49 (20.2%) participants indicated that they did not have regular access to a personal computer/laptop. Regarding the use of technology for educational purposes, 11 (4.5%) reported that they used this technology monthly, 32 (13.2%) used it weekly, and 200 (82.3%) reported that they used it daily.

In terms of accessing the internet at home, 19 (8.7%) of the participants rated their access as fair, 66 (27.2%) rated their access as good, and 158 (65%) rated their access as excellent. When asked what areas of nursing they planned to pursue after graduation, 130 (53.5%) of the participants planned to pursue roles in direct patient care in hospitals or clinics, 35 (14.4%) wanted to pursue roles in academia or as educators, 17 (7%) wanted to pursue roles in public health/community nursing, 14 (5.8%) wanted to pursue administrative/leadership roles, 14 (5.8%) were interested in pursuing roles in nursing informatics, and 33 (13.6%) were undecided about what area of nursing they would pursue.

Table 2 presents descriptive statistics for the C-NICAS and DT-SE scales. Mean scores across the C-NICAS domains were relatively consistent, including information and communication technology (ICT) skills (mean 2.6, SD 0.93), knowledge (mean 2.5, SD 0.87), accountability (mean 2.6, SD 0.89), and use (mean 2.6, SD 0.85). The overall mean score for the C-NICAS was 54 (SD 16.9), suggesting a moderate level of informatics competency among the students. The mean DT-SE score was 2.7 (SD 0.56), indicating moderate self-efficacy in using digital technology.

Table . Descriptive statistics of informatics competency and digital self-efficacy.

Variable	Scores, mean (SD)
Foundational information and communication technology skills	2.6 (0.93)
Information and knowledge management	2.5 (0.87)
Professional and regulatory accountability	2.6 (0.89)
Use of information and communication technology in patient care	2.6 (0.85)
Overall C-NICAS[a]	54 (16.9)
DT-SE[b]	2.7 (0.56)

[a]Canadian Nursing Informatics Competency Assessment Scale.

[b]Digital Technology Self-Efficacy.

Table 3 summarizes the reliability testing results for the C-NICAS. Cronbach α values indicated good to excellent internal consistency for all domains: foundational ICT skills (α=0.70), information and knowledge management (α=0.80), professional and regulatory accountability (α=0.82), and use of ICT in patient care (α=0.90). The overall the C-NICAS demonstrated excellent reliability (α=0.90). The DT-SE scale showed good reliability (α=0.80).

Table . Internal consistency reliability of the Canadian Nursing Informatics Competency Assessment Scale (C-NICAS) and Digital Technology Self-Efficacy (DT-SE) scale.

Scale	Items, n	Cronbach α	Level of internal consistency
Foundational information and communication technology skills	2	0.70	Good
Information and knowledge management	6	0.80	Good
Professional and regulatory accountability	6	0.82	Good
Use of information and communication technology in patient care	10	0.90	Excellent
C-NICAS	26	0.90	Excellent
DT-SE	17	0.80	Very good

Factor Structure of C-NICAS

Exploratory factor analysis supported a multidimensional structure for the C-NICAS, with item commonalities in an acceptable range and excellent sampling adequacy (Kaiser-Meyer-Olkin=0.976). Confirmatory factor analysis indicated an acceptable model fit for the 4-factor model (comparative fit index=1.000; incremental fit index=1.000; root mean square error of approximation=0.081; χ^2_1=2.02). The full factor loading matrix and related statistics are presented in Table 1 in Multimedia Appendix 1, with the corresponding factor loading plot in Figure 1 in Multimedia Appendix 1 and detailed CFA fit indices in Table 2 in Multimedia Appendix 1.

Factor Structure of DT-SE

For the DT-SE, sampling adequacy was strong (Kaiser-Meyer-Olkin=0.930), and 3 factors emerged in the exploratory factor analysis, explaining 67.7% of the total variance. The rotated factor loadings and variance explained are shown in Tables 3 and 4 in Multimedia Appendix 1, and the factor-loading plot is shown in Figure 2 in Multimedia Appendix 1. Confirmatory factor analysis of the DT-SE indicated a suboptimal model fit (χ^2_{119}=877.10; comparative fit index=0.76; root mean square error of approximation=0.146), suggesting the need for further refinement of the scale in this context. The detailed CFA indices are summarized in Tables 5 and 6 and Figure 3 in Multimedia Appendix 1.

Discussion

In this cross-sectional study, the C-NICAS demonstrated excellent internal consistency and a stable multidimensional factor structure, confirming its suitability for assessing informatics competency among undergraduate nursing students at this Saudi institution. The DT-SE scale showed good internal consistency and an interpretable factor structure, although some model fit indices indicated that further refinement may enhance its performance. Overall, the participants reported moderate levels of informatics competency and digital technology self-efficacy, with stronger foundational ICT skills than advanced digital readiness.

Psychometric Properties of C-NICAS and DT-SE

This reliability/validity assessment found that the C-NICAS [20] and DT-SE scale were both highly reliable and valid and thus appropriate for assessing informatics competency and self-efficacy in an educational setting of this type. The strong psychometric properties of both scales indicate that items within each scale group appropriately represent the theoretically supported domains and thus provide a meaningful assessment of competency and self-efficacy among undergraduate nursing students at the University of Ha'il in Saudi Arabia.

The results support similar validation assessments in Canada [21] and demonstrate that the C-NICAS has excellent internal consistency and a valid factor structure across multiple cohorts of undergraduate nursing students. Another similar validation assessment [22] for the Arabic version of the Self-Assessment Nursing Informatics Competencies Scale, which showed high reliability when used to assess nursing informatics competency among Arab nursing students, further supports the use of these measures to assess informatics competency in the Saudi educational context. Together, these studies demonstrate that valid and reliable scales are important for measuring nursing informatics competency.

Conte et al [23] pointed out that there is a possibility of reduced reliability when adapting self-efficacy scales to different cultures. Furthermore, a systematic review of the literature by Al-Qudah et al [24] concluded that nursing informatics scales exhibit variable reliability and validity, depending on the specific population and setting. Both research groups agreed that these scales must be refined and validated over time if they are to be used effectively on an international scale.

Validated and reliable measures of nursing informatics competencies and self-efficacy will provide Saudi nursing educators with data to assess students' readiness to learn, identify strong and weak areas, and provide an evidence base for changes in nursing education programs. The use of valid tools also supports continuing education and contributes to the transformation of the Saudi Arabian health care system by linking nurses' skills to the national digital health objectives.

Although the scales have strengths, their two main limitations are generalizability and fit for culture (especially for the DT-SE). Studies using larger samples and multiple iterations of the scales would assist in further refining the tools, following the authors' recommendations, to ensure continued utility and reliability as standards for health care and informatics continue to evolve in the Kingdom of Saudi Arabia.

Informatics Competency and Digital Self-Efficacy Levels

This study indicates that the undergraduate nursing students at this institution have an average level of informatics competence and a moderate amount of digital self-confidence; thus, they have partially adopted the digital requirements of today's health care environment but demonstrate a gap between what they are taught about clinical informatics and how they apply it in the workplace. Students have digital skills and confidence in performing these tasks; however, their ability to apply and integrate these skills into more complex applications is less developed than their basic skills.

Compared with their global counterparts, nurses in Jordan demonstrated an almost identical profile of moderate-to-high levels of informatics competency as the participants in this study, including strong performance in general basic computer skills and much weaker performance in clinical informatics subdomain areas [25]. A similar pattern has been observed in Australia and several other Arab countries, as well as in many other parts of the world, where nursing students have shown evidence of being competent in routine digital use; however, they are often found to be lacking in specialized areas such as system management and decision-making [26-29]. The similarities among these findings support the notion that this issue is universal in nature.

Recent studies have also reported similar patterns in nursing informatics education. One recent study found that nursing students typically show higher competence in basic computer skills than in clinical information management and decision support tasks [6]. A further study proposed an undergraduate informatics blueprint that stressed progressive development from foundational to advanced competencies and explicit alignment with IMIA and TIGER recommendations, supporting the need for structured, longitudinal integration of informatics in nursing programs [29].

The level of self-confidence exhibited by nurses regarding digital abilities was similarly modest and reflects current global trends, where confidence in using technology for everyday tasks is commonplace, yet proficiency is limited in advanced applications of informatics [13,30]. While early exposure to digital tools, along with some education, support, and resources, has contributed to moderate progress in improving digital self-efficacy among Jordanian nursing students, limitations remain owing to the lack of preparation in advanced informatics, varied faculty expertise, and inconsistency in the availability of adequate technology and digital systems to support digital readiness [3]. Generational changes and increased digital exposure are likely to improve the basic competencies of nursing students; however, instructional and systemic barriers persist.

The data indicate that nursing programs in Saudi Arabia, including the program at this institution, have made some advancements in digital health; however, further strategic investments are needed to fully support the curriculum design, faculty development, and experiential learning necessary to meet the needs of clinical practice. The use of validated assessments, simulations using artificial intelligence technology, and increased emphasis on interprofessional informatics education will be the key next steps [4,31]. Ultimately, while moderate competency and self-efficacy levels suggest an advancement toward meeting the goals of Saudi Vision 2030, the overall implication of this study is that there continues to be a need for strategic reforms at all educational levels to ensure that graduates can assume leadership roles in future digitally advanced health care systems.

Implications for Nursing Education and Curriculum Development

This research has provided many critical findings that are relevant to nursing education, nursing program assessment, and curriculum development here and potentially elsewhere in Saudi Arabia, in support of Saudi Vision 2030 and global digital transformation objectives in health care.

First, because the nursing students in this sample possessed average levels of informatics competence and digital self-efficacy, there is an imperative for nursing curricula to enhance students' learning experiences with respect to digital health and informatics. For example, rather than simply exposing students to digital health as part of their introductory courses, nursing programs should systematically integrate advanced informatics education, simulation-based learning, EHR training, and education on artificial intelligence and decision support systems into the 4-year undergraduate nursing education experience. By doing so, students will be able to progress from a beginner level of digital literacy to being capable of effectively using emerging technologies in the delivery of patient care.

Second, by using these assessments (the DT-SE and C-NICAS) systematically, educators will be empowered to use data-driven insights when making decisions about the ongoing evaluation of nursing programs and curriculum enhancements. Ongoing assessment of nursing students' informatics competence will empower educators to assess potential weaknesses in their students' abilities to engage in clinical practice using digital technologies, adapt to new clinical requirements, and modify the content of their curricula to be consistent with national and international priorities related to digital health.

Additionally, these enhancements will directly contribute to the goals of Saudi Vision 2030, specifically by providing a future-ready nursing workforce that can assist in promoting and implementing advancements in health care through engagement in national eHealth initiatives and the provision of technology-enabled patient care. Furthermore, to ensure the sustainability of the positive outcomes of this study and to continue to use best practices in both educational and clinical environments, it is important for faculty to continuously receive professional development and for the institution to invest in its digital infrastructure.

Finally, the results of this study further emphasize the importance of innovation in curriculum design and competency-based education in developing nurses with the ability to meet the challenges associated with the digital transformation of health systems globally. Through the alignment of nursing education in Saudi Arabia (particularly in institutions similar to the one in which this study was conducted) with these principles, the health care system will be able to develop professionals who can deliver high-quality, safe, technology-enhanced care to patients.

Study Limitations

This study had several important limitations. The generalizability of the findings is limited by the use of a convenience sample recruited from only one university, and the results should therefore be interpreted as reflecting the students at this institution rather than all Saudi nursing students. Since participants were asked to report their own behavior, there is a potential for both recall and social desirability biases due to the self-reporting nature of the items. Furthermore, the cross-sectional nature of the research design precludes making causal statements about the relationships observed between variables, and possible scale adaptation issues may limit the accuracy of the scales in representing the context being studied. There is a possibility that non-response (dropout) bias may have affected the findings as well, because less technologically savvy students may not have been represented.

Recommendations

To address the gaps identified in this study, we recommend that curriculum developers continue to develop and implement advanced informatics content, simulation-based learning, and practical EHR training across undergraduate nursing programs at this and other institutions in Saudi Arabia. In addition, opportunities for faculty development and long-term investments in digital infrastructure are required to support and enhance the digital health competencies of nursing faculty members.

Policymakers should also provide incentives for the continued implementation and development of standardized and psychometrically sound assessment tools, such as the C-NICAS and DT-SE, for the ongoing monitoring and evaluation of curricula at both the institutional and national levels. We believe that this will help Saudi nursing graduates in an increasingly digitalized health care environment.

Future studies should use multi-institutional, longitudinal research designs and incorporate culturally appropriate tools to increase the representativeness of findings and enable follow-up assessments of curricular impact over time. Future research should also include refinement of the DT-SE scale to improve model fit and identify targeted interventions (eg, simulation and AI-based informatics training) to address existing gaps in advanced digital preparedness among nursing students. Future research examining the association between nursing students' informatics competency and patient outcomes will help optimize nursing education to meet national and international priorities.

Conclusion

The validation of assessments that measure digital competency and self-efficacy is necessary to enhance nursing education in Saudi Arabia. This descriptive cross-sectional study administered the C-NICAS and DT-SE to undergraduate nursing students at a Saudi university, finding that both scales demonstrated strong psychometric properties. The results indicated that nursing students displayed moderate levels of informatics competency and digital technology self-efficacy; specifically, they demonstrated adequate basic-level skills but lacked advanced digital competence compared to international standards. The results indicate the urgent need for comprehensive curriculum reform, faculty development, and strategic investments in advanced technology and assessment techniques to ensure that future nursing graduates are prepared to meet the demands of digital health care delivery systems. The data support the alignment of education with the provisions of Saudi Vision 2030.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Exploratory and confirmatory factor analysis results for the Canadian Nursing Informatics Competency Assessment Scale and Digital Technology Self-Efficacy scale, including factor loadings, model fit indices, and variance explained (Tables 1-6; Figures 1-3).

[DOCX File, 173 KB - nursing_v9i1e88075_app1.docx]

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Abbreviations

C-NICAS: Canadian Nursing Informatics Competency Assessment Scale
DT-SE: Digital Technology Self-Efficacy
EHR: electronic health record
ICT: information and communication technology
IMIA: International Medical Informatics Association
TIGER: Technology Informatics Guiding Education Reform

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The Associations of Emotional Intelligence, AI Self-Efficacy, and AI Literacy Among Nursing Undergraduates Under the NUR.S.E.S. Framework: Network Analysis

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Abstract

Background: With the rapid development of generative artificial intelligence (AI) and its deep integration into nursing education, nursing students' AI literacy (AS) has become a critical competency for their professional development. However, the patterns of associations among emotional intelligence (EI), AI self-efficacy (AILS), and AS in relation to comprehensive AS remain unclear.

Objective: Based on the NUR.S.E.S. framework and using network analysis methods, this study systematically mapped the complex relational network among EI, AILS, and AS among undergraduate nursing students. It identified nodes with high centrality and bridging strength within this network, offering preliminary insights that may inform future educational interventions.

Methods: A cross-sectional survey design was used, with 982 undergraduate nursing students from a university conveniently sampled in September 2025 as research participants. Assessments were conducted using the EI Scale, the AILS Scale, and the AS Scale. Using R (version 4.5.1; R Core Team), we constructed a Gaussian graph model, calculated centrality metrics such as node and bridge strength, and assessed network stability using the bootstrap method.

Results: Network analysis showed that emotion regulation (strength centrality=1.355) and evaluative ability (strength centrality=1.323) showed the highest strength centrality, indicating their prominent positions within the network. Emotional perception (bridge strength=0.427) and comfort with AI (bridge strength=0.242) are the most critical bridge nodes, appearing to connect EI with AI technology systems. Simultaneously, the network architecture suggests that AILS may play a bridging role, effectively linking EI (particularly emotional perception as a bridging factor) with higher levels of AS.

Conclusions: Cultivating AS among undergraduate nursing students is a system that deeply integrates emotional, cognitive, and technical confidence. EI was closely associated with AS, and AILS appeared to occupy a bridging position in the network. Educational interventions might consider enhancing emotional perception and comfort with AI, pending validation through longitudinal or experimental designs.

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KEYWORDS

artificial intelligence literacy; emotional intelligence; AI self-efficacy; network analysis; nursing education

Introduction

The rapid advancement of digital health care technologies, particularly the rise of generative artificial intelligence (GenAI) represented by large language models, is profoundly reshaping the practice paradigms and knowledge boundaries within health care [1]. For nursing students who will become the backbone of the future health care system, this represents both an unprecedented opportunity and a formidable challenge to their capabilities [2]. GenAI can be broadly defined as a subset of artificial intelligence (AI) that focuses on creating new, original, human-like content based on the data it is trained on [3]. A 2024 survey by the Digital Education Council reveals that as many as 85% of students frequently use GenAI in their academic work, with ChatGPT (OpenAI) being the most widely adopted platform among them [4]. Another global survey conducted in 2025 across 109 countries, which collected 20,000 responses, similarly indicated that students are extensively using GenAI tools, with ChatGPT usage exceeding 70% [5]. In the face of the widespread adoption of GenAI among students, education must go beyond introducing technological tools. More crucially, we must ensure that future nursing professionals can critically understand, prudently apply, and rationally evaluate AI, thereby transforming technology into a genuine professional enabler [6]. This lays the foundation for nursing students to apply AI tools and technologies appropriately and proficiently.

The American Nurses Association (ANA) asserts that, against the backdrop of emerging AI technologies, nurses applying AI in health care practice require not only ethical guidance but also uphold the core values of care and compassion inherent to nursing [7]. AI literacy (AS) serves as the core competency and vital bridge for integrating ethical guidance and humanistic care into AI application practices. It is regarded as a key competency in nursing education [8]. These capabilities extend beyond merely mastering and applying AI technologies (such as clinical decision support systems and predictive analytics) to encompass the higher-order thinking skills required to independently critically evaluate and assess the outcomes they generate [9]. As the backbone of the future health care system, nursing students are key participants in shaping AI applications in nursing. Their level of AS directly determines whether they can lead the intelligent transformation in this field, thereby profoundly influencing the breadth and depth of their personal career development [10]. Therefore, cultivating AS among nursing students is of paramount importance [11].

However, the cultivation of AS is not an isolated process; it is deeply rooted in the complex psychological, cognitive, and emotional capacity system of individuals [12]. Research indicates that an increasing number of people are turning to GenAI for guidance on interpersonal relationships, self-awareness, and emotional regulation [13]. Emotional intelligence (EI) refers to the ability to recognize, understand, and manage one's own emotions, while also understanding and empathizing with the emotions of others [14]. Higher EI levels are significantly associated with nursing students' stress management, clinical decision-making, and subjective well-being [15]. Research indicates that the use of GenAI can effectively alleviate stress and improve mental health outcomes, while simultaneously enhancing engagement and satisfaction in learning environments [16]. Specifically in the field of nursing education, Ching and Ho [17] found that including AI virtual humans in gamified teaching methods can enhance nursing students' EI. Derakhshan [18] indicates that AI-assisted teaching can enhance students' emotional engagement and goal orientation. Deng and Chen [19] also found that AI-driven environments, by providing personalized feedback and adaptive pathways, enhance their emotional resilience by reducing frustration and boosting students' confidence. These findings collectively reveal that EI not only provides the psychological foundation for students to engage in effective and healthy interactions with AI, but it may also profoundly influence the development and enhancement of their AS by affecting their confidence and initiative when confronting new technologies.

EI provides the intrinsic emotional foundation for nursing students to effectively use AI, while confidence in their mastery of AI technology relies on AI self-efficacy (AILS). AILS is defined as an individual's belief in their ability to perform specific tasks, which directly influences nurses' willingness to adopt AI and their actual use of it [20]. Unlike general self-efficacy, AILS in nursing AI applications manifests as nursing students' confidence in mastering AI tools, overcoming technical challenges, and using them to solve clinical or learning problems [21]. This confidence in specific technical domains serves as the intrinsic motivation driving health care professionals to actively engage with, deeply explore, and persistently use AI tools [22]. Research indicates that enhancing nursing students' self-efficacy is crucial for alleviating psychological distress, ultimately improving their professional well-being and the quality of their future care [23]. In AI-enabled learning environments, Wang et al [24] indicate that self-efficacy and university support significantly enhance students' acceptance of AI-driven blended learning. Gao et al [25] further confirm that integrating AI chatbots into writing instruction can enhance students' AI self-efficacy. Lyu and Salam [26] also indicate that AI-driven personalized learning can enhance students' self-efficacy, motivation, and digital literacy. Additionally, high levels of AILS significantly predict nursing students' willingness to adopt AI technologies and the depth of their usage, thereby enhancing professional growth and adaptability in the rapidly evolving health care field [8].

Thus, EI and AILS jointly constitute the 2 core psychological factors influencing the development of AS among nursing students. EI ensures nursing students maintain essential emotional insight and empathy when interacting with AI and applying it in patient care, thereby providing the necessary human touch to technological implementation. Meanwhile, AILS provides the psychological drive to explore and use AI technologies, motivating students to transform potential technological advantages into realistic nursing capabilities [17]. To systematically guide and cultivate this complex psychological capability system, this study introduces an emerging theoretical framework—the NUR.S.E.S. framework [17]. This framework, recently proposed by Hoelscher and Pugh [27], aims to establish a structured pathway for developing AS within the nursing profession. Compared to generic technology adoption models or general educational technology frameworks, its novelty lies in deeply integrating the development of AS with the humanistic care, ethical responsibility, and clinical leadership inherent to the nursing profession, thereby better aligning with the contextual needs of nursing education. It is an acronym representing 6 core components:

- Navigate AI basics: promote understanding of AI fundamentals as a leadership responsibility critical to patient safety.
- Use AI strategically: purposefully apply AI tools to enhance care quality, safety, and outcomes.
- Recognize AI pitfalls and guide balanced approaches to innovation and risks such as bias, overreliance, and inaccuracy.
- Skills support: advocating for skill enhancement and professional development to prepare for AI integration in nursing.
- Ethics in action: guiding ethical AI use in nursing by promoting transparency, fairness, and accountability.

- Shape the future: directing AI implementation toward outcomes that align with nursing values and advance care equity.

This framework provides nursing educators with a forward-looking theoretical foundation rooted in nursing values, guiding students to develop their humanistic care, critical thinking, and ethical judgment capabilities simultaneously while mastering technical skills. This study used the NUR.S.E.S. framework, marking its first application in nursing education both domestically and internationally. Its internal structure clearly corresponds to core constructs such as EI (corresponding to the E and S dimensions), AILS (corresponding to the S dimension), and AS (corresponding to the N, U, R, and E dimensions), providing a structurally coherent and contextually relevant theoretical foundation for systematically analyzing the complex system formed by these variables.

As a cutting-edge, data-driven approach, network analysis transcends traditional linear assumptions to reveal intricate interactions among variables and precisely pinpoint their relative importance within a system [21]. This method provides a unique, systematic perspective for visualizing and quantifying the dynamic relational structure among EI, AILS, and AS [28]. By analyzing the interrelationships among variables, network analysis not only maps each measurement indicator to the theoretical dimensions of the NUR.S.E.S. framework but also tests whether the framework's predefined dimensional divisions align with the actual patterns of variable associations observed in the data. Specifically, it examines whether variables within the same framework dimension are closely interconnected in the relational network and whether there are significant, unexpected associations between different dimensions, thereby providing empirical support for the framework's validity [29].

Therefore, the objective of this study is to systematically analyze the complex network relationships and underlying mechanisms among EI, AILS, and AS based on the NUR.S.E.S. framework. By constructing a psychological network model, this study aims to identify factors that are associated with nursing students' AS, thereby providing precise targets for educational interventions. We plan to conduct a survey of nursing students at a Chinese university to gain an in-depth understanding of their practical application of AI, including EI, AILS, and AS. By analyzing these findings, we aim to identify existing challenges and provide crucial theoretical foundations and practical guidance for cultivating future nursing professionals who can master intelligent technologies while upholding humanistic care.

Methods

Objects and Methods

A total of 982 full-time undergraduate nursing students from a particular university were selected as research participants. Among them, 117 were male, and 865 were female, with ages ranging from 18 to 24 years (mean age 21.18, SD 0.51 years). The inclusion criteria were (1) full-time undergraduate nursing students enrolled at the university; (2) students who had encountered or used AI-related technologies or tools in their daily studies or lives; and (3) voluntary participation in the experiment with signed informed consent and confidentiality agreements. Exclusion criteria applied to students on formal leave or extended sick leave during data collection. Participants could withdraw freely without affecting their studies or academic performance.

Ethical Considerations

The research procedures have been approved by the Ethics Review Committee of Xijing University (Approval number: XJU-202502). Participants' privacy has been protected. All participants provided written informed consent. No harm was inflicted upon participants. All nursing students had the right to choose whether to participate in this study. Data were securely stored and encrypted.

Instruments

General Demographic Questionnaire

The research team independently developed a questionnaire to collect basic information. This survey aims to systematically examine key social-demographic factors that may influence research outcomes, primarily covering age, gender, home address, prior experience as a student leader, academic year, and average frequency of use of electronic devices and AI tools.

EI Scale

The EI Scale developed by Schutte et al [30] was used to assess students' EI levels. The Chinese version was revised by the Chinese psychologist Caikang [31]. This version has demonstrated good reliability and validity among Chinese students. This scale comprises 4 dimensions, including emotional perception (12 items), self-emotional management (8 items), managing others' emotions (6 items), and emotional application (7 items), totaling 33 items. A 5-point Likert scale was used to score, ranging from "Strongly Disagree" to "Strongly Agree," with values from 1 to 5. Higher scores indicate a higher level of EI among students. The Cronbach α coefficient for the full scale was 0.90, and the test-retest reliability Cronbach α coefficient was 0.78. In this study, the Cronbach α coefficient for the scale was 0.959.

AILS Scale

The AILS scale, developed by Wang et al [32], is used to assess users' self-efficacy when using AI technologies and products. The scale comprises 4 dimensions, including assistance (7 items), anthropomorphic interaction (5 items), comfort with AI (6 items), and technical skills (4 items), totaling 22 items. Scoring uses a 7-point Likert scale from "Strongly Disagree" to "Strongly Agree," with values ranging from 1 to 7. Higher scores indicate greater levels of AILS among users. Confirmatory factor analysis resulted in χ^2_{196}=1.984; comparative fit index (CFI)=0.941; Tucker-Lewis index (TLI)=0.930; root-mean-square error of approximation (RMSEA)=0.079; and standardized root-mean-square residual (SRMR)=0.071. Cronbach α coefficient in this study was 0.953.

AS Scale

The AS Scale was developed by Wang and Chuang [33]. The scale comprises 4 dimensions, including awareness (3 items), usage (3 items), evaluation (3 items), and ethics (3 items). It is based on a 7-point Likert scale ranging from “Strongly Disagree” to “Strongly Agree,” with values ranging from 1 to 7, respectively. Higher scores indicate greater AS among individuals. Confirmatory factor analysis yielded the following indices: CFI=0.99, TLI=0.99, GFI=0.98, RMSEA=0.01, SRMR=0.03. The Cronbach α coefficient for the full scale was 0.830, while the Cronbach α coefficient in this study was 0.864.

Correspondence Table Between the NUR.S.E.S. Framework and Questionnaire Measurement Dimensions

Guided by the theoretical framework of NUR.S.E.S., this study establishes conceptual mappings between the 6 core competency dimensions of the framework (navigate, use, recognize, skills support, ethics in action, and shape the future) and their corresponding measurement variables. This mapping aims to structure the AS of nursing students as defined by the framework into measurable psychological and competency indicators, thereby providing a theoretical basis for subsequent network analysis and testing the intrinsic interrelationships among the framework’s components.

Theoretical Rationale for the Mapping Between NUR.S.E.S. Components and Measured Variables

Overview

The mapping shown in Table 1 follows from the conceptual definitions of each NUR.S.E.S. component as originally articulated by Hoelscher and Pugh [27], combined with established theoretical and empirical literature in nursing education, EI, and self-efficacy research.

Table . Correspondence table between the NUR.S.E.S. framework and questionnaire measurement dimensions.

Framework letters	Representative of core variables	Dimensions corresponding to the questionnaire	Dimensional implications	Mapping dimensions
N	Navigate AI[a] basics	Awareness	• Basic understanding of fundamental AI concepts, application scenarios, and its impact on the nursing field.	"Navigate AI basics" emphasizes initial exploration and foundational understanding of the field of AI. Only by acquiring this foundational understanding can students freely explore the AI knowledge system; therefore, the "awareness" dimension has been selected to measure this ability.
U	Use AI strategically	Use	• The ability to operate and apply specific AI tools in practical nursing education, research, or simulated scenarios.	"Use AI strategically" focuses on practical application. This dimension directly assesses students' ability to apply AI as a tool in specific scenarios, reflecting the practical aspect of "use."
R	Recognize AI pitfalls	Evaluation	• Critically examine and evaluate the accuracy and reliability of AI-generated information.	"Recognizing AI pitfalls" requires critical thinking to identify the limitations and risks of AI. The "evaluation" dimension is precisely the core competency involved in assessing and discerning information, and it aligns closely with the requirement to identify flaws.
S	Skills support	Technical Skills Assistance	• Technical skills: confidence in one's ability to learn and master AI technology itself. • Assistance: believe that AI can serve as an effective tool to assist in completing learning or work tasks.	• "Skills support" comprises 2 aspects: first, confidence in mastering AI skills themselves (technical skills); and second, trust in AI as a supportive tool (assistance). These 2 dimensions together underpin students' self-efficacy at the skills level.

Framework letters	Representative of core variables	Dimensions corresponding to the questionnaire	Dimensional implications	Mapping dimensions
E	Ethics in action Emotional Intelligence (EI)	Ethics, Emotional Perception, Self-emotion Management, Managing Others' Emotions, Emotional Application	• Ethics: understand and adhere to ethical standards such as privacy and fairness involved in the use of AI in nursing practice. • Emotional perception: accurately recognize your own and others' emotional states. • Self-emotion management: the ability to regulate and control one's own emotions. • Managing others' emotions: the ability to influence and regulate others' emotions. • Emotional application: use emotional information to aid in thinking and problem-solving.	"Ethics in action" emphasizes the application of ethics in real-world nursing settings. EI as a whole construct is a foundational capacity for ethical practice, including perceiving, managing, and utilizing emotions. The 4 subdimensions of EI (EI1-EI4) are collectively used to measure EI, not to be split into other letters of the NURSES framework. The network analysis treats these 4 subdimensions as nodes belonging to the same EI community, which supports their theoretical coherence. Therefore, mapping all 4 EI subdimensions to the E dimension reflects the role of EI as a holistic supporter of ethics in action, not a forced segmentation.
S	Shape the future	Comfort with AI, Anthropomorphic Interaction	• Comfort with AI: feeling relaxed and at ease when interacting with AI, without anxiety or a sense of threat. • Anthropomorphic interaction: tends to engage in natural communication with AI in a manner similar to human interaction.	"Shape the future" embodies students' open and proactive approach to leading the development of AI in the field of nursing. Comfort with AI reflects their level of acceptance, while anthropomorphic interactions demonstrate their willingness to collaborate with machines; together, these 2 factors form the psychological foundation for actively shaping the future of nursing.

[a]AI: artificial intelligence.

Navigate AI Basics (N)

Hoelscher and Pugh [27] define this component as promoting understanding of AI fundamentals as a leadership responsibility critical to patient safety. In operational terms, foundational knowledge of AI concepts and applications constitutes the prerequisite for any further engagement with AI technologies [34]. Accordingly, the awareness dimension of the AS Scale [33], which assesses students‘ understanding of basic AI concepts, application scenarios, and potential impacts, serves as a direct measure of this component.

Use AI Strategically (U)

This component concerns the purposeful application of AI tools to enhance care quality, safety, and outcomes [27]. Strategic use implies not only familiarity with AI but the ability to operate and apply specific AI tools in practical nursing education, research, or clinical scenarios. The Use dimension of the AS Scale [33], which captures students' self-reported ability to work with AI tools in task-specific contexts, directly corresponds to this component.

Recognize AI Pitfalls (R)

Hoelscher and Pugh [27] emphasize that balanced approaches to innovation must include recognition of risks such as bias, overreliance, and inaccuracy. This critical evaluative competency is captured by the evaluation dimension of the AS Scale [33], which assesses students' ability to critically examine and judge the accuracy and reliability of AI-generated information.

Skills Support (First S)

The skills support component advocates for skill enhancement and professional development to prepare for AI integration in nursing [27]. This component encompasses both the confidence in one's ability to learn and master AI technology itself and the belief that AI can serve as an effective tool to assist in completing learning or work tasks. The AILS Scale [32] operationalizes these 2 facets through its technical skills and assistance dimensions, respectively, drawing on Bandura's broader theory of self-efficacy as domain-specific confidence in one's ability to execute courses of action required to achieve desired outcomes [20].

Ethics in Action (E)

This component guides ethical AI use in nursing by promoting transparency, fairness, and accountability [27]. Importantly, ethical action in nursing requires not only knowledge of ethical principles but also the emotional capacities that underpin moral sensitivity and compassionate care. A substantial body of nursing literature demonstrates that EI—the ability to perceive, understand, manage, and use emotions—is positively associated with ethical sensitivity and moral reasoning in both nursing students and practicing nurses [8,15,31,35]. For example, Liu et al [36] found that EI mediates the relationship between empathy and moral sensitivity in Chinese student nurses, suggesting that emotional competence is not separate from but foundational to ethical practice [1]. The Schutte EI Scale [30], which measures 4 dimensions of EI (perception of emotion, self-emotion management, managing others' emotions, and emotional application), was therefore selected to capture the emotional competence component of ethical action. These 4 subdimensions are treated as a single conceptual community in the network analysis, consistent with the holistic contribution of emotional competence to ethical practice.

Shape the Future (Second S)

The final component directs AI implementation toward outcomes that align with nursing values and advance care equity [27]. Proactive, leadership-oriented engagement with AI presupposes that nurses feel psychologically comfortable with AI technologies and are willing to engage with them in a natural, quasisocial manner. Positive affective attitudes toward AI, including low anxiety and high comfort, have been identified as psychological prerequisites for adoption and sustained use in health care and educational contexts [21,37,38]. The AILS Scale captures these prerequisites through its comfort with AI and anthropomorphic interaction dimensions [32], which assess relaxed, nonanxious engagement with AI and the tendency to interact with AI in a human-like, conversational manner. These dimensions do not directly measure leadership behaviors but rather the psychological foundation without which proactive shaping of AI's future in nursing is unlikely to occur.

This mapping provides a theoretically grounded operationalization of the NURSES framework into measurable psychological and competency variables, enabling empirical examination of the interrelationships among its 6 components through network analysis. The mapping is not intended as an exhaustive or exclusive operationalization but as a starting point grounded in existing validated instruments and established theoretical links.

Data Collection

Researchers (XF and JW) contacted class administrators at target institutions via social media (WeChat; Tencent Holdings Limited). After explaining the study objectives and procedures and obtaining permission, they joined the corresponding class groups. Study information was disseminated through these class groups. Potential participants voluntarily confirmed their participation online after reading the informed consent form. The research team screened applicants based on predetermined inclusion and exclusion criteria. Students meeting the criteria were invited to participate in the survey. To facilitate organization and enhance response efficiency, researchers distributed electronic questionnaire links uniformly in classrooms during after-school hours. Data collection occurred from September 25 to September 28, 2025, using the online survey platform "WJX" for questionnaire distribution and retrieval. Participants independently completed the questionnaire after clicking the link and could exit at any time during the process. Completing the full questionnaire took an average of 10 - 15 minutes. A total of 986 questionnaires were distributed, with 982 returned. Platform settings ensured only fully completed questionnaires were recorded as valid submissions, eliminating incomplete submissions from being counted. Verification confirmed that returned questionnaires were valid. Data from 982 participants were ultimately analyzed, yielding a valid response rate of 99.59%.

Data Analysis

Descriptive statistics were calculated using SPSS (version 25.0; IBM Corp), with means and SDs for continuous variables and frequencies (percentages) for categorical variables. All continuous variables underwent normality testing in this study, and the results indicated that their distributions were generally normal [39].

Network analysis was performed using R (version 4.3.0; R Core Team). In 2-tailed tests, $P<.05$ was considered statistically significant. A Gaussian graph model was selected to construct the network structure using the R package "*qgraph*" [37]. To reduce spurious correlations and obtain a simplified network, the graph minimum absolute contraction and selection operator was used. The graph minimum absolute contraction and selection operator implements regularization techniques to constrain small partial correlations to zero, effectively eliminating potential false positive edges and yielding sparse, interpretable network structures [40]. To avoid overfitting and determine optimal tuning parameters, an extended Bayesian information criterion model is used to select the best-fitting model. This approach ensures that only the most robust and meaningful connections are retained in the final network.

In a network, nodes represent variables, and edges between 2 nodes represent the unique relationship between them, controlling for the influence of other nodes. Red and blue edges denote negative and positive correlations, respectively. The thickness of the edges corresponds to the strength of the association; thicker edges indicate stronger correlations [41]. The R package "*qgraph*" is used to calculate the strength, proximity, and betweenness centrality of nodes in a network [37]. Strength is defined as the sum of the absolute values of the edge weights connecting a node to all other nodes. Previous studies have shown that strength is the most stable and interpretable centrality measure in networks [42]. Compared to other centrality measures such as closeness and betweenness centrality, strength is more suitable for evaluating the importance of nodes [43]. Therefore, this study adopts strength as the centrality metric, with nodes exhibiting the highest strength values being regarded as the most influential nodes within the network.

Additionally, the R package "*networktools*" was used to calculate bridging strength and identify potential bridging nodes [44]. Bridging strength refers to the sum of the absolute values of the edge weights connecting a node to other community nodes, indicating the node's importance to other communities. Nodes with the highest bridging strength values are considered bridging nodes within the network. Bridging nodes connect multiple domains, meaning interventions targeting these nodes can simultaneously impact multiple domains, which maximizes the effectiveness of the intervention.

Use the R package "*mgm*" to calculate the predictability for each node [45]. Predictability is a metric that reflects the extent to which the variance of a specific node can be explained by all its neighbors in the network. Nodes with high predictability are susceptible to the influence of their neighboring nodes.

The R package "*bootnet*" assesses the accuracy and stability of networks [46]. First, the accuracy of edge weights (the number of bootstrap samples is 1000) was examined by calculating their 95% CIs using nonparametric bootstrapping. Second, the stability of the network model is assessed using the case deletion procedure and the correlation stability (CS) coefficient, which indicates the proportion of samples that can be excluded from the analysis while maintaining at least 0.7 correlation with the original sample. According to network analysis guidelines, the CS coefficient should not fall below 0.25, and a value above 0.50 indicates sufficient stability [47]. Finally, a self-assessment method was used to conduct a difference test, examining variations in edge weights, node strengths, and node bridge strengths.

Results

General Information for Undergraduate Nursing Students

A total of 982 graduate nursing students were included in the statistical analysis, with their characteristics listed in Table 2. The mean age of participants was 21.7 years, and the vast majority (865/982, 88.1%) of participants were female. Among participants, 511 out of 982 (52.0%) resided in rural areas. The number of students in the first, second, third, and fourth years was 246 out of 982 (25.1%) participants, 242 out of 982 (24.6%) participants, 251 out of 982 (25.6%) participants, and 243 out of 982 (24.7%) participants, respectively. Among the 982 undergraduate nursing students, daily active use of GenAI tools was reported as follows: 22 out of 982 (2.2%) participants rarely used them, 608 out of 982 (61.9%) participants used them several times weekly, 297 out of 982 (30.2%) participants used them 3 - 5 times daily, and 55 out of 982 (5.6%) participants used them more than 5 times daily.

Table . General information on nursing undergraduates.

Statistical variable	Frequency, n (%)
Sex	
Male	117 (11.9)
Female	865 (88.8)
Age (years)	
<18	42 (4.3)
18-20	733 (74.6)
20-22	204 (20.8)
≥22	3 (0.3%)
Family residence	
Townships	471 (48.0)
Rural	511 (52.0)
Have you ever served as a student leader?	
Yes	479 (48.8)
No	503 (51.2)
Grade level	
Freshman year	246 (25.1)
Sophomore year	242 (24.6)
Junior year	251 (25.6)
Senior year	243 (24.7)
The average daily time spent using electronic devices (such as smartphones, computers, tablets, etc) is approximately (hours)	
<2	42 (4.3)
2-4	291 (29.6)
4-6	439 (44.7)
6-8	161 (16.4)
>8	49 (5.0)
On average, how often do you actively use AI[a] tools (such as ChatGPT [OpenAI], Wenxin Yiyan [Baidu], Deepseek [DeepSeek Artificial Intelligence Co, Ltd], etc) each day?	
Hardly ever used	22 (2.2)
Several times a week	608 (61.9)
3-5 times daily	297 (30.2)
>5 times a day	55 (5.6)
What is your primary purpose for using AI tools?	
Learning (such as researching information, assisting with homework, etc)	929 (94.6)
Entertainment and Leisure (such as smart chatbots, image/music generation, and video/audio recommendations)	468 (47.7)
Daily life (such as planning itineraries and obtaining health advice)	615 (62.6)
Work efficiency (eg, report writing, PowerPoint [Microsoft Corp] creation, data analysis)	595 (60.6)
Social needs (such as helping edit Moments captions and recommending chat topics)	336 (34.2)
Others	12 (1.2)

Statistical variable	Frequency, n (%)
How familiar do you consider yourself to be with AI technology?	
I have absolutely no idea.	16 (1.6)
I've heard of it but don't know much about it.	117 (11.9)
General understanding	569 (57.9)
Fairly familiar	262 (26.7)
Very familiar	18 (1.8)

[a]AI: artificial intelligence.

Descriptive Statistics of Variables (List in Table 3)

Descriptive statistics for nursing undergraduates' EI, AILS, and AS are presented in Table 3. Normality tests confirmed that all variables were approximately normally distributed. Data were described using mean (SD). SDs fell within normal ranges, with no outliers. Notably, "Emotional Perception (EI1)" demonstrated the highest predictive power and served as the critical component of the entire network.

Table . Descriptive statistics of emotional intelligence, AI self-efficacy, and AI literacy variables among nursing undergraduates (n=982).

Variable	Name	Mean (SD)	Expected influence	Bridge expected influence	Predictability
Emotional intelligence	EI[a]	3.57 (0.55)			
Emotional perception	EI1	3.41 (0.54)	1.248	0.427	0.832
Self-emotion management	EI2	3.51 (0.56)	1.016	0.118	0.788
Managing others' emotions	EI3	3.67 (0.61)	1.099	−0.006	0.801
Emotional application	EI4	3.68 (0.62)	1.355	−0.024	0.840
AI[b] self-efficacy	AILS[c]	4.68 (0.78)			
Assistance	AILS1	4.55 (0.84)	1.075	0.129	0.627
Anthropomorphic interaction	AILS2	4.62 (0.83)	1.091	0.069	0.679
Comfort with AI	AILS3	4.96 (0.98)	0.991	0.242	0.686
Technical skills	AILS4	4.59 (0.92)	0.854	0.077	0.496
AI literacy	AS[d]	4.60 (0.59)			
Awareness	AS1	5.19 (0.95)	0.862	0.015	0.597
Usage	AS2	4.43 (1.12)	0.838	−0.030	0.545
Evaluation	AS3	4.83 (0.94)	1.323	−0.011	0.726
Ethics	AS4	3.94 (1.19)	0.837	−0.033	0.287

[a]EI: emotional intelligence.
[b]AI: artificial intelligence.
[c]AILS: AI self-efficacy.
[d]AS: AI literacy.

Network Analysis of EI, AILS, and AS Among Nursing Undergraduates

Figure 1 illustrates the network structure of EI, AILS, and AS among undergraduate nursing students. Node colors represent theoretical constructs: blue=AILS, green=EI, and red=AS. Letters on nodes denote dimension codes. Red indicates positive correlations; blue indicates negative correlations. Thicker lines denote stronger connections. Of the 66 possible connections, 54 (81.82%) were nonzero, and the network density was 0.82, indicating that the variables were generally closely interconnected within this sample. Among these, 41 were positive correlations and 13 were negative correlations. From the perspective of community structure, the nodes are primarily clustered into 3 distinct communities based on theoretical constructs, including emotional intelligence (EI1-EI4), AI self-efficacy (AILS1-AILS4), and AI competence (AS1-AS4). Connections within each community are relatively dense, while cross-community connections are relatively sparse, which is largely consistent with the dimensional divisions of the NURSES framework. Stronger connections primarily occurred within dimensions rather than between them. The 3 strongest intradimensional connections were EI4 (emotional use)-EI3 (managing others' emotions), AS3 (assessment)-AS1 (awareness), and AILS2 (anthropomorphic interaction)-AILS1 (assistance). The strongest interdimensional connection was between EI1 (emotional perception) and AILS1 (assistance). All edge weights (association strengths) are listed in Table 4.

Figure 1. Network analysis of emotional intelligence (EI), AI self-efficacy (AILS), and AI literacy (AS) among nursing undergraduates. Node colors represent theoretical constructs: blue=AILS, green=EI, and red=AS. Letters on nodes denote dimension codes. Red indicates positive correlations; blue indicates negative correlations. Thicker lines denote stronger connections. AILS: artificial intelligence self-efficacy; AS: AI literacy; EI: emotional intelligence.

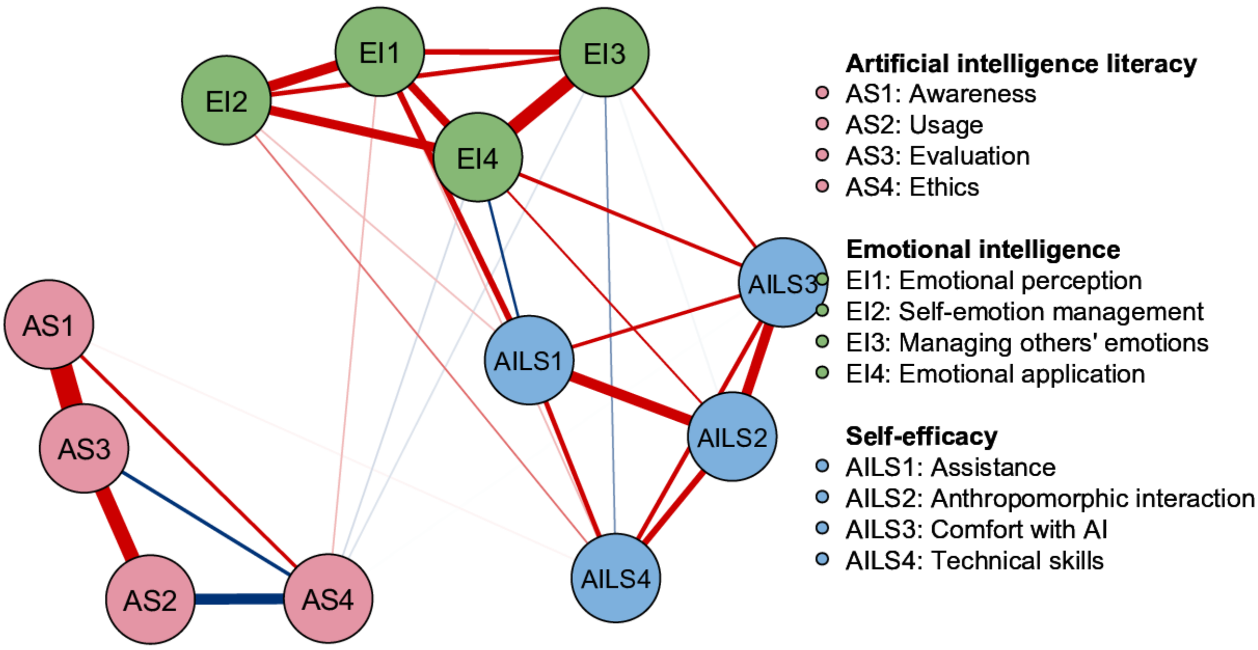


Table . Marginal weights of emotional intelligence (EI), artificial intelligence (AI) self-efficacy (AILS), and AI literacy (AS) among nursing undergraduates.

	EI1[a]	EI2[b]	EI3[c]	EI4[d]	AILS1[e]	AILS2[f]	AILS3[g]	AILS4[h]	AS1[i]	AS2[j]	AS3[k]	AS4[l]
EI1	0.00	0.34	0.20	0.28	0.22	0.11	0.00	0.05	0.00	–0.00	0.00	0.05
EI2	0.34	0.00	0.18	0.31	0.05	0.02	–0.02	0.07	–0.01	0.00	–0.01	0.02
EI3	0.20	0.18	0.00	0.44	0.00	–0.03	0.14	–0.07	0.00	0.00	0.00	–0.04
EI4	0.28	0.31	0.44	0.00	–0.12	–0.02	0.15	0.18	–0.01	0.00	0.00	–0.04
AILS1	0.22	0.05	0.00	–0.12	0.00	0.34	0.15	0.18	–0.01	0.00	–0.01	0.00
AILS2	0.11	0.02	–0.03	–0.02	0.34	0.00	0.33	0.22	0.00	0.00	–0.01	0.01
AILS3	0.00	–0.02	0.14	0.15	0.15	0.33	0.00	0.17	0.00	0.00	0.00	–0.03
AILS4	0.05	0.07	–0.07	0.18	0.18	0.22	0.17	0.00	0.03	–0.03	0.02	0.00
AS1	0.00	–0.01	0.00	–0.01	–0.01	0.00	0.00	0.03	0.00	0.00	0.66	0.15
AS2	–0.00	0.00	0.00	0.00	0.00	0.00	0.00	–0.03	0.00	0.00	0.46	–0.35
AS3	0.00	–0.01	0.00	0.00	–0.01	–0.01	0.00	0.02	0.66	0.46	0.00	–0.15
AS4	0.05	0.02	–0.04	–0.04	0.00	0.01	–0.03	0.00	0.15	–0.35	–0.15	0.00

[a]EI1: emotional perception.
[b]EI2: self-emotion management.
[c]EI3: managing others' emotions.
[d]EI4: emotional application.
[e]AISL1: assistance.
[f]AISL2: anthropomorphic interaction.
[g]AISL3: comfort with artificial intelligence.
[h]AISL4: technical skills.
[i]AS1: awareness.
[j]AS2: usage.
[k]AS3: evaluation.
[l]AS4: ethics.

Node Centrality Measures

The standardized estimates of centrality indicators for factors influencing EI, AILS, and AS among nursing undergraduates are shown in Figure 2. Emotional use (EI4) and assessment (AS3) exhibit the highest strength centrality, indicating that these 2 variables showed the highest strength centrality, indicating they are highly connected within the network. Emotional perception (EI1) and ethics (AS4) exhibited the strongest mediating centrality, signifying their pivotal bridging role in network information transmission with potent moderating capacity; emotional perception (EI1) and awareness (AS1) also demonstrated the most prominent proximity centrality, reflecting their highest information transmission efficiency and accessibility within the network. Stability tests for network centrality metrics revealed correlation stability coefficients of 0.749, 0.749, and 0.361 for node strength, intermediary centrality, and closeness centrality, respectively (see Figure 3). This indicates robust stability for these centrality measures, with node strength demonstrating the highest stability.

Figure 2. Standardized estimates of centrality measures for emotional intelligence, artificial intelligence (AI) self-efficacy, and AI literacy among nursing undergraduates. AILS1: assistance; AILS2: anthropomorphic interaction; AILS3: comfort with AI; AILS4: technical skills; AS1: awareness; AS2: usage; AS3: evaluation; AS4: ethics; EI1: emotional perception; EI2: self-emotion management; EI3: managing others' emotions; EI4: emotional application.

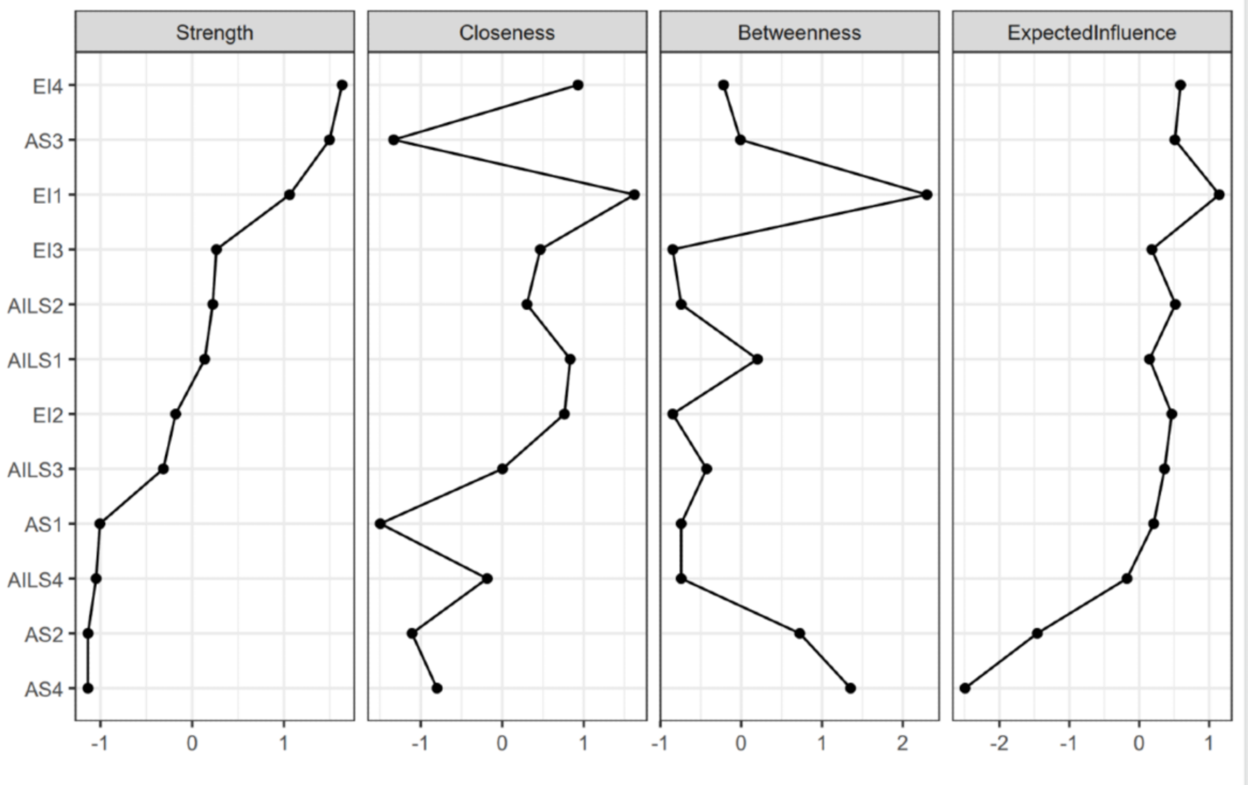
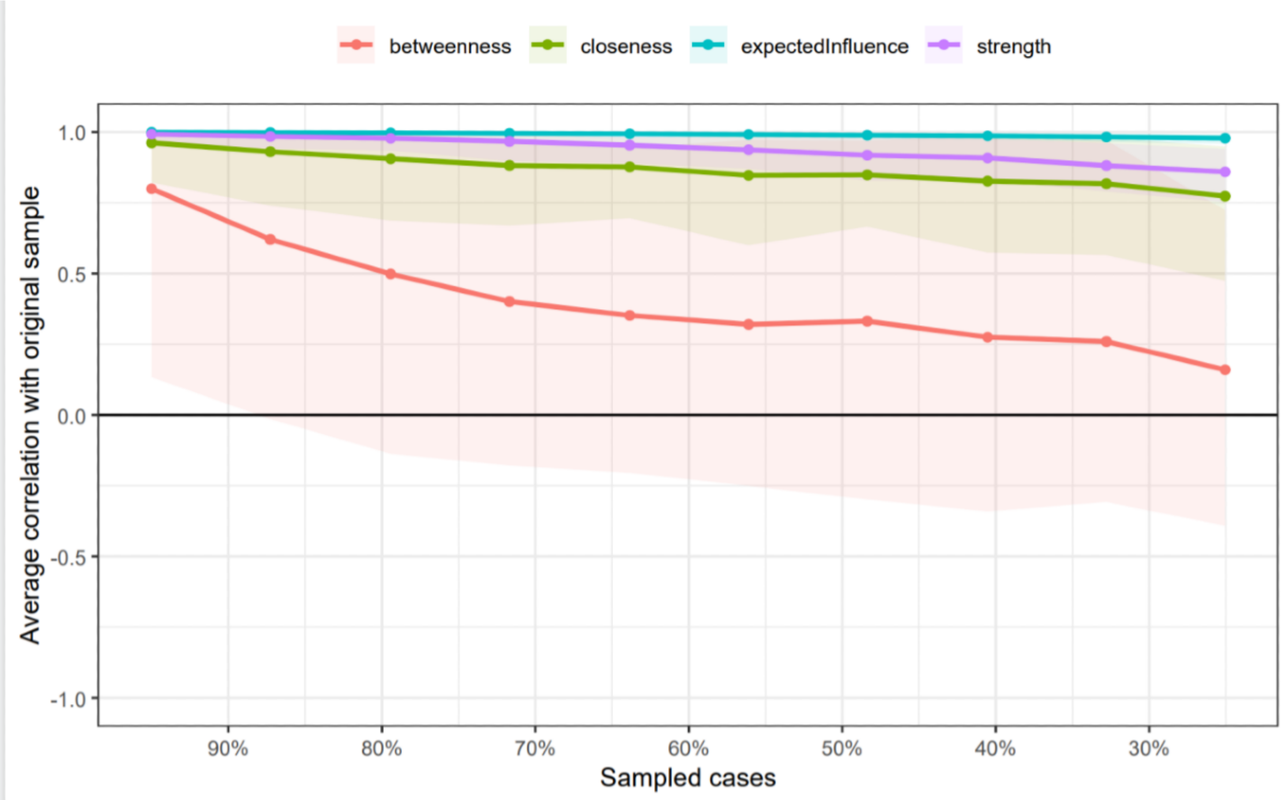


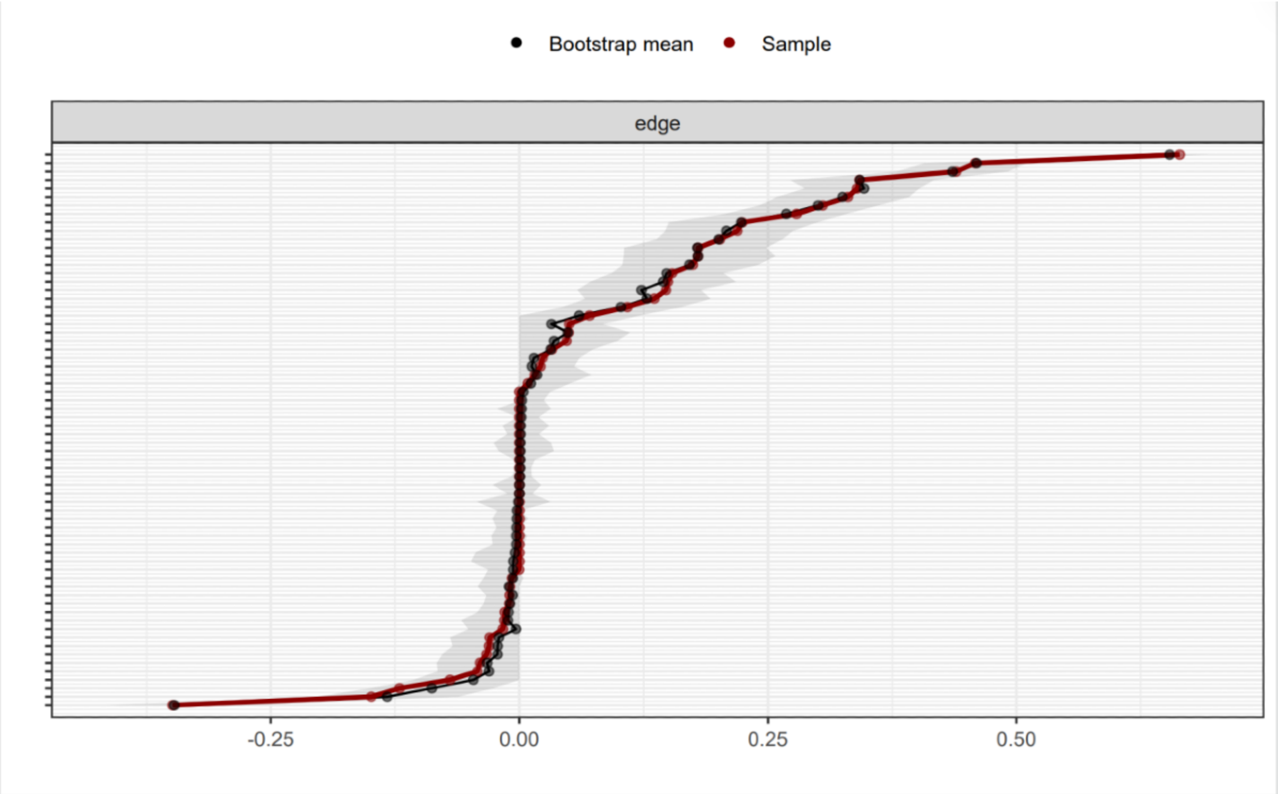
Figure 3. Correlation stability coefficients for node strength, betweenness, and closeness.



Edge Accuracy

The accuracy of edge weights was estimated using nonparametric bootstrapping. Results indicate that the 95% CIs for edge weights in the network are narrow, suggesting that the estimated edge weights in this study are highly precise (Figure 4).

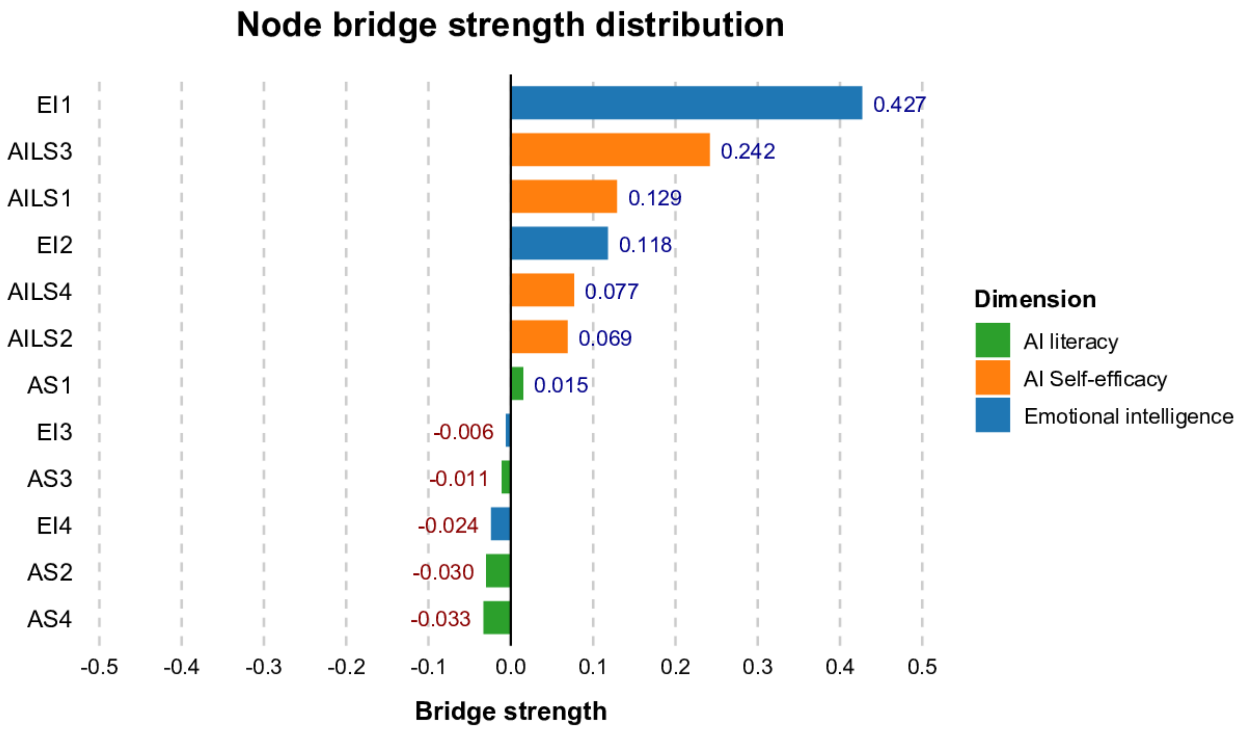
Figure 4. Guiding edge weights for emotional intelligence, artificial intelligence (AI) self-efficacy, and AI literacy among nursing undergraduates with 95% CIs.



Node Bridge Strength

Figure 5 displays the bridge strength for each node. EI1 "Emotion Awareness" (bridge strength=0.427) exhibits the highest bridge strength, followed by ALS3 "Comfort with AI" (bridge strength=0.242), ALS1 "Assistance" (bridge strength=0.129), and EI2 "Self-Emotion Management" (bridge strength=0.118), suggesting they may serve as bridging nodes in this network.

Figure 5. Depicts the bridge strength (z-score) of each node in the network. AILS1: assistance; AILS2: anthropomorphic interaction; AILS3: comfort with AI; AILS4: technical skills; AS1: awareness; AS2: usage; AS3: evaluation; AS4: ethics; EI1: emotional perception; EI2: self-emotion management; EI3: managing others' emotions; EI4: emotional application.



Discussion

Principal Findings

This study is the first to use network analysis methods within the NUR.S.E.S. framework to examine the associations among EI, AILS, and AS among undergraduate nursing students. The network analysis identified that emotion use (EI4) and assessment ability (AS3) showed the highest strength centrality, indicating their prominent positions within the network. Emotion perception (EI1) had the highest bridge strength, suggesting it may serve as a connecting node between the EI domain and the AILS and AS domains. These findings provide insights into the psychological mechanisms underlying the development of AS among nursing students, offer a concrete explanation of how the 6 dimensions of the NURSES framework interact at the psychological level, and provide a critical foundation for the future development of targeted, comprehensive interventions that address the full spectrum from emotional foundations to technical confidence.

Overall Characteristics of EI, AILS, and AS

This study conducted a descriptive analysis of nursing students' EI, AILS, and AS. Results indicate that undergraduate nursing students' AILS (mean 4.68, SD 0.78) and AS (mean 4.60, SD 0.59) were generally at a moderately high level, while EI (mean 3.57, SD 0.55) scored relatively low. This situation highlights a key phenomenon: nursing students possess strong confidence in their ability to learn and master AI technologies and have established a foundational level of AS. However, the development of their EI has not kept pace, consistent with the findings of Bewersdorff et al [38]. From a specific-dimension perspective, within AILS, the "Comfort Level with Artificial Intelligence (AILS3)" dimension scored the highest (mean 4.96, SD 0.98), indicating that nursing students experience relatively positive feelings when interacting with AI. This finding aligns with the research results of Volpato et al [48]. In terms of EI, the "Emotional perception (EI1)" dimension had the lowest mean score 3.41 (SD 0.54), suggesting that nursing students have significant room for improvement in their ability to accurately identify and understand their own and others' emotions. This weakness may directly impact nursing students' empathetic communication and emotional regulation in high-pressure clinical settings, posing a potential risk to patient safety; failure to promptly identify patients' anxiety or distress may delay nursing decisions.

Emotion Perception: the Psychological Bridge Connecting the Emotional World and the AI World

The network structure constructed in this study showed that emotional perception (EI1), defined as the ability to recognize one's own and others' emotional states, was strongly connected to AILS and AS nodes. In this sample, emotional perception had the highest bridge strength, indicating that it was relatively well-connected to nodes in other communities. This pattern is consistent with Fu's [49] finding that emotional competence is associated with mental health and with deeper engagement with AI in educational contexts. The high bridge strength suggests that the ability to recognize emotions may be associated with trust in AI technology, which aligns with previous research showing that individuals with higher EI tend to monitor emotional cues and manage stress effectively [50]. Specifically, the positive connection between emotional perception and the assistance dimension (AILS1) indicated that students who reported greater awareness of their own confusion, anxiety, or sense of accomplishment during technology learning were also more likely to view AI as a helpful tool [51]. This pattern is consistent with the observation by Mosleh et al [35]. that AI integration in teaching creates opportunities for emotional recognition and regulation, which may be easier for students with stronger emotional perception.

Emotional Application and Evaluation: the Engine Driving the Development of AS

The centrality measures showed that emotional use (EI4) and assessment (AS3) had the highest strength centrality, indicating that they were highly connected nodes within the network [52]. This pattern suggests that AS is associated not only with cognitive factors but also with emotional factors. Emotional use, defined as the ability to use emotional information for planning, creativity, and problem-solving, was positively connected with critical evaluation of AI outputs [13]. This finding is consistent with the observation that some individuals turn to GenAI for emotional guidance [50] and that emotional use may help nursing students engage in critical thinking when faced with complex AI outputs [53]. Evaluation ability, which concerns the judgment of AI-generated content [33], was closely connected with emotional use in the network. This pattern aligns with the finding by Deng and Chen [19] that AI-driven environments can support cognitive flexibility and independent judgment, possibly through emotional resilience. These exploratory observations invite further investigation using longitudinal or experimental designs to examine whether and how emotional use and evaluation skills might be related to AS [54].

AILS: a Potentially Important Bridging Node Between Emotion and AS

Network analysis results showed that EI, represented by emotional perception (EI1), had a positive connection with AILS, represented by assistance (AILS1) and comfort with AI (AILS3). For example, the edge weight between EI1 and AILS1 was 0.22. AILS also showed positive connections with AS, represented by usage (AS2) and evaluation (AS3). This pathway pattern, in which EI connected to AILS and AILS in turn connected to AS, is consistent with a mediating structure [55]. However, due to the cross-sectional design, this pattern should be interpreted as exploratory. It suggests that AILS may occupy a bridging position, but formal mediation analysis using longitudinal data would be required to test this hypothesis [49]. Prior research has shown that EI is associated with self-efficacy and with cognitive engagement with AI [49]. The connection pattern observed here is compatible with the idea that confidence in technical skills (AILS4) is associated with more frequent use of AI tools (AS2) [56]; that comfort with AI (AILS3) and anthropomorphic interaction (AILS2) are associated with lower anxiety and more exploration [25]; and that the belief that AI serves as an effective assistant (AILS1) is associated with reduced operational anxiety [53]. These observations are hypothesis-generating and require replication in independent samples with stronger designs. The significance of this approach for clinical practice lies in the fact that only by simultaneously strengthening both the emotional foundation and technical confidence can knowledge be translated into safe and effective clinical practice.

The Deep Mechanisms of AS Revealed by Negative Correlations

The most significant negative correlation was found between “Ethics (AS4)” and “Usage (AS2)” in the network. This indicates that at the current stage, nursing students who are more concerned about AI ethical issues (such as data privacy) may be more cautious in their use of AI tools, even exhibiting lower usage frequency [57]. Although this contradicts findings showing positive correlations between EI and reasons for adopting AI services or adoption/usage intentions [58], it reflects the development of critical thinking. When nursing students recognize the potential risks of technology, they may transition from blind tool users to critical thinkers, adopting more rational, selective use behaviors [59]. This finding resonates with the perspective of Ricon [60] that premature or excessive enthusiasm in medical AI may obscure ethical concerns, while measured caution is a prerequisite for responsible innovation. Participants in one study expressed concerns about potential privacy breaches and the risk of personal data theft [61]. Therefore, educators should not pursue unrestricted usage frequency but instead focus on cultivating students’ high-level application skills grounded in strong ethical vigilance.

Second is the negative correlation between “Emotional Intelligence in Others (EI3)” and “Anthropomorphic Interaction (AILS2).” This negative correlation may reflect multiple mechanisms. First, individuals with high EI are able to clearly distinguish the fundamental differences between human emotional connections and AI-simulated interactions. The ability to manage others’ emotions manifests as the capacity to perceive, influence, and regulate others’ emotions in interpersonal interactions, whereas the tendency toward anthropomorphic interaction is a psychological inclination to ascribe human characteristics to AI and interact with it in a social manner. Nursing students with high EI have a deeper understanding that, although AI can simulate empathetic responses, it lacks genuine emotional intent and reciprocity. Consequently, they consciously avoid viewing AI as an emotional substitute to prevent the development of inappropriate emotional dependence, which is consistent with Dakakni and Safa [62]. Second, cultural factors may play a role. In the context of Eastern culture, which emphasizes interpersonal harmony and emotional connection, nursing education places a high value on “authentic interpersonal interaction.” Nursing students with high EI may have internalized these professional values, leading them to adopt a more cautious or even resistant attitude toward anthropomorphizing AI. Third, from the perspective of clinical practice, this negative correlation carries positive ethical implications. The core of nursing practice lies in establishing trust within therapeutic interpersonal relationships. If nursing students are overly inclined to anthropomorphize AI and blur the boundaries between humans and machines, it may diminish their sensitivity to the emotional needs of real patients. Therefore, the lower tendency toward anthropomorphic interaction exhibited by nursing students with high EI can be viewed as an adaptive strategy for upholding the core values of the nursing profession [63].

System Integration Under the NUR.S.E.S. Framework: Synergistic Development of EI, AILS, and AS

The findings of this study provide empirical support for the NUR.S.E.S. framework, revealing the underlying psychological mechanisms behind its 6 dimensions. Specifically, emotional perception (EI1), as the strongest bridge node, empirically demonstrates the central role of E (EI) and S (social-emotional comfort) as the emotional cornerstones within the framework [64]; emotional application (EI4) and assessment (AS3), as core driving nodes, correspond to E and R (defect identification), respectively, indicating that emotional competence and technical critical thinking share an intrinsic synergistic mechanism; the various dimensions of AILS occupy key positions in the network that connect emotion and cognition, validating the theoretical premise within the framework that S (AILS) serves as the core driving force [65]. Ultimately, the synergy of all these elements achieves the framework's ultimate goal—S (shape the future)—that is, shaping the future [27].

In addition, this study provides an initial exploratory mapping of the interrelated factors associated with AS among nursing undergraduates, and these findings may offer insights for future research. From a practical perspective, nodes with high centrality, such as emotional use and evaluation, could exert influence on the overall network configuration through their connections with other nodes. Bridge nodes, such as emotional perception and comfort with AI, may transmit influences across different domains, making them potential targets for hypothesis-driven interventions. Accordingly, nursing educators might consider several tentative strategies, fostering students' emotional perception skills, which appear to link EI with AILS; creating low-anxiety AI learning environments to enhance comfort with AI; helping students set personalized learning goals and reflect on their emotional responses to strengthen emotional use and critical evaluation; and introducing case-based learning that combines clinical scenarios with AI outputs to ground technical critique and ethical decision-making in empathy for patients' emotional needs. Such a multidimensional approach, addressing emotional, cognitive, and skill components simultaneously, may support the development of nursing students as future professionals who can shape AI integration in nursing practice. However, all suggestions require empirical validation through longitudinal or experimental designs.

Research Significance, Limitations, and Future Directions

This study is the first to visualize, through network analysis, the patterns of association among EI, AILS, and AS in nursing students. It identified nodes that showed high centrality and bridging strength (emotional perception, emotional application, evaluation, comfort with AI). The observed association pattern suggests that emotional competence may be closely linked with technological confidence, which in turn may be linked with AS. These exploratory findings offer preliminary clues for future hypothesis-driven research. However, they do not establish causality, nor do they directly identify effective intervention targets. Any educational implications drawn from these results are speculative and require empirical validation [56].

This study has several limitations. First, the cross-sectional design cannot establish causal relationships between variables. Although the network pattern is consistent with some causal pathways, a reverse pathway (eg, higher AS leading to greater AILS) is equally plausible. Future research should use longitudinal or intervention designs to test dynamic relationships. Second, the sample originated from a single university, limiting generalizability. Cross-regional and cross-cultural comparisons are needed. Third, self-report scales may introduce bias; future studies could incorporate behavioral data and qualitative interviews.

Despite these limitations, this study offers profound theoretical insights and precise practical guidance for cultivating a new generation of nursing professionals who are "technically proficient, confident, and emotionally intelligent" in the era of AI. Future education and research should focus on developing integrated intervention programs that combine emotional education with technical training, empowering nursing students to embrace the challenges of the intelligent health care era fully.

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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Authors' Contributions

Xiaohui Fan: Conceptualization, Methodology, Writing review & editing, Visualization. Jingjing Sun: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing original draft, Writing review & editing, Visualization. Linghui Zhang & Jinrong Wang : Conceptualization, Methodology, Software, Formal analysis, Data curation. BinHao Dong & Xiaohong

Gao: Investigation. Ruihua Jin: Conceptualization, Formal analysis, Resources, Supervision. Panpan Huai: Conceptualization, Formal analysis, Resources, Supervision.
All authors have reviewed and approved the final manuscript and consent to its publication.

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence
AILS: artificial intelligence self-efficacy

ANA: American Nurses Association
AS: AI literacy
CFI: comparative fit index
CS: correlation stability
EI: emotional perception
GenAI: generative artificial intelligence
RMSEA: root-mean-square error of approximation
SRMR: standardized root-mean-square residual
TLI: Tucker-Lewis index

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Exploring Nursing Students' Experiences in a Brief Virtual Reality–Enhanced Workshop: Cross-Sectional Exploratory Study

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Abstract

Background: There is limited evidence on how brief, optional virtual reality (VR) experiences can be used with first-semester nursing students as experiential learning strategies to support understanding of foundational nursing concepts, outside of mandatory coursework or full-scale simulations. Additionally, little is known about students' and teachers' perceptions of VR as a low-stakes, supplemental learning strategy introduced early in nursing education. Examining these experiences can provide insight into the pedagogical value and scalability of VR-enhanced learning within the formal nursing curriculum.

Objective: This study explored students' and teachers' experiences of a brief, optional, VR-enhanced workshop offered outside mandatory coursework in first-semester nursing education and described students' perceptions of cognitive, social, and teaching presence.

Methods: This was a cross-sectional evaluation at a Swedish public university. A single-session workshop, co-designed by nursing teachers and the university library makerspace (implementation context), combined brief headset exposures (sympathetic arousal via a short roller coaster experience and parasympathetic engagement via a short guided meditation), peer vital-sign practice (instructional aid), small-group synthesis, and a guided debrief aligned with the community of inquiry (CoI) framework. Immediately after the session, students completed a demographics questionnaire, a 7-item workshop-specific VR-perception set, and the 34-item CoI instrument, plus 2 open-ended items; teachers provided short reflections. Analyses were descriptive for quantitative data and summative content analysis of open-ended responses. Participants included 11.9% (16/134) of the invited first-semester students (mean age 25 years, SD 5.1; 15/16, 93.8% women; 6/16, 37.5% with prior VR exposure) and 3 teachers.

Results: Most students agreed or strongly agreed that VR enhanced analysis and observation (12/16, 75%), exploration of phenomena (14/16, 87.5%), conceptual understanding and engagement (13/16, 81.3%), teacher support (13/16, 81.3%), and relevance to the session (14/16, 87.5%). CoI ratings indicated moderately positive perceptions (total mean 3.36, SD 0.44 on a 5-point scale), with cognitive presence rated the highest (mean 3.48, SD 0.41) and exploration being the top subdomain (mean 4.48, SD 0.49); design and organization and facilitation were similar (mean 3.42, SD 0.55 each), whereas direct instruction was rated lower (mean 2.88, SD 0.92). Open-ended remarks described links between theory and embodied experience and noted practical challenges.

Conclusions: This study used an early, optional format; the results showed that brief, contrastive VR exposures paired with scaffolded inquiry and a guided debrief were perceived as pedagogically valuable for exploring foundational physiological concepts, while also highlighting feasibility and logistical considerations for routine teaching. Findings are preliminary and reflect session-level perceptions from a small, self-selected sample; nevertheless, they suggest that structured, low-stakes VR may serve as a feasible supplemental strategy in first-semester nursing education, with implications for potential scalability.

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KEYWORDS

virtual reality; education; community of inquiry; cross-sectional studies; experiential learning; education 4.0; academic library makerspace; nursing

Introduction

Background

Contemporary educational paradigms increasingly emphasize the need for immersive, interactive learning environments that integrate theoretical instruction with practical, hands-on experiences, grounded in educational theory and supported by institutional pedagogical frameworks [1-4]. In undergraduate nursing, where foundational concepts about physiology and patient care must be internalized early, there is a growing interest in introducing virtual reality (VR) early in the curriculum as an optional, low-stakes complement to core coursework to spark engagement and support conceptual understanding in the first semester [5].

A growing evidence base suggests that VR can enhance learning by providing immersive, repeatable, and safe experiences that bridge abstract concepts and embodied understanding. Meta-analyses in nursing education have reported positive effects on theoretical knowledge, technical skills, self-confidence, and learner satisfaction when VR is integrated with attention to design features and instructional support [6-8]. At the same time, findings are not uniform: outcomes vary by intervention design and outcome type, and some studies note that while presence increases, learning can suffer when cognitive load is high or scaffolding is insufficient [5,9,10]. Practical considerations, such as cybersickness risks influenced by exposure duration, content, and locomotion, also warrant attention when working with first-time users [11].

There is limited evidence on how brief, optional VR experiences can be used with first-semester nursing students as experiential learning strategies to support understanding of foundational nursing concepts, outside of mandatory coursework or full-scale simulations. Additionally, little is known about students' and teachers' perceptions of VR as a low-stakes, supplemental learning strategy introduced early in nursing education. Examining these experiences can provide important insight into the pedagogical value and scalability of VR-enhanced learning within the formal nursing curriculum. Reports frequently emphasize usability or novelty yet underdescribe how short VR exposures are pedagogically integrated to connect conceptual content (eg, autonomic physiology) with immediate experiences and collaborative sensemaking [5,10].

To guide a purposefully designed, concise activity, we drew on education 4.0 (learner-centered, experience-driven, and digitally supported learning); constructive alignment (coherence among intended learning outcomes, teaching and learning activities, and assessment); and the community of inquiry (CoI) framework (cognitive, social, and teaching presence) [12-18]. Framing VR as one tool within an aligned pedagogical design helps ensure that brief exposures are structured to foster inquiry, link embodied responses to concepts, and support facilitated reflection.

To address these gaps, we implemented and evaluated a brief, optional, VR-enhanced workshop offered outside mandatory coursework in first-semester nursing education. The model combined short headset exposures designed to elicit contrasting autonomic responses, peer practice of vital-sign measurement to support observation and discussion, small-group synthesis, and a guided debrief aligned to the CoI practical inquiry cycle. We describe the implementation and examine students' and teachers' experiences, focusing on students' perceptions of cognitive, social, and teaching presence as indicators of the perceived learning environment [15-17].

Objective

This study explores students' and teachers' experiences of a brief, optional VR-enhanced workshop offered outside mandatory coursework in first-semester nursing education and described students' perceptions of cognitive, social, and teaching presence.

Methods

Design and Reporting

This cross-sectional study evaluated an optional, VR-enhanced workshop using postworkshop surveys (Likert-type items and open-ended responses). No behavioral observation checklists were used. Reporting follows STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidance for cross-sectional studies [19].

Setting, Participants, and Recruitment

The activity took place at a Swedish public university (south central region). All first-semester nursing students (N=134) were invited to participate via announcements on the online classroom platform and brief in-class invitations. Registration remained open for one week, and 16 (11.9%) students who expressed interest received a confirmation message securing their place in the workshop. Participation was voluntary and outside mandatory coursework. In addition, 3 nursing teachers participated across all workshop phases and provided brief reflections. Library makerspace staff co-facilitated implementation (roles are detailed in subsequent sections) but were not included in the teacher feedback items.

Workshop

This optional, supplemental, VR-enhanced experiential learning activity (distinct from a clinical simulation scenario) was offered alongside the first-semester curriculum and was not included in required assessments or mandatory components. Students were divided into 2 groups of 8 for workflow and logistical reasons (nonrandom allocation). Each group completed one VR module, either a short roller-coaster exposure (sympathetic arousal) or a short guided meditation (parasympathetic engagement), followed by inquiry tasks and a guided debrief (Table 1). The workshop was implemented as an optional addition to existing teaching (ie, not part of the school's required simulation infrastructure) to explore perceived experiences with a concise, aligned model.

Table . Time structure of the workshop.

Component of the workshop	Time (min)
Virtual reality exposure and peer vital-sign practice	60
Working on answering the given questions and preparing a PowerPoint presentation	75
Group presentations and reflection	45

Implementation Roles (Contextual)

The workshop was co-designed and co-facilitated by 2 units: nursing teachers (pedagogical design, alignment with first-semester concepts, and facilitation of the debrief and links to physiology) and university library makerspace staff (readiness and comfort protocols for first-time VR use; headset onboarding; hygiene, sanitation, and logistics; and facilitation of information-seeking and source evaluation during the inquiry task). This cross-unit collaboration supported delivery; no evaluation of collaboration effects (eg, feasibility, process outcomes, or comparative effectiveness) was undertaken, and collaboration was not a study outcome.

VR Exposures and Rationale

We selected brief headset exposures to contrast autonomic activation states: (1) sympathetic activation via an approximately 4-minute Epic Roller Coasters track and (2) parasympathetic engagement via an approximately 5- to 6-minute TRIPP guided meditation, primarily to support conceptual understanding of autonomic physiology and secondarily to maintain comfort and accessibility for first-time users [20,21]. Evidence summarized in prior reviews indicates that cybersickness risk is associated with exposure duration, visual stimulation, and locomotion and content; comfort-oriented, shorter sessions are commonly recommended for first-time users [11,22].

Vital-Sign Practice Procedure

Before headset use, each student had resting baseline values recorded (heart rate, blood pressure, respiratory rate, oxygen saturation, and tympanic temperature) using standard training instruments in the student practice ward. To minimize movement artifact and measurement reactivity, spot-checks were obtained immediately after the VR exposure (not during). These measurements were intended to support observations, understanding of sympathetic and parasympathetic responses, and postexperience discussion, rather than research-grade physiological inference; no continuous monitoring was performed, and readings were not designed to isolate specific organ-system mechanisms.

Grouping and Sequence

Two groups of 8 proceeded in parallel (roller coaster *or* meditation). Assigning 1 module per group supported the single-session timebox, comfort for first-time users, and a contrastive learning design that allowed cross-group comparison during synthesis and debrief. Students could reference their own baseline and immediate postexposure readings (eg, heart rate, blood pressure, and respiratory rate) in slides and discussion to illustrate sympathetic vs parasympathetic patterns.

Inquiry Tasks and Presentation (CoI Aligned)

Small groups completed 3 tasks designed to link embodied responses to conceptual understanding and to support the CoI practical inquiry cycle [15,16].

First, explain observations with evidence—locate and use credible sources (textbooks, peer-reviewed literature, and institutional resources) to interpret observed changes consistent with sympathetic vs parasympathetic mechanisms.

Second, synthesize a brief minilesson—prepare a short slide deck that links observations and theory (autonomic physiology; cardiovascular regulation), applies source appraisal, and communicates clearly to peers. Students could optionally include their own heart rate, blood pressure, and respiratory rate comparisons; content on heart dynamics, signaling pathways, and energy metabolism was addressed via literature-based synthesis.

Third, present and debrief (guided)—deliver the minilesson and then participate in a guided debrief aligned with CoI prompts (eg, triggering event, exploration and integration, and bounded resolution). Facilitation emphasized guided reflection and feedback tailored to the goals of the workshop.

Scaffolds: Prompts and Rubrics

Instructors used structured supports to scaffold the activity. The observation log rubric included baseline vs immediate postexposure readings and salient sensations, along with a brief plain-language interpretation. The source evaluation rubric included authority, accuracy, relevance, and timeliness. The synthesis rubric included claim evidence reasoning, alignment to the learning goal, and clarity for peers. These scaffolds guided observation, evidence appraisal, and coherent explanation and were not graded assessments.

The source evaluation rubric included authority, accuracy, relevance, and timeliness. The synthesis rubric included claim evidence reasoning, alignment to the learning goal, and clarity for peers. These scaffolds guided observation, evidence appraisal, and coherent explanation and were not graded assessments.

Data Collection and Measures (Combined)

Students completed an anonymous postworkshop survey with 4 components.

First, the survey collected demographic data on age, gender, and prior VR headset experience.

Second, the survey included 7 VR-perception items that were workshop-specific and targeted perceived analysis and exploration, conceptual understanding and engagement, teacher support, relevance, and the value of learning new technology. These items were tailored to this workshop and were not intended as a validated general instrument; therefore, reliability statistics were not reported for this subscale.

Third, the CoI instrument (34 items) was used and its wording was adapted minimally to the in-person, single-session context (eg, replacing “course” with “workshop activity”) while preserving full coverage of the constructs (cognitive, social, and teaching presence). Given the small sample, we did not estimate reliability in this study; we relied on prior validation literature [15,16].

Fourth, the survey included 2 open-ended questions addressing challenges, barriers, and opportunities for learning with VR, including reflections that could reference sensations experienced. Teachers (nursing teachers) provided brief reflections, whereas makerspace staff co-facilitated implementation but did not complete teacher items.

Ethical Considerations

Participation was voluntary with written informed consent obtained from all participants. Responses were anonymized to protect privacy and confidentiality. Formal ethics review was not required for this type of educational research at our institution and no sensitive personal data were collected [23]. No compensation was provided to participants.

Analysis

Quantitative data were summarized descriptively (no inferential statistics were performed). The 7-item workshop-specific perceptions were reported as distributions; no reliability statistics were calculated. For the CoI instrument, we reported subscale and total scores descriptively and relied on prior validation literature rather than estimating reliability in this small sample. Open-ended responses underwent summative content analysis (2 coders independently open coded the data and reconciled differences through discussion; categories were not assumed to be mutually exclusive) [24].

Results

Overview of Outcomes

Table 2 summarizes students' CoI scores (teaching, social, and cognitive presence and their subdomains); Figure 1 shows agree and strongly agree distributions for the 7-item VR-perception statements, sorted from highest to lowest.

Figure 1. Nursing student ratings concerning using virtual reality (VR) in education.

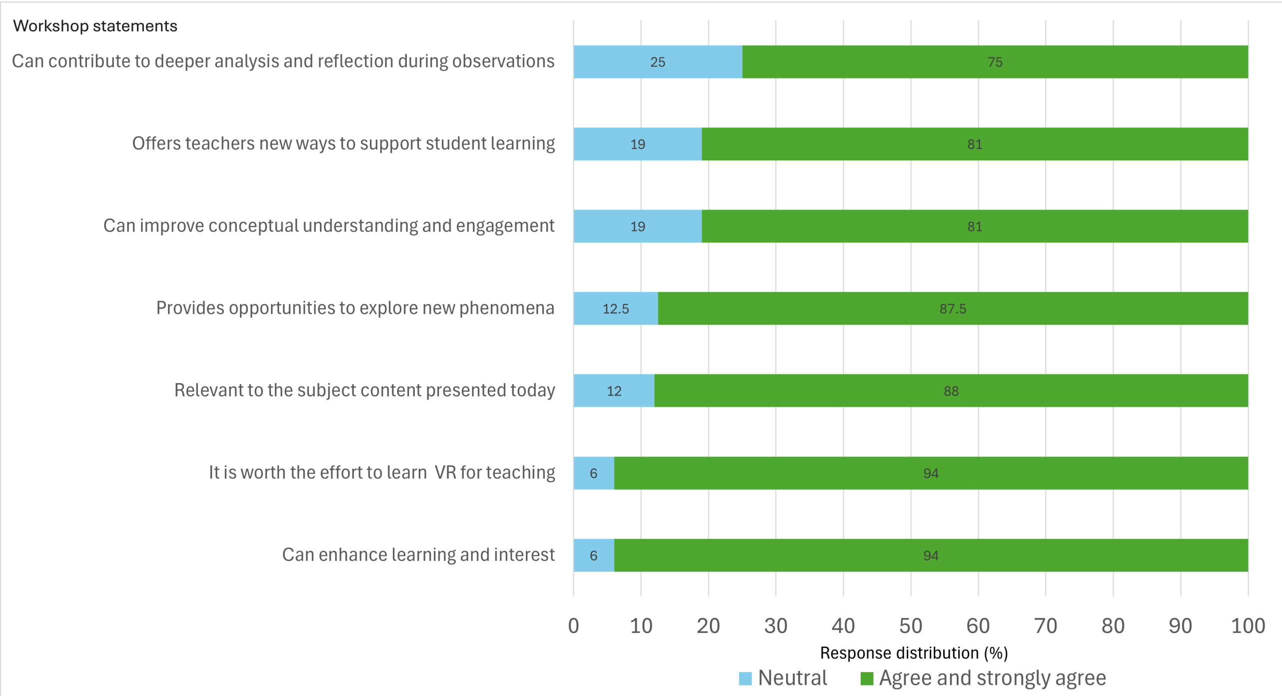

Table . Mean score of the community of inquiry (CoI) survey instrument (n=16).

CoI survey elements	Scores, mean (SD)
Teaching presence	3.28 (0.57)
Design and organization	3.42 (0.55)
Facilitation	3.42 (0.55)
Direct instruction	2.88 (0.92)
Social presence	3.26 (0.60)
Affective expression	3.04 (0.65)
Open communication	3.35 (0.68)
Group cohesion	3.38 (0.69)
Cognitive presence	3.48 (0.41)
Triggering event	3.58 (0.46)
Exploration	4.48 (0.49)
Integration	3.46 (0.46)
Resolution	3.42 (0.49)
Total score	3.36 (0.44)

Of the students at the nursing school (n=134), 16 (11.9%) signed up to participate. The study included 16 students (mean age 25, SD 5.1; range 20 - 38 years), of whom 15 (93.8%) were women. Of the 16 students, 37.5% (n=6) had prior experience using VR headsets. Among these, 2 (12.5%) students had used VR headsets for gaming purposes and 3 (18.8%) students experienced motion sickness or stress during the use of VR. One (6.3%) student did not provide details about their prior experiences with VR. In addition to the students, 3 teachers (mean age 51; SD 10.0, range 43 - 62 years; all male) participated in the workshop. Two teachers had previous experience with VR headsets: one had used them on a few occasions and the other had explored both recreational and pedagogical applications of VR.

Of the 16 students, most agreed or strongly agreed that the VR headsets could increase analysis and observation (n=12, 75%), could help with exploring a new phenomenon (n=14, 87.5%), could increase concept knowledge and engagement (n=13, 81.3%), could create new possibilities for teachers to support their students in learning (n=13, 81.3%), and were relevant to use for the topic of the workshop (n=14, 87.5%) and thought it was worth learning a new technology (n=15, 93.8%; Figure 1).

CoI Results

For interpretability, teaching presence reflects design and organization, facilitation, and direct instruction; social presence reflects affective expression, open communication, and group cohesion; and cognitive presence reflects triggering event, exploration, integration, and resolution. Participants' ratings indicated moderately positive perceptions of the workshop's learning environment (Table 2). Within teaching presence, design and organization and facilitation were similar (mean 3.42, SD 0.55 each), whereas direct instruction was lower (mean 2.88, SD 0.92). Social presence averaged 3.26 (SD 0.60), with subdomains ranging from affective expression (mean 3.04, SD 0.65) to group cohesion (mean 3.38, SD 0.69). Cognitive presence had the highest overall mean 3.48 (SD 0.41), with exploration rated highest among its subdomains (mean 4.48, SD 0.49), followed by triggering event (mean 3.58, SD 0.46), integration (mean 3.46, SD 0.46), and resolution (mean 3.42, SD 0.49). Students referenced their own baseline and immediate postexposure readings (eg, heart rate, blood pressure, and respiratory rate) descriptively to illustrate sympathetic versus parasympathetic patterns; these readings were not analyzed as outcomes.

Qualitative Results (Open-Ended Responses)

Overview

As outlined in the Methods section (summative content analysis), we analyzed anonymous, session-specific open-ended comments. A total of 15 (93.8%) of the 16 students and all 3 teachers provided responses (18/19, 94.7% contributors in total). The unit of analysis was the individual comment. Codes were merged into 3 descriptive categories, and the counts reported represent the number of unique contributors per category. Categories were not mutually exclusive, and the quotations included are illustrative rather than exhaustive [24].

Challenges to VR Use

Participants (9/18, 50%) noted cybersickness and physiological discomfort, headset comfort and time burden, access, logistical, and technical issues, and unfamiliarity and the learning curve.

> *What I can think of is that one can easily become nauseous, and that leads to difficulty concentrating.* [Participant 2402]
>
> *Overall experience can be time-consuming.* [Participant 2403]
>
> *Technical issues. Digital literacy is required in the teacher competency.* [Participant 2419]
>
> *Everyone is not familiar with the technology.* [Participant 2415]

Opportunities for Learning

Students and teachers (16/18, 88.9%) highlighted visualization and immersion to aid understanding and recall, stronger links between theory and observed autonomic responses, low-stakes practice, and a structured debrief that supported collaborative sensemaking.

> *I could experience the connection between theory and practice.* [Participant 2415]

> *It allows for your senses to be used in other ways with VR which allows for learning in new ways.* [Participant 2407]

> *To experience something and the symptoms that arise with it makes it easier to remember in the learning process.* [Participant 2416]

> *To mix learning methods gives you a greater understanding and a wider picture.* [Participant 2411]

Feasibility and Logistics

Practical considerations according to participants (5/18, 27.8%) included equipment availability, onboarding, hygiene, sanitation, and fit adjustments, occasional software and hardware restarts, and scheduling.

> *Technical aspects need to work, both software and hardware.* [Participant 2418]

> *Students need guidance to find the right levels where they do not get caught in technical details.* [Participant 2417]

> *There might be a need to educate the students in VR-basics.* [Participant 2406]

Immediate sensations (eg, nausea, dizziness, and stress) were self-reported by students during the guided debrief and/or the open-ended survey; vital-sign values were not displayed in-headset.

Interpretation

These brief comments help contextualize the session-level experiences but do not provide evidence of longer-term learning or engagement. The counts are descriptive, and no claims of thematic saturation are made, consistent with STROBE guidance for transparent reporting in cross-sectional studies [19].

Link to Cognitive Presence

The qualitative category "opportunities for learning" (16/18, 88.9%) aligns with several components of cognitive presence. Students' noticing was primarily subjective during exposure and later referenced to postexposure spot-check readings in the debrief, which together reflect CoI triggering events. Their emphasis on visualization, immersion, and linking theory to physiological responses corresponds to exploration, which also received the highest quantitative subdomain score (mean 4.48, SD 0.49). References to small-group synthesis activities and the guided debrief illustrate integration, as students worked to make sense of information across sources. Comments referring to feasibility constraints and the brief scope of the workshop help explain why resolution was rated lower than exploration (mean 3.42, SD 0.49 vs mean 4.48, SD 0.49), although it remained moderate overall. Together, the open-ended responses complement and contextualize the quantitative profile of cognitive presence while remaining descriptive and limited to session-level experiences.

Instructor Observations

Instructors noted that the format enabled students to observe VR-elicited physiological responses and link these observations to autonomic physiology concepts during the group debrief. These impressions are limited to the session; given the brief, individual VR exposure and the supplemental nature of the workshop, the study does not provide evidence for sustained changes in active or reflective learning or overall engagement. Terms such as "personal" or "meaningful" engagement were not measured. Peer vital-sign measurements were used to facilitate discussion and illustrate concepts (not to evaluate learning outcomes).

Discussion

Principal Findings

This study explored students' and teachers' experiences with a brief, optional, VR-enhanced workshop introduced outside mandatory coursework in first-semester nursing education. Students perceived the activity as pedagogically valuable for linking autonomic physiology to embodied experience and for exploration within the learning environment. Interpreted through the CoI framework, the overall profile suggested moderately positive perceptions, with the strongest pattern in cognitive presence: exploration. That pattern is consistent with short, inquiry-driven designs that prompt noticing, questioning, and sensemaking during and after exposure [15,16]. In doing so, this study addresses the identified gap by showing how a brief, optional, low-stakes VR exposure can be positioned early in the curriculum and by documenting students' and teachers' perceptions of its pedagogical value and perceived feasibility, with implications for potential scalability as a supplemental strategy. These results reflect session-level perceptions during the workshop's collaborative elements (peer readings, small-group synthesis and presentations, and guided debrief) and should be interpreted cautiously given the brief, optional, single-session design and small sample (n=16); the study did not assess longer-term changes in engagement or learning.

What the Findings Contribute

A central contribution of this work is the demonstration of a low-stakes, early-semester format in which students experience contrasting autonomic states themselves via a short roller-coaster exposure (sympathetic arousal) and a short guided meditation (parasympathetic engagement) and then interpret those experiences through peer discussion, literature-informed minilessons, and a guided debrief. This sequence appears well-suited to catalyzing curiosity (CoI "triggering event" to subsequent "exploration") and to making abstract physiological concepts more tangible early in the curriculum [15,16]. The optional nature and the brief duration likely reduced performance pressure while preserving focus on conceptual understanding and engagement, which helps explain the salience of exploration even in a single session. Students' noticing was primarily subjective during exposure (eg, feelings of arousal or relaxation) and was later referenced to postexposure spot-check readings during the guided debrief and minilessons, providing concrete anchors for interpretation.

Positioned against the broader VR literature, these session-level perceptions align with findings that VR can enhance learning, particularly motivation, satisfaction, knowledge, and skills, when instructional design and scaffolding are explicit [5-8,25]. At the same time, they are consistent with evidence that presence alone does not guarantee learning and that insufficient scaffolding can increase cognitive load and dampen outcomes [5,9]. Our brief, contrastive exposure format with a structured debrief addresses that design dependence by pairing immersive moments with meaning-making activities rather than treating VR as a standalone novelty.

Interpretation in Context (Education 4.0, Constructive Alignment, and CoI)

The workshop design drew on education 4.0 as a high-level orientation to learner-centered, experience-driven, and digitally supported learning, and on constructive alignment to ensure coherence among intended learning outcomes, teaching and learning activities, and reflection [12-14,18]. Notably, vital sign values were not displayed in-headset; students' "triggering events" arose from subjective sensations during exposure and subsequent reference to postexposure spot checks in the debrief. In practical terms, alignment was enacted by contrastive exposures that instantiate target concepts (autonomic arousal vs relaxation), scaffolded inquiry that connects observations to theory (minilessons with source appraisal), and a brief guided debrief aligned with CoI (cognitive, social, and teaching presence) to support sensemaking and closure [15,16]. The study did not conduct competency assessments and does not claim competence gains; rather, it offers exploratory evidence that a concise, optional format can be perceived as pedagogically valuable and feasible for early supplemental use.

Implementation Considerations

Students' reflections and facilitator notes highlighted pragmatic factors important for routine teaching: headset fit and hygiene protocols, onboarding time for first-time users, and occasional software and hardware restarts. Such start-up frictions are common when integrating immersive devices and should be planned for in scheduling and staffing [5]. The brief contrastive design also served a comfort and accessibility function (limited headset time and seated options), which is advisable given that cybersickness risk is associated with exposure duration, visual stimulation, and locomotion; carefully shorter, comfort-oriented sessions are appropriate for novices [11,22].

Implications and Future Recommendations

The findings of this study suggest several practical implications and directions for future research. Positioning early integration of VR as an optional, low-stakes supplement may be beneficial. Offering brief, clearly scaffolded experiences in the first semester may help to prime curiosity and anchor foundational physiology in embodied experience [5,6].

In addition, using contrastive exposures to make mechanistic contrasts vivid (eg, sympathetic vs parasympathetic) and following these with a guided debrief that traces CoI's practical inquiry cycle from triggering events to bounded resolution may support learning [15,16].

Scaffolding with simple tools (observation logs and source evaluation and synthesis rubrics) allows students to produce evidence-informed explanations without adding grading burden [12,13].

Planning for logistics and comfort includes onboarding, sanitation, fit checks, and rapid troubleshooting, and exposures should be kept brief for first-time users [11,22].

Research next steps include moving beyond session-level perceptions to comparative and mixed methods designs that examine knowledge retention, reflective writing quality, and observational rubrics, as well as assessing accessibility (nonheadset alternatives) and scalability (equipment and time models) across cohorts [7,9,25].

Limitations

This study has several limitations that should be considered when interpreting the findings. First, the activity was optional, single-session, and conducted in a single institution with a small, self-selected sample (n=16), which limits generalizability and precludes inference about longer-term effects. Second, outcomes relied on postsession self-report (VR-perception items and the CoI instrument) without objective educational performance measures, comparators, or follow-up; findings therefore reflect session-level perceptions rather than effectiveness or competence.

Third, vital sign readings (eg, heart rate, blood pressure, and respiratory rate) were collected only as instructional aids to support observation and discussion. In this study, we recorded a resting baseline before exposure and spot-checks immediately after exposure; we did not collect data during exposure or conduct continuous physiological monitoring, and values were obtained with standard training instruments by peers rather than research-grade devices. Consequently, these readings are not suitable for physiological inference, characterization of within-session dynamics, or clean separation of phenomena such as anticipatory arousal. Immediate sensations (eg, nausea, dizziness, and stress) were self-reported during the guided debrief and/or in open-ended survey responses and were not systematically assessed with a validated instrument.

Fourth, the 7-item VR-perception set was tailored to this workshop and was not intended as a validated, generalizable scale; therefore, we do not report reliability for this set. For the CoI instrument, we adapted wording minimally to fit an in-person, single-session context, but given the small sample, we did not estimate reliability in this study and instead relied on prior validation evidence reported elsewhere. Finally, equipment and logistical factors and cross-unit collaboration supported implementation but were not evaluated as outcomes.

Taken together, these factors indicate that results should be interpreted as exploratory evidence about perceived learning environment and feasibility for an early, optional, low-stakes VR activity; they do not demonstrate objective learning gains or competency development. Directions for addressing these constraints (eg, comparative designs, larger samples, objective outcomes, structured measures of discomfort, and continuous physiological monitoring) are outlined in the Implications and Future Recommendations section.

Conclusions

A brief optional VR workshop introduced early in nursing education can provide low-stakes, embodied experiences that students perceive as helpful for exploring foundational physiological concepts. When paired with scaffolded inquiry and a guided debrief aligned with CoI, short exposures can prompt curiosity and sensemaking within the formal curriculum, offering a practical, scalable supplement to the required coursework [5,15].

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Data Availability

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

Authors' Contributions

MW, NFC, and LK contributed to the conceptualization of the pedagogical workshop. Data curation was performed by MW and LK. Methodology was developed by MW, NFC, and LK. Original draft preparation was conducted by NFC and MW. Writing, review, and editing were carried out by LK.

Conflicts of Interest

None declared.

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Abbreviations

CoI: community of inquiry
STROBE: Strengthening the Reporting of Observational Studies in Epidemiology
VR: virtual reality

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Perceptions and Intentions of Nursing Students Regarding Digital Health: Cross-Sectional Study

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Abstract

Background: The integration of digital health technologies (DHTs) in clinical practice is accelerating, creating a need for nursing students to develop digital competencies aligned with professional expectations. In Quebec, curricular reforms aim to enhance digital health literacy, but data are limited on students' preparedness.

Objective: This study aimed to assess nursing students' perceptions, self-reported competencies, and willingness to engage with DHTs across different academic years.

Methods: A cross-sectional descriptive survey assessing self-reported digital health competencies, attitudes, perceived training coverage, and intentions was conducted using an online questionnaire administered through Qualtrics. Participants (N=136) were recruited from 3 cohorts: first-year (group 1; n=58, 42.6%), second-year (group 2; n=55, 40.4%), and third-year (group 3; n=23, 16.9%) nursing students. Data were analyzed using descriptive statistics and ANOVAs, with post hoc analyses performed via SPSS.

Results: Significant differences were observed among cohorts concerning digital competencies and access to digital tools. Compared with first-year students (group 1), third-year students (group 3) showed higher proficiency with electronic medical records (group 3: mean 3.29, SD 1.31; group 1: mean 2.59, SD 1.32; P=.01), virtual reality (group 3: mean 4.53, SD 1.11; group 1: mean 2.90, SD 1.44; P<.001), and clinical databases (group 3: mean 4.59, SD 1.00; group 1: mean 3.21, SD 1.55; P<.001). Despite positive attitudes toward DHTs across all groups, training coverage for most digital tools was perceived as low, with the highest levels reported for clinical databases (mean 2.97, SD 1.1). This underscored a substantial gap between institutional expectations and actual digital training across all cohorts.

Conclusions: This study highlights critical gaps in digital health training among nursing students, emphasizing the need for targeted curricular reforms such as the one currently underway at the Université de Montréal. These efforts represent a promising opportunity to better align educational content with the evolving demands of health care systems. Today, preparing students in digital competencies is no longer just advantageous but may soon become essential for the next generation of nurses to navigate and lead within technology-driven care environments.

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KEYWORDS

health IT; digital health education; eHealth competencies; technology adoption in nursing; informatics competency; nursing education; health information systems

Introduction

Macro-Level Context: Digital Shift in Health Care

The digital transformation of health care systems is rapidly redefining how care is delivered, documented, and managed worldwide. Across clinical environments, digital health technologies (DHTs)—including electronic medical records (EMRs), virtual care platforms, and artificial intelligence—are increasingly deployed to enhance care coordination, improve efficiency, and respond to growing service demands [1,2]. In

Quebec, this shift is occurring amid a persistent nursing shortage that places additional pressure on health care institutions and personnel [3]. Strategic investments in digital infrastructure, such as those outlined in the province's 2022 to 2025 technological modernization plan and the federal Pan-Canadian Health Data Strategy, have positioned digital tools as key enablers of more responsive, equitable, and sustainable care delivery [4,5].

Professional Standards and Competencies

To ensure that nurses are prepared to operate within these digitized environments, regulatory and educational bodies have issued guidelines calling for the integration of informatics into nursing practice. The Ordre des infirmières et infirmiers du Québec (OIIQ) emphasizes the importance of digital competencies for safe, ethical, and efficient care across both in-person and virtual settings [6,7]. At the national level, the Canadian Association of Schools of Nursing (CASN) has updated its National Nursing Education Framework to include explicit expectations for digital health literacy among nursing graduates [8]. Together, these standards promote the incorporation of information and communications technologies into nursing curricula as both a professional requirement and a pedagogical priority.

Educational Challenges in Nursing Programs

Despite these mandates, gaps remain in the actual delivery of digital health training across Canadian nursing programs. While students often demonstrate general digital literacy, studies show that they are underprepared to use clinical information systems, navigate electronic records, or interpret data generated by digital tools in real-world practice [9-11]. Furthermore, many programs offer inconsistent or superficial exposure to health ITs (HITs), contributing to low confidence and proficiency among graduates [11]. These limitations risk widening the gap between institutional expectations and actual clinical readiness, particularly as the pace of digitalization continues to accelerate. Previous studies indicate that, although nursing students tend to have a positive attitude toward digital health, their clinical readiness remains limited due to inconsistent exposure to health information systems. Competency frameworks such as those from the CASN and OIIQ underscore the need for structured, progressive integration of digital training into nursing education [7,8]. These limitations contribute to low confidence and perceived readiness among graduates entering technology-rich clinical environments.

Study Rationale in the Quebec Context

Although several studies have examined nurses' perceptions of digital health tools, few have focused on nursing students in Quebec, where the educational structure, regulatory environment, and pace of curricular reform differ from those of other Canadian provinces [12]. Given recent efforts at the Université de Montréal (UdeM) to revise its undergraduate nursing program to better align with CASN and OIIQ guidelines, it is crucial to understand students' current perceptions, competencies, and intentions regarding DHTs. To our knowledge, this is the first study in Quebec to use a cohort-comparative design to examine digital health preparedness among nursing students. Grounded in the technology acceptance model and the OIIQ digital competency framework, this study aimed to identify year-based differences in perceptions and training gaps, thereby informing targeted curricular reforms to support Quebec's digital health transformation [12,13].

This study was conceptually inspired by the behavioral framework by Paré et al [14] examining medical students' intention to integrate DHTs, which combines elements from the theory of interpersonal behavior by Triandis [15] and the technology acceptance model [16]. The survey content was further adapted to the nursing context using insights from the 2020 National Survey of Canadian Nurses on the use and impact of DHTs in practice. The final instrument was reviewed and validated in collaboration with experienced nursing professors from the Faculty of Nursing (Faculté des sciences infirmières in French; FSI) at UdeM to ensure relevance and clarity for nursing students.

Research Objectives

This study had the following objectives:

- Explore the perceptions and intentions of nursing students regarding their knowledge, experiences, and training related to HITs and their beliefs, attitudes, and intentions concerning the use of HITs in their future professional practice
- Compare these perceptions and competencies based on students' year of study to identify potential differences across cohorts
- Provide recommendations for improving HIT-related education in response to the identified needs

Methods

Design, Setting, and Participants

This study used a cross-sectional descriptive design. It was conducted at the FSI at UdeM in May 2023. The target population included 1274 students enrolled in the FSI at UdeM. A target sample size of 300 was chosen based on recommended minimum thresholds for descriptive surveys in large student populations [17] to ensure reasonable representation as no formal power calculation was required for this exploratory design. Eligible participants were all students currently enrolled in an undergraduate nursing program who provided informed consent.

It is important to note that participant distribution across academic years was uneven. This reflects actual enrollment sizes within the program during the data collection period.

Ethical Considerations

This study was reviewed and approved by UdeM's Research Ethics Committee in Sciences and Health (2023-4300) and was supported by the FSI. All participants provided informed consent electronically before starting the survey and could withdraw at any time without consequence. Data were collected anonymously to ensure participant privacy and confidentiality. No financial or other compensation was provided for participation.

Recruitment

UdeM was selected as the research site due to its status as a major higher education institution in Quebec and the diversity of its undergraduate nursing student population. Recruitment was conducted electronically through the FSI, which emailed an initial invitation and one reminder to all eligible students via their institutional addresses. Interested participants accessed the study by clicking a secure link leading to the consent form and the online questionnaire. Participation was voluntary and anonymous. Although IP addresses were not collected to ensure confidentiality, the use of institutional email distribution and limited reminders minimized the risk of multiple entries.

Data Collection

Data were collected through an online self-administered questionnaire designed specifically for this study administered via Qualtrics (Qualtrics International Inc), a platform designed for web-based research that offers basic descriptive statistics tools while ensuring secure data handling.

The questionnaire took approximately 15 minutes to complete and included an open-ended question at the end, allowing participants to share additional comments. Although this open-ended question was included at the end of the questionnaire to capture additional student perspectives, these responses were not systematically analyzed in this study. An exploratory review of these responses was conducted to inductively identify recurring themes and enrich the interpretation of the quantitative findings by reflecting participants' lived experiences and unprompted perspectives.

The survey was developed to operationalize key constructs from the conceptual framework described above. Specific items were adapted from the study by Paré et al [14] and the 2020 National Survey of Canadian Nurses to align with the nursing context and relevant DHTs. The draft instrument was then reviewed and refined in collaboration with experienced nursing faculty at UdeM to ensure content validity and clarity. The final version included 15 items (Table S1 in Multimedia Appendix 1) and is available in Multimedia Appendix 2.

Variables

This study assessed nursing students' perceptions, competencies, and training needs related to HITs across 4 main categories of variables.

Sociodemographic and Academic Variables

Sociodemographic and academic variables included the year and type of academic program; the participants' age, sex, and gender; languages of interaction; daily use of digital devices; previous professional experience in the health care sector; and current or intended professional setting after graduation.

HIT Competencies and Training

Using Likert-type scales, participants assessed their level of proficiency with various technologies (1="none," 2="very low," 3="low," 4="moderate," 5="high," and 6="very high"), the extent to which HITs were covered in their nursing education program (1="not covered at all," 2="poorly covered," 3="moderately covered," 4="well covered," and 5="very well covered"), and the level of expertise they believed was necessary for clinical practice (1="no training needed," 2="basic training," 3="functional or intermediate training," and 4="expert or specialized training).

Perceived Impacts of HITs

Participants were asked to rate the perceived impact of DHTs on key aspects of the nursing profession, such as quality of care and work life. The question was phrased as follows: "Do you believe that the use of digital health technologies has, or will have, an impact on the following dimensions of the nursing profession?" Responses were collected on a Likert scale (1="very negative impact," 2="negative impact," 3="neutral impact," 4="positive impact," and 5="very positive impact"). An open-ended question followed, allowing respondents to elaborate or provide additional comments.

Statistical Analysis

Students were grouped into 3 categories based on their year of study: first year of the integrated diploma of college studies–bachelor's degree (*diplôme d'études collégiales–baccalauréat* in French; DEC-BAC) and regular bachelor's degree (*baccalauréat* in French; BAC) programs (group 1), second year of the DEC-BAC and BAC programs (group 2), and third year of the DEC-BAC and BAC programs (group 3). All Likert scale variables were treated as continuous variables and analyzed using means and SDs.

For categorical variables, frequencies and percentages were reported for each group as well as for the total sample. Group comparisons were conducted using exact *P* values from chi-square tests. For continuous variables, valid sample sizes, means, and SDs were presented. Group means for Likert scale variables were compared using one-way ANOVA followed by Tukey post hoc tests where appropriate.

An exception was made for the variable "training coverage—scheduling software," where the Welch correction for unequal variances was applied and post hoc comparisons were conducted using Games-Howell tests. All statistical analyses were performed using the SPSS software (version 28; IBM Corp), with a significance level set at 5%.

Results

Sociodemographic and Academic Variables

Overview

A total of 173 students accessed the questionnaire. The response rate for the item identifying participants' academic year within the nursing program was 78.6% (136/173). After grouping, group 1 comprised 42.6% (58/136) first-year students, group 2 comprised 40.4% (55/136) second-year students, and group 3 comprised 16.9% (23/136) third-year students.

Participant Profile

Across all groups, more than 67% (92/136) of participants were aged between 18 and 25 years, with group 3 standing out at 80% (19/23) in this age range (P=.03). This group also reported significantly higher access to a laptop (P=.02). Use of digital tools for specific activities was also significantly greater among groups 2 and 3 (P=.01). Additionally, a higher proportion of group 3 participants reported working in the provincial public health care sector (P=.003; Table S2 in Multimedia Appendix 1).

HIT Competencies and Training

HIT Proficiency Levels

Proficiency levels across all work-related HITs were generally rated from low to moderate. Group 2 stood out in terms of proficiency with EMRs (P=.01), whereas group 3 demonstrated higher proficiency with virtual reality (P=.001) and clinical databases (P=.001; Table S3 in Multimedia Appendix 1).

Training Coverage by Group

Regardless of the specific HIT in question, coverage within the curriculum was generally perceived as very limited to minimal. Group 1 reported greater coverage in the use of scheduling software (P=.007), whereas group 3 reported more extensive coverage in database training (P=.004; Table S4 in Multimedia Appendix 1).

Required Expertise for Professional Use of HITs

Participants generally believed that most HITs required little to no specific expertise for professional use. An exception was noted for group 2, which reported a significantly higher need for basic or intermediate training in the use of health care robots (P=.02; Table S5 in Multimedia Appendix 1).

Perceived Impacts of HITs in the Nursing Profession

Perceptions of the impact of HITs on the nursing profession were consistent across all groups. Most students believed that DHTs have a positive or very positive impact on key aspects such as quality of care, therapeutic relationships, and productivity (Table S6 in Multimedia Appendix 1).

Narrative Comments

Of the 136 respondents, 31 (22.8%) provided written responses to the open-ended question. Most comments reflected key patterns observed in the quantitative results, particularly regarding the perceived lack of formal training in DHTs. Several students reported learning to use digital tools only during clinical placements, consistent with the limited curriculum coverage ratings found across cohorts. One respondent noted that “[w]e only learn to use digital tools during internships,” whereas another remarked that “[a]t university, we have no training on the software we encounter in practice.”

Others described barriers to accessing technologies during clinical placements due to their student status:

> *As a nurse it’s fine, but as a student, it’s complicated when we don’t have the access.*

These comments aligned with cohort-based differences observed in digital tool use and confidence levels.

However, the responses also surfaced dimensions not captured in the structured survey. Several participants mentioned psychosocial or physical impacts of digital tool use, including “less sleep, eye strain, and a more sedentary lifestyle” and “technology sometimes limits social interaction, which affects mental health.” A few students proposed improvements, such as earlier exposure to clinical systems or greater consistency in tools across health care settings:

> *It would help to learn some of the clinical software in advance.*

> *Please standardize the digital documents, it would simplify things when moving between institutions.*

While broadly aligned with the quantitative trends, these narrative comments introduced experiential nuances, such as well-being, autonomy, and implementation barriers, that were not accessible through the Likert scale items alone.

Discussion

Principal Findings

Both the OIIQ Comité jeunesse and the OIIQ [6,12] emphasize the importance of access to IT that supports nurses’ clinical decision-making, optimizes care processes, and enhances patient safety, as well as maintaining professional and ethical standards.

Similarly, the CASN, through its National Nursing Education Framework [8], underscores the importance of integrating nursing informatics competencies into academic programs to better prepare future professionals for the increasing technological demands of clinical environments.

However, our findings indicate that students perceive their current training as insufficient. Their self-assessed proficiency with digital tools was limited, and coverage of key HITs was generally perceived as weak without a clear progression across academic years despite students showing an interest in these tools and their potential impact on nursing practice.

These observations suggest a concerning disconnect between the evolving expectations of the health care system and students’ perceived preparedness despite the clear guidelines set forth by both the OIIQ and CASN. This aligns with findings by Kleib et al [11], who identified persistent gaps in digital health education that were exacerbated by pedagogical approaches that often overestimate students’ technological competencies and fail to adequately prepare them for clinical realities.

The narrative comments reinforced this disconnect by providing concrete examples of students’ perceived lack of preparation, particularly in relation to clinical software. The comments also highlighted barriers that were not captured in the structured survey, such as restricted access to digital tools during placements and the personal toll of technology use on well-being. These experiential accounts complement the quantitative findings and emphasize that perceived readiness is shaped not only by curricular content but also by the conditions of access, support, and emotional experience within clinical environments.

The fact that many participants in our study believed that high-level proficiency was unnecessary for the effective use of HITs may reflect a limited understanding of their relevance in nursing practice. Kleib et al [11] emphasize that, while students often demonstrate basic digital literacy, this does not necessarily translate into clinical competence. Consequently, students may underestimate the complexity and significance of digital tools in real-world settings. These findings highlight the pivotal role of nursing educators in bridging this gap by explicitly integrating digital competencies into nursing curricula and grounding them within authentic clinical contexts to foster both awareness and applied proficiency.

Despite these challenges, the surveyed students remained generally optimistic about the role of HITs, with most believing that these technologies will have a positive or even very positive impact on the nursing profession. This optimism reflects a growing awareness of the digital shift in health care and aligns with the strategic directions promoted by the OIIQ and CASN, who advocate for stronger digital health training in nursing education [7,8].

Beyond these overarching findings, notable differences emerged between academic years in terms of access to digital tools, proficiency with specific technologies, and perceived curriculum coverage. This study identified several statistically significant differences in how students from each cohort perceived and interacted with HITs.

The 18- to 25-year age group predominated across all cohorts, particularly in group 3, where it represented 83% (19/23) of the participants. Group 3 students also reported greater access to digital tools, especially laptops, and more advanced use of EMRs, virtual reality, and databases. These findings are consistent with the broader and more in-depth training coverage that this group reported for these tools.

The observed differences in competencies and training exposure likely reflect curricular progression, with third-year students benefiting from more extensive clinical placements, capstone projects, and practical assignments that integrate digital tools. In addition, group 3 students may have greater opportunities for independent learning and part-time work in health care settings, reinforcing their proficiency with EMRs and clinical databases. In contrast, group 1 students are typically at the beginning of their program, focused on foundational theoretical content with limited hands-on exposure to applied digital health systems.

Group 2 students stood out for their more frequent use of digital tools and a higher reported need for advanced competencies in health care robotics. Meanwhile, group 1 students reported better coverage related to scheduling software, likely reflecting academic needs specific to first-year studies.

Taken together, these findings reveal a persistent and concerning gap between current digital health needs and the perceived preparedness of nursing students, echoing the concerns expressed by the OIIQ [7]. They underscore the importance of continuing efforts to integrate digital health competencies into nursing education in a structured and strategic manner.

Limitations and Future Research

Methodological and Contextual Limitations

Of the 1274 targeted students, 136 (10.7%) completed the questionnaire, representing 45.3% (136/300) of the sample size required to ensure statistical representation. While the target of 300 respondents was chosen based on practical guidelines for descriptive surveys, the absence of a formal power calculation means that the study may be underpowered to detect smaller effect sizes or subtle group differences, particularly given the uneven distribution across cohorts.

The unequal sample sizes between academic years may also have limited the statistical power for some comparisons. However, this limitation mirrors real enrollment patterns and was accounted for using appropriate statistical analyses.

Although no data were available to confirm a nonresponse bias, the relatively low participation rate raises the possibility of such a risk. Therefore, it is possible that respondents had characteristics or perceptions that differed from those of nonrespondents, potentially limiting the generalizability of the findings.

Additionally, the self-administered nature of the questionnaire introduces the possibility of self-selection and self-assessment bias. Students who chose to participate may have been more comfortable with technology or more aware of digital health issues, potentially skewing responses toward more favorable or more critical perceptions than would be typical. Moreover, as the study was conducted at a single institution, UdeM, the transferability of the findings to other educational, institutional, or cultural contexts is limited. The uneven distribution of participants across groups, particularly the low number of participants in group 3, further reduces the robustness of statistical comparisons and may have hindered the detection of significant effects in certain analyses.

In addition, while this study included an open-ended question that generated valuable narrative insights, these data were reviewed only through an exploratory, unsystematic process and were not coded or analyzed using a formal qualitative methodology. As such, they cannot be considered representative or exhaustive. Even so, the added value of these responses, particularly in revealing experiential and emotional dimensions absent from the structured survey, suggests that future research would benefit from an intentionally designed mixed methods approach. Incorporating qualitative inquiry from the outset guided by a clear theoretical framework would allow for a more comprehensive understanding of how nursing students engage with digital technologies across educational and clinical contexts.

Future Research Directions

The FSI at UdeM is currently in the process of implementing a revised version of its undergraduate program in response to recent recommendations from the CASN that emphasize the importance of developing digital competencies aligned with current clinical demands and realities.

In this context, a pretest-posttest design with independent cohorts comparing students who completed the old curriculum with those trained under the revised program would offer valuable insights into the impact of the reform on digital health literacy, integration, and appropriation. Additionally, consultations with key stakeholders within the faculty, including teaching staff, program directors, educational advisors, and student representatives from each cohort, could provide critical institutional perspectives on the validity of the findings presented in this study. As part of a complementary qualitative component, this triangulated approach would not only contextualize the results but also help assess how curriculum reform may influence digital health teaching practices.

Several additional methodological avenues could be explored to build on this work and deepen understanding of students' perceptions and competencies regarding HITs. First, replicating the study across multiple nursing schools through a multisite comparative design would help assess the transferability of findings beyond the UdeM context. Second, adopting a mixed methods approach to combine quantitative questionnaires with qualitative interviews could yield a more nuanced understanding of student expectations, perceived barriers, and enabling conditions for meaningful engagement with digital tools. Finally, longitudinal studies conducted throughout the academic journey would allow for documentation of digital competency development over time in relation to different education milestones and ongoing curricular adjustments.

Conclusions, Implications, and Recommendations

This study reveals a significant gap between institutional expectations and perceptions of digital health training by nursing students, particularly in their proficiency with essential tools such as EMRs and clinical databases. Despite recognizing the value of digital technologies, students reported limited curricular coverage and confidence in using them.

These findings call for targeted reforms in nursing education, including the integration of hands-on training, digital simulations, and interactive modules. To address these gaps more concretely, nursing programs could implement several specific measures: (1) dedicated simulation laboratories focused on EMRs and clinical software; (2) mandatory digital health literacy modules that introduce students to national and provincial informatics frameworks; and (3) interprofessional digital health workshops that mirror real-world collaborative settings involving nurses, physicians, and allied health professionals. These recommendations are further supported by students' own accounts, which reflect both a desire for earlier, more practical exposure to digital tools and a recognition of the limitations in their current training environment.

The current curriculum revision at UdeM offers a timely opportunity to evaluate the implementation outcomes of such changes. Future studies using a clearly defined pretest-posttest design, with precise cohort tracking to distinguish students enrolled before, during, or after curriculum reforms and collecting detailed data on external exposure to HITs (eg, work settings) could help assess the true impact of these reforms.

Broader research across institutions and through mixed methods or longitudinal approaches will be crucial to strengthening the evidence base literature. In an increasingly technology-driven health care landscape, equipping the next generation of nurses with robust digital competencies is no longer optional and has become a professional imperative.

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Data Availability

The datasets generated or analyzed during this study are not publicly available due to privacy and institutional restrictions but are available from the corresponding author on reasonable request.

Authors' Contributions

AC conceptualized the study and led project administration. AC and GP developed the methodology and supervised the study. SH-D curated the data and performed the formal analysis. FAES conducted validation. AC and SH-D wrote the original draft of the manuscript. All authors (AC, SH-D, GP, and FAES) reviewed and edited the manuscript and approved the final version.

Conflicts of Interest

AC serves as an associate editor for the *Journal of Medical Internet Research*. The other authors declare no conflicts of interest.

Multimedia Appendix 1

Descriptive and comparative tables summarizing participant characteristics, technology proficiency, training coverage, and perceived expertise requirements across student groups.
[DOCX File, 37 KB - nursing_v9i1e77051_app1.docx]

Multimedia Appendix 2
Study questionnaire assessing nursing students' perceptions, experiences, and attitudes toward digital health technologies.
[DOCX File, 50 KB - nursing_v9i1e77051_app2.docx]

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Abbreviations

BAC: baccalauréat

CASN: Canadian Association of Schools of Nursing
DEC-BAC: diplôme d'études collégiales–baccalauréat
DHT: digital health technology
EMR: electronic medical record
FSI: Faculty of Nursing
HIT: health information technology
OIIQ: Ordre des infirmières et infirmiers du Québec
UdeM: University of Montreal

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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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Barriers and Enablers for Sustaining Nurse-Led Use of Clinical Decision Support Tools for Antibiotic Stewardship: Qualitative Study

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Abstract

Background: Clinical decision support (CDS) tools embedded in electronic health records in the form of integrated clinical prediction rules provide a potentially effective intervention to reduce inappropriate antibiotic prescribing for acute respiratory infections. However, their effectiveness has been limited by workflow barriers and low adoption by health care providers. Nurses are well positioned to implement evidence-based protocols using CDS tools. In a multicenter randomized controlled trial, a nurse-led implementation strategy for acute respiratory infection integrated clinical prediction rules was evaluated for use in primary care and urgent care settings.

Objective: This study aimed to examine nurse and nurse leader perspectives on the sustainability of an electronic health record–integrated CDS tool for antibiotic stewardship and explored factors influencing its potential long-term integration into ambulatory nursing practice beyond the clinical trial.

Methods: We interviewed 22 nurses and nurse leaders from 37 clinics across 3 academic medical centers that participated in the clinical trial. Two semistructured interview guides, one for nurses and one for nursing leadership, were developed to understand the barriers and facilitators to implementing a decision aid tool for nurses and to elicit challenges specific to nursing interactions with the CDS tool. Interviews were recorded and transcribed. Using thematic content analysis and iterative coding, our team collaboratively identified emerging themes related to sustainability and refined the results with consensus.

Results: Five themes emerged: (1) importance of staffing stability and capacity, (2) impact of dedicated clinic resource availability, (3) variable nurse readiness with CDS-guided clinical care, (4) influence of openness to change and a nurse-supportive clinic culture, and (5) ongoing need for training and support. Specific recommendations for future actions were also noted.

Conclusions: Our findings revealed specific barriers and facilitators to the sustainability of a CDS tool from the nursing perspective that can inform further implementation of nurse-led delegation protocols in the ambulatory setting. Future solutions should consider mapping physical workflows, scheduling specific to nurse visits, continuing education, and treating cough and sore throat as 2 distinct processes.

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KEYWORDS
clinical decision support systems; electronic health records; nursing; antibiotic stewardship; ambulatory care facilities

Introduction

Antibiotic resistance is a growing global health concern, exacerbated by the overprescription of antibiotics for acute respiratory infections (ARIs) [1]. Despite available evidence-based guidelines and clinical decision support (CDS), physicians often prescribe antibiotics inappropriately due to perceived patient expectations, time pressures, and cognitive fatigue [2]. To address this issue, clinical prediction rule (CPR) systems have been developed and integrated as integrated clinical prediction rules (iCPRs) into electronic health records (EHRs) as CDS to assist physicians in making informed antibiotic prescribing decisions [3,4]. However, their impact has been limited by low provider adoption rates [5,6]. Evidence suggests that registered nurses (RNs) have the potential to implement evidence-based protocols [7,8], participate in antimicrobial stewardship [9], achieve high patient satisfaction and symptom resolution [7], and demonstrate higher adoption rates of CDS tools than physician-led initiatives [10].

Building on this potential, the multicenter, step-wedge, cluster randomized controlled trial (iCPR3 RCT) evaluated whether RNs could effectively use iCPR tools to guide evidence-based care for patients presenting with ARIs in ambulatory care settings [11,12].

An early implementation assessment identified several potential barriers and facilitators to adopting the nurse-driven CDS tools [10]. As the iCPR3 RCT concluded, we sought to understand whether nursing departments would consider continuing to use iCPR tools in clinical practice after research support was withdrawn. We also aimed to identify barriers that may hinder sustained use within ARI workflows beyond the study period. By examining these perspectives, our goal was to identify strategies to sustain nurse-led use of iCPR tools in clinical practice as a means to improve patient outcomes [13].

Methods

Research Design

We used semistructured interviews and thematic analysis to examine the perspectives of RNs and nurse leaders regarding the sustainability of the iCPR tools, including aspects of implementation, usability, and perceived impact. For the purposes of this study, we defined sustainability as the extent to which nurses would continue to use a tool as part of standard clinical workflows beyond the study period and without research personnel implementation support or incentives.

Ethical Considerations

The study protocol and procedures were approved by the NYU Langone Health Institutional Review Board (NYULH study number i19-01222), which served as the study's single institutional review board. We received a waiver of written informed consent for this study. All study data reported in this manuscript are deidentified. Compensation was provided in accordance with institutional policies.

Nurse iCPR Intervention

The nurse intervention used a structured delegation protocol, wherein the specific clinical task of assessing the need for antibiotics in low-acuity ARI patients was transferred from a physician to an RN. Provider-to-nurse delegation is operationalized through protocol-driven authorization of nursing tasks by a licensed provider, with accountability retained by the delegating provider. In the iCPR3 RCT, the intervention consisted of triage followed by in-person CDS-guided RN visits for patients with low-acuity ARI symptoms. The EHR-integrated CDS included a triage note template to assess symptoms and acuity and 2 reason-for-visit-specific (ie, sore throat or cough) note templates with iCPRs that guide RNs to complete an evidence-based risk calculator as part of the visit [12]. The resulting risk score is linked to an order set for diagnostic testing, prescriptions, and patient instructions.

All tasks performed by RNs as part of the intervention—triage, symptom assessment, use of CDS tools, and execution of evidence-based care pathways—are well within the scope of nursing practice and align with their clinical training. The iCPRs used were previously found to be effective for reducing inappropriate antibiotic prescribing when used by physicians [2,4,11]. The intervention aimed to standardize care delivery and reduce unnecessary antibiotic use in outpatient settings.

The intervention was implemented as a pragmatic stepped-wedge cluster randomized trial across 43 primary and urgent care practices in 3 academic health systems affiliated with the University of Utah, the University of Wisconsin, and NYU Langone. To be eligible for participation, practices were required to have at least 1 RN full-time equivalent capable of performing triage within the EHR and conducting RN on-site visits. Nurses in the intervention group received 1 hour of online training prior to 1 hour of in-person training on how to use the iCPR tool, including background on the iCPRs, EHR-based walkthroughs of using the iCPR tool within the CDS, demonstration videos simulating the tool in a live clinical encounter, and clinical training for physical examinations [11]. Complete study procedures are reported elsewhere [12].

Study Design

We conducted remote video interviews (via Zoom and Webex) lasting approximately 30 minutes between September 2024 and January 2025. Each participant was interviewed by a trained research team member from the corresponding health system (NH, KM, AY, VT) using 1 of 2 semistructured interview guides. Our team developed these interview guides, 1 for RNs and 1 for leadership, based on a series of open-ended structured questions previously used in a validated survey to understand the barriers and facilitators to implementing a lupus decision aid tool for nurses [14]. We adapted the questions to explore relevant Consolidated Framework for Implementation Research (CFIR) constructs, as well as address conditions specific to the ambulatory care environment and the iCPR intervention; we retained all other aspects of the survey [15]. Interviews consisted of questions to understand barriers and facilitators related to tool use, clinical team interactions, what worked well, any competing priorities, strategies for mitigating issues, and future adoption sustainability (see Tables S1 and S2 in Multimedia Appendix 1). Probing questions were used to verify the interpretation of participant responses, and recommendations were solicited for continued use of the iCPR tool in clinical workflows.

Participants

We recruited a convenience sample of RNs and nurse leaders (did not have to be an RN) from primary care clinics and urgent care centers participating in iCPR3. Participants were considered eligible if they expressed familiarity with the iCPR tool and, if they were nurse participants, had completed a nurse visit using the tool. Participants were recruited via email by study personnel at each site. Recruitment procedures varied slightly by study site due to local policies and conditions. Specifically, given the proportionately large number of clinics at the University of Wisconsin (21 clinics vs 9 and 7 clinics at NYU and Utah, respectively) and with the objective of obtaining diverse perspectives, participants were recruited as a stratified convenience sample from the top and bottom 5 performing clinics, based on the average number of nurse visits completed per week per clinic volume at randomization. In addition, University of Utah participants were offered a US $25 gift card as an incentive, whereas other study sites did not provide financial incentives due to institutional policies around employee compensation. A member of the study team verbally reviewed the study information with each participant to ensure understanding; all participants then provided verbal agreement to participate.

Thematic Analysis Procedures

We conducted a thematic content analysis to identify themes related to sustainability by extracting high-level themes from the data while examining the frequency of concepts or keywords [16]. Each interview was audio-recorded and transcribed using an automated service (Landmark Associates). One team member (NH) reviewed each file for transcription accuracy prior to analysis. Transcripts were analyzed, and a codebook was developed using Dedoose [17].

We first conducted a joint analysis of 2 interviews to allow the study team members to become accustomed to the codebook, make updates to codes, and resolve conflicts. All study team members were trained in qualitative techniques. Next, 2 team members coded each transcript independently, and then all coders (VT, NG, MB, KM, AT) met as a team to compare and resolve disagreements. During this process, we reviewed for thematic saturation, ensuring the sample met this criterion based on the diminishing need to update code definitions. Our analysis focused on the barriers and facilitators to sustainability of iCPR tool use beyond the study end date. Once all transcripts were coded, we reviewed the data code by code to ensure definitions had remained consistent. All coders then reviewed each excerpt to collectively derive emerging themes related to barriers, facilitators, and recommendations for solutions. Emerging themes were grouped into high-level categories through consensus. This study adhered to the COREQ (Consolidated Criteria for Reporting Qualitative Research) guidelines for qualitative studies involving interviews and focus groups [18].

Results

Descriptive Results

We invited 56 eligible individuals to participate and conducted 22 individual interviews across the 3 sites, each lasting 15 to 45 minutes. Participants included 9 nurses (1 NYU, 8 Wisconsin) and 13 nurse leaders (4 NYU, 2 Utah, 7 Wisconsin); demographic information was not collected from either group. Due to limited tool use during the study, no nursing participants from the University of Utah elected to participate in the interviews.

Through thematic analysis, we identified 5 overarching themes related to nurses' and nurse leaders' perspectives on the implementation, effectiveness, and sustainability of the iCPR intervention as part of standard care processes. The 5 themes that emerged included: (1) importance of staffing stability and capacity; (2) impact of dedicated clinic resource availability; (3) variable nurse readiness with CDS-guided clinical care; (4) influence of openness to change and a nurse-supportive clinic culture; and (5) ongoing need for training and support.

Importance of Staffing Stability and Capacity

One of the most prominent themes concerned the need to have sufficient trained RNs staffed and available in the clinic to support the time needed to triage patients and conduct nurse visits. In addition to nurse staffing, participants emphasized concerns related to physician and support staff levels. Contributing to these concerns, many participants (20, 91%) discussed issues related to staff turnover, including the challenges of retaining staff, training new staff, and implications for using the iCPR tool workflows.

When questioned about barriers to using the iCPR tool, one nurse stated:

> *We are staffed with only three nurses, which is not a lot… One of our nurses left in May of last year to work elsewhere. Then, we hired a new nurse. Our third nurse went on maternity leave. Then when she came back, the other nurse had to leave for other reasons too. We've kind of just been at this [struggle] of not being able to consistently have a good number of staffing.* [N 3.18]

The shortage of nursing support staff often required nurses to cover multiple roles, making it challenging to prioritize tasks and manage workload effectively. One participant stated:

> *…some clinics can't handle it… they don't have enough people to even answer the phones.* [N 3.3]

With full staffing, nurses expressed confidence in executing the iCPRs:

> *We are pretty much fully staffed… it has not been a burden to participate and be a part of this survey and process… it's certainly helped our patients.* [N 3.3]
>
> *We could have two nurses and visits at the same time and patients aren't having to wait.* [N 3.2]

Additionally, staff turnover was linked to challenges in familiarizing and educating new staff regarding the iCPRs due to limited training time. Increasing awareness among new nurses completing orientation who lacked exposure to the study was discussed. One nurse stated:

> *Now that I'm thinking about it, there's a whole bunch of nurses that started that they weren't probably there when it first started. They don't even know about it, and I don't know if it's part of their orientation packet.* [N 1.7]

A key subtheme involved virtual triage coordination, where nurses working remotely were able to triage patients by phone and monitor clinic appointment availability. Approximately one-quarter of the participants (6, 27%) felt that this workflow disrupted nurse visit appointment availability.

> *It's a small nursing team so you have anywhere from two to three nurses working on a given day and then with the nurses that have the option to work remote now sometimes you only have one RN [registered*

> *nurse] in clinic. That impacts availability for appointments, so I think that is always a challenge.* [N 3.11]

Another participant expressed difficulties coordinating with colleagues not physically in the same place, since the phone triage nurse at Wisconsin and NYU sites was typically different from the nurse who conducts the in-person nurse visit, highlighting staffing coordination in a hybrid care setting.

> *Sometimes, if you're at home triaging the patient, and they could use a nurse visit, trying to coordinate that with colleagues can be hard if it's a busy day. You don't really know what's going on over there [in the clinic]…* [N 3.15]

Impact of Dedicated Clinic Resource Availability

The impact of clinic resource availability, including physical space for nurse visits and scheduling accessibility, was identified as a barrier to uptake of the in-person nurse visit component of the iCPR workflow. The ability to manage the patient care continuum was disrupted when examination rooms were unavailable. One nurse stated:

> *…we don't necessarily have a place to go with our patients…again, sometimes we are just running around trying to find a location for the patient to be assessed in and to complete the visit in.* [N 3.4]

Discussion of the physical clinic setup highlighted that the lack of available examination rooms posed challenges. One RN stated:

> *We've always had to kind of just find a room on the fly for any of our nurse visit types each day, whether they're iCPR or not. A day like today, all of our exam rooms are occupied by the providers that are here. Our plan is just when the patient comes, if there is an available room, just kind of quickly utilize that.* [N 3.18]

Alternatively, when the clinic set aside dedicated rooms for nurse visits and triage, it reportedly streamlined workflows and supported iCPR tool uptake.

> *Structurally, we had a room all ready to do nurse visits that we do for other things. That was easy enough to adopt this [iCPR] into that.* [N 3.3]

> *We have a designated room for nurse visits every day 'cause we have nurse visits every day, and it's an exam room at the front of the clinic, and we have everything that we need in there.* [N 3.10]

Coupled with dedicated room space, time set aside for nursing appointments facilitated iCPR care workflows. One clinic workaround included having patients with sore throats or coughs come in at prescheduled time slots so that nurses and testing resources (such as throat swabs) were available. This allowed the clinic to structure the schedule in a way that allowed nurses to complete patient care activities.

> *I know that one of the things that we tried to focus on and try to do too, as far as our department, is we tried to make sure that we had like the 11:00 and 1:00 p.m. slots available for the nursing and cough and sore throat visits…* [N 3.4]

Variable Nurse Readiness With CDS-Guided Clinical Care

Among RNs who received training, there was variability in their comfort when providing clinical care guided by the iCPR tools. This was expressed as resistance to the delegation portion of the intervention regarding adherence to the iCPRs, staying within their scope of practice, and compatibility with their clinical skills.

Some nurses felt organizational resistance to operationalizing the delegation protocol, which required nurses to practice to the full extent of their qualifications. One nurse leader expressed that the intervention enables nurses to function within the bounds of what they are licensed to do, but existing clinic workflows may not be able to accommodate them.

> *It's asking our nurses to work at the top of our license. The problem is that it takes—the way that they've worked in urgent care for so many years, it causes a change in that workflow…Some of the leaders have been more willing to facilitate that process, and some have not.* [L 2.14]

Nurses expressed discomfort and uncertainty when triaging patients with cough-related symptoms, particularly when required to perform comprehensive respiratory assessments such as auscultating lung sounds. This hesitation often stemmed from fear of missing critical findings and potentially causing harm, which made them reluctant to fully engage with the iCPRs designed for these cases.

> *…there's a lot of nurses who do not like the cough part. They don't like to listen to lungs, and the reason is they're afraid they're going to miss something and harm patients.* [L 3.20]

Educating nurses was highlighted as a potential means of addressing these barriers. One nurse leader shared:

> *Training of new people training is huge, so I think and many people have to be hands on… mixture of hands-on CBT [Computer Based Training] all of that to reach the nurses…but I think training is key.* [L 3.20]

Conversely, nurses reported a strong sense of satisfaction with the sore throat iCPR, noting its simplicity and efficiency, allowing patient assessments to be completed in as little as 15 minutes.

> *The sore throat one we'll use constantly. That is very much something that has been, in my opinion, and I think our providers, everybody really, has been very successful.* [N 3.3]

Influence of Openness to Change and a Nurse-Supportive Clinic Culture

Nurse Factors

A supportive clinic culture, openness to change, and positivity toward nurse support influenced the use and sustainability of the iCPR-guided nurse delegation workflow. Within clinic culture, the perceptions of support from providers and patients emerged as subthemes, and leadership support was seen as crucial in facilitating the usage of the iCPR tool. Participants reported that leaders who actively listen to nurses and maintain ongoing dialogue foster a supportive environment that encourages new practices. Nurse leaders agreed that supporting staff was a success factor.

> *I think just making sure that staff are feeling confident and comfortable with the process, hearing where there's issues…I think just hearing what the staff is experiencing, trying to support them through any issues that are coming up, and making sure that they're confident in their training to conduct the visits.* [L 3.11]

> *Ongoing discussions with the nursing team to make sure that they feel supported.* [L 3.1]

The overall clinic culture was perceived to be particularly critical. One nurse described the culture of being open to novel processes.

> *…I think that our culture, to use that term for sure, is exceptional in that way. As far as being open to adopting things. Moving forward with nursing skills and nursing involvement in clinic practice is certainly something we focus on as a group and with our leadership.* [N 3.1]

Another participant reported the benefit of a shared value system within the clinic:

> *We have an excellent connection between each other. I think we all work for each other and with each other. There is a shared value system there that was very apparent and that is healthy in many ways… If my boss wasn't that interested in this, I think that we as a group would still be very interested together. We would have just done it by ourselves.* [N 3.1]

Moreover, nurses expressed aspects of professional fulfillment due to spending more time with patients:

> *Talking to the patients is great. Sometimes it's nice, the ones that you talk to, then you get to do a nurse visit.* [N 1.7]

> *Once again, I think it's great for us. It's great for the patient. I think being accessible and giving our patients what they need is—just been a really nice experience.* [N 3.2]

Provider Factors

Factors related to providers were found to be an essential subtheme of the clinic culture. Overall, the provider's acceptability of the processes was viewed as necessary for the sustainability of the iCPR3 tool.

> *We'd have to get the… medical director on board to really get the providers engaged with this. I do feel like providers are one of the bigger barriers. The nursing teams can do this work, but unless we work in collaboration, it'd be pretty hard to have it be sustainable.* [L 2.14]

When medical directors showed interest in teaching and experimenting with new workflows that incurred time savings, the tool's adoption by RNs was supported.

> *If they perceive, or if it's a reality that this program takes visits away from them, rather than gives them more time to see other patients. Then that could be a deterrent and also just their own understanding of how nursing practice can be used. I think in ambulatory it's sometimes disinterested.* [L 1.13]

> *When the doctors like to teach…then it's very helpful. Some doctors… don't even want to do the study…but the ones that want to teach then, that's very helpful.* [N 1.7]

Engagement from a medical director through collaboration was deemed important for facilitating clinic change.

> *It's doable, it's just, again, it's change management. It's really having everybody on board. Probably something that would help it move along better would be all the leaders and medical director meeting and deciding this is the right process….* [L 2.14]

Patient Factors

Patient engagement varied by location and was viewed as tightly connected to the clinic culture. Some nurses reported challenges in communicating the iCPR outcome to patients, especially when the patient had certain expectations connected to receiving antibiotics as part of the visit.

> *We have a low compliance rate in our clinic. When they come to see us, sometimes even when you're like, "You're not gonna see a doctor. You're just gonna see a nurse." They just want to come in and get antibiotics… When they come in and see us, I'm really like, "You're not gonna [get antibiotics]," but sometimes does not go over well with our patient population.* [N 3.10]

A number of issues also described a conflict between the delegation process and the patient's preference for provider type.

> *We do get some that are not interested in having the nurse visit type because they are looking to discuss other remedies or other treatment options, or their complexity medically is sometimes a barrier.* [N 3.18]

> *I think our patient population is different than other clinics. I think that that has made it a little bit harder… We do get pushback from our patients. They're like, 'Well, you're not a doctor,'…*
>
> *[N 3.10]*

However, some patients appreciated the extra access to appointments and were willing to have a nurse visit and were satisfied with the nurse visit.

> *I feel like patients are very agreeable and willing to come in to see a nurse, after we've explained exactly what's gonna happen… Patients have been really*

> *appreciative. No cost, they get in the same day, which is really what they're looking for…* [N 3.2]

Clinic Communication

General clinic communication was the final subtheme related to clinic culture. A nurse leader expressed interest in having more usage data about the study's progress to communicate with the staff for positive reinforcement.

> *…if people know the why we're doing it that helps…It really comes down to great patient care, antibiotic stewardship, how many visits we did. All of that. I think if we have that data, then as we train, we can bring that forward and show people why we're doing it.* [L 3.20]

Nurse participants also reported satisfaction connected to the receipt of feedback on the iCPR use.

> *I think it's been very positive and we—you guys send out the statistics and it reinforces that we are doing a good job and that always obviously makes me feel good that you are making a difference and… because obviously it's helping everybody. It's helping our patients. It's helping us.* [N 3.2]

Group communication and decision-making as a team were noted as key to the sustainability of clinic initiatives.

> *Again, it's about everyone deciding together that this is the right path and the way we want to go. Then moving it forward as a group so that it's not over here at this clinic but not at this clinic…It's just making sure you've got both nursing and operations, if we're going to really operationalize something and put it into permanent status.* [L 2.14]

Another participant emphasized the importance of teamwork among colleagues, noting the ability to share experiences and seek advice from others to navigate challenges.

> *My co-workers, my colleagues, us working together was another really important piece… Have you done this? Did you run into that?* [N 3.3]

In addition, communication tools were reported to provide support beyond programmatic issues and were seen as helpful in solving acute technology issues.

> *The Webex group was helpful troubleshooting technology issues. They were really good with the patient care part, but, if a technology issue came up, the Webex group was really helpful.* [N 3.6]

Ongoing Need for Training and Support

Participants felt that additional training, specifically hands-on training, would enhance the program's sustainability.

> *… Can we retrain? Can we have champions at the site who can help? Training of new people training is huge, so I think and many people have to be hands-on. Is it a mixture of hands-on CBT [computer-based training]… I think training is key.* [N 3.2]

Another participant reported that recurrent training would help with maintaining skills:

> *Offering skills' refreshers every once in a while if this is gonna be an ongoing thing would be helpful too.* [N 3.15]

> *I think education and I think not just a one and done education…at the time of hire, at the time of roll out or sustainability, but then I almost think something yearly just for people to review, ask questions, do hands on skills again* [L 3.20]

In the context of simulation training, a playground or safe, interactive environment was described to bridge this gap, providing a way for learners to practice skills without real-world consequences. One nurse leader was enthusiastic about ways to integrate hands-on training with the iCPR intervention.

> *I would say the hands-on training was fantastic for the nurses. They really appreciated it. It made them feel much more comfortable… in a setting where they can use the playground and practice the swabbing and stuff… making sure we can do a real-world, full-picture visit for practice would be really helpful.* [L 3.6]

Both nurse and nurse leader participants considered nursing leadership support to be part of the sustainability of this program. One of the nurse leaders described their approach as:

> *Just making sure the nurses are comfortable and have the training and education that they need. If the cough part is a barrier, working to get them hands-on training, making sure they've got swabs that they need, stethoscopes that they need, and just being support for them. If they don't have a buddy in the clinic that day, maybe I step in and do it with them.* [L 3.6]

Recommendations Based on Participant Feedback

Participants provided several recommendations to enhance the sustainability of the iCPR tool in nursing practice (Table 1).

Table . Recommendations.

Recommendation	Representative quote
Identify clinic champions	“have champions at the site.” “we’re going to need a provider champion.”
Educate patients	Educate the patients more on “This is what we’re doing.”
Organize frequent lunch and learns	“circling back to another … skill driven practice type session might be helpful just to make sure … we still feel confident that we can conduct it and not feel too flustered.”
Perform triage in advance	“When the first person that gets the [triage] call says, “Oh, they have a cough or a sore throat.” That’s very helpful because right away it’s identified …"
Map physical workflows	“… in the future … you can see the layout of how things are, then you can maybe give a suggestion or tell us something to make a different flow that works somewhere else.”
Incorporate into routine practice and policy	“… has to make it a delegation process … more than anything.”

Discussion

Principal Findings

The examination of the perceptions of nurses and nurse leaders familiar with the implementation of a CDS-guided nurse intervention for ARIs revealed several barriers and facilitators to the sustainability of the tools’ use beyond the conclusion of the study. Factors perceived as contributing to sustainability emerged within 5 themes, including (1) the importance of staffing stability and capacity; (2) the impact of dedicated clinic resource availability; (3) variable nurse readiness with CDS-guided clinical care; (4) the influence of openness to change and a nurse-supportive clinic culture; and (5) the ongoing need for training and support. By touching on the characteristics of the intervention, clinic setting, and individuals, these themes highlight several CFIR domain constructs and strategies at the individual and organizational levels to be considered when seeking to develop a sustainable CDS-guided intervention [15,19]. The most pertinent constructs identified in this research are local attitudes and conditions, partnerships and connections, structural characteristics such as physical and work infrastructure, organizational culture, available resources and space, the roles of innovation deliverers (nurses) and recipients (patients), as well as strategies for tailoring and adapting the use of the iCPR tool.

Individual-Level Strategies

Our analysis highlighted that nurses expressed lower confidence when using the iCPR tool for conditions requiring more complex or subjective clinical assessments, such as listening to breath sounds, compared to workflows perceived as more straightforward, such as visual inspections for sore throat evaluations. Indeed, several participants indicated a preference for sustaining use of the sore throat iCPR workflow only. This gap in confidence suggests a need for targeted skill development. Simulation-based training offers a valuable strategy to build these skills in a realistic, low-risk environment. Regular simulations can help nurses practice nuanced assessments, receive real-time feedback, and strengthen clinical judgment. Incorporating iCPR-related scenarios into onboarding and ongoing education can reinforce competence and confidence. Fostering a culture of continuous learning, with structured supervision and feedback, is essential for supporting effective and sustained implementation [20]. In alignment with CFIR individual constructs [15], the identification of subject matter experts could further assist and support access to information and knowledge.

Organizational-Level Strategies

As seen with many health care interventions, staffing levels were perceived as a key factor influencing long-term sustainability [21]. Inadequate ambulatory clinic nurse staffing impedes staff mastery of new procedures, restricts training time, and hinders comprehension of essential tools, such as EHR CDS modules [22]. Moreover, the increased complexity of ambulatory nursing requires nurse leaders to proactively adjust outpatient staffing models to meet evolving demands [23]. Staffing models were not adjusted to accommodate iCPR3; instead, participating units were only required to have at least one nurse. This model worked well for some clinics but not all. In settings with limited staffing, nurses may be forced to prioritize urgent clinical tasks over engaging with new initiatives, making it difficult to implement interventions effectively. Our findings suggest that a “one size fits all” approach may be inadequate. Instead, staffing models should be tailored to the needs of each clinic, particularly when new interventions are introduced. Due to national nursing shortages, calibrating nurse staffing is more important than ever before [24]. Adequate staffing enables nurses to focus on their patient care activities [24,25], allowing for better adherence to the CPRs. Study participants highlighted encountering challenges integrating new hires, resulting from turnover, and upskilling nurses who have transferred from other specialty areas. Prior to intervention implementation, analyses of turnover rates, percentage of new hires, and overall patient volume should be considered to ensure appropriate staffing availability, aligning with the CFIR construct of general staffing levels to support the functional performance of the inner setting [16]. Strategic planning should incorporate anticipated staffing fluctuations and allow flexibility in response to sudden staffing interruptions. The use of alternative staffing models, such as virtual nursing resources, needs to be considered. While an efficient use of nursing resources in some settings [26], hybrid work environments may contribute to barriers to care coordination and in-person visits.

Availability of clinic resources, especially physical space, was emphasized as a barrier more than expected. Success with the iCPR workflow hinged on ready access to supplies, designated rooms for nurse consultations, a supportive physical layout, and timely provider availability. Compared to inpatient hospital care, the outpatient environment is known to often lack infrastructure support [27]. When nurses had to search for appropriate locations to assess patients upon arrival, both efficiency and patient experience suffered. In contrast, clinics that reserved rooms specifically for nurse visits reported smoother workflows and better outcomes. As per the CFIR physical infrastructure construct, the impact of the layout and configuration of the space affects functional performance [15]. In nonambulatory clinics, similar issues have been previously observed, indicating that both ambulatory and nonambulatory settings face challenges related to resources. Despite progress in CDS tools, considerable barriers remain, especially regarding workflow integration and resource allocation [27]. Future implementations should therefore include a thorough assessment of space and workflow needs, ensuring that dedicated nurse-visit rooms and adaptable layouts are built into the design from the onset [28].

Clinics with positive experiences using the iCPR tools often reported a strong organizational culture characterized by teamwork, openness to change, and leadership that valued nurse autonomy, clinical expertise, and collaborative practice. Supportive leadership and a team-based approach further enabled the effective coordination between nurses and providers required to implement and sustain a new CDS intervention. As recognized by updated CFIR constructs, local attitudes and beliefs influence future use [15]. Participants also emphasized the importance of involving patients in shared decision-making, underscoring the need to respect patient preferences and set clear expectations during care encounters. This finding suggests that fostering a culture that empowers nurses, supports interdisciplinary collaboration, and centers patient engagement may be key elements to the successful nurse adoption of CDS tools in the ambulatory care setting [29].

Recognizing that the iCPR RCT took place in ambulatory settings connected to academic medical centers, there are insights that may translate to nonacademic centers. While community centers may be less resourced for experimentation and have underdeveloped nursing platforms, nurses in nonacademic settings often work at the top of their license out of necessity for patient throughput [30]. Prior to implementing the recommended strategies that connect to our findings, it will be important to compare workload patterns and assess the need for delegation protocols prior to implementing a similar intervention.

Limitations

Several limitations should be noted. This study was conducted within academic medical centers, which are typically characterized by greater infrastructural resources and institutional support, potentially limiting the generalizability of findings for community or resource-constrained settings. Additionally, we did not account for the differences in institutional policies, patient populations, or resource constraints as part of our examination. While thematic saturation was achieved, the final sample size was relatively small, and the sample skewed toward nurses at one site and toward nurse leaders rather than frontline nursing staff, which may have introduced hierarchical bias in perceptions of implementation. However, given low intervention engagement during the RCT at the Utah and NYU sites and that Wisconsin had the most nurses using the tool, we believe the sample was a representative of the iCPR RCT site variability. Participant selection may have been subject to response bias, as we used a convenience sample and did not stratify responses based on participants' familiarity with technology, experience, or frequency of tool usage. Because use of the intervention tools was part of the inclusion criteria, we did not assess the perspectives of nurses who did not perform a nurse visit or who did not participate in the RCT. In addition, participants were recruited and interviewed by known study personnel at their corresponding sites, which may have led to social desirability bias and impacted candor in participant responses. Lastly, this analysis does not include an examination of tool utilization or patient-level outcomes and their influence on perceived sustainability.

Conclusion

This qualitative analysis underscores the multifaceted nature of sustaining a CDS-guided nurse iCPR intervention for ARIs in ambulatory care settings after a formal study period. The findings reveal that sustainability hinges not only on the design of the intervention but also on contextual factors such as staffing adequacy, resource availability, nurse confidence, organizational culture, and ongoing training. Importantly, variability in nurse comfort with CDS tools and differential success across clinic settings suggest that tailored implementation strategies are essential. Future efforts should prioritize clinic-specific readiness assessments, targeted skill development, and leadership engagement to enhance the long-term viability of nurse-led CDS interventions in clinical workflows.

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Data Availability

The datasets generated during this study are not publicly available due to privacy restrictions but may be made available from the corresponding author upon reasonable request.

Authors' Contributions

Conceptualization: VLT, ADT, NH, MB, KM, LX, HB, AY, RH, DMM, DF, ERS
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Methodology: VLT, ADT, NH, MB, KM, LX, HB, AY, RH, DMM, DF, ERS
Formal analysis: VLT, ERS, NH, MB, KM, AY, ADT
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Funding acquisition: DM, DF, RH

Conflicts of Interest

None declared.

Multimedia Appendix 1
iCPR survey tool questions.
[DOCX File, 18 KB - nursing_v9i1e83567_app1.docx]

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Abbreviations

ARI: acute respiratory infection
CDS: clinical decision support
CFIR: Consolidated Framework for Implementation Research
CPR: clinical prediction rules
EHR: electronic health record
iCPR: integrated clinical prediction rules
RCT: randomized controlled trial
RN : Registered Nurse

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Association Between Electronic Health Record–Based Nursing Workload and Turnover: Retrospective Cohort Study

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Abstract

Background: Nurse turnover remains a major challenge for health systems, yet objective, scalable measures of workload that predict turnover are limited. Electronic health record (EHR) audit logs offer a potential data source to quantify nursing work patterns.

Objective: This study aimed to evaluate the association between EHR-derived measures of nursing workload and turnover among inpatient nurses.

Methods: We analyzed work-related activities of staff nurses from medical and surgical inpatient units at a large academic medical center from January 1, 2022, to December 31, 2022. Data included deidentified demographics (age, sex, years since licensure, and service group), shift characteristics (number of shifts worked, proportion of night shifts, timing, and location), and measures of work activities derived from EHR audit logs. Audit logs were used to develop measures related to nurse workload, including (1) nurse activities (information review, medication administration, alert management, navigation, documentation, and communication), (2) patient load (based on the number of unique patient charts accessed), and (3) cognitive load (based on the number of patient switches). For nurses who left, we excluded the 6 weeks immediately preceding termination (washout period) and measured workload during the preceding 6-week period; for those who remained, a random 6-week working period was selected. Associations between workload measures and turnover were assessed using mixed-effects logistic regression, adjusting for demographics and shift-related characteristics.

Results: Among 432 nurses (n=363, 84% female; median age 27, IQR 23-36 years), contributing 6812 shifts and approximately 13 million audit log actions, 84 (19%) left the institution in 2022. A higher proportion of medication administration actions was associated with higher odds of turnover (odds ratio [OR] 2.20, 95% CI 1.36-3.54), whereas greater alert engagement (OR 0.48, 95% CI 0.32-0.72) and more years since licensure (OR 0.57, 95% CI 0.38-0.84) were associated with lower odds of turnover.

Conclusions: EHR-derived workload measures, particularly greater medication administration burden and lower alert engagement, were independently associated with the risk of nurse turnover. Patterns of EHR use may help identify nurses at higher risk of leaving an institution and can potentially inform targeted workforce retention strategies.

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KEYWORDS

electronic health records; nursing workload; clinical informatics; nurse turnover; workforce retention

Introduction

Nurse turnover has increased exponentially over the past decade, posing a threat to health system stability. In the United States, annual turnover rates rose from approximately 18% in 2016 to approximately 29% immediately following the COVID-19 pandemic [1-3]. Globally, the scale of the problem is equally alarming, with similarly high rates of nurses reporting intentions to leave their organizations [4-6]. High nursing turnover destabilizes care teams, increases medication errors, reduces quality of care, and imposes substantial operational and financial burdens on health care systems [3].

Despite the considerable challenges associated with nurse turnover, its underlying drivers remain poorly understood. Prior work has often linked nurse turnover to factors such as demographics, organizational dynamics [7,8], and workload [1,2,9], primarily relying on observational methods such as surveys, interviews, and focus groups [10-12]. For example, Zheng et al [6] used responses to questionnaires to assess factors such as professional fulfillment, emotional exhaustion, and self-efficacy as contributors to turnover. Other studies have used similar methods to characterize the contributors to nurse turnover and have found high perceived workload, low workplace commitment, poor team collaboration, and lack of recognition from supervisors to be key contributors to nurse burnout and intentions to leave [13,14]. Although these studies provide considerable insights, they depend heavily on self-reported assessments, require significant human effort, and are subject to recall bias, response bias, and limited scalability [1].

Electronic health record (EHR) audit logs offer a scalable approach to quantify nursing workload, capturing time-stamped data on EHR use, including documentation, information review, medication administration, messaging activities, and even indicators of cognitive load such as patient switches and on-screen interruptions [15-17]. However, despite the availability of detailed EHR interaction data from audit logs, little is known about how measures of day-to-day nursing work activities relate to turnover.

In this study, we address this gap by investigating the association between EHR-based measures of nursing workload and subsequent turnover among inpatient nurses at a large academic medical center. By linking nurse work activity metrics with real-world employment outcomes, we aim to provide new insights into how daily clinical work patterns may relate to nurses' decisions to leave their roles.

Methods

Study Setting, Participants, and Inclusion Criteria

This retrospective cohort study included all staff nurses who worked at least 1 clinical shift on a medical or surgical inpatient unit at a large academic medical center in St. Louis, Missouri, between January 1, 2022, and December 31, 2022. Temporary or visiting nursing staff and individuals not officially employed by the hospital were excluded.

Ethical Considerations

This study was approved by the Washington University Institutional Review Board (IRB#202306138) with a waiver of informed consent. All data were deidentified prior to analysis, and no individually identifiable information was available to the study team. Appropriate measures were taken to protect participant privacy and maintain data confidentiality throughout the study. Participants were not directly involved in the research and did not receive any compensation.

Data Sources

We obtained deidentified data on eligible nurses from three primary sources: (1) employment records, which provided demographic and employment details (age, sex, years since nursing licensure, duration of employment, and turnover status [ie, whether the nurse left the hospital system in 2022]); (2) nurse shift records, which included daily punch-in and punch-out times, nursing unit (eg, general medicine unit, postprocedure unit, or general surgical unit), level of care (eg, acute, intermediate care, or observation), and clinical service group (medical or surgical); and (3) EHR-based audit logs extracted from Epic (Verona, Wisconsin) Clarity tables (ACCESS_LOG), which provide time-stamped records of nurses' EHR interactions and the corresponding patient charts.

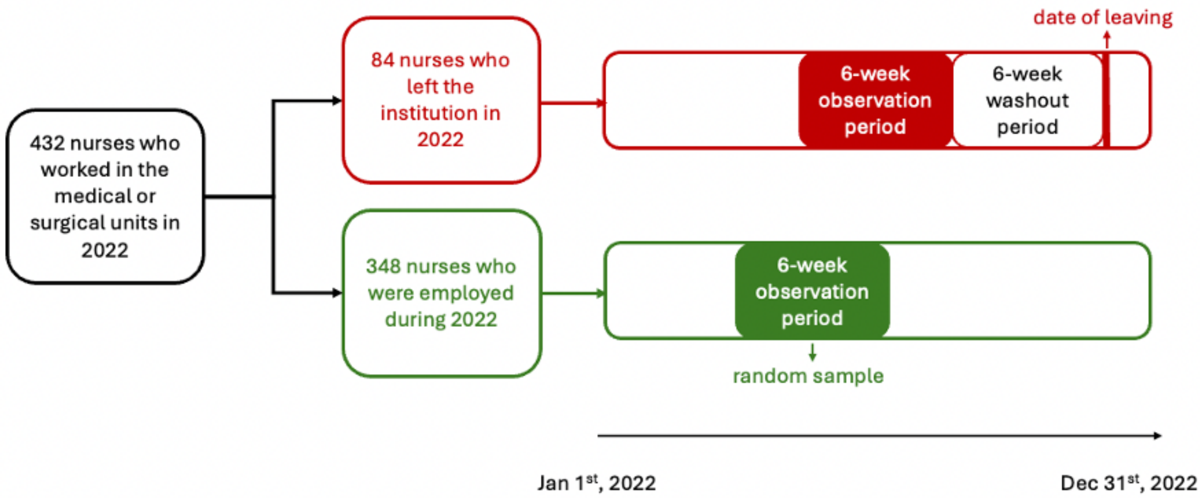
Experimental Design

To examine the relationship between EHR-based measures of nurse workload and turnover, we classified nurses into 2 groups: those who left the institution during the 2022 calendar year ("left" group) and those who remained employed throughout the year ("stay" group).

To ensure temporal comparability between groups, we constructed a standardized 6-week observation window for each nurse. The choice of the 6-week period was based on discussions with nursing collaborators across various units rather than on specific empirical evidence.

For nurses who left, we imposed a 6-week washout period before their termination date to avoid capturing behavioral changes occurring after the decision to leave. We then analyzed shifts during the 6-week window immediately preceding the washout period (Figure 1; the red vertical bar marks the date the nurse left, and the filled red bar shows the observation window).

Figure 1. Overall study design. Nurses were grouped into those who were employed at the end of the calendar year (2022) and those who left the institution. For those who left the institution, the date of leaving was used to define a 6-week washout period, and the 6 weeks prior to the washout period were used as the "data period" to calculate the workload metrics. For those who stayed, a random 6-week period during the calendar year was selected for workload metric calculation.



For nurses who remained employed, we randomly selected a 6-week working period during the year-long study period (Figure 1; the filled green bar shows the observation window). This approach ensured consistent observation lengths while minimizing temporal bias and reducing the likelihood that observed behaviors reflected impending departure rather than typical workload.

Data Processing

Each audit log entry included a time stamp, user identifier, patient identifier, and the specific EHR action performed, allowing us to quantify both the frequency and the type of EHR interactions for each nurse during each shift. Audit log events were linked to each nurse's shift by matching time stamps to staffing punch-in and punch-out records, which defined the temporal boundaries for measurement for each shift. To characterize individual nurse workload patterns, we derived shift-level metrics and then summarized these across shifts within each nurse's observation window (ie, 6 weeks).

We first used punch-in and punch-out time records to calculate overall schedule-related metrics for each nurse, including the total number of shifts worked during the 6-week observation period and the proportion of shifts occurring during overnight hours (defined as shifts with punch-in or punch-out times between 7 PM and 7 AM; Figures S1 and S2 in Multimedia Appendix 1). These variables were included to adjust for potential differences in workload and turnover risk associated with shift patterns.

Workload metrics included three domains: (1) EHR-based nursing activities, (2) patient load (with the number of unique patient charts accessed per shift used as a proxy), and (3) cognitive effort (with patient-switching actions used as a proxy) [18,19].

To characterize the composition of EHR-based nursing activities, we relied on prior time-and-motion studies that provided detailed insights into nursing workflows in the EHR [20]. The categorization framework was developed through an iterative process involving audit log experts and clinical domain experts (coauthors LT and SL) familiar with clinical and nursing workflows. Audit log actions were initially mapped to functional task types using vendor documentation and institutional data dictionaries and then refined through multiple rounds of structured clinician review to ensure face validity and interpretability.

Specifically, we categorized EHR actions into 6 EHR-based nursing activities: information review (eg, viewing patient reports, storyboard, and clinical notes); medication administration (eg, barcode scanning, barcode processing, and reviewing administration data); documentation (eg, interacting with flow sheets and clinical forms); workflow navigation (eg, accessing the inpatient system list and loading patient lists); active alert management (eg, acknowledging best practice advisories, reviewing medication warnings, or taking recommended actions); and communication (eg, secure chat communication; refer to Table 1 for category descriptions). Table S3 in Multimedia Appendix 1 provides the complete actions of audit log mapping to activity categories.

Table . Nurse workload categories, their description, and associated example metrics from audit logs[a].

Categories	Description	Example metrics (from audit logs)
Information review	Encompasses nurse activities involving the examination and evaluation of patient-specific data and associated clinical documentation	• Report with patient data viewed • Storyboard viewed • Flow sheet viewed
Medication administration	Involves clinical workflow and procedural tasks required for the administration of medications	• Barcode scanned • MAR[b] barcode processed • MAR administration viewed
Documentation	Activities focused on entering, updating, or interacting with clinical documentation	• Flow sheet accepted • Flow sheet data copied forward • Inpatient work list task edited
Navigation	Actions related to moving through the Epic system to access different functions or patient records	• Visit a loaded Navigator template • Inpatient system list accessed • Radar dashboard accessed
Active alerts	Interactions with system-generated alerts and clinical decision support advisories	• Best practice advisories acknowledged • Medication warning displayed • Patient chart advisories viewed
Communication	Activities using secure messaging apps to facilitate communication and care coordination among the health care team	• Secure chat conversation opened • Secure chat conversation created • Secure chat activity accessed

[a]A full list of the audit logs for each category is provided in Multimedia Appendix 1.

[b]MAR: Medication Administration Record.

We calculated the number of patient switches per shift as a proxy for cognitive effort, reflecting the frequency with which nurses transitioned between patient charts during active EHR use [15,17]. Consistent with prior work, a patient switch was defined as a transition from one patient's chart to another within 5 minutes, to reflect active transitions rather than idle time [17].

Additional workload measures included the total number of EHR actions per shift, the number of unique patient charts accessed per shift (ie, patient load), and time spent using the EHR per shift. Time spent using the EHR, measured in minutes, was calculated from audit log data by summing the time intervals between successive audit log actions, excluding intervals exceeding 5 minutes, which were considered periods of inactivity [18,19].

To summarize these workload indicators at the individual nurse level, we aggregated each nurse's total task-based EHR actions, unique patient charts accessed, and patient switches across the entire 6-week observation period. Specifically, we calculated the proportion of each nurse's EHR actions falling into each activity category by dividing task-specific action counts by the nurse's total EHR actions. For shift-level workload frequency measures, we computed the median value of each metric across all observed shifts for each nurse. Together, these task-based EHR activity proportions and shift-level workload frequency measures served as the primary exposure variables, capturing individual differences in overall EHR-based workload.

Covariates in the regression models included demographic characteristics and shift-related patterns. Demographic characteristics included age, sex, years since licensure, and primary clinical service group. Shift-based factors included the total number of shifts worked and the proportion of night shifts.

All data processing and feature engineering were conducted in Python (version 3.9.10; Python Software Foundation) using the following libraries: Pandas (version 2.2.2) for data manipulation, Matplotlib (version 3.10.3) and Seaborn (version 0.13.2) for visualization, and Scikit-learn (version 1.6.1) and Statsmodels (version 0.14.4) for data preparation [21-26].

Outcome

The primary outcome was nurse turnover, defined as a binary variable indicating whether the nurse left the organization during the 2022 calendar year.

Statistical Analysis

Descriptive statistics were calculated as medians and IQRs or frequencies and percentages. Univariable comparisons between nurses who stayed and those who left were conducted using the Wilcoxon rank-sum test for continuous variables and the chi-square test for categorical variables. Because task-specific action categories are compositional and collectively sum to approximately 100%, we conducted a collinearity analysis using variance inflation factors to assess potential multicollinearity among these variables (Table S1 in Multimedia Appendix 1). On the basis of this assessment and input from clinician experts, the workflow navigation category demonstrated substantial collinearity with other task categories, particularly information review, and was therefore excluded from multivariable modeling to improve model stability and interpretability; information review was retained given its clinical relevance.

To assess the association between EHR-based nursing workload measures and turnover, we used a mixed-effects logistic regression model with random intercepts for nursing units to account for the contribution of each unit's culture and work environment to turnover. The statistical model adjusted for demographic factors (age, sex, years since licensure, and service group), shift characteristics (number of shifts worked and proportion of night shifts), and workload intensity (total EHR actions, patient switches, and number of patients cared for). All continuous predictors were standardized using IQR scaling prior to modeling. Thus, reported odds ratios (ORs) and 95% CIs represent the association with a 1-IQR increase (from the 25th to the 75th percentile) in each continuous predictor.

To assess robustness, we conducted a sensitivity analysis using a shorter 2-week washout period prior to each nurse's departure. Statistical analyses were performed using R (R Foundation for Statistical Computing) with the lme4 package [27].

Results

Sample Characteristics

The analytic sample included 432 inpatient nurses who collectively contributed 6812 shifts and more than 13.8 million EHR audit log actions during the study period (Table 2). Of these nurses, 84 (19%) left the institution (Figure 1). The sample was predominantly female (84%), with a median age of 27 (IQR 23-36) years. In total, 60% (n=259) of the nurses worked on surgical services and 40% (n=173) worked on medical services.

Table . Study cohort characteristics stratified by turnover status (N=432).

Turnover status in 2022	All participating nurses	Nurses who stayed (n=348)	Nurses who left (n=84)	*P* value
Number of shifts	6812	5543	1269	N/A[a]
Number of audit log actions	13,807,571	11,228,809	2,578,762	N/A
Age (years), median (IQR)	27 (23-36)	28 (23-37)	26 (24-31)	.58
Sex, n (%)				.67
Female	364 (84)	295 (85)	69 (82)	
Male	68 (16)	53 (15)	15 (18)	
Clinical service group, n (%)				.60
Surgical unit	259 (60)	206 (59)	53 (63)	
Medicine unit	173 (40)	142 (41)	31 (37)	
Years since licensure, median (IQR)	2 (1-6)	3 (1-9)	1 (1-3)	.01[b]
Shift characteristics, median (IQR)				
Shift counts	17 (12-20)	17 (12-20)	17 (13-19)	.12
Proportion of night shifts (%)	10 (0-94)	11 (0-94)	7 (0-94)	.75
EHR[c] workload intensity, median (IQR)				
EHR time per shift time (%)	33.87 (28.67-39.09)	33.87 (28.57-39.52)	33.85 (28.93-37.99)	.82
EHR time per shift (minute)	260 (216-302)	261 (215-305)	257 (217-289)	.54
Patient charts accessed per shift	6 (5-9)	6 (5-9)	6 (5-9)	.82
Patient switches per shift	61 (44-82)	60 (44-85)	64 (46-80)	.50
EHR actions per shift	2088 (1464-2723)	2122 (1430-2751)	1964 (1566-2595)	.99
EHR task composition (percentage of total EHR actions), median (IQR)				
Documentation	5.96 (4.75-8.10)	5.91 (4.69-8.15)	6.16 (5.02-7.94)	.38
Medication administration	8.75 (6.65-11.98)	8.54 (6.44-11.69)	9.61 (7.41-12.49)	.02[b]
Navigation	9.41 (5.09-15.50)	9.31 (4.86-15.66)	9.84 (5.71-14.41)	.82
Information review	69.55 (57.30-74.58)	69.58 (57.72-74.84)	69.42 (56.16-74.02)	.67
Active alert	0.16 (0.09-0.27)	0.17 (0.09-0.31)	0.14 (0.06-0.19)	.01[b]
Communication	0.73 (0.36-1.38)	0.71 (0.36-1.35)	0.83 (0.43-1.38)	.31

[a]N/A: not applicable.

[b]Indicates statistical significance at the *P*<.05 level.

[c]EHR: electronic health record.

Nurses who left the organization were younger on average (median 26 vs 28 years), although this difference was not statistically significant. They had substantially fewer years since licensure (median 1, IQR 1 - 3 years vs median 3, IQR 1 - 9 years). Sex distribution and clinical service group were similar between groups.

Univariable Analysis

Shift patterns did not differ meaningfully between nurses who stayed and those who left, with a comparable number of shifts worked during the observation window (median 17 in both groups) and similar proportions of night shifts.

Overall EHR workload intensity—including median EHR time per shift, proportion of shift time spent in the EHR, total EHR actions, number of unique patient charts accessed, and number of patient switches—was nearly identical between groups (all *P*>.30).

However, 2 EHR task composition measures differed significantly. Nurses who left had a higher proportion of medication administration actions (median 9.61%, IQR 7.41% - 12.49% vs median 8.54%, IQR 6.44% - 11.69%; *P*=.02) and a lower proportion of active alert engagement (median 0.14%, IQR 0.06% - 0.19% vs median 0.17%, IQR 0.09% - 0.31%; *P*=.01). No significant differences were observed across other EHR activity categories, including documentation, information review, navigation, or communication (Table 2).

Multivariable Analysis

In mixed-effects logistic regression models adjusting for demographic characteristics, shift patterns, and workload intensity, task composition emerged as the primary workload-related predictor of turnover (Table 3). An increase in the proportion of medication administration actions from the 25th percentile (6.65%) to the 75th percentile (11.98%) was associated with more than twice the odds of leaving the institution (adjusted OR 2.20, 95% CI 1.36 - 3.54). Conversely, an increase in active alert engagement from the 25th percentile (0.09%) to the 75th percentile (0.27%) was associated with substantially lower odds of turnover (adjusted OR 0.48, 95% CI 0.32 - 0.72).

Table . Multivariable analysis showing the association between nursing workload components, demographics, work-related aspects, and turnover.

Variables	Scaled odds ratio (95% CI)	*P* value
Age (years; as of 2022)	1.04 (0.61 - 1.79)	.88
Sex (male vs female)	0.79 (0.39 - 1.59)	.50
Clinical service group (surgical vs medicine)	1.05 (0.53 - 2.07)	.90
Years since licensure	0.57 (0.38 - 0.84)	<.01[a]
Number of shifts worked	0.79 (0.56 - 1.12)	.18
Proportion of night shifts	0.89 (0.47 - 1.67)	.72
Median EHR[b] actions per shift	1.43 (0.80 - 2.54)	.23
Median patient charts accessed per shift	1.07 (0.87 - 1.32)	.53
Median patient switches per shift	0.93 (0.64 - 1.35)	.70
Information review (percentage of total EHR actions)	0.93 (0.44 - 1.96)	.84
Medication administration (percentage of total EHR actions)	2.20 (1.36 - 3.54)	<.01[a]
Documentation (percentage of total EHR actions)	0.95 (0.70 - 1.31)	.77
Active alert (percentage of total EHR actions)	0.48 (0.32 - 0.72)	<.01[a]
Communication (percentage of total EHR actions)	0.96 (0.61 - 1.51)	.86

[a]Indicates statistical significance at the *P*<.05 level.

[b]EHR: electronic health record.

Years since licensure also remained significant; an increase from the 25th (1 year) to the 75th percentile (6 years) was associated with lower odds of leaving (adjusted OR 0.57; 95% CI 0.38-0.84). No other demographic variables, shift characteristics, or workload intensity measures demonstrated significant associations with turnover.

Sensitivity Analysis

A sensitivity analysis using a 2-week washout period before departure produced results consistent with the primary analysis, supporting the robustness of the associations identified (Table S2 in Multimedia Appendix 1).

Discussion

In this study, we investigated the association between EHR-based nursing workload and the likelihood of leaving the institution. We found that fewer years since nursing licensure and performing a higher fraction of medication administration actions were associated with higher odds of turnover. We also found that an increased fraction of active EHR alerts was associated with lower odds of turnover. Taken together, these findings have implications for understanding and potentially redesigning EHR-based nursing workload.

There are several possible explanations for the finding that a higher fraction of medication administration actions was associated with higher odds of turnover. The association of medication administration and documentation with chronic stress and burden has been well-documented [28]. Medication administration is a complex, multistep process involving identifying patients due for medications, prioritizing schedules, accessing centralized dispensing systems, and individually retrieving medications. These tasks may also include secondary nurse verification or additional preparation steps, most of which are not captured in EHR audit logs. Balancing complex medication schedules and performing detailed documentation can lead to mental fatigue and a persistent sense of "catching up" on charting. Over time, this may contribute to emotional exhaustion and increase the likelihood of turnover intention or actual departure [29,30]. During medication workflows, nurses may also encounter various interruptions—from unit alarms to emergency scenarios and interprofessional requests—which further elevate workload and burden [31]. Additionally, increased medication administration burden may serve as a proxy for higher patient complexity, with sicker patients requiring more frequent interventions, although we could not directly measure patient complexity in this study.

We also found that a higher proportion of active alert engagement was associated with lower odds of turnover. For this study, active alerts were defined as audit log events requiring explicit acknowledgment, often surfacing high-priority safety checks or patient status cues that help structure nurses' decision-making. Nurses engaged with a median of 1.5 active alerts per shift (IQR 1.0 - 3.0), indicating that these events are infrequent and unlikely to represent a significant burden. Rather, they may function as a helpful tool that enhances situational awareness, reinforces clinical priorities, and reduces cognitive load by externalizing key reminders. Therefore, nurses who engage with these alerts may experience greater clarity, support, and alignment with expected workflows, mitigating the sense of chaotic work environments that contribute to turnover. Although we could not differentiate alert types, the small absolute variation in alert fractions across clinicians (0.09% to 0.27%) likely reflects the low frequency of these high-salience events rather than differences in overall workload. Differences in alert engagement may signal how effectively nurses interact with digital workflow supports. Importantly, our model adjusted for demographics, shift type, clinical service, and overall EHR activity, making it less likely that this association reflects underlying workload differences alone. Future work characterizing alert content, cognitive load, and perceived usefulness may clarify whether active alert engagement functions as an indicator of supportive digital environments that promote clinician engagement and retention.

This study has several strengths. It was a longitudinal study that included all nurses at a large academic medical center over 1 year (432 nurses, 6812 shifts, >13 million audit log actions), providing a detailed and objective assessment of EHR-based workload. Our audit log measures captured granular shift-level behaviors, offering a scalable framework to quantify workload patterns that may influence clinician retention. Consistent with prior time-and-motion studies, we found that nurses spent approximately 34% of each shift on EHR activities, including documentation, chart review, and medication management, highlighting the substantial cognitive and administrative demands of modern nursing work [20].

This study also has several limitations. First, this was a single-center study of specific inpatient settings over 1 year. Although we had a large sample, findings may not generalize to other institutions or regions. In addition, the cohort was relatively young (median age 27 years) and in an early career stage (median 2 years since licensure), which may not reflect the broader nursing workforce. Turnover drivers in this population may differ from those in more experienced nurses (eg, career development vs long-term occupational strain), which may influence the observed associations.

Second, audit logs do not capture all aspects of nursing work—such as direct patient care, interpersonal interactions, or work with other technologies (eg, medication-dispensing systems). Thus, our workload measures reflect EHR-based workload only. However, prior research demonstrates that audit logs offer an objective measure of cognitive and administrative workload, capturing a critical aspect of modern clinical practice that can influence clinician engagement and retention [15,32].

Third, our dataset was limited to nurses directly employed by the institution; in other words, the service time only reflected their tenure as employees. If a contingent or agency nurse transitioned to direct employment, their prior service as a nonemployee was not reflected. Furthermore, agency or travel nurses who were not direct employees of the health system were not included in our sample.

Fourth, patient complexity and exact nurse-patient assignments could not be fully accounted for. Patient load was derived from EHR audit logs and operationalized as the number of unique patient charts accessed per nurse, rather than staffing assignment data. Although we adjusted for patient load using this measure and included unit type as a covariate, these proxies may not fully capture patient complexity or staffing patterns. Because nurses may access charts for patients who are not formally assigned to them, this measure may not precisely reflect true patient assignments, introducing potential measurement imprecision. Medication administration–related EHR activity may reflect higher patient complexity, medication burden, or assignment to higher-intensity units rather than workload strain alone, and residual confounding by unmeasured clinical factors (eg, patient acuity) remains possible. Direct measures of patient acuity (eg, case-mix index or high-risk medication exposure) were not available in this dataset.

Fifth, our analysis focused on nurses who fully left the organization and did not include those who transferred internally to other units. To avoid mixing data from prior assignments, our observation window was restricted to each nurse's current unit. Although internal transfers were relatively few, they may still create administrative burden, incur training costs, and pose temporary staffing challenges, which warrants further study alongside complete organizational turnover. Additionally, turnover was defined based on recorded separation from employment, and the reason for leaving (eg, voluntary resignation, termination, or contract completion) was not available, which may introduce heterogeneity in the outcome.

Sixth, workload metrics were aggregated at the nurse level using medians and proportions across shifts to align exposure measurement with a nurse-level outcome of turnover. Although this approach reduces noise in shift-to-shift variability and reflects overall workload exposure during the observation period, it may obscure within-nurse variability, including high-burden shifts. As such, infrequent but extreme workload experiences may not be fully captured. Multilevel shift-based modeling could potentially help in characterizing such patterns.

Finally, we applied a 6-week washout period, based on input from clinical collaborators, to account for the time nurses typically take to decide to leave the organization. We acknowledge that individual decision timelines vary; however, sensitivity analyses using a shorter, 2-week washout period confirmed the robustness of our findings.

Despite these limitations, this study demonstrates a scalable, data-driven approach to quantifying EHR-based nursing workload and its association with turnover. Findings highlight the potential of granular workload measures to identify patterns of digital work allocation that may relate to clinician retention. Future work should integrate direct measures of patient complexity and qualitative assessments of unit culture, interpersonal dynamics, and institutional factors, as well as validate these measures across diverse health systems, to better understand how digital workload interfaces with nurse engagement, burnout, and workforce stability.

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The authors declared that no financial support was received for this work.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Association between electronic health record–based nursing workload and turnover.

[DOCX File, 71 KB - nursing_v9i1e89645_app1.docx]

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Abbreviations

EHR: electronic health record
OR: odds ratio

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Voice-Based Structured Nursing Documentation Using Automatic Speech Recognition and Large Language Models: Development and Evaluation Study

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Abstract

Background: For clinical nurses, manually entering information into hospital information systems (HISs) remains time-consuming and prone to omissions. Although speech recognition can reduce the need for manual entry, its use in clinical settings has historically been limited by code-switching, medical terminology, and noisy ward environments. Recent advances in customized automatic speech recognition (ASR) and large language models (LLMs) now make speech-based, structured documentation aligned with nursing frameworks such as DART (data, action, response, and teaching) increasingly feasible.

Objective: This study developed and evaluated an integrated ASR and LLM system that transforms spoken nursing input into structured DART notes and evaluated its accuracy, usability, and clinical feasibility within HIS workflows.

Methods: A code-switching nursing speech corpus from emergency and ward settings was used to fine-tune the Whisper large-v2 model with parameter-efficient adaptation. The LLM generated schema-constrained DART records from ASR transcripts, which were verified by nurses before being uploaded to the corresponding HIS fields. Evaluation included mixed error rate for ASR accuracy, F_1-scores, and agreement statistics for DART classification, hallucination assessments based on factual correctness, and analysis of nurse feedback on system use.

Results: The fine-tuned ASR model reduced the mixed error rate from 44.79% to 6.67%. DART generation achieved a macroaveraged F_1-score of 0.82 (95% CI 0.80 - 0.84) and met the noninferiority margin relative to human transcripts (δ=−0.04). The hallucination rate was 2.51%. During deployment, the monthly volume of valid nursing notes generated through voluntary use of the ASR system increased from 32,724 to 65,417, where each note represented a single documentation entry generated per patient care episode. Among 120 participating nurses, 91 (75.8%) reported reduced workload and improved completeness.

Conclusions: The integrated ASR and LLM system was feasible and showed strong performance, with good acceptance among clinical nurses. It reduced the manual documentation burden, improved record completeness, and demonstrated the value of an ASR- and LLM-supported workflow for nursing documentation.

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KEYWORDS
automatic speech recognition; code-switching; large language model; nursing; documentation; nursing records

Introduction

Taiwan has faced a sustained shortage of clinical nurses, driven largely by low retention among licensed professionals rather than limited training capacity. The national nursing practice rate—representing the percentage of licensed nurses actively working in the profession—remains at only 59.1% [1]. This low retention of qualified staff exacerbates the clinical shortage, and excessive workloads and long shifts are strongly associated with burnout and turnover intention [2-4]. Documentation occupies a substantial portion of clinical workflow time, and existing digital systems have not fully reduced the need for manual input. As hospitals have expanded the use of hospital information systems (HISs), additional documentation requirements have emerged, prompting efforts to standardize formats and improve system integration [5]. Structured and interoperable records support continuity of care, and structured handoff protocols improve communication quality [6,7].

Moreover, higher perceived nursing information system quality is linked to greater use, satisfaction, and retention, while electronic record use embedded in routine workflows reduces documentation workload and intention to leave [8,9]. These findings highlight the need for documentation tools that are structured, interoperable, and well-integrated into daily clinical practice.

Many hospitals have introduced structured documentation frameworks to improve consistency and communication. Among these, the Focus Charting method has been particularly influential in Taiwan. Originating in the late 1980s [10] and adopted locally in the early 1990s [11], it organizes each nursing note around a defined patient focus and follows the DART (data, action, response, and teaching) pattern to support concise and standardized recording of observations, interventions, patient responses, and teaching activities. Implementation studies have reported clearer note organization, improved execution of care plans, and enhanced interdisciplinary collaboration in intensive care settings [12]. However, structured formats alone do not resolve the documentation burden. Even with electronic templates, nurses must still enter most information manually, and flowsheets—standardized tabular records used for tracking routine, time-sequenced clinical parameters such as vital signs—may occupy a substantial portion of each shift [13]. These limitations highlight the need for intelligent support that preserves the clarity of DART records while reducing repetitive manual effort.

Automatic speech recognition (ASR) has been explored as a way to reduce manual documentation effort, with multisite evaluations reporting higher efficiency and satisfaction [14,15]. In Taiwan, a longitudinal study involving 21 nurses (using a corpus of 30,112 words) found that mean accuracy improved from 87.06% to 95.07% across 4 evaluation sessions as users developed more stable speaking speeds and volumes [16]. Furthermore, an ASR system designed for code-switching—the practice of alternating between languages, such as Mandarin and English, within a single utterance—achieved a word error rate (a standard metric representing the percentage of transcription errors) of 12.3% in intensive care settings [17].

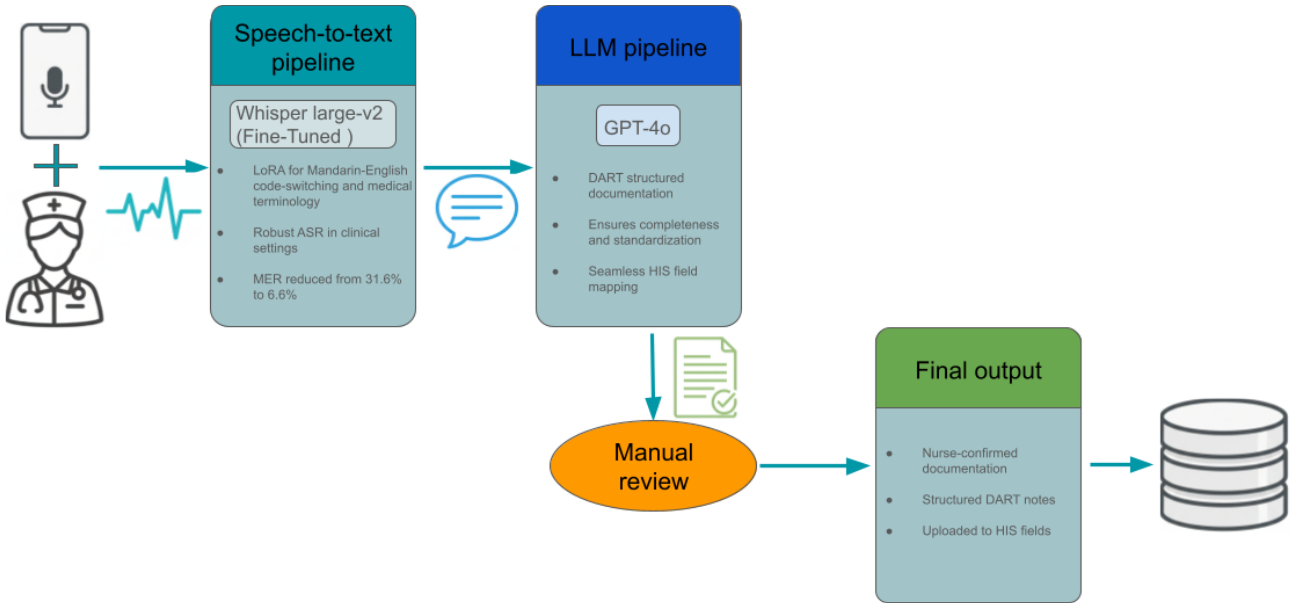
Recent reviews suggest that clinical speech technologies are rapidly evolving toward large language model (LLM)–driven ambient clinical intelligence, with mature commercial solutions (such as Heidi, Tortus, and Rebrief.ai [Rebrief Inc]) being successfully deployed in various settings to provide summarization, repurposing, and assistive autonomy [18]. However, although these ambient scribes excel in standard clinical encounters, their direct application to Taiwanese nursing workflows presents significant challenges. First, commercial systems are primarily optimized for monolingual or standard bilingual speech and often struggle with the dense, specialized Mandarin-English code-switching and local abbreviations prevalent in Taiwanese hospital wards. Second, existing tools typically generate generalized clinical summaries (eg, subjective, objective, assessment, and plan notes), lacking the fine-grained, schema-constrained precision required for specialized nursing frameworks such as DART and its direct interoperability with local HISs. Therefore, a bespoke ASR and LLM pipeline is necessary to address these specific linguistic and structural demands. To bridge this gap, this study developed and evaluated an integrated voice-to-report system that combines a domain-adapted ASR model with an LLM to generate structured DART nursing documentation aligned with HIS fields. The system was assessed using transcription accuracy, DART classification performance, and noninferiority testing, and its feasibility and workflow impact were examined during real-world deployment.

Methods

Study Design and System Overview

This development and evaluation study implemented a mobile-based nursing documentation system designed to convert voice input into structured clinical records (Figure 1). The system was deployed at China Medical University Hospital (CMUH) to evaluate its feasibility, transcription accuracy, and impact on documentation workflow. During routine care, nurses recorded observations and interventions using a mobile device. Audio input was processed by a domain-adapted Whisper ASR model trained on a Mandarin-English code-switching corpus and adapted to the medical terminology common in nursing communication. Transcribed text was subsequently processed by GPT-4o (OpenAI) using a schema-constrained prompt to generate standardized DART notes primarily in Mandarin while preserving English medical terminology. Nurses reviewed the generated content and triggered its upload to predefined HIS fields.

Figure 1. Workflow of the voice-to-DART (data, action, response, and teaching) documentation system. ASR: automatic speech recognition; HIS: hospital information system; LLM: large language model; LoRA: low-rank adaptation; MER: mixed error rate.



The system was developed in-house by the Artificial Intelligence and Robotics Innovation Center at CMUH. The codebase and intellectual property are proprietary. Due to strict patient privacy regulations and direct HIS integration, the software and raw datasets are not publicly available. However, to ensure methodological reproducibility, all model hyperparameters, evaluation frameworks, and complete schema-constrained prompt templates are fully detailed in this paper and Multimedia Appendix 1.

Dataset and Ground-Truth Preparation

The ASR model was trained and evaluated on nursing speech data from 3 complementary sources. The primary corpus, CMaiSpeech, comprised spontaneous Mandarin-English code-switched recordings from 525 nurses across multiple clinical units, characterized by frequent English medical terms and abbreviations. Table 1 summarizes the counts and durations of CMaiSpeech by category. Two synthetic corpora (approximately 9 hours) were generated using neural text-to-speech models from 1838 drug names and 1566 clinical terms to enrich underrepresented medical vocabulary. A real-world clinical dataset (totaling approximately 6 hours, 1608 utterances) captured authentic ward conversations, including vital-sign reporting and handovers. All recordings were normalized and resampled to 16-kHz pulse code modulation to ensure acoustic consistency. These datasets collectively served as the domain-adapted speech material used for training and evaluating the Whisper-based ASR model in nursing contexts.

In addition, a validation dataset of 327 nurse-authored documentation samples was constructed. Each sample included an audio recording collected during routine care, a manually transcribed reference serving as the ASR gold standard, and structured DART annotations verified by clinical nurses. This dataset was used to evaluate ASR transcription accuracy, LLM-based DART structuring, and agreement between fine-tuned and zero-shot conditions under a consistent reference standard.

Table . Counts and audio durations by category in the CMaiSpeech dataset.

Category	Item count (N=7055), n (%)	Audio length (seconds)[a]
Diastolic BP[b]	20 (0.28)	36.57
Glasgow Coma Scale eye response component	20 (0.28)	99.61
Pain index	20 (0.28)	46.05
Pulse	20 (0.28)	34.27
Systolic BP	20 (0.28)	39.34
Body temperature	20 (0.28)	39.10
Vital signs[c]	1035 (14.67)	12,350.10
Nursing notes[c]	5900 (83.65)	75,149.10

[a]Total duration of all audio samples within each category.

[b]BP: blood pressure.

[c]Categories representing full-length clinical recordings captured during routine nursing documentation activities.

ASR Model Adaptation and Evaluation

Whisper is a multilingual Transformer-based ASR model pretrained on 680,000 hours of diverse speech data [19]. Although its large-scale pretraining supports robust zero-shot generalization, accuracy declines in nursing-specific communication, where frequent Mandarin-English code-switching, dense medical terminology, and numerous drug abbreviations remain underrepresented. These discrepancies limit its direct applicability to structured nursing documentation.

Prior studies have demonstrated that domain-targeted fine-tuning markedly improves Whisper's performance in medical and mixed-language contexts. Previous studies reported gains in ASR and named entity recognition on Mandarin speech [20], and further improvements were achieved using domain-adapted fine-tuning and prompting on Mandarin-English medical data [21]. Building on these findings, Whisper (large-v2; OpenAI) was adapted to the nursing domain through low-rank adaptation–based parameter-efficient fine-tuning, which introduced trainable low-rank matrices into frozen weights to reduce computational cost while preserving performance [22]. The model was trained on a domain-specific nursing speech corpus and evaluated using mixed error rate (MER) to assess bilingual transcription accuracy relative to the baseline model.

Prior to MER calculation, a rigorous text normalization pipeline was applied to both reference and hypothesis transcripts to ensure consistent scoring. All full-width alphanumeric characters were converted to half-width equivalents, and punctuation marks were removed. Original casing for English text and medical abbreviations (eg, "SpO_2" and "BP") was strictly preserved to evaluate the model's ability to output correctly capitalized clinical terms. Crucially, numeric values, including decimals, were evaluated as independent, contiguous tokens rather than as split characters to accurately reflect their semantic weight in clinical parameters such as vital signs.

LLM Integration and Evaluation

The LLM was integrated to convert ASR transcripts into structured nursing documentation following the DART schema. GPT-4o (accessed via Azure OpenAI, application programming interface version 2024-12-01-preview), a multimodal variant of the GPT-4o family optimized for instruction following and multilingual text generation, was used for schema-based text structuring [23]. The model hyperparameters were consistently set to a temperature of 0.7, a top_p of 0.95, and a maximum of 16,000 tokens. A schema-constrained prompting strategy was applied to ensure consistent field separation and syntactic completeness, informed by prior evidence that structured prompting improves validity in clinical text generation [24]. The generation process used a dual-prompt structure: a system prompt defining the explicit task instructions and schema constraints, and a user prompt containing the ASR transcript. Two prompting configurations (a minimal version and a schema-constrained version) were compared during preliminary testing, and the schema-constrained configuration was selected for deployment. The full system prompt template is provided in Multimedia Appendix 1.

Model outputs were postprocessed to verify structural integrity and mapped to predefined HIS fields. LLM performance was evaluated on the 327-case validation dataset using field-level and macroaveraged F_1-score values across DART categories. The 95% CIs were estimated using 1000 paired bootstrap resamples at the case level. Noninferiority was tested using a predefined margin of δ=0.05, with noninferiority established when the lower bound of the ΔF_1-score CI exceeded −0.05. This 5% margin aligns with recent clinical evaluations of LLM-generated medical documentation, where a <5% variance is considered clinically acceptable for draft generation [25], and serves as a standard threshold in medical artificial intelligence performance evaluations [26]. From a clinical safety perspective, because the system captures data directly at the bedside via mobile devices, it inherently mitigates the high, undocumented risk of human memory decay and omission associated with traditional delayed documentation at the nursing station. Furthermore, because the system strictly requires human-in-the-loop verification prior to HIS submission, this minor structural variance during the drafting stage was deemed an acceptable trade-off for reduced documentation burden, while human oversight securely mitigates the risk of high-severity clinical errors.

Agreement Method

Three input conditions were compared while holding the structuring LLM constant: (1) human transcripts (reference), (2) Whisper large-v2 (zero-shot), and (3) Whisper large-v2 (fine-tuned). The primary end point was the F_1-score for DART slot classification against adjudicated references. A predefined noninferiority margin of δ=0.05 for ΔF_1-score was applied, and 95% CIs were estimated using paired bootstrap resampling. Noninferiority was established when the lower bound of the ΔF_1-score CI exceeded −0.05.

Field-level consistency was assessed because the "data," "action," "response," and "teaching" components of the DART framework represent distinct documentation intents. Labels were binarized (present-or-absent) after whitespace trimming, and both percent agreement and Cohen κ were calculated to adjust for chance agreement under skewed prevalence distributions [27].

It should be noted that the binarized F_1-score and agreement metrics were specifically chosen to evaluate the system's capability in initial structural triaging, ensuring that the LLM correctly maps spoken intents to the corresponding DART fields. Because the system operates within a strict human-in-the-loop workflow in which nurses must review and adjust the drafted text prior to HIS submission, achieving high structural accuracy significantly reduces manual documentation burden, even if minor within-field reallocations are occasionally required. To address content accuracy and penalize clinically incorrect information within these fields, the FactualCorrectness metric was used separately during the hallucination assessment.

Hallucination Assessment

Hallucination was defined as any generated content that lacked support from the corresponding reference transcript for the same case. Evaluation followed the FactualCorrectness metric from the Retrieval-Augmented Generation Assessment (RAGAS) framework (precision mode), which decomposes model output into atomic claims and verifies each claim against the reference transcript [28,29]. A fixed Azure OpenAI model (GPT-4o, application programming interface version 2024-12-01-preview; temperature=0.7, top_p=0.95) was used as the evaluator via a LangChain wrapper to ensure consistent claim-level scoring. For each case, the 4 DART fields were concatenated into a single response, and both generated and reference texts were normalized prior to evaluation.

Mean factual-correctness precision and its complement (hallucination rate) were reported, along with the proportion of notes exhibiting hallucination under strict (<1.00) and relaxed (<0.95) thresholds. All computations were performed in Python (version 3.12; Python Software Foundation) using the RAGAS library [30].

System Use and User Feedback

To evaluate real-world feasibility and system adoption, use metrics were monitored during the initial deployment period at CMUH. Monthly use was quantified by extracting the total number of system-generated records from the application logs between March 2025 and August 2025.

Additionally, user feedback was collected to assess system acceptability and its impact on clinical workflow. Nursing staff from diverse clinical units, including wards and intensive care departments, voluntarily provided evaluations after integrating the system into their routine practice. The evaluation mechanism captured both quantitative satisfaction ratings (categorized as favorable or dissatisfied) and qualitative comments regarding user experience. Descriptive statistics were used to summarize the quantitative use and satisfaction data, while qualitative feedback underwent thematic analysis to identify common themes related to documentation efficiency, manual workload, and system accuracy.

Ethical Considerations

This study was approved by the Institutional Review Board of CMUH (CMUH110-REC2-181 and CMUH110-REC2-187). Since this was a retrospective study utilizing deidentified data, the requirement for informed consent was waived by the institutional review board. Patient privacy and data confidentiality were strictly maintained throughout the study, and no compensation was involved.

Results

Evaluation Dataset Characteristics

The evaluation dataset comprised 327 annotated nursing documentation samples, as described in the Methods section. Across transcripts, the corpus contained 12,136 Chinese characters, 1361 English words, and 1130 numeric tokens, equivalent to approximately 11.2 English words per 100 Chinese characters (Table 2, panel A). A total of 540 DART annotations were identified: 257 (47.6%) for “data,” 123 (22.8%) for “action,” 123 (22.8%) for “response,” and 37 (6.9%) for “teaching” (Table 2, panel B). The lower frequency of “teaching” entries reflects routine documentation patterns and was accounted for when estimating field-specific CIs. This dataset served as the common benchmark for evaluating both ASR and LLM outputs.

Table . Token composition and DART (data, action, response, and teaching) annotation distribution in the evaluation dataset.

Panels and categories	Distribution, n (%)	Count per sample[b], mean (SD)
Panel A: token[a] composition (n=14,627)		
Chinese characters	12,136 (83.0)	37.11 (24.31)
English words	1361 (9.3)	4.16 (5.56)
Numeric tokens	1130 (7.7)	3.46 (4.97)
Panel B: DART annotation distribution (n=540)		
Data	257 (47.6)	0.79 (0.41)
Action	123 (22.8)	0.38 (0.49)
Response	123 (22.8)	0.38 (0.49)
Teaching	37 (6.8)	0.11 (0.32)

[a]Token counts were computed from manual transcripts after text normalization; Chinese tokens represent individual characters, English tokens represent space-delimited words, and numeric tokens represent digit sequences.

[b]Values were calculated by dividing counts by the total number of samples (n=327).

ASR Model Performance

Whisper large-v2 was evaluated using MER, computed at the character level for Chinese and at the word level for English. In the zero-shot condition, MER was 44.79%. After low-rank adaptation–based fine-tuning on the nursing corpus, MER decreased to 6.67%, corresponding to an 85.11% relative error reduction (Table 3).

Table . Performance of Whisper large-v2 on the evaluation dataset.

Models	Mixed error rate (%)	Relative error reduction (%)
Zero-shot model[a]	44.79	—[b]
Fine-tuned model[c]	6.67	85.11

[a]Zero-shot: Whisper-Large-v2 inference without domain adaptation.

[b]Not applicable.

[c]Fine-tuned: Whisper-Large-v2 adapted using low-rank adaptation LoRA on the nursing speech corpus.

DART Classification Performance

DART classification performance was evaluated under 3 input conditions: human-transcribed references, fine-tuned ASR, and zero-shot ASR (Table 4). A schema-constrained prompting strategy was used for all analyses after preliminary comparison showed higher slot-level completeness and F_1-score performance than a minimal prompt.

Table . Per-field DART (data, action, response, and teaching) F_1-score performance with 95% CIs under 3 input conditions.

Fields	Zero-shot[a], F_1-score (95% CI)	Fine-tuned[b], F_1-score (95% CI)	Human transcript[c], F_1-score (95% CI)
Data	0.89 (0.85 - 0.92)	0.90 (0.87 - 0.93)	0.91 (0.89 - 0.94)
Action	0.59 (0.53 - 0.66)	0.77 (0.73 - 0.81)	0.83 (0.79 - 0.86)
Response	0.72 (0.67 - 0.77)	0.82 (0.79 - 0.85)	0.85 (0.82 - 0.88)
Teaching	0.62 (0.56 - 0.68)	0.78 (0.73 - 0.82)	0.83 (0.79 - 0.86)
Macroaverage[d]	0.70 (0.68 - 0.72)	0.82 (0.80 - 0.84)	0.85 (0.83 - 0.87)

[a]Zero-shot inference without domain adaptation.

[b]Fine-tuned using low-rank adaptation on the nursing speech corpus.

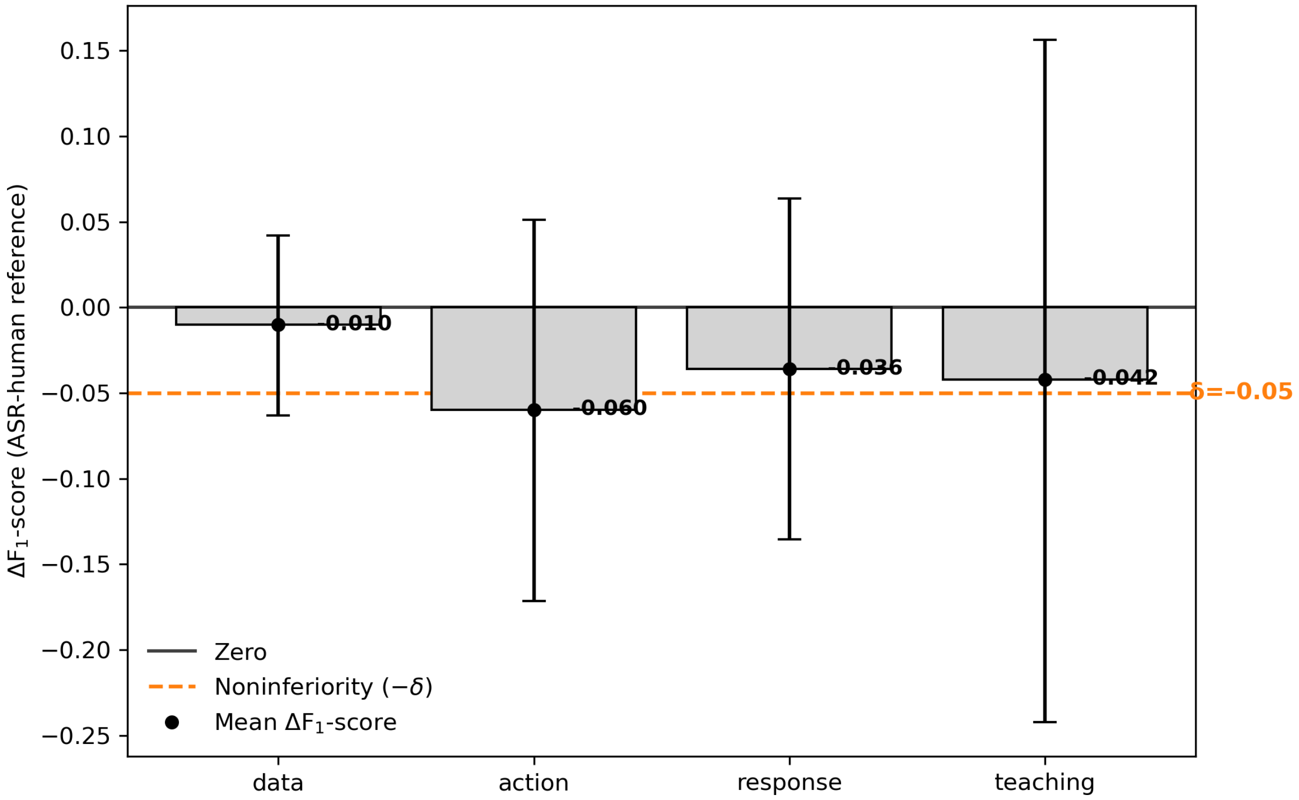
[c]Manually transcribed references used as the gold standard for automatic speech recognition evaluation.

[d]Unweighted mean F_1-score across data, action, response, and teaching fields.

With this configuration, overall F_1-score values were 0.85 for human transcripts, 0.82 for fine-tuned ASR, and 0.70 for zero-shot ASR. The difference between fine-tuned ASR and human input (ΔF_1-score=−0.03) fell within the predefined noninferiority margin (δ=0.05). Field-level ΔF_1-score values ranged from −0.01 (for "data") to −0.06 (for "action"). Zero-shot ASR showed uniformly lower performance across all fields.

Figure 2 presents field-level ΔF_1-score estimates with 95% CIs. All field means remained within the noninferiority boundary, supporting noninferiority at the macro level.

Figure 2. Field-level ΔF_1-score values (automatic speech recognition [ASR]–human reference) with 95% CIs and the noninferiority boundary (δ=−0.05).



Agreement Evaluation

Concordance was assessed across the 3 input conditions while holding the LLM constant. Agreement between classifications derived from the fine-tuned ASR and human transcripts ranged from 88.38% to 96.94%, with Cohen κ ranging from 0.66 to 0.86 across the "data," "action," "response," and "teaching" fields (Table 5), corresponding to substantial to almost perfect agreement [28]. For the "data" field, raw agreement was 95.41% with κ=0.66, a pattern consistent with imbalanced class prevalence. Overall, slot-level results were consistent with the macrolevel noninferiority findings.

Table . Agreement and Cohen kappa for DART (data, action, response, and teaching) fields comparing large language model outputs generated from fine-tuned automatic speech recognition with outputs from human transcripts.

Fields	Agreement[a] (%)	Cohen κ[b]
Data	95.41	0.66
Action	88.38	0.75
Response	89.91	0.79
Teaching	96.94	0.86

[a]Percent agreement between large language model outputs generated from fine-tuned automatic speech recognition transcripts and human transcript inputs.

[b]Chance-corrected agreement coefficient computed using the standard Cohen kappa formulation.

Hallucination Evaluation

Hallucination rates were evaluated using the FactualCorrectness metric from the RAGAS framework in precision mode (Table 6). With human transcripts, the mean hallucination rate was 2.35% (SD 9.93%; 95% CI 1.27–3.43), and hallucinations were detected in 28 (8.56%) samples (95% CI 5.99–12.10). Fine-tuned ASR yielded a mean hallucination rate of 2.51% (SD 10.86%; 95% CI 1.33–3.70), with hallucinations detected in 26 (7.95%) samples (95% CI 5.48–11.40). Zero-shot ASR showed higher hallucination rates, with a mean rate of 8.98% (SD 23.99%; 95% CI 6.36–11.60) and hallucinations detected in 65 (20%) samples (95% CI 16.01–24.69).

Table . Hallucination rates of large language model outputs across different input sources.

Input sources	Hallucination rate[a] (%), mean (SD)	Samples with hallucination[b], n (%)
Human transcript	2.35 (9.93)	28 (8.56)
Fine-tuned ASR[c]	2.51 (10.86)	26 (7.95)
Zero-shot ASR	8.98 (23.99)	65 (20.00)

[a]Computed using the FactualCorrectness metric (precision mode), representing the proportion of hallucinated tokens relative to all generated tokens.

[b]Percentage of evaluation samples containing at least 1 hallucination (n=327).

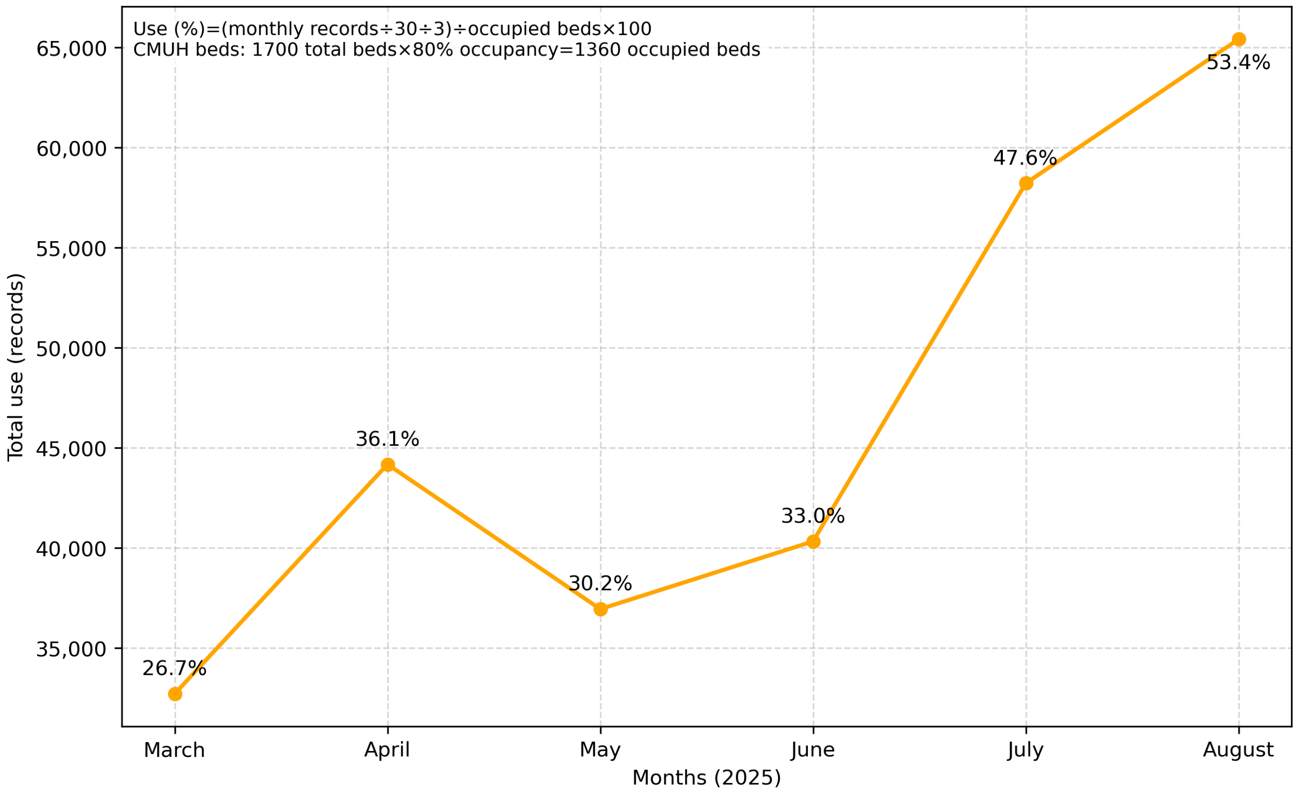
[c]ASR: automatic speech recognition.

System Use and User Feedback

Following deployment, the system was increasingly incorporated into routine documentation at CMUH. Monthly use nearly doubled between March 2025 and August 2025, rising from 32,724 to 65,417 valid DART notes generated and uploaded to the HIS through voluntary use of the system (Figure 3). This upward steady increase indicates expanded use across clinical units during the initial deployment period.

User feedback was collected from a subset of nursing staff who voluntarily provided evaluations (n=120, representing approximately 12.2% of the 982 nurses actively working in the 44 participating units across wards and intensive care departments). Among these participants, 91 (75.8%) nurses reported a favorable experience, whereas 29 (24.2%) expressed dissatisfaction. Positive feedback emphasized reductions in manual transcription burden and improvements in documentation efficiency, whereas negative feedback primarily concerned occasional recognition inaccuracies and the continued need for verification. Although the feedback sample does not represent all users, it reflects the perspectives of frontline staff actively engaged with the system. Detailed departmental participation is provided in Multimedia Appendix 2. Collectively, these findings demonstrate that the system is both technically feasible and operationally acceptable in real-world clinical environments.

Figure 3. Monthly system use at China Medical University Hospital (CMUH) from March 2025 to August 2025.



Discussion

This study designed and implemented a speech-based documentation system that integrates a domain-adapted ASR model with an LLM to generate structured nursing records and evaluated its performance in real clinical settings. The fine-tuned Whisper large-v2 model achieved a MER of 6.6%, demonstrating high accuracy for Mandarin-English nursing speech. With schema-guided LLM structuring, the system reached an F_1-score of 0.82, which was statistically noninferior to human-transcribed input, and exhibited a low hallucination frequency (2.51%). These findings indicate that domain-adapted ASR combined with LLM-based structuring can produce structurally consistent draft documentation that, alongside routine human verification, reduces cognitive and transcription burden in routine practice.

Field deployment demonstrated that the system could be incorporated into routine clinical workflows. By enabling point-of-care mobile dictation directly at the bedside, the system effectively replaced the traditional, error-prone workflow of delayed, memory-reliant documentation at the nursing station, directly addressing the critical pain points exacerbated by high nurse-to-patient ratios. System use doubled over the 6-month observation period. Because the hospital operates at a consistently high and stable capacity, this increase in absolute volume was not driven by fluctuations in patient census. Rather, as the system was deployed as an optional tool, this steady growth reflects successful voluntary adoption, supported by continuous iterative optimizations based on user feedback. Feedback from nursing staff further supported its usability. Most respondents reported reduced manual effort and improved efficiency, while negative feedback focused on recognition accuracy and the need for verification, which aligns with the human-in-the-loop design. Participation across 6 major ward categories indicates that the system was used in a wide range of clinical settings.

Several limitations warrant consideration. First, the dataset was modest and sourced from a single institution, which may constrain generalizability. Second, user feedback was voluntary and may overrepresent individuals who were more engaged with the system, and long-term patterns of use were not assessed. Third, our evaluation of structural content accuracy and hallucination relied primarily on an LLM-as-a-judge framework (RAGAS). The primary purpose of this evaluation was to conduct a strict semantic fidelity check, ensuring that the LLM strictly formatted the ASR transcripts into the DART schema without altering, inferring, or omitting clinical facts. Although RAGAS performs robust semantic contradiction checks, traditional non-LLM baselines (eg, exact string matching) were deemed unsuitable because of the heavy code-switching and spoken-to-written paraphrasing inherent in nursing documentation. Although senior nursing staff qualitatively reviewed the generated drafts within our human-in-the-loop workflow, the lack of a formal, quantitative manual fidelity evaluation on a stratified sample of high-risk note types by nursing professionals remains a limitation. Future work should include multisite validation; evaluation of interoperability with diverse HIS environments; dedicated quantitative manual safety reviews by senior nurses to further validate that the LLM does not alter critical nursing parameters (eg, medication dosages and invasive device settings); and longitudinal assessment of impacts on documentation quality, workflow efficiency, and staff satisfaction.

Funding

The authors declare that no financial support was received for this work.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Prompt templates for DART (data, action, response, and teaching) versions 1 and 2 used to guide large language model–based structuring of nursing narratives into DART records.

[DOCX File, 20 KB - nursing_v9i1e88567_app1.docx]

Multimedia Appendix 2

Distribution of user feedback by ward category.

[DOCX File, 13 KB - nursing_v9i1e88567_app2.docx]

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Abbreviations

ASR: automatic speech recognition
CMUH: China Medical University Hospital
DART: data, action, response, and teaching
HIS: hospital information system
LLM: large language model
MER: mixed error rate
RAGAS: Retrieval-Augmented Generation Assessment

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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)

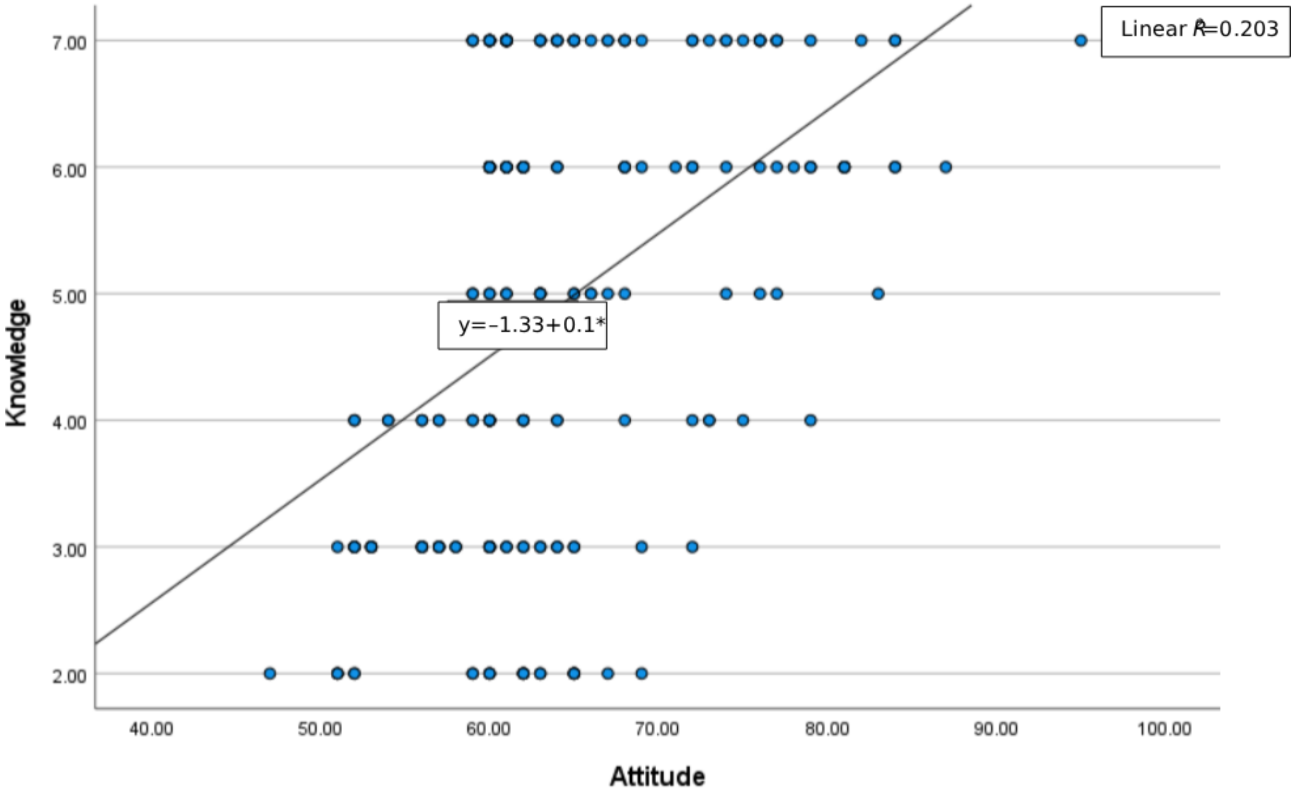
Table . Correlation between study variables (N=203).

	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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Nurses' Evaluation of a Service Robot for Inpatient Care: Technology Acceptance Study

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Abstract

Background: The integration of robotic systems into nursing practice is increasingly discussed as a potential strategy to alleviate workload and support care processes in response to demographic changes and staffing shortages. However, the acceptance of nursing staff as primary end users remains a critical determinant for successful implementation. Despite technological advances, the practical requirements and perspectives of nursing staff have not been adequately considered in research and development efforts to date.

Objective: Building on the user-centered development approach applied, this study aimed to examine nursing staff's evaluation of a service robot designed to assist with routine tasks in inpatient care, as well as their intention to use it, while accounting for technology-specific and psychological determinants of acceptance.

Methods: A total of 30 nurses tested the robot across 3 application scenarios (information service, item delivery, and beverage delivery) in a simulated care setting, alternating between the roles of nurse and care recipient. Acceptance-related constructs, including intention to use, were measured using the Technology Usage Inventory. General attitudes toward robots were assessed via the General Attitudes Towards Robots Scale. Participants' prior experience with robotics was also documented. Spearman rank correlations and Mann-Whitney *U* tests were used for analysis.

Results: The robot was rated positively across all dimensions. Usability was high (median 20, IQR 18-21; scale range 3 - 21), as was perceived usefulness (median 21, IQR 16-24; range 4 - 28). Skepticism was low (median 10.5, IQR 7-12; scale range 4 - 28), and accessibility was moderate (median 10, IQR 8-13; scale range: 3 - 21). Intention to use was strong (median 224.5, IQR 157-248; scale range 0 - 300) and correlated positively with usability (r_s(28)=0.505; *P*=.004), perceived usefulness (r_s(28)=0.74; *P*<.001), and accessibility (r_s(28)=0.628; *P*<.001), and negatively with skepticism (r_s(28)=–0.516; *P*=.004). More positive personal attitudes toward robots were also associated with higher perceived usefulness (r_s(28)=0.549; *P*=.002) and greater intention to use (r_s(28)=0.483; *P*=.007). No significant differences in intention to use were found between participants with and without prior robotics experience (*U*=83.5; *P*=.62).

Conclusions: The findings indicate a high level of acceptance among the participating nursing staff for the developed service robot within the tested scenarios. Considering the chosen user-centered development approach, they further underscore the need for strategies that combine participatory design, transparent communication of system capabilities and limitations, and structured opportunities for hands-on experience. Such measures, together with proactive knowledge transfer and skills development, are essential to sustainably leverage the practical potential of service robotics in nursing practice.

Trial Registration: OSF Registries osf.io/ems7b; https://osf.io/ems7b

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KEYWORDS

nursing; inpatient care; digital health; assistive technology; robotics; service robotics; technology acceptance; human-robot interaction; user-centered design

Introduction

Background

Against the backdrop of an aging population and a shortage of nursing staff [1,2], robotic assistance is being discussed as a promising form of support in inpatient and hospital care [3,4]. A recent scoping review by Ohneberg et al [5] identified assistive robotic systems in nursing and categorized applications into domains, including information and data-related support, monitoring and safety functions, communication and telepresence, and task-oriented assistance in everyday care processes, alongside socially assistive functions targeting emotional care and cognitive support. Against this broader landscape, this paper focuses on service robotics as one class of assistive robotic systems in inpatient care.

Service Robotics in Nursing: Scope and Status Quo

Service robotics denotes technical systems that support people in the partially or fully automated execution of services and tasks. In addition to information-processing and sensory functions, service robots can move autonomously or carry out complex tasks comprising several work steps and materials [5]. Current developments in the nursing context aim at deploying service robots to support administrative tasks such as digital patient data collection and assistance during medical rounds [6,7]; logistical functions, including the transport of medication, supplies, and laundry [8-10]; as well as physically demanding care activities like patient lifting, transferring, and hygiene-related procedures involving both personal care and environmental cleaning tasks [11-14]. At present, the use of assistive robotic systems in nursing remains heterogeneous and occurs primarily during development phases and pilot implementations, although wider practical implementation is anticipated in the coming years [5,15,16].

Early evidence suggests that diverse stakeholder groups, such as nursing staff, are generally open to the integration of robotic assistance, provided that the technology complements rather than replaces human care [4,17]. The expectation is for robots to act as collaborative assistants, reducing the high workload without fully substituting nurses' tasks [18,19]. Their introduction, however, entails a fundamental transformation of nursing work processes [3,5,20]. Consequently, in light of these systemic changes, end user acceptance emerges as a critical factor in the development and deployment of assistive robotic systems in nursing, as it has been consistently identified as a key enabler for successful implementation, as well as for their effective and efficient long-term use [21,22].

Conceptual Background: Technology Acceptance and Intention to Use

In technology research, acceptance is commonly defined as users' willingness to use a technology for the tasks it is intended to support [23]. This broad definition is typically operationalized in technology-acceptance frameworks through users' perceptions of a technology's characteristics and its suitability for intended tasks and conditions of use. In turn, these perceptions shape intention to use, with intention to use serving as the most proximal predictor of actual system use [24,25].

A prominent intention-based framework is the technology acceptance model (TAM) by Davis [26]. The TAM explains intention to use primarily through perceived usefulness and perceived ease of use, linking these perceptions to attitudes toward using the technology and, ultimately, to behavioral intention. While the TAM has been widely applied in health care contexts, its comparatively narrow focus has been criticized for failing to capture the full complexity of technology acceptance in such settings [27]. This critique aligns with a growing body of research highlighting limitations of established acceptance models and calling for broader conceptual frameworks that account for both technical attributes and individual-level factors, a perspective supported by recent reviews [28,29] and empirical studies [30-32].

In contrast to TAM's parsimonious focus, broader implementation-oriented models such as the unified theory of acceptance and use of technology extend the explanatory scope by incorporating social and organizational determinants relevant to real-world implementation [25]. Diffusion-of-innovation perspectives, in turn, address adoption dynamics over time at the system level [33]. These approaches, as well as more general behavioral and health-behavior frameworks such as the theory of reasoned action, the theory of planned behavior, or the health belief model, were not adopted because this study targets technology-specific acceptance perceptions in a workplace context rather than implementation processes or health behavior change [34-36].

Nursing Staff Perspectives on Robotic Assistance

From this perspective, nursing staff perceptions and acceptance criteria are particularly relevant given their role as the primary end users of assistive robotic systems. Although nursing staff play a central role in implementation and everyday use of such systems, their perspectives have long been underrepresented in technology acceptance research [3,37]. Recent studies have begun to address this gap, offering initial insights into nurses' acceptance criteria. However, findings to date point to a complex and multifactorial picture.

Consistent with prior technology acceptance research, the robot's perceived usefulness remains pivotal. Nurses are more likely to adopt a system that demonstrably reduces workload by assisting with physically demanding tasks such as lifting, transferring, or routine deliveries [3,38,39]. Ease of use is equally critical, as increased operational complexity or system failure can offset intended benefits [40]. Acceptance is further shaped by perceptions of reliability and safety. Only a system that performs dependably and poses no risk to care recipients is likely to be entrusted with responsibilities in patient care [41].

Beyond these technology-related considerations, individual-level factors such as attitudes, perceptions, and prior experiences play a critical role. A key factor is nurses' general attitude toward technology and robots in particular. Nurses who are technologically inclined or have had positive experiences with new technologies tend to be more receptive to robotic assistance [21,32,42,43]. Multiple studies, including a large-scale survey of nursing staff, have repeatedly found that prior experience and knowledge specifically related to robotics positively influence acceptance. Nurses with first-hand experience and greater confidence in operating such systems consistently evaluate their usefulness and applicability more positively [31,38,44].

Taken together, this evidence suggests that acceptance is not a static reaction to technological features, but a dynamic process shaped by individual attitudes, prior experiences, and progressive familiarization. Moreover, empirical findings highlight the importance of early end user involvement in fostering acceptance. When nurses are engaged in planning, adaptation, and decision-making processes, they are more likely to perceive the robot as useful and aligned with their workflow, which in turn strengthens their intention to use the system in everyday nursing practice [45].

Rationale and Objectives

Building on the limited routine deployment of assistive robotic systems in nursing and the multifactorial acceptance determinants outlined above, further evidence is needed from hands-on evaluations of concrete prototypes that are aligned with nursing workflows and professional requirements. Involving nursing staff in participatory development and providing opportunities for direct interaction are widely considered crucial to avoid technology-driven implementation and to ensure that robotic systems fit the practical realities, values, and needs of nursing practice [5,19,20,41].

The research and development project RoMi (Roboterunterstützung bei Routineaufgaben zur Stärkung des Miteinanders in Pflegeeinrichtungen), funded by the German Federal Ministry of Education and Research, aimed to develop a mobile service robot to support routine nonclinical tasks in inpatient care, such as information provision and logistical activities. Nursing staff were actively involved in key phases of the project, including the examination of contextual and ethical prerequisites for robot use [46], investigations of preferences regarding robot design and interaction characteristics [47-49], and the codevelopment of application scenarios, capability requirements, and evaluation criteria for context-sensitive human-robot collaboration [19].

Following this user-centered development approach, the resulting functional prototype was evaluated in an end user study with nursing staff. The study examined participants' general attitudes toward robots, their evaluation of the developed service robot, and their intention to use it. Accordingly, we conceptualized acceptance in terms of intention to use and its multifactorial determinants, integrating both technology-related appraisals and individual-level factors. This paper aimed to advance a differentiated understanding of the usage potential of service robots in nursing, as well as the factors influencing their acceptance and prospective integration within inpatient care settings.

Methods

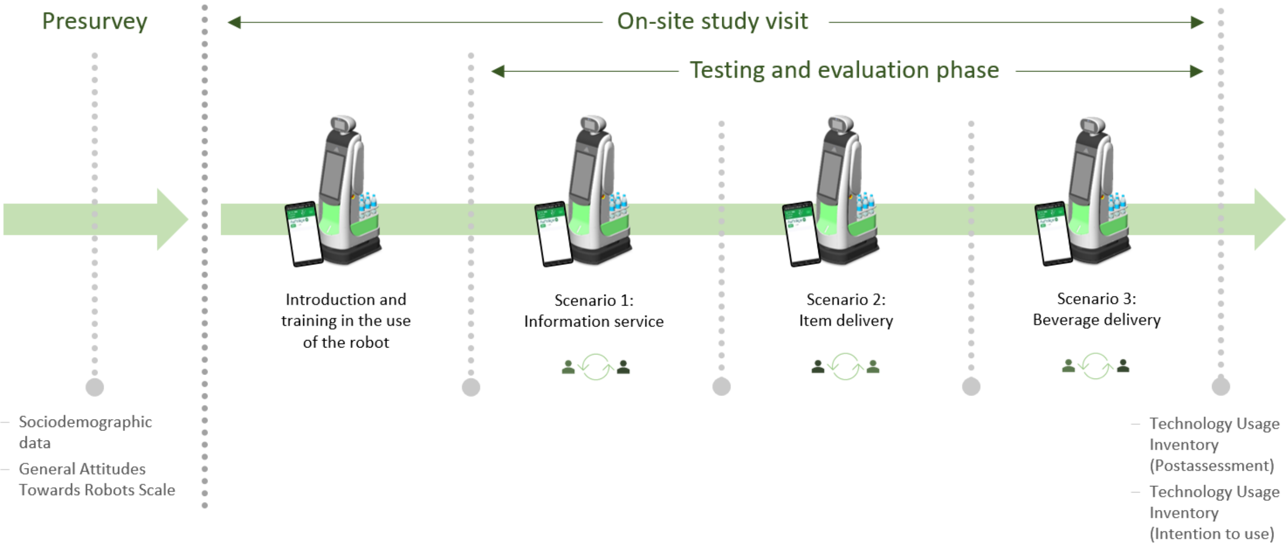
Procedure

The study consisted of an online presurvey and a subsequent testing and evaluation phase of the developed service robot. To recruit participants, various inpatient care facilities were informed about the study, enabling interested individuals to contact the study team directly. Once interest was expressed, potential participants received the study information and consent form, followed by the scheduling of a telephone consultation. During this call, the study's objectives, design, and procedures were reiterated, and the inclusion criteria were assessed. These included (1) minimum age of 18 years; (2) current or past occupation as a nurse, nursing assistant, geriatric nurse, geriatric nursing assistant, pediatric nurse, occupational therapist, remedial therapist, or physical therapist in inpatient care or daycare; and (3) sufficient proficiency in the German language.

After providing informed consent, participants received a link to the online presurvey, which gathered sociodemographic data and included the General Attitudes Towards Robots Scale (GAToRS). Appointments were then arranged for the testing and evaluation phase, which took place at the research laboratory of the Geriatrics Research Group at Charité—Universitätsmedizin Berlin. Each session involved 2 participants who alternated between the roles of nurse and care recipient. Participants first received structured instruction and hands-on training covering safety procedures as well as the use of the robotic system and its smartphone app for task management and status monitoring.

The service robot was then tested and evaluated across three predefined application scenarios: information service, item delivery, and beverage delivery. These scenarios had been developed and refined in earlier empirical studies conducted within the RoMi project [19,46]. Each scenario was completed twice by every participant, once in each role. To ensure consistency, all received standardized written instructions outlining the required interaction procedures. After performing both roles within a scenario, the session proceeded to the next. Following the test phase, participants completed the posttest section of the Technology Usage Inventory (TUI), including the intention to use (ITU) scale, for the evaluation of the service robot. Each session lasted approximately 90 minutes. Figure 1 illustrates the overall study procedure.

Figure 1. Study procedure.



Robot

The service robot evaluated in this study was developed within the RoMi research project and represents an iteratively adapted prototype. A semihumanoid mobile service robot was selected to match the RoMi focus on routine, nonclinical support tasks, including information provision and logistics. Other systems such as patient-handling, telepresence, or socially assistive robots were not considered within RoMi because they address different task classes.

The developed service robot is based on the workerbot6 platform by pi4_robotics. Throughout the project, the platform was iteratively refined for the care setting, with technical implementation led by pi4_robotics. Iterative refinements were informed by empirical studies on robot design and interaction preferences led by Humboldt-Universität zu Berlin and by industrial design concepts contributed by Hochschule für Technik und Wirtschaft Berlin [47-49]. The authors affiliated with Charité—Universitätsmedizin Berlin contributed the user-centered workstream by conducting studies with nursing staff on practical and ethical considerations of robot use and translating the findings into the development and refinement of application scenarios, interaction sequences, and the associated capability requirements and evaluation criteria for the service robot [19,46].

The research prototype ultimately resulting from the RoMi project and evaluated in this study is shown in Figure 2. The service robot has a height of 175 cm and a weight of 133 kg.

Figure 2. Developed service robot (image used with permission from pi4_robotics).

Based on initial design investigations showing that a human-like appearance can contribute to the acceptance and perceived competence of robots, an anthropomorphic embodiment was chosen [46,47]. The robot's head unit features a screen displaying animated eyes and a mouth, as well as an integrated camera that detects human presence and enables context-sensitive autonomous interaction (eg, in patient rooms or at loading stations). A microphone for speech recognition is also embedded in the head section to enable low-effort voice input, which aligns with caregiver preferences for speech-based interaction [46-48].

The torso is equipped with a front-mounted 21.5-inch touchscreen display that provides graphical feedback on the robot's status and serves as an additional interface for human-robot interaction. This visual channel was intended to enhance interaction transparency and comprehensibility while accommodating potential age- or disease-related changes in the communicative abilities of care recipients [46]. Loudspeakers and an emergency stop button are positioned on both sides of the robot to support clear feedback and immediate shutdown in case of safety concerns. Lateral, arm-like structures function as rails that support a fold-out tray mounted at the rear, enabling the transport and handover of small items without requiring complex manipulation. The back of the robot also houses a beverage dispenser, which is capable of holding twelve 0.5 liter bottles and is equipped with integrated sensors and compartment lighting to support structured loading and ensure correct retrieval during beverage delivery.

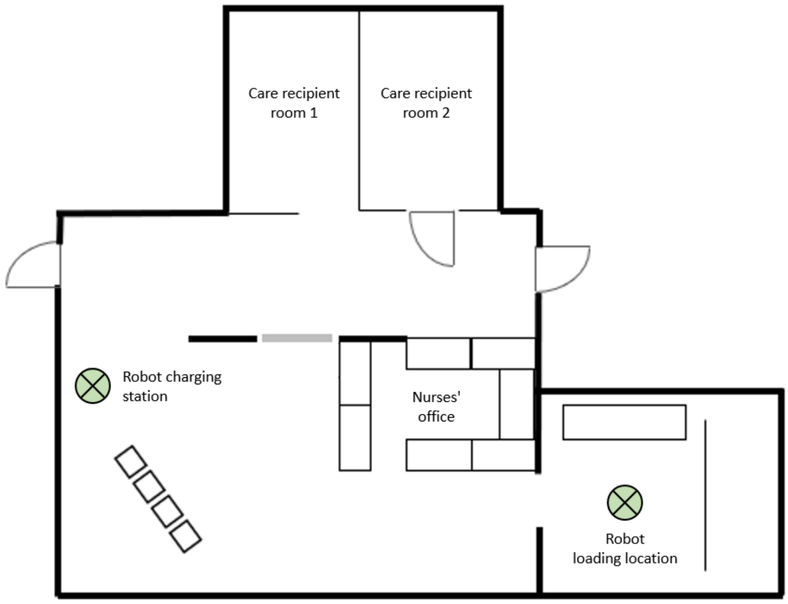
The robot is mounted on a mobile platform that enables autonomous navigation based on a map configurable for the ward environment. The robot's navigation was configured with a safety-oriented low-speed profile (maximum 1.4 km/h) appropriate for shared indoor environments, consistent with RoMi project findings that caregivers perceive slower approach speeds as more comfortable and safer [49]. Moreover, the system incorporates a range of obstacle detection sensors. Upon encountering an obstacle, the robot first reduces speed and attempts to navigate around it. If avoidance is not possible, it stops and waits until the path is clear, thereby prioritizing safe behavior in the presence of uncertainty.

Throughout the study, participants used a smartphone app as the primary tool for giving instructions to the robot. The app also provided posttask status information.

Setting

To align the interaction with the robot more closely with the professional care context, a simulated nursing ward environment was set up in the research laboratory (Figure 3). The setup included a nurses' office, 2 patient rooms, and a storeroom serving as the loading station. To minimize mutual influence, partition elements were installed to ensure that participants could not observe each other's interactions while alternating roles.

Figure 3. Setup within the laboratory setting.



Application Scenarios

To standardize exposure to the robot, participants completed 3 scripted application scenarios that operationalized typical nonclinical support tasks and specified role-dependent interactions between the participant in the nurse role, the participant in the care recipient role, and the robot. Tasks were assigned via the robot's instruction and status-monitoring app.

Information Service

The participant in the nurse role created a notification task in the app by selecting the room and entering a free-text message. The robot navigated to the room, signaled arrival with a bell sound, and waited until a person entered its detection area. After person detection, the participant in the care recipient role confirmed readiness to receive the notification via voice or touchscreen. The robot then delivered the message via audio and on-screen output and offered an option to repeat it. If no repetition was requested, the robot returned to the charging station.

Item Delivery

The participant in the nurse role initiated a delivery task in the app by selecting the room and entering a free-text item list. The robot navigated to a predefined loading area and, after person detection, provided voice and on-screen loading instructions. The participant in the nurse role placed the items on the rear tray and started execution on the touchscreen. The robot delivered to the room, signaled arrival, and prompted a confirmation-based handover. The participant in the care recipient role confirmed via voice or touchscreen and retrieved the items, after which the robot returned to the charging station.

Beverage Delivery

This scenario comprised a standard and an extended sequence (phases 1 and 2). In phase 1, the participant in the nurse role configured deliveries for 2 rooms in the app using drop-down selection, loaded beverages into illuminated bottle holders at the loading area following robot guidance, and started execution on the touchscreen. The robot delivered to the room of the participant in the care recipient role using the standard arrival, person detection, confirmation, and pickup sequence. The second room delivery was conducted by study staff to complete a second standardized delivery sequence while keeping participant roles constant. In phase 2, 8 additional deliveries alternated between the 2 rooms. The participant in the care recipient role remained in one room and performed predefined interaction variations for deliveries to their room. These included a misunderstanding prompting repetition followed by rejection, as well as acceptance while using a walker and a wheelchair. In phase 2, the remaining deliveries were again handled by study staff. Rejected deliveries were documented in the app as not completed.

Across all scenarios, the participant in the nurse role performed typical documentation tasks in parallel to autonomous robot operation to reflect realistic time management practices. They also verified task completion in the app and documented the outcomes in accordance with the study protocol. Full scripts and step tables are provided in the supplementary material (Multimedia Appendix 1).

Measures

With regard to sociodemographic variables, the following data were collected: age, gender, highest educational qualification, current occupation, and previous experience with robots.

In addition, the GAToRS was applied. The GAToRS is a validated multidimensional instrument that accounts for both positive and negative attitudes toward robots. It comprises four subscales: (1) personal level positive attitude (P+), (2) personal level negative attitude (P–), (3) societal level positive attitude (S+), and (4) societal level negative attitude (S–). Thus, the scale captures (1) perceived comfort and pleasure and (2) discomfort and fears toward robots on a personal level, along with (3) rational hopes and (4) rational fears on a societal level. The questionnaire shows Cronbach α coefficients ranging from 0.74 to 0.84 across the 4 scales [50].

Furthermore, the TUI was used. The TUI is a validated questionnaire used in technology acceptance research to capture evaluations and selected determinants of intention to use for emerging technologies, encompassing technology-related perceptions and user-related factors. Subscales were selected a priori in line with the study focus on the immediate postinteraction evaluation of the service robot. Accordingly, we administered the postuse subscales usability, usefulness, skepticism, and accessibility together with the separate ITU scale. Reported internal consistencies (Cronbach α) for these subscales range from 0.70 to 0.81 [51].

Participants

A total of 30 participants took part in the study. The mean age was 43.2 (SD 11.2; range 22‐67) years. The sample consisted of 20 women and 10 men.

At the time of participation, 11 individuals were employed as geriatric nurses and 2 as geriatric nursing assistants. Additionally, 3 participants worked as nurses and another 3 as pediatric nurses. Six were employed as nursing assistants. Five participants had previously worked in nursing and were currently employed in health care delivery-related fields, including nursing education (n=1), case management (n=1), health care controlling (n=1), and research (n=2).

Almost one-third of participants (n=9) reported prior experience with robotics, either in private (n=7), professional (n=1), or other contexts (n=1).

Data Analysis

Data were analyzed using IBM SPSS Statistics (version 29), applying both descriptive and inferential statistical methods. Within the GAToRS dataset, 10 missing items were identified without any discernible pattern. No variable exhibited more than 6.7% missing values. Given that previous studies have shown minimal differences in the performance of various imputation techniques when only 5%‐10% of values are missing [52,53], the use of simple imputation was deemed methodologically appropriate. Accordingly, mean imputation (series mean) was applied in SPSS.

Descriptive statistics are reported as means with SDs or, where appropriate, as medians with IQRs. As normal distribution could either not be assumed or was clearly absent, nonparametric tests were applied. Spearman rank correlation coefficient was used to assess statistical associations, and the Mann-Whitney *U* test was conducted for group comparisons. Statistical significance was set at α=.05, with correlations significant at the 0.01 level additionally highlighted.

Ethical Considerations

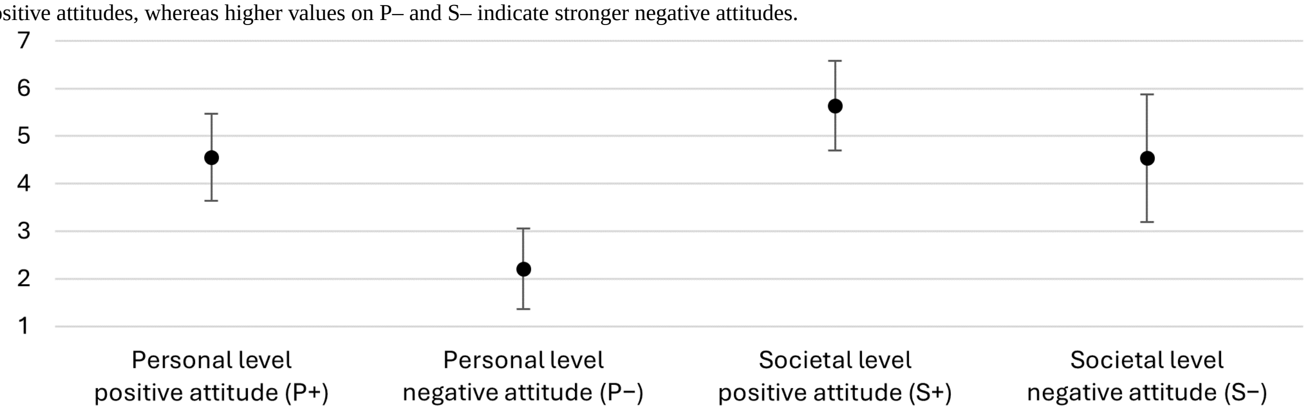
The study was conducted in accordance with the Declaration of Helsinki and the International Council for Harmonisation Guideline for Good Clinical Practice [54]. The study protocol was reviewed and approved by the Ethics Committee at the Institute of Psychology, Humboldt-University, Berlin (2023‐14). All participants provided written informed consent prior to participation. Upon completion of the study, participants received financial compensation of EUR 30 (US $35). Privacy and confidentiality were ensured through data pseudonymization, secure storage of study data, and access restricted to authorized members of the research team.

Results

Participants' General Attitude Toward Robots

To assess participants' baseline attitudes toward robots, the GAToRS was applied (Figure 4). Each subscale yields scores from 1 to 7. Higher scores on P+ and S+ indicate stronger positive attitudes, whereas higher scores on P– and S– indicate stronger negative attitudes.

Figure 4. Results of the General Attitudes Towards Robots Scale subscales. The scale captures attitudes on two levels: personal (positive attitude=P+, negative attitude=P–) and societal (positive attitude=S+, negative attitude=S–). The x-axis displays the 4 subscales, and the y-axis shows the subscale scores. The dots represent the means, and the error bars indicate the SDs. The subscales range from 1 to 7. Higher values on P+ and S+ indicate stronger positive attitudes, whereas higher values on P– and S– indicate stronger negative attitudes.



At the personal level, positive attitudes ranged from 2.6 to 6.6 (mean 4.6, SD 0.9), while negative attitudes ranged from 1 to 4 (mean 2.2, SD 0.8).

At the societal level, positive attitudes showed the highest mean value across all subscales, with scores ranging from 3.2 to 7 (mean 5.6, SD 0.9). In contrast, negative attitudes showed the greatest variability, with scores between 1.8 and 7 (mean 4.5, SD 1.3).

Evaluation of the Developed Service Robot

The general evaluation of the developed service robot was conducted using the TUI, focusing on the immediate postintervention responses. The results included the subscales usability, usefulness, skepticism, and accessibility (Figure 5), as well as the separate ITU scale (Figure 6). Higher scores indicate greater endorsement of the respective construct.

Figure 5. Results of the Technology Usage Inventory subscales. The x-axis displays the four subscales (usability, usefulness, skepticism, and accessibility), and the y-axis shows the subscale scores. The dots represent the medians, the error bars indicate the IQRs, and horizontal dotted lines mark the scale limits (usability and accessibility: 3 - 21; usefulness and skepticism: 4 - 28). Higher values indicate greater endorsement of the respective construct.

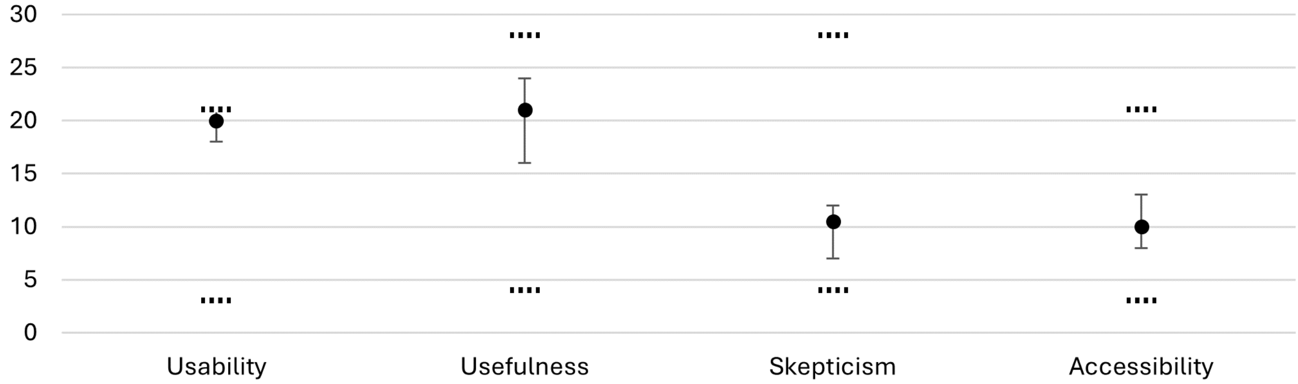
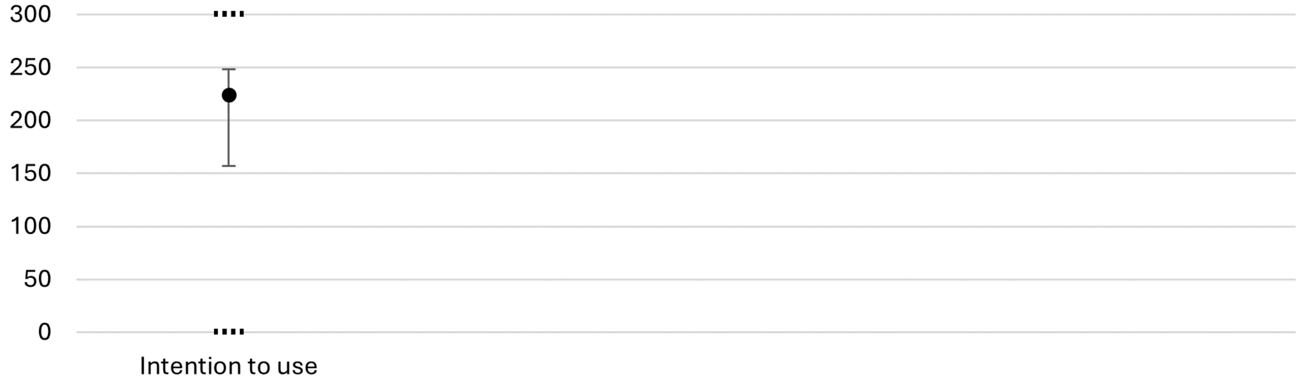


Figure 6. Results of the Technology Usage Inventory intention to use scale. The x-axis displays the scale, and the y-axis shows the score. The dot represents the median, the error bar indicates the IQR, and horizontal dotted lines mark the scale limits (0 - 300). A higher value indicates a stronger intention to use the technology.



Usability scores were between 14 and 21, with a median of 20 (IQR 18-21). Usefulness showed the widest spread among the 4 subscales, with values from 6 to 28, a median of 21 (IQR 16-24). Scores for skepticism varied from 4 to 24, with a median of 10.5 (IQR 7-12). Accessibility was rated between 3 and 21, with a median of 10 (IQR 8-13). For the ITU scale, scores spanned from 0 to 300, with a median of 224.5 (IQR 157-248).

Analysis of Dependencies and Influencing Factors

To measure the strength of the linear relationship between the participants' general attitude toward robots, based on the GAToRS, and the dimensions of the TUI, a Spearman correlation analysis was computed (Table 1).

Table . Results of the Spearman correlation analysis between the General Attitudes Towards Robots Scale and the Technology Usage Inventory.

	Usability	Usefulness	Skepticism	Accessibility	Intention to use
Personal level positive attitude					
r_s	0.057	0.549[a]	–0.317	0.457[b]	0.483[a]
P value	.76	.002	.09	.01	.007
N	30	30	30	30	30
Personal level negative attitude					
r_s	–0.270	–0.359	0.436[b]	–0.309	–0.226
P value	.15	.052	.02	.10	.23
N	30	30	30	30	30
Societal level positive attitude					
r_s	0.122	0.187	0.085	–0.072	0.179
P value	.52	.32	.66	.71	.34
N	30	30	30	30	30
Societal level negative attitude					
r_s	–0.153	–0.387[b]	0.479[a]	–0.576[a]	–0.159
P value	.42	.03	.007	<.001	.40
N	30	30	30	30	30

[a]Correlation is significant at the 0.01 level (2-tailed).

[b]Correlation is significant at the 0.05 level (2-tailed).

P+ showed a significant positive correlation with perceived usefulness ($r_s(28)=0.549$; *P*=.002), indicating a strong effect size [55]. Significant positive correlations were also found with accessibility ($r_s(28)=0.457$; *P*=.01) and intention to use ($r_s(28)=0.483$; *P*=.007), corresponding to medium effect sizes [55]. No significant correlations were observed with usability or skepticism.

P– correlated significantly positively with skepticism ($r_s(28)=0.436$; *P*=.02), suggesting a medium effect size [55]. No significant correlations were found with usability, perceived usefulness, accessibility, or intention to use.

S+ did not exhibit any significant correlations with the dimensions of the TUI.

S– was significantly negatively correlated with perceived usefulness ($r_s(28)=-0.387$; *P*=.03), indicating a medium effect size [55]. Additionally, a significant positive correlation was found with skepticism ($r_s(28)=0.479$; *P*=.007), also reflecting a medium effect size [55]. A significant negative correlation was further observed with accessibility ($r_s(28)=-0.576$; *P*<.001), corresponding to a strong effect size [55]. No significant correlations were found with usability or with intention to use.

To further examine associations between the TUI subscales (usability, usefulness, skepticism, and accessibility) and its ITU scale, an additional Spearman correlation analysis was conducted (Table 2).

Table . Results of the Spearman correlation analysis between the Technology Usage Inventory subscales (usability, usefulness, skepticism, and accessibility) and its intention to use scale.

	Intention to use
Usability	
r_s	0.505[a]
P value	.004
N	30
Usefulness	
r_s	0.740[a]
P value	<.001
N	30
Skepticism	
r_s	−0.516[a]
P value	.004
N	30
Accessibility	
r_s	0.628[a]
P value	<.001
N	30

[a]Correlation is significant at the 0.01 level (2-tailed).

Usability (r_s(28)=0.505; *P*=.004), perceived usefulness (r_s(28)=0.740; *P*<.001) and accessibility (r_s(28)=0.628; *P*<.001) showed significant positive correlations with intention to use. Skepticism, however, yielded a significant negative correlation (r_s(28)=−0.516; *P*=.004). All 4 correlation coefficients exceeded the threshold of 0.5, indicating strong effect sizes according to Cohen's criteria [55].

Table 3 presents the comparison of the TUI subscale scores between participants with and without prior robotics experience, analyzed using the Mann-Whitney *U* test.

Table . Results of the Technology Usage Inventory by robotics experience.

TUI[a] subscales and robotics experience	Participants, n	Median (IQR)	*U* test	*z*-score	*P* value
Usability					
No	21	20 (18-21)	73	−1.019	.31
Yes	9	21 (19-21)			
Usefulness					
No	21	22 (16-23)	82	−0.567	.57
Yes	9	21 (18-26)			
Skepticism					
No	21	11 (7-13)	75.5	−0.865	.39
Yes	9	8 (7-11)			
Accessibility					
No	21	11 (8-13)	93.5	−0.045	.96
Yes	9	9 (8-12)			
Intention to use					
No	21	211 (157-247)	83.5	−0.498	.62
Yes	9	241 (166-269)			

[a]TUI: Technology Usage Inventory.

Usability was rated slightly higher by participants with prior experience in robotics (median 21, IQR 19-21) compared to those without (median 20, IQR 18-21). Yet, this difference did not reach statistical significance (U=73; P=.31).

Perceived usefulness was also rated comparably across both groups, with slightly higher scores among participants without prior robotics experience (median 22, IQR 16-23) than among those with experience (median 21, IQR 18-26), but this difference also failed to achieve statistical significance (U=82; P=.57).

Regarding skepticism, participants with prior robotics experience reported lower levels (median 8, IQR 7-11) compared to those without (median 11, IQR 7-13). Similarly, this difference was not statistically significant (U=75.5; P=.39).

Accessibility was perceived as slightly higher by participants without prior robotics experience (median 11, IQR 8-13) relative to those with experience (median 9, IQR 8-12). Once again, this difference did not attain statistical significance (U=93.5; P=.96).

Finally, the intention to use was higher among participants with prior robotics experience (median 241, IQR 166-269) than among those without (median 211, IQR 157-247). However, the difference on this scale was not statistically significant either (U=83.5; P=.62).

Discussion

Summary of Key Findings

This study investigated nursing staff's general attitudes toward robotics, as well as their evaluation of and intention to use a newly developed service robot intended to support routine tasks in inpatient care settings. The quantitative analyses revealed a differentiated pattern of findings.

The GAToRS was used to assess participants' perceptions of robots. Ratings on the P+ subscale, which measures trust in robot developers, trust in robots, and comfort in interacting with robots, were moderately high across the sample. Consistent with this, ratings on the P– subscale, assessing discomfort with using robots, apprehension about misunderstandings, and unease in physical proximity to robots, were low and showed little variability. Responses on the S+ subscale, which captures perceived societal benefits of robots such as task delegation, safety, and assistance in meaningful activities, were consistently high. The S– subscale, which includes concerns about job displacement, reduced human interaction, and the necessity for regulatory oversight, yielded moderate ratings with a broader distribution of responses compared to S+.

The evaluation of the developed service robot was carried out using the TUI, focusing specifically on the subscales usability, perceived usefulness, skepticism, accessibility, and the ITU scale. Participants reported high ratings on usability, which measures the extent to which the robot is perceived as user-friendly and easy to operate. Similarly, ratings on the usefulness subscale, reflecting the perceived practical benefit of the robot in supporting everyday activities, were consistently high across the sample. The skepticism subscale, which captures distrust, perceived risks, and critical attitudes toward the technology, received low ratings. In contrast, accessibility, which assesses perceived affordability and the ease with which the robot can be acquired, was rated lower compared to the other dimensions. Participants' ratings on the ITU scale, measuring the reported willingness to acquire and use the robot, were high.

Correlation analyses integrating the GAToRS demonstrated that individually positive attitudes toward robots were associated with higher perceived usefulness and accessibility, as well as a stronger intention to use the system. Individually negative attitudes were primarily linked to elevated skepticism. On the societal level, negative perceptions were associated with increased skepticism and diminished ratings of usefulness and accessibility. Notably, perceived societal optimism toward robots showed no statistically significant associations with any of the TUI dimensions.

Further correlational analyses identified multiple statistically significant linear relationships between dimensions of the TUI and the behavioral intention to use the service robot. Usability, usefulness, and accessibility were positively associated with intention to use, whereas skepticism correlated negatively.

In addition, prior experience with robotics did not exert a significant influence on either the evaluation of the developed system or the intention to use it.

Interpretation of Key Findings

The positive evaluation and high intention to use the developed service robot may be attributable to the user-centered development approach adopted. Within the framework of the RoMi project, the objective of designing the system through the active participation of nursing staff was successfully achieved. The robot was iteratively refined, both technically and with regard to its application scenarios, based on insights from prior empirical studies [19,46-49]. The early and continuous integration of end users facilitated a development trajectory that was aligned with the actual demands of everyday nursing practice, in contrast to predominantly technology-driven design strategies. The favorable assessments of usability and usefulness, as well as the pronounced intention to use the system, thus provide empirically grounded support for the effectiveness of participatory design approaches, consistent with findings from previous research [5,19,41,46].

Analyses of the TUI dimensions further demonstrate that usability, usefulness, accessibility, and skepticism all serve as strong predictors of the intention to use. These findings extend beyond the core constructs of the TAM and underscore the necessity of adapting and expanding the model for health care contexts through the inclusion of additional context-sensitive factors [29].

The strong positive correlation identified between usability and the intention to use the developed robot aligns with established findings in technology acceptance research. Usability has consistently been shown to be a critical determinant of adoption in health care contexts, particularly among nursing staff operating under time constraints [56]. Technologies that are intuitive and easy to integrate into nursing workflows are more likely to be accepted and used consistently [5,57].

Similarly, the strong positive correlation between perceived usefulness and intention to use reflects the importance of demonstrable benefits in practice. In nursing, adoption decisions are often contingent on clear advantages to patient care and workflow efficiency [28]. Robots that reduce workload and improve care outcomes are more likely to gain acceptance [21]. These findings indicate that pilot implementations and use-case demonstrations play a key role in fostering both perceived usefulness and adoption in nursing environments.

The strong positive correlation between perceived accessibility and intention to use further highlights the relevance of economic and logistical considerations in adoption decisions. The data suggest that nursing staff are more likely to engage with robotic systems when these are perceived as affordable and readily available. This finding is consistent with previous research identifying cost-related factors, such as initial investment and maintenance expenses, as potential barriers to implementation [21,58]. Strategies that improve economic accessibility, including subsidies, leasing models, or evidence of long-term cost-effectiveness, may therefore be critical to facilitate broader integration into nursing practice.

The strong negative correlation identified between skepticism and the intention to use the developed service robot underscores the importance of psychological and attitudinal barriers in shaping acceptance. In this study, skepticism was operationalized through items addressing perceived risks, potential disruption to daily routines, and a negative balance of expected benefits and drawbacks. These findings are consistent with previous research showing that concerns related to safety, reliability, and professional roles can hinder the acceptance of robotic systems [22]. Addressing such concerns requires more than technical refinement: regulatory clarity, comprehensive training, and transparent communication about system capabilities and limitations are considered essential [21,22,59], with particular emphasis on framing robotic systems as supportive rather than substitutive.

The findings related to the GAToRS clearly differentiate between societal and individual levels. The subscale S+ reflects an abstract acknowledgment of the potential societal benefits of assistive robotic systems within the surveyed sample. However, S+ is not significantly associated with the evaluation of the developed service robot or with the individual intention to use it. This dissociation may suggest that an intellectual consensus on the societal benefits of robotics is not sufficient to translate into concrete behavioral readiness within the everyday practice of nursing.

In contrast, S– exhibits a substantially stronger association with the evaluation of the service robot. The subscale is significantly negatively correlated with the perceived usefulness and accessibility of the system and positively correlated with skepticism. Similar to S+, S– does not exert a direct influence on the individual intention to use. However, this asymmetry between S+ and S– may reflect a negativity bias, whereby societal-level concerns impair specific perceptions of the robot, while positive societal-level attitudes remain largely ineffective in shaping individual evaluations [60]. Accordingly, implementation strategies should not only emphasize potential benefits but also proactively address negative societal narratives—for example, through transparent communication that highlights the robot's role in supporting nursing staff, as well as clear information on potential risks and the corresponding safety measures [59].

At the individual level, a contrasting pattern emerges. P+ is positively associated with perceived usefulness and accessibility of the service robot, and also correlates with a stronger intention to use. As expected, nursing staff who reported a generally favorable disposition toward robotics evaluated the developed service robot more positively and demonstrated a higher intention to use it in future practice.

Although scores on P– were generally low in this sample, the subscale showed a significant positive correlation with skepticism. However, no significant associations were observed with usability, perceived usefulness, accessibility, or intention to use. Once again, an asymmetry becomes apparent. While positive dispositions are associated with more favorable evaluations across multiple outcome variables, negative dispositions are primarily linked to increased skepticism. Notably, this asymmetry contrasts with the pattern observed at the societal level, where negative attitudes exert a broader influence. In this sense, the expected negativity bias appears attenuated at the individual level, suggesting that favorable personal attitudes toward robotics may be more impactful in shaping evaluative outcomes than negative ones.

In summary, the data suggest that societal-level attitudes (S+ or S–) may shape the broader cognitive context in which robotic systems are perceived, whereas individual-level factors (P+ or P–) and concrete user experiences are ultimately more decisive for actual readiness to adopt such technologies. From a practical perspective, these findings underscore the importance of proactively counteracting negative societal narratives surrounding robotics—especially by addressing concerns about job displacement and by ensuring transparent communication of potential risks and existing safety measures, particularly those concerning care recipients [21,41]. In addition, positive individual experiences with robotic systems should be facilitated at an early stage, for example, through hands-on sessions or pilot implementations at the ward level [5,41]. A combined approach that integrates risk-sensitive communication with experience-based benefit framing constitutes a promising strategy for fostering the acceptance of service robots in nursing practice.

Another noteworthy observation is the unexpectedly limited influence of prior experience with robotics on the intention to use the developed service robot. In contrast to previous studies that describe prior exposure as a facilitator of technology acceptance [31,38,44], the present results show no statistically significant differences in the evaluation of usability, usefulness, skepticism, accessibility, or intention to use. Although minor trends in the expected direction were observable, the absence of significant group differences may be attributable to several explanatory factors, including structural characteristics of the research and development project and aspects of its methodological implementation. First, the user-centered and participatory development process likely enhanced the system's approachability across experience levels. The continuous involvement of nursing staff throughout the design and refinement phases may have resulted in a solution that is intuitively operable, useful, and closely aligned with everyday nursing practice—even for users without prior exposure. Second, the selected application scenarios should have addressed tasks that are broadly accepted and perceived as meaningful within the professional nursing context. When the service robot's intended use is seen as relevant and beneficial, prior technical familiarity may become less decisive for acceptance. Third, the standardized, hands-on training provided to all participants ensured a uniform introduction to the system and likely helped reduce disparities in user confidence and system understanding. As a controlled intervention, this training could have mitigated differences in prior experience, thereby contributing to a more consistent evaluation of the system across groups.

These considerations indicate that a lack of prior experience does not necessarily constitute a major barrier to acceptance, especially when supportive conditions are present. Such conditions may involve user-centered system and scenario design that enables experience-independent access, along with targeted training efforts to reduce uncertainty and strengthen user competence.

Limitations

The interpretations of these findings are informed by methodological considerations. The sample size of 30 participants was adequate for an exploratory study and allowed for the identification of relevant patterns. However, it inherently limits the generalizability of the results. Subtle effects, such as potential associations with prior robotic experience, may not have been captured.

Additionally, a potential selection bias cannot be ruled out. Given that participation was voluntary, individuals with a greater affinity for technology may have been overrepresented, which could have contributed to a more favorable evaluation of the developed service robot. While such bias cannot be entirely avoided in applied research, it should be considered when interpreting the observed positive ratings.

Furthermore, the controlled laboratory setting, while beneficial for standardization and internal validity, only partially captures the complexity and situational variability of everyday nursing practice. Similarly, the relatively brief interaction period with the service robot prevents conclusions about sustained use or long-term integration into professional routines.

While acknowledging the study's limitations, this paper lays a foundation for future research by demonstrating the system's readiness for field testing and offering valuable insights into the factors influencing nursing staff's acceptance of service robots.

Conclusion

This study investigated a service robot developed to support routine tasks in inpatient care. A total of 30 nurses tested the system in 3 application scenarios (information service, item delivery, and beverage delivery), alternating between the roles of nurse and care recipient. Overall, the robot was evaluated positively, with high ratings for usability and perceived usefulness, low levels of skepticism, and moderate accessibility. The reported intention to use the system was high, indicating a substantial level of acceptance and a likely readiness for practical use in the tested application scenarios. The findings thus confirm the relevance of both the selected scenarios and the robot's potential to support these tasks.

The significant correlations observed between acceptance-related dimensions and the intention to use underline the necessity of a multilayered strategy that extends beyond technical optimization. User-centered design processes, transparent communication regarding system capabilities and limitations, as well as opportunities for personal orientation and hands-on experience, are essential to align robotic systems with the practical requirements, expectations, and concerns of nursing staff.

As the field of robotics in nursing advances, these aspects should be systematically integrated into future research, development, and nursing education. Ultimately, such an approach is essential to ensuring not only that the deployment of service robots in nursing is technically feasible but also that their potential to alleviate the physical and cognitive burden on nursing staff is fully realized, thereby enabling their effective and sustainable integration into the future of nursing practice.

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Regarding the preparation of the manuscript, ChatGPT based on GPT-5.2 was used solely for linguistic refinement of text drafted by the authors. It was not used to generate scientific content, analyses, interpretations, or conclusions. The authors take full responsibility for the final manuscript.

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Data Availability

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

Authors' Contributions

CF and RK conceptualized the study design. CF and RK recruited the study participants. CF and RK supervised the study visits. CF and RK collected, analyzed, and interpreted the data. The manuscript draft was written by CF and RK, with critical revisions and editing provided by AH-S. All authors read and approved the final manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Application scenarios.
[PDF File, 224 KB - nursing_v9i1e86824_app1.pdf]

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Abbreviations

GAToRS: General Attitudes Towards Robots Scale
ITU: intention to use
P+: personal-level positive attitudes
P–: personal-level negative attitudes
RoMi: *Roboterunterstützung bei Routineaufgaben zur Stärkung des Miteinanders in Pflegeeinrichtungen* (translation: robotic support for routine tasks to strengthen collaboration in care facilities)
S+: societal-level positive attitudes
S–: societal-level negative attitudes
TAM: technology acceptance model
TUI: Technology Usage Inventory

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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

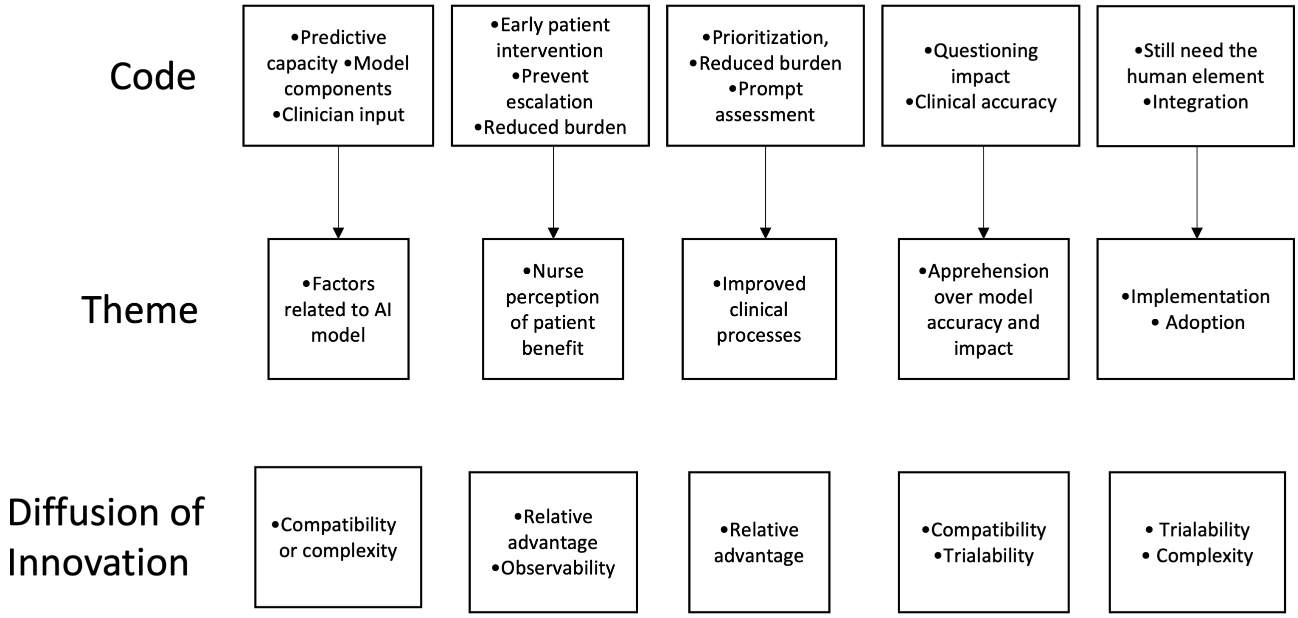
Participants' comments further explained their perceptions about the development of symptom prediction models, including: (1) factors related to the AI model (compatibility or complexity), (2) nurse perception of patient benefit (relative advantage or observability), (3) improved clinical processes (relative 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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Readiness Assessment for AI in Nursing Care Projects: Multimethods Study

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Abstract

Background: Integrating artificial intelligence (AI) systems into nursing care often encounters obstacles stemming from unmet requirements and insufficient engagement with well-documented sociotechnical pitfalls. Readiness models offer a systematic way to evaluate project preparedness and to build the capabilities needed for successful artificial intelligence in nursing care (AINC) research, development, and implementation. As of yet, an evidence-based AI readiness assessment prioritizing AINC projects and accounting for their diversity in care settings is missing.

Objective: This study aimed to develop a comprehensive artificial intelligence nursing care readiness assessment (AINCRA) to support planning, execution, and evaluation of AINC projects.

Methods: In a sequential exploratory multimethods bottom-up approach to maturity model development, key AI readiness dimensions and attributes were identified to develop a pilot readiness assessment. The pilot version was grounded on insights from an expert workshop (n=21) and expert interviews (n=14), an online survey (n=53), a rapid review (n=292), and a nominal group consensus process. A systematic literature review (n=7) further triangulated AI readiness attributes. Finally, a think-aloud interview study and focus group discussions involving experts (n=18) from nursing practice, nursing science, and AI research and development who had conducted AINC projects prior to data collection validated the attributes.

Results: The resulting AINCRA encompasses 5 core dimensions: regulatory, processual, technical, social, ethical, and community building requirements and aspects. Including 69 attributes and capabilities of AI nursing care readiness, the core dimensions reflect key areas of action where AINC project stakeholders can influence project outcomes. Clinical partners can assess their organization's maturity level in relation to the implementation of AI. An assessment of each dimension and its attributes across 5 maturity levels allows reflecting on and proactively shaping individual project approaches. Overall, experts regarded AINCRA as a useful instrument for the development, management, and evaluation of AINC projects while emphasizing that established principles of good practice in project and data management should not be neglected when using AINCRA as a project management tool.

Conclusions: AINCRA enables practitioners from AI research and development, clinical partners, and nursing and health scientists to plan, evaluate, and enhance AI projects across their lifecycle, thereby supporting effective AI integration in nursing care. While AINCRA was developed within the European and German legal framework for AI in health care settings, respective attributes can be adapted to international requirements.

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KEYWORDS

artificial intelligence; nursing; care; readiness; maturity model

Introduction

Artificial intelligence (AI) systems promise to contribute to process optimization, workload reduction, patient safety, and quality assurance in nursing care worldwide [1-3]. Following the European Commission's guidelines on AI system definition as entailed in the European Union's Artificial Intelligence (EU AI) Act, AI systems in nursing care refer to machine-based systems developed to function with different degrees of autonomy and potentially adapt over time after being deployed [4]. AI systems process input data to produce outputs such as predictions, content, recommendations, or decisions based on explicit or implicit goals, and these outputs can affect physical or digital environments [4]. Main AI techniques encompass machine learning (ML) approaches including methods such as supervised learning, unsupervised learning, self-supervised learning, and reinforcement learning, or deep learning [4]. Additionally, AI systems include logic- and knowledge-based approaches that infer from encoded human knowledge or symbolic representation of the task to be solved [4]. Logic- and knowledge-based methods encompass areas such as knowledge representation, inductive logic programming, inference engines, expert systems, symbolic reasoning, and search and optimization techniques [4], highlighting diverse methodological possibilities for the development of AI systems in nursing care. Currently, opportunities for AI system development arising from applying generative AI models specifically trained on electronic medical record (or nursing record) data [5] further expand the scope of methods and use cases.

While AI is already supporting clinical decision-making of nurses in wound assessment [6] or diabetes care [7], monitoring and detection of risks and clinical deterioration throughout the care process [8-10], or nursing documentation via hybrid speech assistants [11,12], many unexplored use cases in acute and long-term care persist [13]. Furthermore, studies aiming to assess the effectiveness of AI systems in nursing care under real-world conditions using designs capable of determining cause-and-effect relationships are still scarce [14,15]. The potential benefits and expectations of artificial intelligence in nursing care (AINC) are high and are emphasized by professional associations and the World Health Organization, in light of growing global challenges to ensure high-quality care despite a declining number of health care professionals and increasingly complex disease and care trajectories of patients [16,17]. Funding bodies are investing in AI research and development (R&D), and the number of AINC projects is growing. In Germany, for example, the Federal Ministry of Health and the Federal Ministry of Research, Technology and Space support AINC projects in the areas of new care models, health care research, assistance of nurses and family caregivers, and enhancing autonomy and quality of life of people in need of care.

AINC projects face not only technical and regulatory requirements (eg, aspects of interoperability, compliance with national or international data laws, such as privacy and data protection laws, medical device regulations, or the EU AI Act) but also procedural, ethical, and social challenges of AI development and deployment (eg, the micro-, meso-, and macro-level impact of AI on nursing care, ethical-normative values of nursing and care, and translational factors such as acceptance of AI or added practical value) [14,18,19]. This applies to the planning, implementation, and evaluation phases of AINC projects. Project leaders encounter different care settings with many possible use cases for AI (such as AI systems for care in hospitals, nursing homes, outpatient care, or in initial, further, and continuing education) [2], with each care setting influencing the project process with its own unique organizational logic and culture. AI systems may be more complex to implement and use than many other digital technologies [20]. Organizations that aim to develop, deploy, and use AI systems face technical and human-centered challenges that can be overcome by building AI maturity and ensuring they are well-prepared for AI within their organizational context [20-22]. We propose that the same holds true for AINC projects, for which a systematic, comprehensive reflection of AI readiness attributes across various dimensions can help align, justify, and document actions and strategies across all project stages, and may serve as a motivation to foster communication and collaboration within interprofessional project consortia.

Maturity or, often synonymously used, readiness models provide structured guidance to enhance capabilities for effective (AI) technology integration [20,23,24]. Transferred from insights on organizations, readiness models provide features and guidance that help AINC projects to consider context-specific factors while not overlooking humanistic objectives and aspects of sociotechnical interplay next to focusing on technical and regulatory requirements [20,21]. There is a growing body of both theoretical and empirical research on readiness and maturity models [24]. Among these, stage growth models are particularly prevalent in information systems research [24]. These models typically define a progression of maturity levels, applied to an organization or process, ranging from minimal capability to full maturity, outlining an expected or ideal development path, accompanied by a measurement instrument [23,24]. As an example, in hospitals, the maturity model for ML systems [25] is structured around 3 dimensions: organization, adopter system, and patient data. These are broken down into 12 attributes and assessed across 5 maturity levels [25]. The model addresses aspects such as ML strategy, technical infrastructure, ML expertise, user acceptance, and the quality and standardization of patient data [25]. However, so far, an evidence-based AI readiness assessment prioritizing AINC projects and accounting for their diversity beyond R&D on ML in diverse nursing care settings is missing. Hence, the objective for our research is to develop a comprehensive artificial intelligence nursing care readiness assessment (AINCRA) tool for planning, conducting, and evaluating AINC projects responsibly. Therefore, in a sequential exploratory multimethods study, we ask the following questions:

1. What are dimensions, attributes, and levels of a readiness assessment intended to support those responsible for AINC projects as a reflection tool during the planning, implementation, and evaluation phases of their projects?
2. How do experts with practical experience in planning, implementing, and evaluating AINC projects understand

and use the AINCRA, and how do they assess it with regard to selected evaluation criteria?

We present AINCRA as a tool for decision-makers in R&D and clinical partners in AINC projects to reflect on their handling of prerequisites and aspects of these projects and for designing AINC projects in a promising and successful way. Further, we compare with recommendations for the development of maturity models and common criticisms of maturity models [24] to highlight methodological strengths and weaknesses of AINCRA.

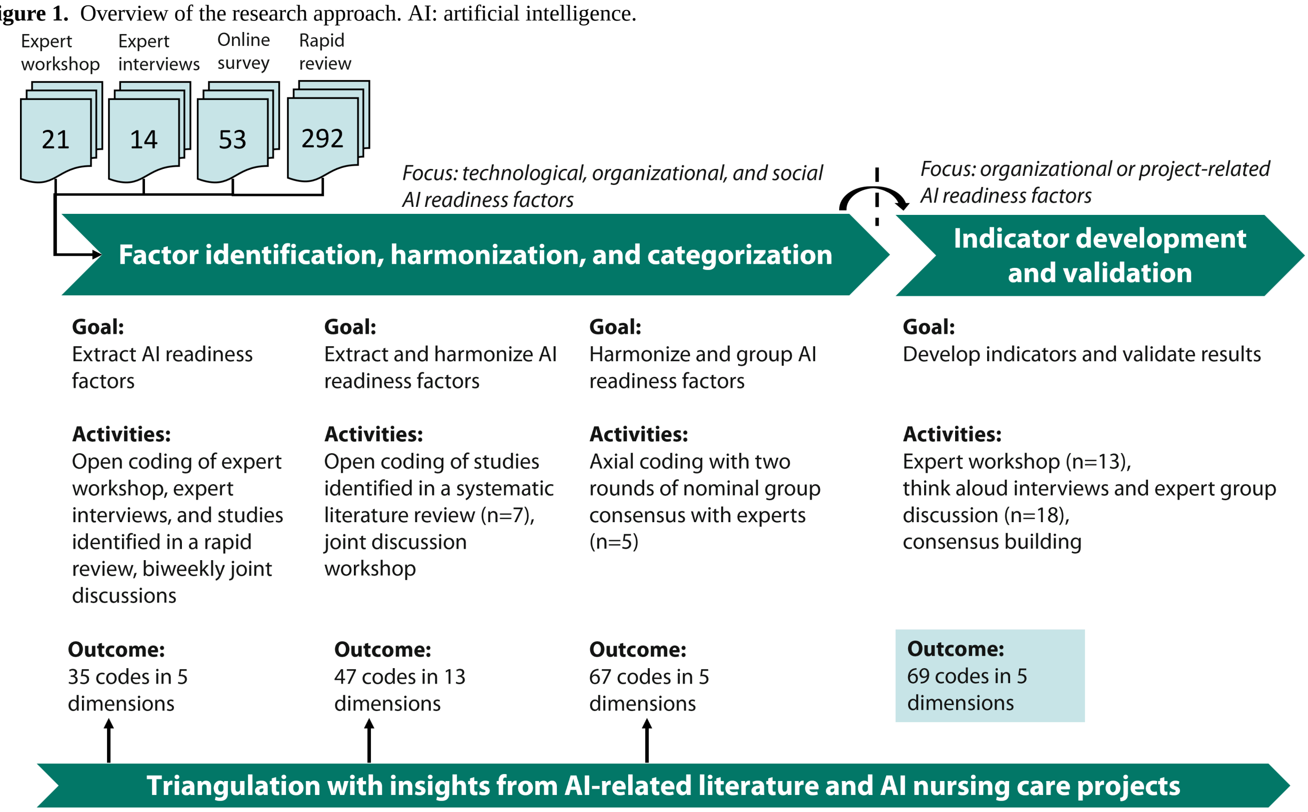
Methods

Overview

We conducted a sequential exploratory multimethods study following established design recommendations and structures of maturity models [20,23,24] to develop AINCRA. Figure 1 presents the research approach, highlighting goals, activities of data collection, analysis, and outcomes for the study period lasting from December 2021 to March 2025. In a stepwise bottom-up approach, we categorized AI readiness factors into capabilities, applying an iterative validation process. Building on preliminary qualitative and quantitative findings from our research group [3,13], we extracted AI readiness factors and conducted a complementary systematic literature review to inform the development of an initial AINCRA version as well as guiding questions for subsequent think-aloud interviews and discussions with experts. Additionally, we triangulated results and findings from the different steps of data collection with insights from AI-related literature and from 8 AINC projects we had been involved in or which we had been accompanying during the last 5 years by repeatedly comparing preliminary drafts of AINCRA with documented project plans to assess completeness.

We follow the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 statement for reporting systematic reviews (Checklist 1) [26]; furthermore, the COREQ (Consolidated Criteria for Reporting Qualitative Research; Checklist 2) [27] and criteria on mixed methods reporting [28] guide this research where applicable. A short description of the rationale, basic methods of development, and a short generalized overview of the AINCRA dimensions has been published elsewhere [29].

Figure 1. Overview of the research approach. AI: artificial intelligence.



Systematic Literature Review: Information Sources, Eligibility Criteria, and Review Protocol

Leading health and information sciences databases Scopus, PubMed, ACM Digital Library, AIS Electronic Library, and EconLit were searched in February 2023 for English- or German-language articles published from 2012 onward which either refer to a specific AI readiness assessment tool (defined by containing at least one specific question or evaluation criterion of AI readiness or maturity with a qualitative assessment option) or refer to frameworks or single studies that theoretically or empirically define AI readiness. Further, articles had to refer to AI readiness of institutions, organizations, projects, teams, or higher-level units (sectors and disciplines). Health care and nursing settings differ from other business sectors and societal areas, among other things, in that they often process highly sensitive personal data and aim to make it usable for AI systems. In addition, they are based on different sociocultural and organizational logics compared to, for example, the agricultural or logistics sector or the timelines and work culture of data science [30]. Therefore, following the assumption that AI readiness models established for other sectors cannot be transferred directly to the nursing care context, publications had to refer to nursing or health care settings. Eligibility criteria were established before conducting the initial searches, and a review protocol was developed but not registered.

Search Strategy and Selection Process

The search strategy followed a block building approach [31] applied to title, abstract, and keyword searches using the Boolean operator OR within a single block and the Boolean operator AND across blocks to combine the search terms and synonyms for the blocks encompassing “artificial intelligence,” “readiness,” and “assessment” are depicted in Multimedia Appendix 1. Two independent reviewers (KS and DW) screened titles, abstracts, and full texts according to predefined inclusion and exclusion criteria using the online resource Rayyan [32]. Conflict between reviewers was resolved by including a third reviewer (DD).

Data Collection Process and Data Items

Data extraction was carried out by one reviewer (KS) in a data extraction form created in Microsoft Excel for this purpose. Data items extracted from each included study entail the following: reference (author, year of publication, and title), country in which the study data were collected, objective of study, study design as stated, setting as stated; population: type and sample size (N); definition of AI: presented (yes or no), definition as stated; AI readiness: addressed (yes or no), definition as stated, explicit readiness assessment presented (yes or no), level of application (organization, project, team, and setting), health or nursing care addressed (yes or no), reporting of attribute origin (yes or no), origin of attributes as stated, number of attributes, description or labels of attributes, and labels of dimensions; readiness framework: presented (yes or no), name as stated, empirically tested (yes or no); success factors and challenges: reported (yes or no), success factors and challenges as stated; limitations as stated; ethics vote obtained: yes or no; funding; conflicts of interest. Missing data were coded as not reported.

Study Risk of Bias Assessment, Effect Measures, and Synthesis Methods

As a conclusion on the effectiveness of interventions was not an intended result of the systematic literature review, we did not conduct a risk of bias assessment and other assessments associated with good practice of methodology for meta-analysis. Results were summarized narratively after inductively developing structuring categories for readiness descriptions and dimensions, as well as for readiness attributes. Key findings are described narratively in the results section and supplemented with tables and figures where appropriate.

Think-Aloud Interviews and Group Discussions

Think-aloud interviews and group discussions were conducted online and digitally recorded with OBS Studio (version 29.1.3; OBS Project) in December 2024 and January 2025. Due to individual availability, 3 experts did not participate in a group discussion but answered group discussion guiding questions (Multimedia Appendix 1) in an interview following the think-aloud task. Details about the involved researcher’s background and relationship with participants are provided in Multimedia Appendix 1.

Selection and Recruitment of Expert Participants

We applied a purposive sampling approach [33] by sending personalized, electronic invitations to 42 experts who had either been actively involved in AINC bar camps held by our study team in the past or had conducted and published AINC-related R&D in Germany and were known to the study team. A total of 19 of 42 experts replied (response rate of 45.24%), and 17 experts consented to participation. The reason for nonparticipation was unavailability during the data collection phase. Additionally, all project leads of AINC projects in the German funding program “Making Repositories and AI Systems Usable in Everyday Care” were contacted via email and invited to participate or invite members of their project teams to participate. The possibility for participation was also advertised in the newsletter for said funding program, resulting in recruitment of one participant. We also asked the funding body to propose additional experts but did not receive a response.

Ethical Considerations

The ethics committee of the German Society of Nursing Science granted ethical clearance and approved this study (application 22 - 030). Participation was voluntary, and participants received no monetary or immaterial incentives or compensation. After receiving written information including statements on data protection, privacy, and confidentiality as well as concordance with the European General Data Protection Regulation, all participants provided a written informed consent to participation as well as to the pseudonymized analysis of the data obtained and to the publication of anonymized results. The study was not of an interventional nature. Participants were considered a nonvulnerable population, and participation was not classified as of particular risk.

Data Collection

An interview guideline structured and semistandardized the data collection process, which started with a 5-minute introduction of the interviewers, including their academic degree, field of research, and personal involvement in the research project, followed by an overview of the data collection process, an explanation of data protection, consent, and voluntary participation. After that, participants were asked to introduce themselves (name, work setting, and focus) and provide a short statement on their experiences with AINC projects and implementing AINC settings. A 10-minute introduction to the objectives of the study and AINCRA, during which participants were able to ask questions for clarification, made way for the 30-minute think-aloud interview. Participants were assigned to online breakout rooms with 1 or 2 members of the study team who also took field notes. The AINCRA dimension to be discussed was accessible on a Miro Board on which participants could navigate freely. Using the prompt outlined in the “Results” section, participants reflected on an AINC project they either had conducted, were conducting at the time of data collection, or were planning. They were asked to imagine that they are alone in the room and to talk to themselves. All thoughts were allowed to be expressed. If they were silent for a longer period, the interviewer asked them to continue to speak. Concurrent verbal probing [34] completed the think-aloud interview strategy. After the think-aloud interview, participants were guided into an online meeting room, where one researcher (KS) moderated the 35-minute group discussion structured by the guiding questions (Multimedia Appendix 1). Other researchers took field notes and asked follow-up questions at the end of the discussion but did not intervene. Guiding questions were based on prior national research on maturity model development [35], and refined in consultation with project members. A 5-minute exit phase concluded data collection, during which participants were informed about the availability of results and invited to the final study event. Afterward, researchers held a 15-minute debriefing to discuss key impressions and themes from their field notes.

Qualitative Content Analysis

Applying a deductive qualitative content analysis approach [36], coding was done by 5 members of the study team (KS, JA, LB, AN, and JP) using a coding form developed in Microsoft Excel for this purpose. Deductive content analysis allows for retesting existing data in a new context, involving testing of models [36]. Units of analysis are the participants' verbal contributions during the think-aloud interviews and focus group discussion. Audio files recorded during the think-aloud interview were randomly assigned to one coder, who listened to the recording, transcribed anchor statements, and paraphrased them. A second coder (KS) reviewed all transcripts and codes to validate the first coder's analysis. The structured categorization matrix [36] consisted of all dimensions and attributes of the AINCRA pilot version. For each interviewed person and AINCRA dimension, attribute, and level description, statements were documented as anchor statements. The same was done for statements on the relevance of attributes and suggestions made for revision or changes to AINCRA. The coding framework for the focus group discussion followed the guiding questions, with the overall coding process being the same as for the think-aloud interviews, using an unconstrained categorization matrix, where various categories were formed within the deductive framework based on the principles of inductive content analysis [36].

Mixing of Results and Consensus-Building on Final AINCRA Version, Translation Strategy

Overall, our integration strategy consisted of the following steps: deriving AI readiness attributes and dimensions from prior work and the results of the systematic review. Building on this, an initial AINCRA version was developed, including the definition of attributes for discussion with experts. The results of these discussions were taken into account in the development of the final AINCRA version: in a half-day consensus-building workshop, results from the think-aloud interviews and focus group discussions were reviewed by 6 members of the study team and discussed one last time against overlapping or contrasting themes derived from the systematic literature search. Further, consensus on which changes suggested by the experts should be incorporated into the final AINCRA version was established by discussion, and the final AINCRA version and a user manual were developed in German and English language. As the qualitative data collection was conducted in the German language, results were first compiled in German and then translated into English for publication. Primary translation was performed by the first author (KS) who was the main researcher involved in data collection and data analysis. All members of the study team had access to the German-language results and validated and revised the translated results, with multiple researchers having extensive experience in English-language knowledge transfer and dissemination of research results (DF, FB, KWO, MS, JP).

Results

Overview

Multimedia Appendix 2 presents the final AINCRA and Multimedia Appendix 3 contains the AINCRA user manual. An open-access online version of AINCRA is available [37]. In the following, we outline the iterative research process to contextualize the results contributing to the final AINCRA, before presenting an overview of AINCRA and its recommended application.

Preliminary Database

First, we built on preliminary work from our working group which has been published elsewhere: data from a rapid review [3] including 292 publications on AI systems in nursing care, an expert workshop with 21 experts (including nurses, nursing directors, health care managers from hospitals, nursing homes, and home care services, digitalization officers and professionals with experience in digital health or routine nursing data analysis, informal caregivers, nursing scientists, and researchers in nursing education, computer science, AI, and ethics) as well as interviews with 14 experts and an online survey (n=53) were used to identify success factors and prerequisites of AINC projects [13]. Five initial key dimensions (namely, regulatory requirements, processual and translational requirements and aspects, technical requirements, social and ethical aspects, and community building) entailing 35 codes emerged as a result of qualitative structuring content analysis involving deductive as well as inductive category and code building.

Systematic Literature Review on AI Readiness Models in Health Care and Nursing

Second, we conducted a systematic literature review to identify existing AI readiness models focusing on nursing or health care settings and harmonize AI readiness capabilities, attributes, and dimensions with results from the first step. Screening of 4748 records identified from 5 leading health and information sciences databases resulted in the inclusion of 7 single publications (Figure 2) which reported either at least one question or evaluation criterion of AI readiness with a qualitative assessment option or a framework for theoretically or empirically defining AI readiness in health care or nursing care.

Figure 2. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram of identification of studies via databases. AI: artificial intelligence.

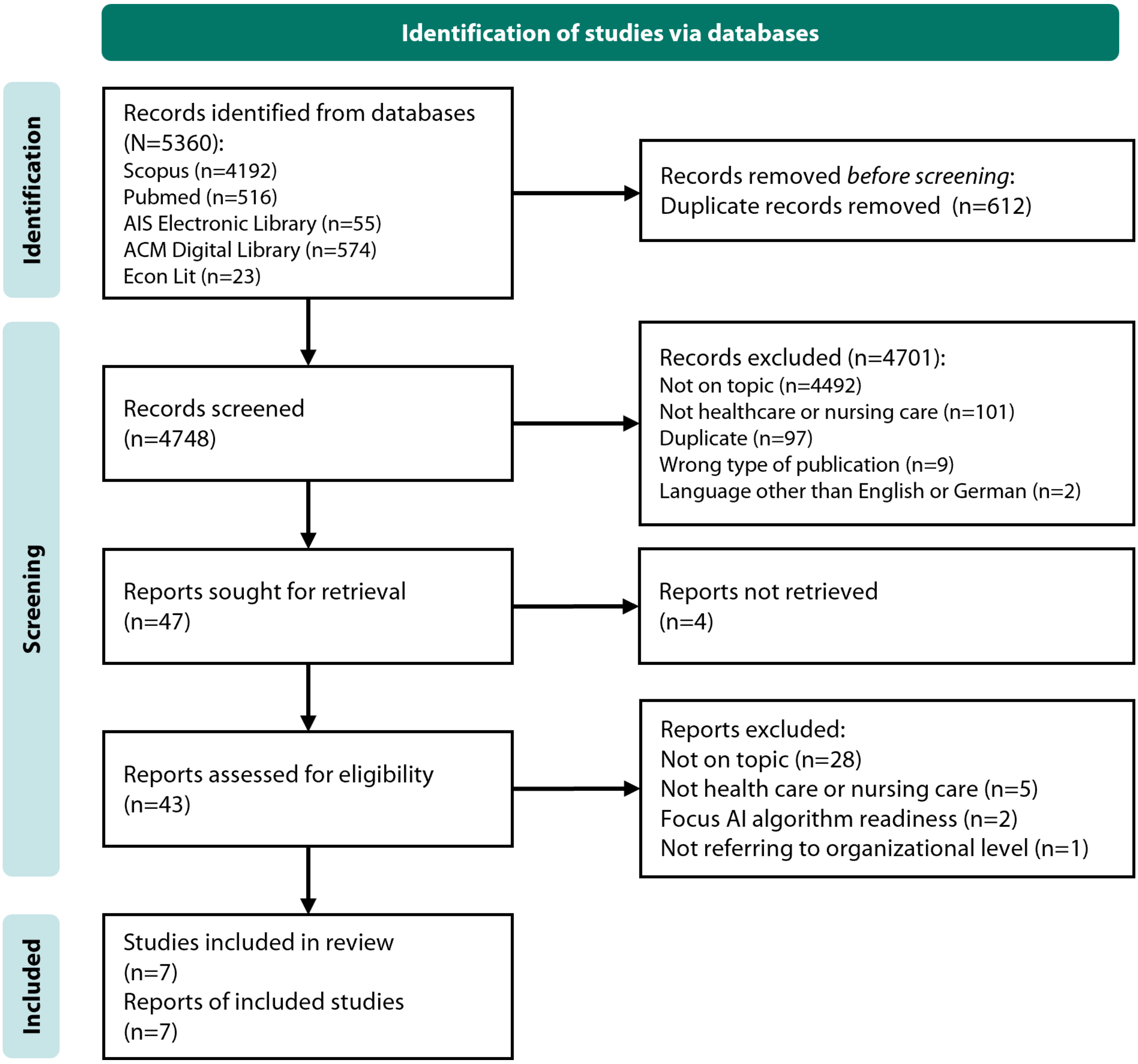


Table 1 provides an overview of the included studies and reports, 3 of which used observational designs with cross-sectional surveys among health care and IT professionals [38-40]. One study applied a qualitative design [25], 1 paper was classified as an expert reflection [41], and 2 papers did not report specific study designs to derive their results from [30,42]. Health care settings focused on either hospitals or selected professional groups or remained unspecified, without referencing specific nursing care settings in acute or long-term care. Overall, we extracted 74 single AI readiness attributes, which we inductively grouped into 47 codes in 13 AI readiness dimensions depicted in Table 2.

Table . Overview of included studies (N=7).

Reference; country of origin	Design	Aim	Population (N)	Reporting of				Number of readiness attributes
				Definition of AI[a]	Definition of AI readiness, explicit perspective	Readiness assessment description	Origin of readiness attributes	
Abuzaid et al 2022 [38]; United Arab Emirates	Observational, cross-sectional survey	Investigate knowledge, perception, readiness, and challenges regarding AI integration into radiology practice	Radiology professionals (n=153)	Y[b]	N[c] Organizational readiness	N	N	3
Alami et al 2020 [41]; International	Expert reflection	Bring forward the importance of studying organizational readiness to integrate AI applications	Not applicable, experiences with AI systems to support clinical decision-making reported	Y	Y Organizational readiness	Y Adapted framework from Jennett et al [43]	Y	Not applicable, readiness dimensions reported
Andersson et al 2021 [39]; Sweden	Observational, cross-sectional survey	Establish a foundation for a Swedish perspective on the potential effect of AI on the medical physics profession	Medical physicists (n=163)	N	N Workplace preparedness	N	Y	2
Chang 2020 [30]; country not reported	Unclear	Not reported	Not applicable	N	N	Y	N	10
Pumplun et al 2021 [25]; Germany and Switzerland	Qualitative	Explore factors that influence the adoption process of ML[d] systems for medical diagnostics in clinics; demonstrate how factors can be used to determine the ML maturity score of clinics	Medical experts and suppliers with profound knowledge in the field of ML (n=22)	Y	N	Y Maturity Model for ML Systems in Clinics	Y	12

Reference; country of origin	Design	Aim	Population (N)	Reporting of				Number of readiness attributes
				Definition of AI[a]	Definition of AI readiness, explicit perspective	Readiness assessment description	Origin of readiness attributes	
Weinert et al 2022 [40]; Germany	Observational, cross-sectional survey	Investigate factors influencing AI readiness as well as possible barriers to AI adoption and implementation in hospitals; assessed the status quo regarding the dissemination of AI tools in hospitals	Hospital chief information officers (n=40)	Y	Y Organizational readiness	Y Model by Jöhnk et al [21]	Y	47
Wiljer and Hakim 2019 [42]; Canada	Unclear	Not reported	Not applicable	Y	N	Y AI-enabled organization	N	Not applicable, readiness dimensions reported

[a]AI: artificial intelligence.
[b]Y: yes.
[c]N: no.
[d]ML: machine learning.

Table . Dimensions of AI[a] readiness derived from the literature (thematic, nonhierarchical grouping).

AI readiness dimension	Number of codes	Derived from
Personnel resources and competencies	12	[25,30,38-42]
Strategic planning	7	[25,30,38,40-42]
Data quality	8	[25,30,40,41]
Financial resources and investments	4	[25,30,40,41]
Acceptance and stakeholder participation	3	[30,39,41]
Technical infrastructure	3	[25,30,40]
Data protection and data safety	2	[30,41]
Intangible assets	2	[30,40]
Leadership culture	2	[25,30]
Needs and problems (in clinical practice and of patients)	1	[41]
Practical benefit and added value	1	[41]
Time resources	1	[40]
Organizational culture	1	[30]

[a]AI: artificial intelligence.

Axial coding and contrasting of these 74 readiness attributes with the 35 codes extracted in step 1 provided the database for 2 rounds of nominal group consensus involving 5 experts (2 nursing scientists, 1 ML expert, 1 information systems specialist, and 1 expert representing the German association for digitalization in the social economy with experience in consulting of clinical partners) to harmonize and group AI readiness factors. By merging semantically equivalent attributes and removing those not directly influenced by AINC stakeholders, the AI readiness attributes were reduced to 67 codes in 5 dimensions, serving as the baseline for the development of a pilot AINCRA version.

Indicator Development and Expert Validation

The pilot AINCRA version included feedback from 13 AINC project experts to establish a common AI readiness vocabulary for level distinctions. Building on vocabularies of existing maturity or readiness models [23,44], expert feedback was obtained from researchers and practitioners working in ongoing AINC projects at the time of data collection during a 45-minute bar camp session in September 2024 which was open for participation for all people currently used in 1 of 9 AINC projects in the German Ministry for Research, Technology and Space's funding program "Making Repositories and AI Systems Usable in Everyday Care." Further, level labels, frequencies, and numbering reported in the literature [23,25] were discussed with these experts, resulting in the decision to adopt 5 levels (1: initial, 2: assessing, 3: determined, 4: managed, and 5: optimized) with the possibility to rate an attribute as not applicable depending on the type of AINC project, AI system, or organizational features of clinical partners. The complete AI readiness vocabulary for level distinction is included in Multimedia Appendix 3. The use of the vocabulary and the 67 attributes derived from the third step of the research process as input for GPT-4o (OpenAI)–generated 335 level descriptions, which, after expert review and revision by all members of the study team, were incorporated into the AINCRA pilot version.

Finally, to evaluate the AINCRA pilot version, we applied a think-aloud interview approach [45,46] including a concurrent think-aloud session and reflexive group discussion with 18 experts with a proven track record in carrying out AINC projects to refine AINCRA dimensions, attributes, level distinctions, and descriptions. The think-aloud approach can be useful to "better understand thought processes during assessments as a strategy to describe what [an] assessment is measuring" [46]. Further, the think-aloud approach provided information about the cognitive thought processes of AINC project stakeholders using AINCRA "pertaining to usability problems they would encounter" [47] to reflect on a specific AINC project. Considering possible ways to evaluate maturity models, we followed good-practice recommendations by involving experts "on the type of process that is intended to be improved by the maturity model, but who have not been involved in the actual development of the maturity model" [48].

Characteristics of Think-Aloud Study Participants

At the time of data collection, 10 experts are involved in AINC projects outside of the German funding program "Making Repositories and AI Systems Usable in Everyday Care," while 8 experts are working in ongoing AINC projects in said funding program (characteristics of participants are depicted in Multimedia Appendix 1). Eight experts report less than 5 years of experience with AINC projects, while 5 experts indicate experience of 5 years or longer. These 5, as well as 5 experts who did not report conclusively on the duration of their experience, had also been involved in projects focusing on developing and implementing other digital technologies in nursing care, digitalization, and advancement of IT infrastructures in hospitals and long-term care for several years. Considering the main AINC project stakeholder groups regarding the composition of project consortia, 9 experts represent a nursing or health science perspective, often accompanied by responsibilities and roles connected to project coordination, while in some cases also holding topic-related qualifications or work experience such as nursing informatics expertise. Five experts represent clinical partners in AINC projects, and 5 experts represent AI R&D, 2 of them working for tech companies compared to 3 experts working for institutes affiliated with universities or independent research institutions. In the think-aloud interview, 13 experts reflect on an ongoing AINC project, 4 experts reflect on a completed project, and 1 expert reflects on a project in planning.

Think-Aloud Interview and Expert Group Discussion

Individual 30-minute think-aloud interviews and subsequent 35-minute group discussions were conducted online by 1 to 3 members of the study team in an overall 90-minute session. All participants received an overview of all AINCRA pilot version dimensions and attributes in advance. However, detailed level descriptions were only presented during the interview, along with the verbal prompt to evaluate an ongoing, in planning, or past AINC project they were familiar with. They were asked to do so by using the attributes and level descriptions of one or more selected AINCRA dimensions, referring to a recalled point in time (eg, planning, implementation, or evaluation phase), while verbalizing all their thoughts aloud. Since we anticipated the pilot version to be a complex and time-consuming assessment, participants were only presented with selected dimensions, never all of them. The selection was made with knowledge of the participants' areas of expertise, with a slight emphasis on process-related requirements. This focus was chosen because these dimensions included attributes that are described in the literature as being often neglected in AI maturity models [20], and which, according to our preliminary study, are known to significantly influence project flow and success [13].

We obtained expert statements and comments on 64 of 67 attributes with a total of 70 suggestions for changes to the AINCRA pilot version (Multimedia Appendix 1). Changes suggested included adding definitions, or explanations, or examples for selected terms (eg, "data champion" and "ontological representation"), simplification of terms, reordering and grouping of attributes within 1 dimension or across 2 dimensions, splitting of attributes, and adding of examples in level descriptions (eg, sponsor role as a required responsibility when compliance with the EU Medical Device Regulation is mandatory for the AI system). Some comments highlighted the need for adding information to the AINCRA user manual without resulting in changes to dimensions, attributes, or level descriptions. Overall, 37 of 70 (53%) changes suggested were realized in the final AINCRA version.

In the group discussions, experts rated and discussed the AINCRA dimensions, attributes, and level descriptions they had applied to their own AINC projects in the think-aloud interview. An overview of the discussed evaluation criteria with their respective guiding questions for the discussion can be found in the "Methods" section. In summary, AINCRA was assessed as a valuable tool for AINC project development, management, and evaluation by the experts. However, some experts pointed out that not all influencing aspects of AINC projects can be foreseen using AINCRA, and that a project process can also be set up without applying AINCRA. Further, general aspects of good practice of project or data management that still need to be considered in each project should not be overlooked when focusing on AINCRA as a project management tool. Multimedia Appendix 1 displays expert ratings and feedback for each evaluation criteria. Results for each evaluation criteria are summarized below and highlighted with selected expert statements.

Benefits and Consequences of Applying AINCRA

Considering benefits and consequences of applying the AINCRA to AINC projects, experts generally see added value. Advantages of applying the complex AINCRA are seen by some as being more suited to larger research projects rather than smaller initiatives or in-house projects, while others also recognize its value for those smaller endeavors. Added value was also noted for project consortia with little prior experience in conducting AINC projects. For clinical partners, AI R&D, and nursing or health science research partners in AINC projects, AINCRA is seen as useful for decision-making, planning, grant applications, coordination among partners, identifying resources and expertise, aligning goals, managing projects, and conducting evaluations. Experts also pointed out AINCRA's usefulness for AINC project funding bodies, as AINCRA may support documentation, monitoring, evaluation, and comparison of AINC projects. Expert participants representing tech companies pointed out that AINCRA may help with their project management activities, client consulting, and long-term support of AI implementations.

> *I think another advantage is that with [AINCRA], you can already identify project risks [...] during project planning, for example the area of social and ethical success factors [...] which is very helpful if such a dimension is already represented here.* [IP2, 00:48:18]

Results of AINCRA may lead to various consequences for AINC projects: positive consequences entail advantages in grant applications for high-scoring applicants, identification of improvement areas and necessary changes, support for go or no-go AINC project decisions, and early reflection on and evaluation of an AI system's practical value. However, an AINCRA result may evoke emotional effects in the individuals conducting the assessment, influencing their motivation to engage with AINC readiness attributes or to push an AINC project forward. Low AINCRA scores may cause frustration or disappointment but can also spark motivation and ambition to improve. However, low-level placement may demotivate clinical partners or discourage participation if initial AINC readiness appears too low and difficult to improve.

> *Especially if the requirements are not met at the beginning, it can quickly give the impression that one doesn't want to do it and doesn't see the benefit for the effort that has to be put in, even though there actually is one.* [IP14, 00:54:16]

Rater Entity

When asked who should carry out the assessment, experts agree that AINCRA is unlikely to be effectively carried out by a single individual. Depending on the dimension and attribute, different individuals should be involved, or AINCRA should be conducted collaboratively, either in a group or in a tandem (eg, between clinical and AI R&D partner) within an interprofessional team. For assessing processual and translational requirements and aspects, suitable raters include experienced personnel from the clinical partner with nursing and digitalization expertise, and IT staff of the clinical partner in collaboration with nursing management with a focus on joint assessments by AI R&D and clinical partners. Conducting AINCRA as a guided, participatory assessment involving frontline nurses was stated as a suitable approach. However, some experts caution against including certain roles (eg, nursing assistants) and emphasize that nurses should be supported during their involvement. Experts also raise the question of who holds responsibility for the AINCRA result, especially if the result impacts, for example, project funding decisions.

> *I think it would be good if the evaluation is done at the start by the project consortium, not by the individual specialists [...] it would be good if everyone in the consortium, with its different disciplines, is clear about [...] all five dimensions [...] so that together they have a clearer idea of what lies ahead.* [IP3, 00:52:05]

Attainability of Levels

Assessing the attainability of AINCRA levels, overall, experts view the levels as realistic and reflective of the diversity among clinical partners and AINC projects. However, not all levels appear to be achievable. They emphasize that this should not necessarily be the expectation for AINC projects, as attainability of levels depends on the dimension assessed and the project context. Level 5 is ambitious and currently hard to reach for most clinical partners. But experts emphasize that level 5 should be a long-term goal and is seen as achievable, especially for clinical partners with extensive AINC project experience, but is considered unrealistic for R&D projects. Level 4 is regarded as the upper realistic limit for R&D projects and a desirable target for clinical partners. Level 3 is also seen as a satisfactory goal for clinical partners. While level 2 was not discussed in detail, for level 1, experts point out that some clinical partners already start AINC projects while scoring above level 1.

> *I would definitely say that we have developed. There were some levels that, from our perspective, were not achievable. But the question is also whether that's the goal. Maybe it's enough to say that you get through with a 3.* [IP11, 00:51:18]

Achievability of Levels

Reflecting on past AINC projects that, from the experts' point of view, were successful, experts discussed the achievement of the AINCRA levels regarding the level at the start of a project and the evolution of levels throughout the project process until completion. Overall, the achievement of AINCRA levels is rated as depending on individual goals and structures of an

AINC project. Progression is inherent to AINC projects, as no project meets all requirements from the start. Participation in an AINC project can lead to the development of new structures and processes at the clinical partner organization that go beyond AINCRA attributes. In contrast, some AINC projects may not show improvement despite great efforts to advance AINC readiness attributes. All types of development trajectories are possible, with advancement, remaining, or regression of levels. Entry levels and basic conditions may help industry (or R&D) partners to more easily identify suitable clinical partners, with level 1 being rated not as a general exclusion criterion, but a knockout criterion for certain attributes (eg, data availability).

> *I do believe that there can be deal-breaker criteria in attributes. Off the top of my head, I thought of data quality and data availability in our project. Especially structural things – if those aren't in place, we don't need to start an AI project. If my data are just scattered on paper.* [IP13, 00:53:24]

Step Size of Levels and Influenceability of Attributes

Step size of AINCRA levels is rated as sufficient, appropriate, and distinct with little in-depth discussion. Influenceability of the AINCRA attributes was discussed in depth: most attributes are considered influenceable within AINC projects. However, some less influenceable attributes are still important, such as regulatory requirements or legal framework changes, which are typically beyond a project's control. Experts highlight influenceability as a reflection criterion, especially when a project receives a low maturity level rating. Attributes considered particularly influenceable are related to attitudes, acceptance, knowledge, and willingness to change of stakeholders at the clinical partners' organization. Limited influenceability is assigned to attributes requiring fundamental corporate decisions (eg, developing and committing to an internal AI strategy) as well as attributes dependent on external conditions of clinical partners (eg, staff shortages, turnover, and financial resources).

> *[AINCRA attributes are] all topics that I can address within the project.* [IP11, 00:55:39]

Availability of Information, Comprehensibility, and Applicability

Discussion of the availability of the information or data needed to carry out the AINCRA revealed that the required information is rated as available or obtainable with reasonable effort for AINC project stakeholders by the experts. Involving additional stakeholders is emphasized, supporting the previous assessment that AINCRA should be conducted as an interprofessional assessment. However, the availability of additional stakeholders may be limited, for example, if IT staff of clinical partners have competing responsibilities and carrying out AINCRA is considered a lower priority compared to other tasks.

> *All [attributes] I have seen so far [.] are definitely such that you can either answer them yourself or at least know who to turn to in order to get the information.* [IP12, 01:14:26]

Regarding the comprehensibility of the AINCRA, some experts consider the instrument to be low-threshold and emphasize its comprehensibility for AINC project leaders. However, some wording is not familiar to all nursing professionals. There is also concern about whether nonnative speakers in nursing leadership or administrative roles will understand the expressions and terminology used in AINCRA. Referring to statements made in the think-aloud interview, experts provide suggestions for logically ordering, rephrasing, or explaining selected attributes, as details of the attributes and level descriptions were rated as not quickly to be grasped.

> *So, I would assess it as very understandable [...] of course, during the [think aloud interview], I naturally picked out the things I understand in order to be able to answer them [...] the comprehensibility depends on who from the consortium is conducting the assessment [...] regarding nursing topics, the IT partners probably would have said, 'I don't understand anything about that at all' [...] it depends on who is sitting in front of it and which professional domain it is.* [IP2, 01:03:33]

For the applicability of AINCRA, experts assess the AINCRA pilot version as a complex, text-heavy instrument that, when applied thoroughly, can take several hours to complete depending on the dimension rated. This long application duration may reduce acceptance of AINCRA. Initial use in particular requires time to understand the instrument and is not necessarily intuitive. However, experts expect that the time required will decrease over time and that the application will become easier with continued use. Conducting AINCRA in an interprofessional team enhances its applicability. Some experts attest to the very good usability of AINCRA, though it should be noted that no expert applied the entire instrument. Application seems challenging for stakeholders in long-term care facilities due to lack of expertise in certain attributes. Experts discussed whether a shortened AINCRA version could be provided.

Comparability and Completeness

Comparability of AINCRA results between AINC projects is assessed heterogeneously between the experts, with some pointing out that comparability is difficult, and others emphasizing that comparability of individual dimensions and attributes is possible. Further, multiple practice partners within one AINC project may be compared with AINCRA, as well as multiple AINC projects within the same funding program, and comparability can be ensured through external evaluation.

> *Of course, it's a self-assessment tool [...] the question is whether it's answered honestly and whether that allows for comparability. If it's evaluated in a review process by external parties, then I do believe that good comparability can be achieved.* [IP8, 00:21:20]

Completeness of AINCRA overall is rated as given, with some experts highlighting suggestions for additions or change. These address the inclusion of staff representatives of clinical partners as important stakeholders, allowing for custom attributes to be added by users, and enabling mapping of multiple clinical partners within a single AINC project.

Overview of AINCRA Dimensions, Attributes, and Levels

AINCRA consists of 69 AINC readiness attributes across five dimensions: (1) regulatory requirements and aspects (9 attributes), (2) processual and translational requirements and aspects (40 attributes), (3) technical requirements and aspects (6 attributes), (4) ethical and social requirements and aspects (11 attributes), and (5) community building requirements and aspects (3 attributes). Table 3 provides an overview of the 5 dimensions. For each attribute, 5 maturity levels are described, a recommendation for stakeholders considered as most suitable as assessors is given, along with a reference to the source from which the attribute or the justification for the relevance of the attribute is derived (Multimedia Appendix 2).

Table . Overview of AINCRA[a] dimensions.

Dimension	Description
Regulatory requirements and aspects (9 attributes)	• This dimension takes into account the necessary legal frameworks and data protection regulations that require an analysis of the data and an examination of data-sharing models to enable the use of AI[b] systems in everyday nursing practice.
Processual and translational requirements and aspects (40 attributes)	• This dimension captures the human, material, temporal, and intangible resources available for AI in nursing care projects in care facilities or hospitals, as well as their general and AI-specific level of digitalization. • It also assesses the maturity of overarching strategies for AI, data governance, and IT governance, as well as plans for long-term external support and evaluation of AI implementation. • Engagement with the implementation of needs-based research and development of AI systems—focused on practical benefits and added value—as well as the existing AI-related knowledge and competencies within care facilities and clinics, is intended to support the seamless integration of AI systems into existing care processes. • This dimension also includes reflection on attitudes toward AI, acceptance of AI technologies, and trust in their use in daily nursing practice, to foster adoption and address concerns of those affected by the deployment of AI.
Technical requirements and aspects (6 attributes)	• This dimension addresses the availability and functionality of the technical infrastructure, including aspects of data protection and data security, which are essential for reliable data use and analysis. • To ensure smooth, secure, and efficient data integration and exchange between different systems and stakeholders in everyday nursing practice, this dimension also considers the integration of AI systems into data infrastructures or data platforms, as well as the use of technical interoperability standards and nomenclatures.
Social and ethical requirements and aspects (11 attributes)	• This dimension encompasses ethical and methodological considerations related to voluntariness, privacy, fairness, and transparency, as well as the ethical and normative value orientations of the field and individual practice partners. • Engaging with the impacts of AI use at the micro, meso, and macro levels, along with a responsible approach to data handling, is intended to support the use of AI systems in everyday nursing practice.
Community building requirements and aspects (3 attributes)	• This dimension aims to promote a network that strengthens knowledge exchange and the collective advancement of AI systems in everyday nursing practice. Researchers, developers, and stakeholders from nursing practice and nursing management are involved in this network.

[a]AINCRA: artificial intelligence nursing care readiness assessment.

[b]AI: artificial intelligence.

AINCRA dimension 1, regulatory requirements and aspects, involves the assessment of how detailed and specific methodological and regulatory decisions, definitions, and limitations are being addressed by an AINC project. This includes, among other things, attributes reported by Pumplun et al [25] for analyzing the dataset, as well as the operationalization of data-sharing models [30,41,49]. In the latter case, for example, the degree of finalization and the progress of the implementation of the model serve as reflection criteria. This dimension also relates to the engagement with requirements arising from the EU AI Act. AINC project stakeholders recommended for assessing dimension 1 are mainly individuals representing AI R&D, supplemented by a clinical partners' and nursing science perspective for some attributes. An example of the attributes 1.6 Data-sharing Models and 1.9 EU AI Act, corresponding level descriptions, recommended rater entity, and sources of attribute origin is shown in Table 4.

AINCRA dimension 2, processual and translational aspects and requirements, evaluates the resources, general as well as AI-specific digital readiness, and strategic planning in place for implementing AINC. It considers infrastructure, staff skills, governance, and external support, as well as how well AI aligns with care needs and existing workflows. It also examines staff attitudes, acceptance, and trust in AI to support successful integration into everyday practice. Most attributes are targeted at the clinical partner, whose expertise is crucial for assessing this dimension and which needs to be supplemented by nursing science and AI R&D expertise to arrive at a comprehensive assessment. This is reflected, for example, in attributes targeting the degree of digitization, which includes the use of data quality standards [25], the availability of data champions [30] as a personnel resource, or the systematic demonstration of practical benefit and added value of an AI system (Table 4).

AINCRA dimension 3, technical requirements and aspects, focuses on the technical infrastructure needed for reliable and secure data use in AINC projects. It includes data protection, system integration, and the use of interoperability standards to ensure smooth data exchange and effective AI implementation in clinical practice. The main AINC project stakeholder to assess dimension 3 is AI R&D. While the technical infrastructure at clinical partner sites is an essential and priorly described prerequisite for AINC project success [30,41,49], we recommend especially assessing IT infrastructure with a focus on AI compute capabilities and dedicated hardware, for which requirements are often underestimated or not clearly communicated between AI R&D and clinical partners during initial AINC project planning (Table 4).

AINCRA dimension 4, ethical and social requirements and aspects, covers ethical and methodological aspects such as voluntariness, privacy, fairness, and transparency. It also considers the values of the nursing field and its practitioners, as well as the broader impacts of AI use and responsible data handling to support ethical AI integration in daily nursing care. Dimension 4 should be assessed from a multifaceted perspective, including nursing science and clinical partners. In collaboration with clinical partners and AI R&D, nursing scientists should drive the assessment of whether and how structured engagement with ethical-normative values of nursing and care [49] is operationalized in an AINC project. The same holds true for reflecting on the impact of AI on the nursing profession [49], and how this impact informs AI system development, implementation, and evaluation (Table 4).

Table . Examples of attributes and level descriptions across the AINCRA[a] dimensions.

Dimension and attribute number	Attribute	Level 1 (initial)	Level 2 (assessing)	Level 3 (determined)	Level 4 (managed)	Level 5 (optimized)	Not applicable	(Joint) Assessment by (rater entity)	Source
Regulatory requirements and aspects									
1.6	Data-sharing models	• Data-sharing models relevant to the AINC[b] project are unknown or unclear. • No considerations regarding appropriate models and approaches exist.	• Initial considerations and steps toward defining and implementing a data-sharing model are being taken. • However, the model is not finalized, and necessary people and procedures are not yet fully clarified.	• The data-sharing model and approach are defined, and most legal, organizational, and technical requirements are identified. • Contact persons and responsibilities are known, but detailed negotiation and implementation have not started.	• The data-sharing model and approach are defined and known to all project participants. • All legal, organizational, and technical requirements are fully identified and documented in a structured manner. • Responsible contacts are involved and took part in detailed negotiations. • Implementation includes appropriate regulatory, organizational, and technical safeguards	• The model and processes of data sharing have been implemented with all necessary regulatory, organizational, and technical safeguards. • Fulfillment of requirements is proven (eg, through internal and external certification). • Data sharing and usage are fully documented, and documentation is regularly reviewed. • Processes and structures evolve based on audit results.	• Not applicable	• AI[c] R&D[d]	[30,41,49]

Dimension and attribute number	Attribute	Level 1 (initial)	Level 2 (assessing)	Level 3 (determined)	Level 4 (managed)	Level 5 (optimized)	Not applicable	(Joint) Assessment by (rater entity)	Source
1.9	EU[e] AI Act	• No consideration of the EU AI Act in the AINC project. • No awareness of which parts of the project are affected.	• Initial steps to comply with the EU AI Act are underway. • A basic overview exists, but the requirements are inconsistently implemented. • Responsibilities and external actors are not fully clarified.	• The AINC project is committed to compliance with the EU AI Act. • A broad overview exists, responsibilities are defined. • Many requirements are implemented or planned, but coverage and documentation are not complete.	• The AINC project is committed to AI Act compliance and has a structured overview of legal requirements. • Responsibilities are clear and implementation follows a defined process standard. • All requirements are planned or fulfilled with explicit deadlines and sufficient resources (time, personnel, and other). • Implementation is well-documented, tested, and regularly monitored.		• Not applicable	• AI R&D • Nursing Science • Clinical partner	Emerged from this research

Dimension and attribute number	Attribute	Level 1 (initial)	Level 2 (assessing)	Level 3 (determined)	Level 4 (managed)	Level 5 (optimized)	Not applicable	(Joint) Assessment by (rater entity)	Source
						• Full compliance with the EU AI Act is ensured. A complete and structured legal framework exists and is shared with all participants. • Responsibilities are clear, and implementation follows international standards (eg, ISO/IEC 42001). • All requirements are planned or fulfilled with explicit deadlines and sufficient resources (time, personnel, other), documented, tested, externally certified, and continuously			

Dimension and attribute number	Attribute	Level 1 (initial)	Level 2 (assessing)	Level 3 (determined)	Level 4 (managed)	Level 5 (optimized)	Not applicable	(Joint) Assessment by (rater entity)	Source
						improved.			
Processual and translational aspects and requirements									

Dimension and attribute number	Attribute	Level 1 (initial)	Level 2 (assessing)	Level 3 (determined)	Level 4 (managed)	Level 5 (optimized)	Not applicable	(Joint) Assessment by (rater entity)	Source
2.9	Clinical partner: personnel resources: available data champions[f]	• There are no data champions (at the clinical partner) in the AINC project, and the use of data is not actively promoted or supported.	• First data champions (at the clinical partner) are being identified, but their role is not yet formalized or recognized.	• Some data champions (at the clinical partner) are active, their role is defined, and they promote a data culture in selected areas.	• Data champions (at the clinical partner) are established and work across departments to promote and support data use.	• Data champions are fully integrated into the organizational structure (of the clinical partner) and actively drive a data-driven culture forward.	Not applicable	• Clinical partner with IT staff • AI R&D	[30]
2.32	• Practical benefit and added value of the AI system	• The practical benefit or added value of the AI system is unknown, or no clear practical benefit or added value is evident. • The AINC project is predominantly theoretical.	• The potential benefit of the AI system is recognized, but concrete indicators or criteria for capturing the benefit and added value are unclear. • Initial steps to evaluate the added value are being taken but are not consistently recorded and documented.	• The AI system shows a recognizable practical benefit, which is represented by concrete indicators or criteria. • However, end points are only partially captured, or the benefit is only partially realized.	• The practical benefit of the AI system is clearly defined and is systematically implemented and demonstrated within the AINC project.	• The AI system generates significant practical benefit and added value, which is continuously measured and optimized using clearly defined criteria and indicators.	Not applicable	• AI R&D • Nursing Science • Clinical Partner	[30,41]
Technical requirements and aspects									

Dimension and attribute number	Attribute	Level 1 (initial)	Level 2 (assessing)	Level 3 (determined)	Level 4 (managed)	Level 5 (optimized)	Not applicable	(Joint) Assessment by (rater entity)	Source
3.2	Use of technical interoperability standards and nomenclatures	• No use of interoperability standards or nomenclatures.	• Initial steps toward using and considering interoperability standards and nomenclatures in the development of the AI system within the AINC project, but not yet fully implemented.	• Interoperability standards and nomenclatures are partially considered and used in the development of the AI system within the AINC project, but not consistently.	• Extensive use and integration of interoperability standards and nomenclatures in the development of the AI system within the AINC project.	• Complete and optimized use of interoperability standards and nomenclatures in the development of the AI system within the AINC project, regularly updated and applied across all relevant areas.	Not applicable	• AI R&D • Nursing Science	[30,41,49]
3.6	IT infrastructure: AI compute: hardware	• No dedicated AI hardware available.	• Dedicated AI hardware is available but not yet connected, eg, to data interfaces.	• Dedicated AI hardware is available and connected (eg, to data interfaces). It is possible to transfer data into the runtime environment for model development.	• Dedicated AI hardware is available and connected. Standardized interfaces are in place for data transfer and for offering model predictions. • Continuous testing and maintenance of the AI system is possible.	• Fully optimized and up-to-date dedicated (hardware and software) runtime environments are available. • Model development and maintenance are implemented according to modern CI or CD components.	Not applicable	• AI R&D	Emerged from this research

Dimension and attribute number	Attribute	Level 1 (initial)	Level 2 (assessing)	Level 3 (determined)	Level 4 (managed)	Level 5 (optimized)	Not applicable	(Joint) Assessment by (rater entity)	Source
Social and ethical requirements and aspects									
4.4	Engagement with ethical-normative values of nursing and care, and individual clinical partners	• No engagement with ethical values (has taken place) in the AINC project.	• Initial ideas on how to engage with ethical-normative values in the AINC project exist but are not concrete or systematic.	• Methods to engage with ethical-normative values are defined but are only partially implemented or exclude some stakeholders.	• Regular, systematic, and documented engagement with ethical-normative values including all stakeholders is part of the AINC project.	• Regular, systematic, and documented engagement with ethical-normative values including all stakeholders is part of the AINC project, and is adapted as needed.	Not applicable	• AI R&D • Nursing Science • Clinical Partner	Emerged from our prior research [49]
4.6	Reflection on the impact of AI on the nursing profession	• The general influence of AI on nursing is acknowledged, but there is no project-level reflection.	• Initial reflections on the impact of AI on the nursing profession are present. • However, reflections are unsystematic and without an effect on system development, implementation, or evaluation.	• Systematic reflection on the impact of AI on the nursing profession is part of the AINC project but lacks influence on development, implementation, or evaluation.	• Comprehensive reflection on the impact of AI on the nursing profession that informs system development, implementation, and evaluation is part of the AINC project.	• Fully integrated reflection on the impact of AI on the nursing profession is included in the AINC project results and documentation.	Not applicable	• AI R&D • Nursing Science • Clinical Partner	Emerged from our prior research [49]
Community building requirements and aspects									

Dimension and attribute number	Attribute	Level 1 (initial)	Level 2 (assessing)	Level 3 (determined)	Level 4 (managed)	Level 5 (optimized)	Not applicable	(Joint) Assessment by (rater entity)	Source
5.3	Strategic partnerships	• Existing strategic partnerships are unknown or there are no strategic partnerships in the AINC project or among individual project partners.	• Initial strategic partnerships are being explored, but have not yet been fully concluded or formalized.	• Strategic partnerships are partially established, but not all partners in the AINC project have strategic partnerships. • Clinical partners in particular do not have strategic partnerships outside of the project consortium.	• Comprehensive strategic partnerships are established. • Clinical partners also have strategic partnerships outside of the project consortium. • Existing strategic partnerships are regularly reviewed and expanded, especially on a national level.	• Proven and effective strategic partnerships are established for all partners in the AINC project. • Existing strategic partnerships are continuously and internationally expanded.	Not applicable	• AI R&D • Nursing Science • Clinical partner	[42]

[a]AINCRA: artificial intelligence nursing care readiness assessment.

[b]AINC: artificial intelligence in nursing care.

[c]AI: artificial intelligence.

[d]R&D: research and development.

[e]EU: European Union.

[f]Data Champions understand the types of data generated at the clinical partner, advocate for proper data handling, and mediate between nursing staff and IT. They ensure data are correct, complete, and up to date, identify and resolve data collection issues, enhance staff data literacy through training, and raise awareness about the importance of data in nursing care and research.

AINCRA dimension 5, community building requirements and aspects, promotes a collaborative network to support knowledge exchange and the shared development of AI systems for nursing care, involving researchers, developers, and professionals from nursing practice and management, ideally reaching beyond single-project boundaries and striving for national and international networks and shared knowledge. All AINC project stakeholders can assess dimension 5 with AI R&D and nursing science, especially reflecting on their involvement in technical knowledge transfer [49], while clinical partners should also reflect on existing strategic partnerships and how to foster these [42] (Table 4).

Applying AINCRA

AINCRA is primarily designed as a self-assessment tool for AINC project partners. It addresses topics such as the use and benefit of AINC, data representativeness and sharing, participatory design, and ethical and professional implications of AI implementation. AINCRA can be used at any project stage: a single assessment provides a snapshot of current AI readiness, while repeated assessments enable monitoring progress over time. It may also serve as an external evaluation tool. In all cases, AINCRA should be applied by an interprofessional team, ideally involving representatives from

AI R&D, nursing science, and clinical partner organizations. The tool can be used for an entire AINC project or for selected dimensions or sub-areas.

Interpreting AINCRA

In the absence of an internationally agreed consensus on which factors most strongly determine the success of AINC projects, AINCRA does not produce an overall score. Instead, it prompts users to reflect systematically on all dimensions and attributes, which are consistently considered important for project success. AINCRA results provide a snapshot of an AINC project's current readiness with regard to known prerequisites for successful AI development and implementation in nursing care. The tool can be used in context analysis, project planning, and formative evaluation to identify areas for further development or prioritization, and in summative evaluation to reflect on factors that influenced project outcomes. Across all project phases, AINCRA supports alignment, justification, and documentation of strategies while fostering constructive, content-focused dialogue among project partners.

Discussion

Principal Findings

Despite AI's high potential to support nursing care, many use cases in acute and long-term care are still underexplored [13], and R&D projects face multifaceted challenges when designing, implementing, or evaluating AI systems in everyday nursing care. In this study, we systematically developed dimensions, attributes, and levels of AI readiness based on published empirical evidence as well as insights from experts with practical experience in conducting AINC projects. Integrating findings from prior work, a systematic literature review and expert discussions directly shaped the development of AINCRA. Attributes and dimensions identified in earlier work provided an initial conceptual structure that was operationalized in a first AINCRA version. This version served as the basis for think-aloud interviews and discussions with experts during which the relevance, clarity, and completeness of individual attributes were critically examined. Feedback from these discussions led to the refinement and consolidation of attributes and informed adjustments. As a result, the final AINCRA reflects a synthesis of theoretical grounding, empirical evidence, and practical expert insight. The resulting AINCRA comprises 5 dimensions and 69 AI readiness attributes across 5 readiness levels that can guide AINC project planning, implementation, and evaluation. While experts with practical experience in conducting AINC projects rated the readiness level 5 (optimized) as ambitious and often unrealistic for AINC projects, they recognized AINCRA's value and overall benefit to support AINC projects, especially with respect to early identification and thus avoidance of common pitfalls of these projects.

A major strength of AINCRA is its comprehensive inclusion of evidence-based, previously established AI readiness factors, with a focus on processual and translational aspects. Prior research on a sociotechnical perspective for responsible AI maturity models has shown that organizations often focus on technical and business assessments when developing and deploying AI systems, while overlooking critical ethical, social, and human dimensions [20]. We argue that this holds true for AINC projects as well, so that they will benefit from recognizing and systematically addressing the importance of both technical and social aspects [20]. In addition, AINCRA sets itself apart from other freely available or commercial instruments, such as the analytics maturity assessment model promoted by the Healthcare Information and Management Systems Society through its consistent focus on the specific application context of nursing care. Many of the models existing before the AINCRA development have not been thoroughly reviewed by the scientific community. Therefore, they were not identified during the systematic literature review. AINCRA goes beyond preexisting models, offering a framework that is both more specialized and scientifically validated for use in AINC projects. As most attributes were derived from and may be transferred to a global context, we see overall generalizability of our results, even though AINCRA was developed within the European legal framework for AI in health care settings. While experiences of AINC experts stem from a German health care and research system perspective that may differ from other countries' prerequisites and available resources, for example, for funding AINC project staff, technical infrastructure or knowledge transfer and dissemination activities, as well as structures, processes, and outcomes of nursing care, we believe that European-centric attributes can be easily adapted to other regional or national requirements.

Implications for AI R&D, Nursing Science, and Clinical Partner Organizations

Given the widely reported issue that actors from health care and information science often do not share the same domain language in R&D projects and frequently work past one another [50], creating transparency and a common understanding of project aims and key concepts should be a shared goal among AINC project partners. AINCRA contributes to achieving this goal by raising awareness of relevant aspects. It also provides a foundation for decision-making at the project initiation phase, helping to determine which partners need to be involved, at what stages, and with what level of resource commitment. Additionally, it enables a better estimation of the risks and costs associated with AI development and deployment. By operationalizing and making the AINC project's progress more visible across different domains and project partners, it fosters a shared basis for discussion and terminology, promoting more effective collaboration.

Leveraging the potential of AI in health and nursing care requires robust estimates of a variety of factors relevant for such an investment, including implementation time, associated costs, regulatory risks, and technology acceptance among potential users and patients [21,25,30]. These estimates call for a thorough understanding of the status quo of health care institutions with respect to a variety of dimensions as detailed in AINCRA. The structure provided with AINCRA can support strategic decisions on investments by providing reliable insights on the efforts required to implement AI technology in clinical practice. The attributes developed in this study can also help to identify gaps and future areas of improvement with regard to AI technology in nursing practice. In addition, the insights gained in expert interviews help to manage expectations in translating and disseminating AI research to nursing practice. It is evident that an assessment of AI readiness will be challenging or even impossible without transdisciplinary teams that combine expertise in technical, regulatory, and ethical questions with expertise in nursing care.

Although AINCRA is extensive and complex, by advocating for an interprofessional approach, it enables a comprehensive evaluation of AINC projects, due to its high level of detail, ensuring that no blind spots are overlooked. Furthermore, AINCRA is applicable to a wide range of projects, as the term AI is defined broadly, making it relevant across various areas within the field.

Comparison With Design Recommendations and Common Criticism of Maturity Models

Eight requirements for designing maturity models [23] were applied throughout the AINCRA development process. Table 5 outlines how these requirements were addressed and implemented in this study. Above all, the comprehensive comparison with existing maturity models, alongside an iterative approach and the sequential expert evaluation of attribute and level descriptions, strengthens the presented research.

Table . Incorporation of design recommendations in the AINCRA[a] development process.

Requirement (R) derived from [23]	Incorporation of requirement through...
R1: Comparison with existing maturity models	• Systematic literature review • Further development of own prior work • Focus on AI[b] readiness or maturity models in health or nursing care
R2: Iterative procedure	• Research process with 3 iterations
R3: Evaluation	• Application and rating of AINCRA pilot version through experts
R4: Multimethodological procedure	• Sequential exploratory multimethods design
R5: Identification of problem relevance	• Rating and confirmation of AINCRA's relevance in expert group discussions
R6: Problem definition	• Results of preliminary work [13]
R7: Targeted presentation of results	• Feedback from the target group of intended users • Use of discipline-specific terminology • Development of a standard vocabulary for level distinctions together with the intended users
R8: Scientific documentation	• Study documents • Ethics application • Mandatory reporting for funding body • Open access publication of AINCRA

[a]AINCRA: artificial intelligence nursing care readiness assessment.

[b]AI: artificial intelligence.

Three main criticisms of maturity models [24] should be reflected on regarding AINCRA's internal and external validity: (1) lack of a solid theoretical foundation without grounding elements such as maturity levels and dimensions in established academic literature [24], (2) lack of sufficient empirical support for the selection of dimensions or variables, and (3) lack of a clear definition of how maturity should be measured [24]. While we rigorously aimed to address the first 2 criticisms during development by review of the academic literature and iterative evaluation and consensus building with domain experts, a degree of ambiguity in the measurement of AINC readiness remains. This arises partly from the nature of AINCRA as a self-assessment instrument. On the other hand, it is worth noting that AINCRA provides qualitative but not quantitative criteria for assigning a maturity level. Hence, an answer to the question, for example, whether simply participating in one regional network is sufficient to meet the requirements for community building attributes, or whether involvement in at least 3 different networks is needed, remains open to interpretation. Users may assess individual attributes with varying degrees of realism and flexibility. Further operationalization is therefore strongly recommended.

Limitations and Future Research

Our results have limitations that call for further research. First, experts commented on 66 of 69 readiness attributes only. Attributes 2.39 strategies for long-term external support: software and hardware: upgrades, 2.40 strategies for long-term external support: software and hardware: maintenance, and 2.29 financial resources and investments: exploring alternative financing models for including clinical partners remained without comments. Why these attributes were not addressed, even though they have been identified as relevant for AI [41], is not obvious. Most likely is the limited time span of the think-aloud task, which may have constrained responses. Toward the end of the task, experts focused particularly on attributes they found interesting or especially relevant. Besides, not all invited experts participated. The findings are based on the expertise of a subset of participants. Although key stakeholders were represented, it cannot be assumed that data saturation was fully achieved, as not all invited experts took part in the study, and data collection concluded after interviewing all experts who had agreed to participation.

Second, as research on organizational AI readiness has previously highlighted as a relevant limitation [21], while AINCRA was developed to systematize key attributes of AINC readiness, overlaps with readiness or frameworks for adopting and implementing other digital technologies can be recognized, such as stakeholder acceptance as a key attribute for technology adoption [51]. However, the project-specific perspective of AINCRA expands preexisting frameworks, which predominantly adopt an organizational perspective, thus providing AINC projects with a reflective tool and instrument to support project management.

Third, we decided against substantially shortening or prioritizing AINC readiness attributes, despite suggestions from some experts. This makes AINCRA more time-consuming and potentially less practical for everyday project work. However, this decision is informed by our experiences with multiple AINC projects over the past 5 years, which show that many projects underestimate their complexity and are affected by domain-specific blind spots that hinder collaboration. At the same time, our findings do not fully clarify how individual attributes interact or which should be addressed together when strengthening AINC readiness. While we applied an established method for maturity model evaluation that is being used in information science for decades [48], future research may strive for validating our results by applying AINCRA to real process improvement activities [48] in future AINC projects.

Conclusion

In a field where many use cases remain underexplored and R&D projects often face substantial barriers, AINCRA offers structured guidance to enhance AI readiness for research, development, and implementation of AI projects in nursing care. AINCRA provides a balanced integration of technical, organizational, ethical, and social aspects of AI readiness, addressing a common shortcoming of existing maturity models that tend to prioritize technical or business considerations. Its nursing-specific focus further distinguishes it from other generic or commercially available assessment instruments, making it both context-sensitive and scientifically grounded. Overall, AINCRA offers both a practical tool for current projects and a foundation for future research and refinement in the evolving field of AI systems in nursing care.

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The authors declare the use of generative AI in the research and writing process. According to the GAIDeT taxonomy, the following tasks were delegated to GAI tools under full human supervision: Translation. The GAI tool used was: ChatGPT 5. Responsibility for the final manuscript lies entirely with the authors. GAI tools are not listed as authors and do not bear responsibility for the final outcomes. Declaration submitted by: Kathrin Seibert Additional note: We used ChatGPT-5 to assist with translating the German language full AINCRA version and user manual to English language. We used for GPT-4o to generate initial level descriptions based on the AI readiness vocabulary for level distinction developed by the authors for this study.

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Data Availability

All data generated or analyzed for the systematic literature review are included in this published article and its supplementary information files. The datasets generated and analyzed based on think-aloud interviews and focus group discussions are not publicly available, to ensure participant privacy but are available from the corresponding author upon reasonable request. Data are stored in a controlled access data storage at the University of Bremen.

Authors' Contributions

Conceptualization: KS, DD, FB, DF, DB, KW
Data curation: KS
Formal analysis: KS, JA, AN, JP, LB, DW
Funding acquisition: FB, DF, DB, KW
Investigation: KS, JA, AN, RG, LB
Methodology: KS, DD, AN, DF
Project administration: KS, DD
Supervision: KS, FB, DF, KW
Validation: KS, SJ, FB, AN, RG, MS, DF, JP, LB, KB, KW
Visualization: KS, LB

Writing – original draft: KS
Writing – review & editing: DD, JA, SJ, FB, AN, RG, MS, DF, JP, LB, DW, KB, DB, KW

Conflicts of Interest

None declared.

Multimedia Appendix 1
Additional methods information and results.
[PDF File, 968 KB - nursing_v9i1e84148_app1.pdf]

Multimedia Appendix 2
Artificial intelligence nursing care readiness assessment full version.
[PDF File, 1459 KB - nursing_v9i1e84148_app2.pdf]

Multimedia Appendix 3
Artificial intelligence nursing care readiness assessment user manual.
[PDF File, 6038 KB - nursing_v9i1e84148_app3.pdf]

Checklist 1
PRISMA 2020 checklist.
[PDF File, 68 KB - nursing_v9i1e84148_app4.pdf]

Checklist 2
COREQ checklist.
[PDF File, 297 KB - nursing_v9i1e84148_app5.pdf]

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Abbreviations

AI : artificial intelligence
AINC : artificial intelligence in nursing care
AINCRA : artificial intelligence nursing care readiness assessment
COREQ: Consolidated Criteria for Reporting Qualitative Research
EU AI: European Union artificial intelligence
ML: machine learning
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
R&D : research and development

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Developing a Cross-Device Platform for Robotic Systems in Nursing Care: Mixed Methods Feasibility Study

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Abstract

Background: Aging populations and rising chronic illness prevalences are increasing demands for nursing care, while staff shortages threaten care quality. Robotics offer potential support, yet usability, workflow integration, and user acceptance remain major barriers.

Objective: This study aims to develop and evaluate the feasibility, usability, and acceptance of a cross-device platform for controlling robotics in nursing using a participatory, user-centered approach.

Methods: A convergent mixed methods feasibility study was conducted across 4 iterative workshops with 13 nurses from 2 German health care facilities. Quantitative measures included the System Usability Scale (SUS), Technology Usage Inventory (TUI), and Technology-based Experience of Need Satisfaction (TENS-Interface). Qualitative data were collected via think-aloud protocols and focus groups. Data integration supported iterative platform refinement and assessment of usability, acceptance, and satisfaction of psychological needs.

Results: Participants exhibited high curiosity, perceived usefulness, and strong intention to use robotics, with low skepticism. SUS scores indicated acceptable usability. TENS-Interface scores showed increased autonomy and competence following workflow simplification and stepwise interaction logic. Qualitative findings emphasized intuitive control, personalized interventions, centralized management of multiple technologies, integration with documentation systems, and structured training. Triangulation of quantitative and qualitative data confirmed that iterative, user-centered refinements enhanced usability, acceptance, and platform effectiveness.

Conclusions: Cross-device platforms integrating robotics can be successfully developed through participatory, user-centered methods. Technical usability, personalization, workflow integration, and structured training are key for adoption. The study demonstrates that technological barriers, rather than human resistance, are primary constraints to integrating robotics into nursing practice and can be mitigated through iterative co-creation aligned with real-world care contexts.

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KEYWORDS

digital assistive technologies; digital transformation; human–technology interaction; customization; user-centered design; cocreation; intention to use; health care; long-term care; feasibility study

Introduction

Background

Worldwide demographic shifts, including population aging and the increasing prevalence of chronic illness, are driving a growing demand for nursing care, while persistent shortages of qualified nursing professionals threaten the quality and availability of services [1-4]. Robotic systems have therefore been proposed as a promising strategy to support nursing care; however, their implementation in routine practice remains challenging [5]. According to International Organization for Standardization (ISO) 8373:2021 [6], a robotic system is defined as a programmable, actuated mechanism capable of performing physical tasks autonomously or semi-autonomously under the control of a control system. Through the integration of sensors, actuators, and control components, robotic systems can interact with their environment and execute predefined or adaptive actions. This broad definition includes service and assistive robots used in health care settings, such as telepresence robots and mobile manipulators.

In nursing contexts, robotic systems have been shown to support psychosocial and rehabilitative processes, with reported benefits for emotional well-being, cognition, social interaction, and quality of life among older adults [7]. Robots are also used in rehabilitation and physical therapy as well as in psychosocial interventions [8]. Beyond direct patient care, robotic technologies can support organizational processes, including telepresence, virtual consultations, and the training of nursing staff, and can assist with logistical tasks such as transporting medication and materials, disinfection, and procedural support [9]. Despite these potential benefits, most robotic systems remain at early stages of development or testing, and only a limited number have been implemented in routine care settings [10,11]. Moreover, the high financial investment required for acquisition and maintenance continues to be a major barrier to widespread adoption [11].

Previous research indicates that the successful implementation and integration of robotic systems in nursing care depends not only on technical performance but also on user acceptance, contextual implementation processes, and the systematic involvement of end users throughout development and evaluation phases. International reviews and empirical studies consistently demonstrate that sociocultural, organizational, and user-centered factors play a decisive role in facilitating practical adoption, beyond the technical design of robotic systems alone [10,12,13].

Nursing staff generally report a willingness to engage with robotic technologies, driven by perceived benefits such as workload reduction, increased efficiency, and improvements in care quality [14,15]. However, many existing robotic systems do not adequately meet users' needs with regard to usability, adaptability to individual patient requirements, and integration into established care workflows [7,8,11]. In particular, a lack of intuitive interaction concepts and standardized, cross-device solutions often results in complex and inconsistent operation [8,16,17]. Furthermore, the absence of common standards for the external control of robotic systems remains an unresolved challenge [16,18]. Participatory development approaches, such as cocreation [19] and design-based research [20], have been shown to address these challenges by actively involving end users throughout the design process. Early and continuous stakeholder involvement not only improves system usability and acceptance but may also positively influence care processes and outcomes by aligning technological solutions with user needs and care contexts [21-24]. Nevertheless, robotic systems that provide simple, cross-device, and adaptable interaction concepts and that are co-designed directly with nursing staff remain scarce [24].

Objective

Robotic systems have the potential to support nursing practice; however, their uptake is limited by insufficient usability and limited adaptability to individual care needs. The Educational Exploration Robot Application Platform (EduXBot) project addresses this gap by developing a simplified and unified interface that enables nursing staff to operate existing robotic systems. The accompanying mixed methods feasibility study pursued two objectives: (1) primary objective: to assess the usability, technology acceptance, and user experience of the EduXBot platform among nursing staff within the framework of an iterative, user-centered design process and (2) secondary objective: to develop a multilevel benefit concept for the platform through an in-depth qualitative evaluation using think-aloud and focus group methods to identify perceived value and areas for further improvement.

Together, these objectives aimed to evaluate the platform's effectiveness and its potential to support the sustainable integration of robotic systems into nursing practice.

Methods

Conceptual Framework

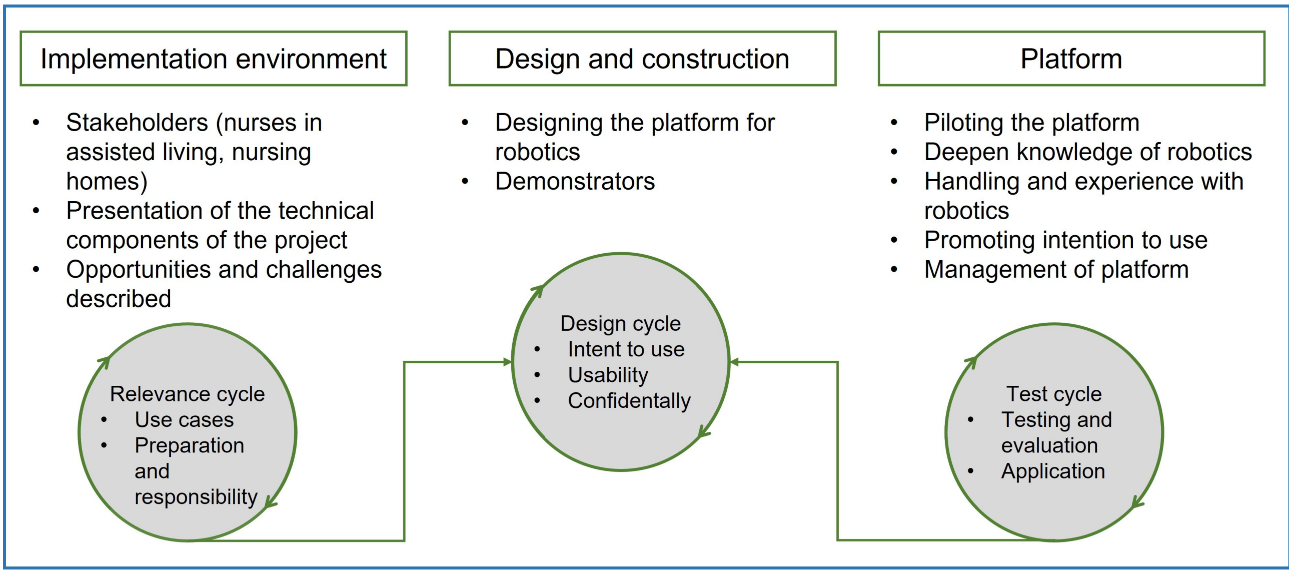
The EduXBot project aims to develop an interaction and control platform that simplifies the use of robotic systems in nursing care. The development process follows a participatory and user-centered approach, explicitly incorporating the expectations, experiences, and practical requirements of end users throughout all phases of the project. This process fosters the development of innovative, practical, and user-centered solutions that are more likely to be adopted in everyday practice [25].

The development process was grounded in user-centered and cocreative principles that combine iterative engagement with end users and structured design cycles. Although Farao et al [26] described a user-centered framework that integrates iterative design and stakeholder engagement, our approach emphasizes active collaboration with end users throughout iterative prototyping, evaluation, and refinement phases consistent with cocreative design practices in participatory technology development.

This methodological approach supports the development of a tailored end product based on nurses' domain expertise while systematically considering potential implementation consequences [26-28]. Previous research has shown that cocreative and user-centered approaches can improve relevant outcomes and increase the usability and acceptance of technological systems in health care settings [29,30].

Figure 1 illustrates the integration of relevance, rigor, and design cycles to align nursing practice requirements, scientific evidence, and iterative platform development: the relevance cycle, which captures the realities and needs of end users; the rigor cycle, which draws on the existing scientific knowledge base; and the design cycle, which translates these inputs into the iterative development of the technical product [31-33]. Through this framework, requirements for the robotic systems addressed in the study can be systematically identified and practically operationalized. The close collaboration between researchers and end users further enables active user involvement in product evaluation, thereby supporting the functionality, usability, and overall success of the platform.

Figure 1. User-centered and cocreative design framework (adapted from Farao et al [26]).



Within this collaborative framework, EduXBot does not seek to develop new robotic hardware. Instead, it focuses on providing an extensible interaction and control platform for existing robotic systems. The platform is designed as a flexible and open system architecture that integrates diverse robotic, sensor, and interaction technologies into a unified interface. Its modular design allows nursing staff with varying levels of technological expertise to configure and use the system, thereby supporting a layperson-oriented approach to human-technology interaction. This design was developed in close collaboration with end users to ensure relevance and usability in nursing practice.

Study Design

An iterative feasibility study accompanied the development of the EduXBot platform. The study was conducted as a convergent mixed methods design in accordance with Creswell and Plano Clark [34], with quantitative and qualitative data collected in parallel and analyzed independently. Quantitative data were used to assess usability, technology acceptance, and the fulfillment of psychological needs, while qualitative data captured nursing staff's experiences, perceptions, and interaction processes. Following separate analyses, both data strands were integrated to enable a comprehensive interpretation of the findings and to inform the iterative development of the platform. This mixed methods approach aligns with a pragmatic research paradigm, in which methodological choices are driven by the research questions and support a triangulated understanding of the research problem.

Two health care facilities in Germany served as practice partners. Facility 1 was a long-term inpatient care facility. Facility 2 was a regional health center providing acute inpatient care, outpatient services, and long-term inpatient care. Both institutions had previously participated in technology-related research projects and agreed to collaborate in this study. Facility managers were informed about the project and asked to encourage nursing staff to participate.

Participants were recruited using purposive sampling with the aim of maximizing variation in age, gender, and professional experience, thereby capturing a broad range of perspectives relevant to the research topic [35]. The inclusion of nurses from diverse backgrounds enhanced the heterogeneity and informational value of the study sample. Participation was voluntary, and scheduling constraints or other commitments could limit participation or lead to withdrawal during the study.

Instruments

Quantitative Instruments

Surveys were administered at 4 measurement time points (T0-T3) during each development iteration and included the Technology Usage Inventory (TUI), System Usability Scale (SUS), and Technology-based Experience of Need Satisfaction (TENS-Interface). All instruments were administered as self-report questionnaires completed individually by each participant.

The TUI [36] assessed participants' intention to use robotic systems by measuring technology-related and psychological factors. For this study, the TUI was adapted to address robotic systems in general and was administered once per measurement point. We analyzed 7 subscales: curiosity, fear of technology, interest, skepticism, accessibility, usability, and usefulness. Higher scores indicate stronger expression of the corresponding construct, while lower scores indicate weaker expression. Scale sum scores were converted into stanine values ranging from 1 (well below average) to 9 (well above average).

The SUS [37] measured the usability of each technology integrated into the EduXBot platform. Collecting SUS scores for individual technologies allowed the identification of technology-specific usability issues, providing targeted feedback for iterative development. Medians and IQRs were aggregated to provide a generalizable estimate of the platform's overall usability, aligning the technology-level measurements with the study's primary focus on platform-level usability. Scores ≥68 were considered indicative of acceptable usability, supported by adjective-based interpretations from "outstanding" to "very poor."

The TENS-Interface [38] is a standardized questionnaire that assesses the extent to which a technology interface meets users' psychological needs (autonomy, competence, relatedness) in human-technology interaction. It was administered from T1 onward, when a prototype was available, and focused specifically on the interaction platform interface.

Qualitative Methods

Qualitative data were collected through think-aloud sessions and focus groups. During think-aloud sessions, participants performed predefined tasks for each technology, verbalizing their thoughts and experiences while interacting with the platform [39]. Standardized instructions ensured consistency, enabling systematic observation of interface interaction and usability. Sessions were audio-recorded and transcribed for analysis.

Focus groups were conducted after each workshop [40,41] to refine the platform iteratively. Participants discussed their experiences with the current prototype; evaluated its compatibility with daily care workflows; and identified unmet needs, usability barriers, and desired functionalities. Focus groups were guided by predefined questions, audio-recorded, and transcribed verbatim. Findings were systematically fed back into the design process and informed subsequent platform refinements.

Data Collection

Prior to the initial measurement (T0), a needs assessment workshop (Table 1) was conducted involving nurses, nursing scientists, and developers. Participants were introduced to existing robotic technologies and collaboratively generated potential application scenarios. Based on practical relevance and technical feasibility, 4 use cases were selected to guide the development of EduXBot prototypes:

1. Conversational partner: implemented via the Double3 telepresence robot, which recognizes residents by voice or face and can respond to personal preferences and topics
2. Telepresence: also using the Double3, enabling remote participants to communicate and engage in activities on site
3. Safe walking partner: implemented via the Go1 4-legged bionic robot, providing monitoring during walks and reporting falls
4. Record/playback of personal events: implemented using the PICO 4 virtual reality (VR) headset, allowing the recording and immersive playback of events such as family birthdays or facility celebrations, to support biographical work

Table . Overview of the 4 iterative workshops at the 4 measurement time points (T0-T3).

Measurement time point	Thematic focus	Use cases	Technologies	Instruments
T0	Define requirements	• Conversational partner • Telepresence • Record/playback of personal events	• Double3 • PICO 4	• TUI[a] original questionnaire (pre-post version) • SUS[b] • Think-aloud • Focus group
T1	Explore concept framework and interaction design	• Conversational partner • Telepresence • Record/playback of personal events • Safe walking partner	• Double3 • PICO 4 • Go1	• TUI II parallel questionnaire (complete version) • SUS • TENS-Interface[c] • Think-aloud • Focus group
T2	Testing the prototype for interaction design	• Conversational partner • Telepresence • Record/playback of personal events	• Double3 • PICO 4	• TUI II parallel questionnaire (complete version) • SUS • TENS-Interface • Think-aloud
T3	Test simplified step-by-step processes and integrated control	• Conversational partner • Record/playback of personal events • Safe walking partner	• Double3 • PICO 4 • Go1	• TUI II parallel questionnaire (complete version) • SUS • TENS-Interface • Think-aloud • Focus group

[a]Technology Usage Inventory.

[b]System Usability Scale.

[c]Technology-based Experience of Need Satisfaction.

Data were collected at 4 time points (T0-T3), each corresponding to one iterative development cycle. Workshops followed a standardized structure and integrated evaluation of both the interaction platform and selected technologies. Depending on the development stage, not all technologies nor use cases were presented at every workshop. Table 1 summarizes the technologies and use cases tested at each workshop, along with the applied quantitative and qualitative instruments and thematic focus.

A prototype, defined as a preliminary version of a product or system used to evaluate and refine its key characteristics, design, and functionality prior to final implementation, was used throughout the study [42,43]. Participants interacted in small groups (up to 3 individuals) at station-based setups, rotating between stations to test the prototype and technologies available for that workshop. Usability was assessed at the individual level using the SUS immediately after task completion at each station, ensuring that responses reflected individual perceptions rather than group-based consensus.

After station-based testing, participants completed the TUI and TENS-Interface questionnaires independently and individually, capturing overall intention to use and psychological need satisfaction related to the platform. To minimize potential social influence, participants were instructed to complete all questionnaires independently, and no collective rating nor group agreement was requested at any point during data collection.

Each workshop concluded with a focus group discussion in which participants collectively reflected on experiences, workflow compatibility, usability barriers, and suggested refinements. Insights from think-aloud sessions and focus groups were systematically fed back into the iterative development process and informed subsequent platform and technology adaptations.

Data Analysis

Quantitative data were analyzed using SPSS version 28 (IBM Corp) [44]. Continuous variables are reported as medians and IQRs, and categorical variables are reported as absolute and relative frequencies. Missing data were handled using pairwise deletion.

Group differences in cumulative SUS and TUI scores at T3 were examined using 1-way ANOVA considering factors such as gender, qualification, and facility. Assumptions of normality and homogeneity of variances were tested, with the Welch correction applied if homogeneity was violated. Post hoc Bonferroni tests were planned but not conducted due to nonsignificant effects. Pearson correlations were calculated to examine relationships between usability (SUS), intention to use (TUI subscales), and psychological need satisfaction (TENS-Interface) at T3. Hierarchical regression analyses assessed predictors of intention to use, with SUS, TENS-Interface, and TUI subscales entered in blocks. Model assumptions (linearity, independence of residuals, homoscedasticity, multicollinearity) were checked prior to interpretation.

Qualitative data were analyzed using inductive content analysis following the method by Kuckartz and Rädiker [45] with MAXQDA version 24.10.0 (VERBI Software) [46]. Transcripts from think-aloud sessions and focus groups were initially coded independently by two researchers (PM, RV). Both methods addressed the same overarching research question—platform design and adaptation of use cases. Coding of the two data sources was therefore integrated in a single schema, enabling triangulation, consistent identification of emerging themes, and comprehensive interpretation across data sources.

Codes were iteratively grouped into subcategories and overarching categories through discussion until consensus was reached. The coding process included systematic comparison across iterations to capture the evolution of requirements, usability challenges, and user perceptions. Intercoder reliability was assessed using Cohen kappa coefficient.

Qualitative data collection was structured according to predefined iterative development cycles rather than aiming for theoretical saturation. The number and timing of think-aloud sessions and focus groups were determined by the 4 development iterations, with each workshop representing 1 iteration of platform refinement. Data collection concluded upon completion of the final iteration, ensuring that all planned prototypes had been systematically evaluated. Emerging themes and usability issues were continuously reviewed after each iteration and directly informed subsequent platform adaptations. This approach was chosen because the study's objective was to iteratively refine the platform in close collaboration with end users, rather than to achieve saturation of qualitative data.

Mixed methods integration followed a convergent design [34], incorporating both formative and summative integration of quantitative and qualitative data. Formatively, findings from think-aloud sessions and focus groups were continuously fed back into the iterative development process to refine the platform. Summatively, quantitative and qualitative results were triangulated, comparing and integrating findings across data sources to provide a comprehensive understanding of platform usability, technology acceptance, and practical value in nursing workflows. This triangulation allowed complementary perspectives, convergence, and divergence to be identified and interpreted in context.

Ethical Considerations

The study received ethics approval from the ethics committee of the Medical Faculty of Martin Luther University Halle-Wittenberg (approval 2023 - 190, August 31, 2023) and was registered at the German Clinical Trials Register (DRKS00034195). Written informed consent was obtained from all participants, and no financial compensation was provided. Data were collected anonymously to ensure participant privacy and confidentiality.

The methodological rigor of the study was ensured by adhering to the Good Reporting of a Mixed Methods Study (GRAMMS) checklist [47] and the Mixed Methods Appraisal Tool (MMAT) [48]. The comprehensive study protocol has been published elsewhere [49].

Results

Participants

Between February 2024 and May 2025, 13 nurses from 2 health care facilities participated in the study. Some nurses participated in multiple iterations, yielding a total of 33 participation units across the 4 development iterations. Participants could not be clearly categorized into core or ad hoc groups due to variable attendance; however, each nurse participated in at least 2 iterations.

Participants' age, gender, professional qualifications, and experience are summarized in Table 2. Age and professional experience were calculated at the time of each participant's first iteration to account for staggered entry. Professional experience was defined as years since completion of formal nursing education or training. Median age was 46 (IQR 10.5) years, and the median length of professional experience was 15 (IQR 13.5) years. Most participants held managerial nursing roles, supplemented by support staff and occupational therapists, providing diverse perspectives for assessing the integration of the platform into daily care routines.

Table . Demographic characteristics of participating caregivers at the 4 measurement time points (T0-T3).

Characteristics	T0 (n=8)	T1 (n=9)	T2 (n=8)	T3 (n=8)
Age (years), mean (SD)	45.6 (9.1)	47.8 (9.3)	50.1 (7.8)	48.3 (9.5)
Gender, n (%)				
Male	1 (12.5)	1 (11)	1 (12.5)	1 (12.5)
Female	7 (87.5)	8 (89)	7 (87.5)	7 (87.5)
Qualification, n (%)				
3-year duration of training	1 (12.5)	1 (11)	0 (0)	1 (12.5)
3-year duration with professional training	2 (25)	1 (11)	1 (12.5)	1 (12.5)
Nursing service management	3 (37.5)	3 (33)	3 (37.5)	3 (37.5)
Studies	1 (12.5)	2 (22)	2 (25)	1 (12.5)
Other qualification	1 (12.5)	2 (22)	2 (25)	2 (25)
Professional experience (years), mean (SD)	13.5 (9)	16.3 (10.8)	16.9 (10.8)	18 (10.5)
Facility, n (%)				
Facility 1	6 (75)	7 (78)	7 (87.5)	6 (75)
Facility 2	2 (25)	2 (22)	1 (12.5)	2 (25)

Quantitative Evaluation

Participants exhibited higher openness to robotics than the general population, as indicated by above-average TUI stanine scores relative to the normed reference population [36]. Table 3 presents TUI subscale scores including curiosity, fear of technology, interest, usability, usefulness, skepticism, and accessibility. Scores are reported as medians and IQR, with stanine values indicating relative positioning versus the normed reference population. Median intention to use at T0 was 255 out of 300 and remained stable across iterations. High scores were observed for curiosity (median 23 from a possible total of 28) and perceived usefulness (median 22 from a possible total of 28), whereas skepticism was low (median 9 from a possible total of 28). These results indicate general interest in and acceptance of robotics.

Table . Technology Usage Inventory (TUI) subscale scores at the 4 measurement time points (T0-T3).

TUI subscale	Max score	T0 score		T1 score		T2 score		T3 score	
		Median (IQR)	Stanine	Median (IQR)	Stanine	Median (IQR)	Stanine	Median (IQR)	Stanine
Curiosity	28	22 (6.5)	7	22 (9.75)	7	20 (7.5)	7	23 (9.25)	8
Fear of technology	28	9 (13.5)	5	7 (11)	4	7 (3.75)	4	10 (7.5)	5
Interest	28	18 (12)	6	23 (2)	7	24 (5.5)	7	24 (6.75)	7
Usability	23	18 (4.75)	6	14 (5.5)	4	14 (2.75)	4	17 (5.5)	6
Usefulness	28	22 (4.5)	9	24 (3.5)	9	24 (9)	9	22 (5.5)	9
Skepticism	28	7 (5.75)	2	9 (7.5)	3	10 (4.5)	4	9 (5.75)	3
Accessibility	23	11 (9)	6	11 (4)	6	11 (3.75)	6	11 (3.75)	6
Intention to use	300	255 (69.5)	8	246 (58.5)	7	254 (40.25)	8	262 (46.5)	8

SUS scores were assessed per technology and aggregated to evaluate overall platform usability (Table 4). Median and IQR are reported. Overall usability decreased slightly from “excellent” at T0 to “good” at T3 but remained within the acceptable range. Double3 usability improved over time, whereas Go1 and PICO 4 showed declines, with Go1 falling below the usability threshold at T3. SUS data for Go1 were not available at all measurement points, limiting trend interpretation.

Table . System Usability Scale (SUS) scores per technology and overall at the 4 measurement time points (T0-T3).

Technology	T0 score, median (IQR)	T1 score, median (IQR)	T2 score, median (IQR)	T3 score, median (IQR)
Double3	68 (22.5)	71 (19.25)	80 (12.5)	75 (—[a])
PICO 4	85 (12)	85 (30)	69 (15)	70 (27.5)
Go1	—	70 (10)	—	64 (34.38)
Overall	74 (15.7)	75 (18.25)	74 (12.5)	72 (27.81)

[a]Not applicable.

Table 5 shows caregivers’ perceived satisfaction with autonomy, competence, and relatedness while interacting with the platform. Data were collected using the TENS-Interface from T1 onward. Autonomy and competence increased across iterations, indicating growing confidence and mastery, while relatedness showed minor fluctuations. Overall, the platform interface effectively supported caregivers’ needs, particularly autonomy and competence.

Table . Technology-based Experience of Need Satisfaction (TENS)–Interface subscale scores at 3 of the 4 measurement time points (T1-T3).

TENS-Interface	T1 score, median (IQR)	T2 score, median (IQR)	T3 score, median (IQR)
Autonomy	18 (3.5)	19 (3.75)	22 (5)
Competence	20 (3.5)	20 (3.5)	23 (3)
Relatedness	16 (5)	18 (1.75)	17 (3.75)

The 1-way ANOVA revealed no significant differences in cumulative SUS nor TUI scores at T3 based on gender, qualification, or facility. Pearson correlations indicated strong associations between SUS and TUI usability (r=0.809), usefulness (r=0.773), and intention to use (r=0.751). Intention to use was highly correlated with perceived usefulness (r=0.926). Higher skepticism correlated with lower usability (r=−0.856) and usefulness (r=−0.736). Greater technology interest correlated with higher curiosity (r=0.861). Higher qualification levels were associated with lower technology fear (r=−0.800), and more professional experience was associated with lower interest in technology (r=−0.766). Competence in handling the interface correlated strongly with autonomy (r=0.912) and positively with technology interest (r=0.716).

Hierarchical regression analyses indicated that perceived usefulness (β=0.908, P<0.001) and fear of technology (β=0.102, P=0.04) were significant predictors of intention to use robotics ($F_{1,6}$=1557.926; P<0.001; R^2=0.998; adjusted R^2=0.997). Multimedia Appendix 1 provides the complete results of the ANOVA, correlation matrices, and regression models.

Qualitative Evaluation

The qualitative evaluation comprised 7 think-aloud protocols and 3 focus group discussions conducted across 4 iterative workshops. The analysis yielded 36 codes, which were condensed into 13 subcategories and grouped into 4 overarching categories reflecting platform requirements: usability and interaction (category 1), intervention design and implementation (category 2), training and skill development (category 3), and structural prerequisites (category 4). The full coding framework is provided in Multimedia Appendix 2.

Category 1 encompasses user-friendliness and interaction with the platform. Participants emphasized the need for simple and familiar operating concepts, such as gesture- and voice-based input, as well as a streamlined selection process with options for customization. As one caregiver put it, “What’s important is that it’s simple, easy to use, and works in just a few steps” (T1, Nurse 3). The platform should also enable centralized management of multiple technologies and provide interfaces to existing systems.

Category 2 focuses on intervention design and implementation. It emphasizes technological autonomy, flexible planning and booking systems, and coordination by nursing staff. Personalization emerged as a central requirement, necessitating adaptation of content to the biographies, mobility levels, and cognitive limitations of care recipients. Participants also highlighted the value of user-specific profiles to support personalization and efficiency: “You would need to create a profile so you can tap on the user who is supposed to use it, and everything that was previously stored for that person is already there” (T1, Nurse 3). Interventions were expected to be meaningful and to provide recognizable benefits, thereby supporting individualized care.

The platform was also expected to support training and skill development among care professionals (category 3). This included the provision of structured content, manuals, and step-by-step guides to facilitate independent learning, regardless of prior digital skills. As one participant noted, “If we were to work with it now, we would first need a written, step-by-step guide telling us exactly what we have to do” (T1, Nurse 2). In addition, participants emphasized the need for information on care processes and for safe practice environments in which new technologies could be tested.

Structural prerequisites (category 4) describe the framework conditions required for successful implementation. These included stable internet infrastructure, access to technical support, and compliance with privacy and data protection regulations. Financial considerations were also emphasized: “Usability and cost have to match. You need something that really makes sense” (T1, Nurse 13). Available resources and the cost-effectiveness of the technology were perceived as decisive factors influencing the platform’s long-term adoption.

Initial intercoder agreement was low (16.28%, κ=0.16), likely due to inconsistent segment boundaries. After refining the coding procedures, including the use of sentence-bounded segments and consolidation of enumerations, agreement increased to 82.19% (κ=0.81), indicating reliable coding for analysis.

Iterative Development and Final Operating Concept

The platform was refined through 4 iterative workshops, during which qualitative findings were continuously triangulated with quantitative measures (SUS, TUI, and TENS-Interface). This iterative process enabled the identification and resolution of usability and workflow-related issues across successive development stages.

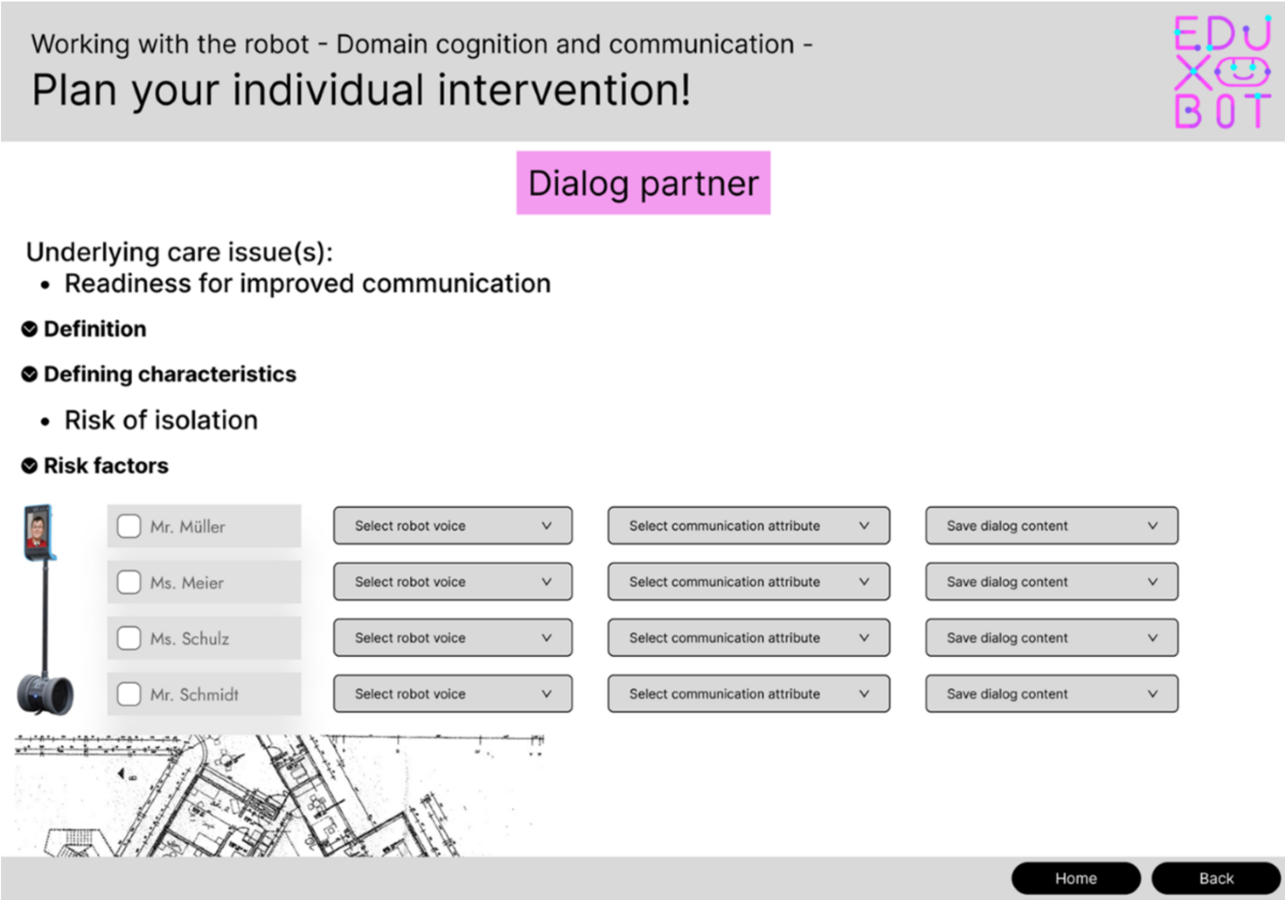
Iteration 1: Initial Requirements

In the first iteration, participants defined core requirements for the platform. A tablet-based interface using familiar gestures (eg, tap, swipe, pinch-to-zoom) and voice input was preferred, enabling centralized control of multiple technologies. Integration with existing documentation systems was considered essential to avoid additional workload. Participants also favored concise, context-sensitive guidance: “Sure, absolutely. A brief description. So that the employee knows that I can use it for that purpose” (T0, Nurse 1). Quantitative baseline data indicated acceptable usability and a moderate intention to use robotics.

Iteration 2: Conceptual Prototype

The second iteration translated these requirements into a visual prototype. The prototype displayed all workflow steps on a single screen, including process information (care problem definitions, risk factors) presented in expandable drop-down menus, personalization options for technological interventions, and information on technology availability and location. Figure 2 shows the platform prototype.

Figure 2. Prototype representation of the Educational Exploration Robot Application Platform (EduXBot) platform (iteration 2).



Although participants valued the transparency of having all information readily accessible, extensive vertical scrolling was perceived as inefficient and contrary to the goal of minimizing interaction steps: "So it's important that it's simple, easy to use, and can be done in just a few steps" (T1, Nurse 3). The introduction of user profiles reflecting mobility, cognitive abilities, and biographical background to support personalization was positively received. Participants consistently emphasized that interventions should provide a discernible benefit and enable caregivers to actively support residents' experiences: "What's the goal? What's the benefit?" (T1, Nurse 7).

At the same time, participants reiterated the need for written instructions ("So if we were to work with it now, we would first have to get it in writing, know step by step what we have to do" [T1, Nurse 2]) and brief training ("You have to practice a little bit, the handling, it takes some getting used to" [T1, Nurse 2]), particularly for more complex technologies.

Quantitative measures indicated stable usability and intention to use. The TENS-Interface showed moderate satisfaction with autonomy, competence, and relatedness. These metrics substantiate the qualitative findings, indicating that usability and acceptance were generally adequate but could benefit from workflow simplification and clearer guidance.

Iteration 3: Functional Prototype

In the third iteration, development shifted toward technical implementation. Full functional integration was available only for the PICO 4, while other technologies were simulated. This partial implementation revealed new usability challenges related to system feedback and transparency.

The management of VR content involved storing videos in a backend system, requiring several preparatory steps prior to use. System states were represented graphically using checkmark symbols: A single gray checkmark indicated assignment to a resident, two gray checkmarks indicated availability on the tablet, and two blue checkmarks indicated availability on the VR headset. Participants perceived this symbolic logic as lacking intuitive clarity: "Dots and hooks in blue, gray, and so on. It's not intuitive" (T2, Nurse 7).

Additional confusion arose from synchronization issues between the tablet and the VR headset. Synchronization had to be actively initiated via an eye icon within the video control bar. Participants instead tapped the video preview on the tablet, expecting the VR headset to mirror the same content. Although participants relied on a paper-based manual containing step-by-step instructions, several emphasized that intuitive design should ultimately reduce reliance on such materials.

The absence of explicit safety alerts was identified as a critical shortcoming. During simulated testing of the walking partner use case, participants stressed the need for clear error or event notifications, particularly in the case of falls: "It runs in a specific area, detects falls, and alerts nursing staff via the nurse call system" (T2, Nurse 10).

SUS scores for the PICO 4 decreased slightly, indicating usability challenges during partial implementation. In contrast, TENS-Interface scores showed modest improvements in competence and autonomy. This suggests that participants recognized the platform's potential despite ongoing functional limitations.

Iteration 4: Final Operating Concept

The fourth iteration resulted in a guided, step-by-step workflow aligned with nursing reasoning: (1) contextual information on the care problem clarifying the intended nursing objective of the intervention (Figure 3); (2) selection of the appropriate technology, including system feedback on availability, current usage, and battery status (Figure 4); (3) assignment of the intervention to one or more care recipients (Figure 5); (4) individualization of intervention parameters and scheduling via a booking system (Figure 6); and (5) a final overview summarizing all selected settings with an explicit confirmation step (Figure 7). These figures present the final operating concept.

Figure 3. Contextual information on the care problem.

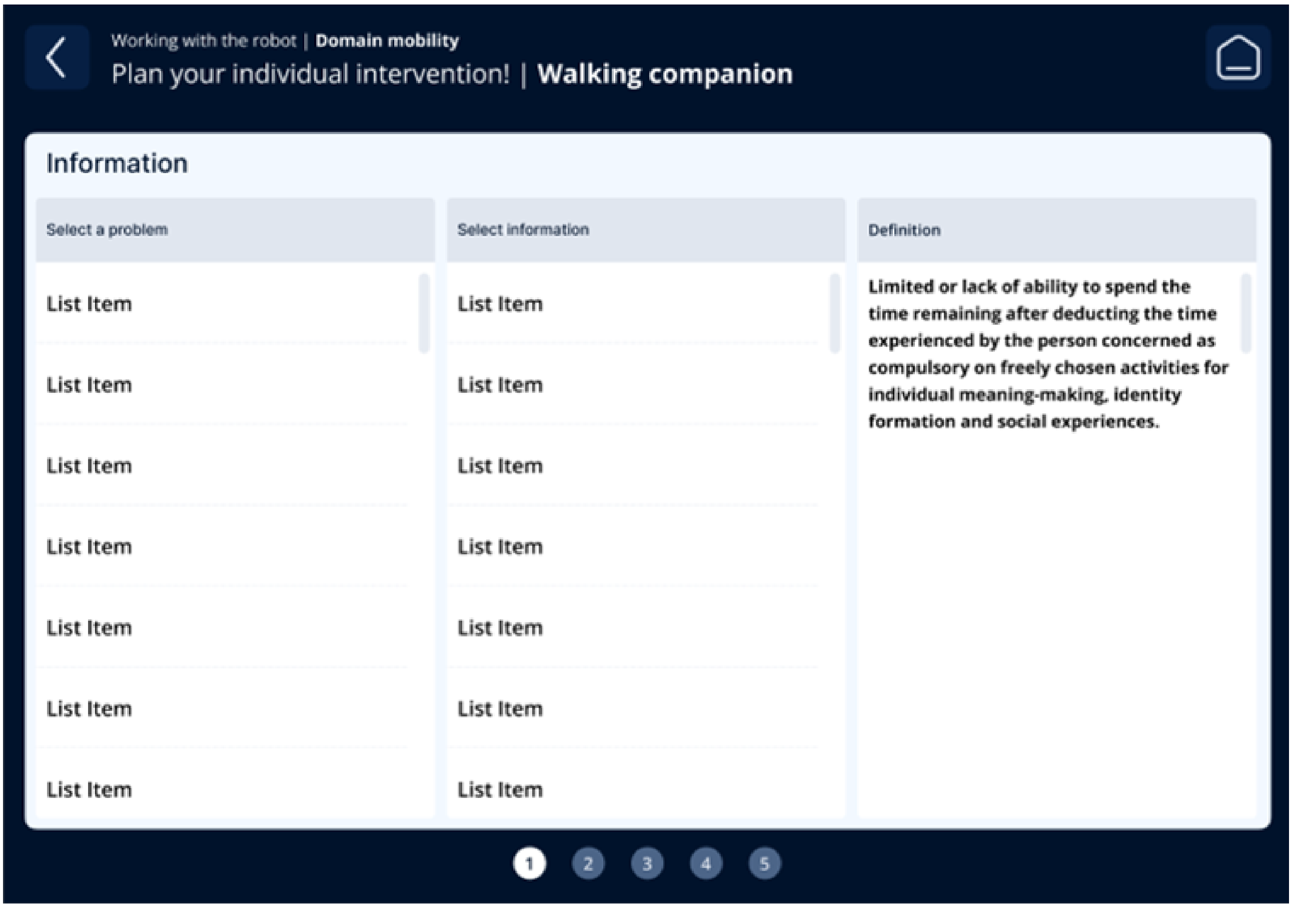


Figure 4. Selection of the appropriate technology.

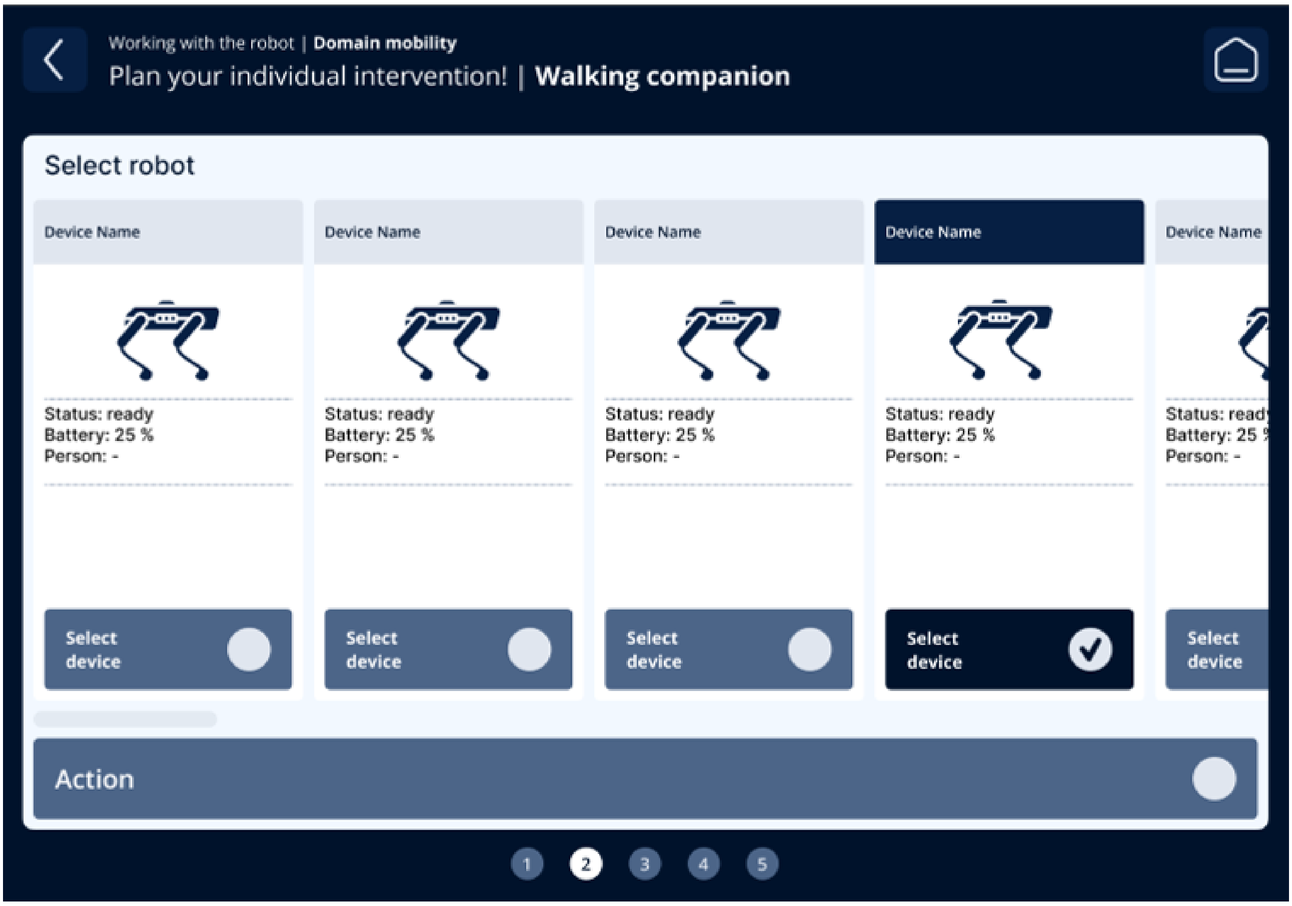


Figure 5. Assignment of the intervention.

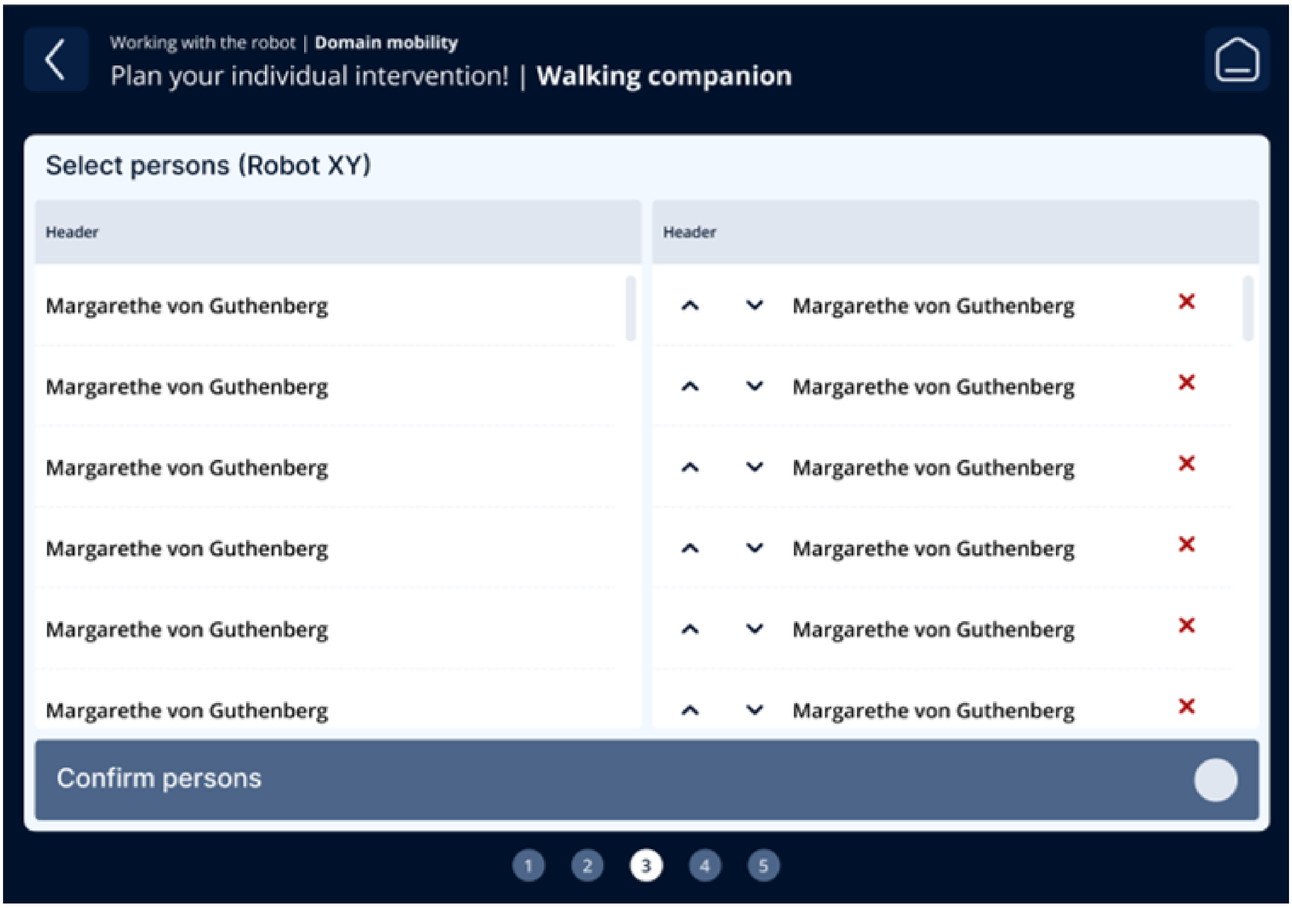


Figure 6. Individualization of intervention parameters and scheduling.

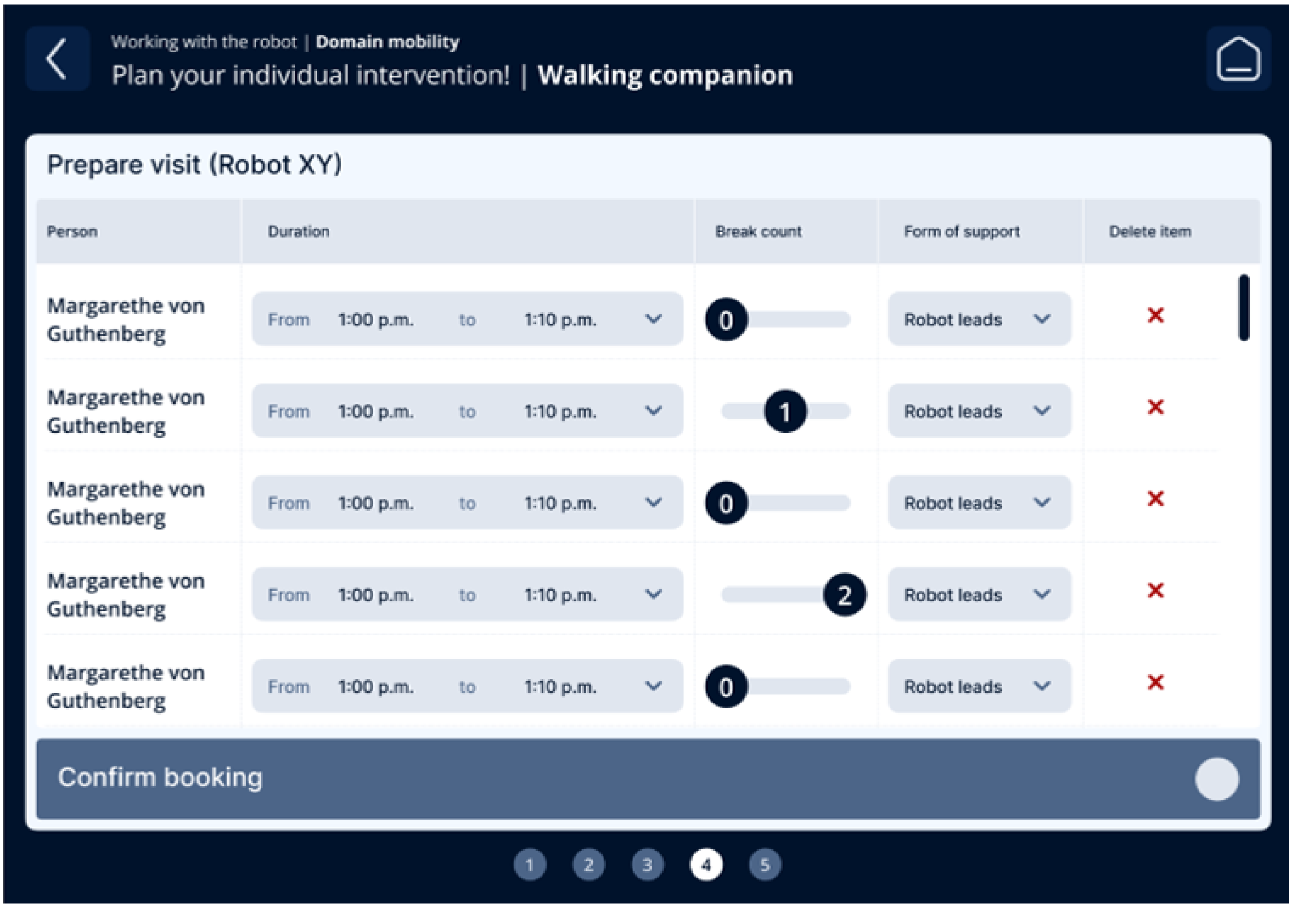
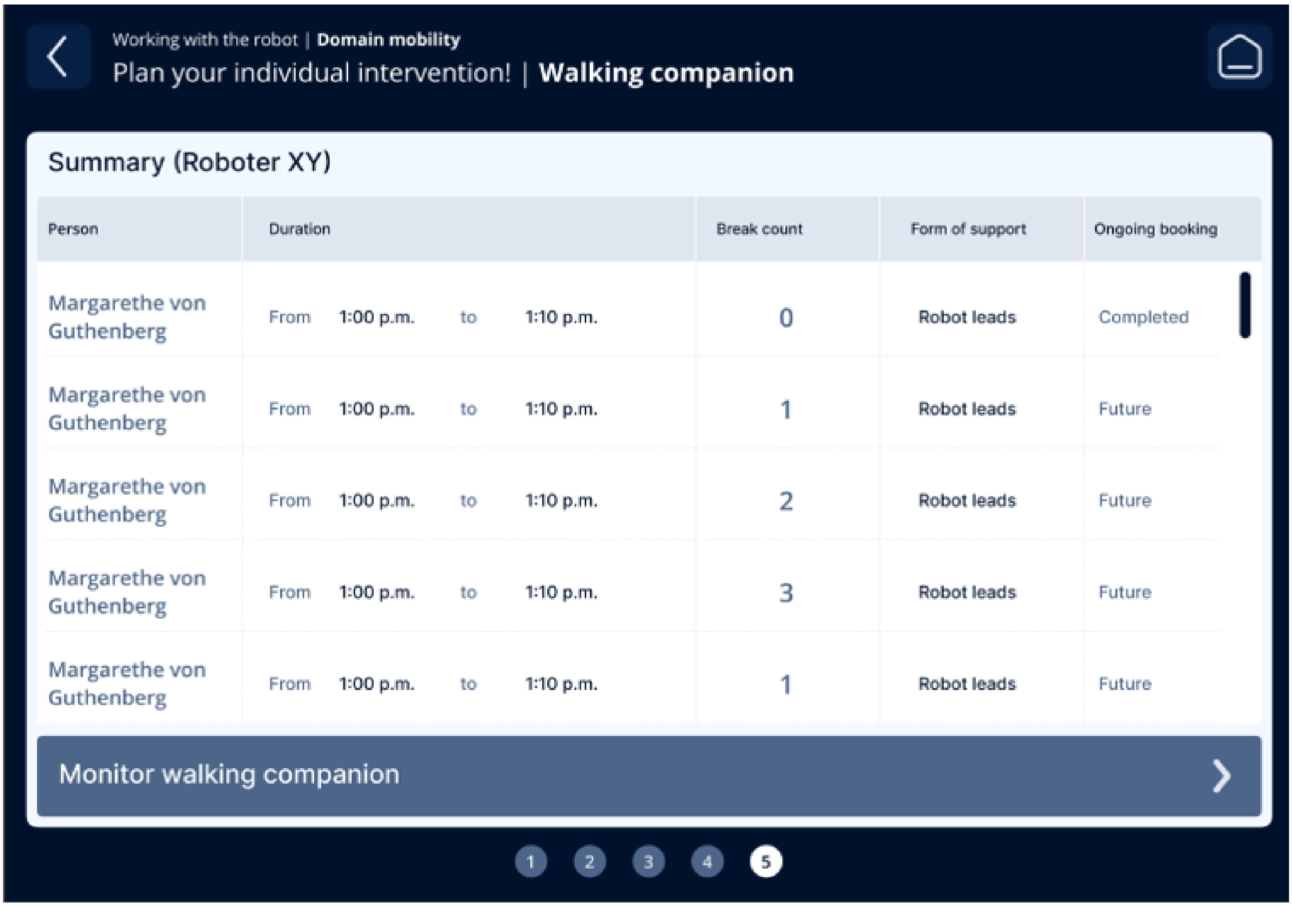


Figure 7. Final overview summarizing all selected settings.



The execution and monitoring of interventions were also revised. Care professionals retained the ability to enter an ongoing intervention at any time. Preparatory steps, such as file transfers to the tablet or synchronization with the PICO 4, were executed automatically and presented to users via a unified loading indicator. Safety-related events (eg, falls) were implemented as high-priority alerts using prominent pop-up notifications combined with audible warning signals. In addition, a conceptual interface to existing documentation systems was introduced to support routine care documentation, using standardized text modules to demonstrate the transfer of intervention-related information.

Quantitative data indicated stable or improved usability, a high intention to use, and increased satisfaction with autonomy and competence, suggesting that the revised workflow successfully addressed previously identified barriers.

Discussion

Integrative Overview

This study examined the feasibility, acceptance, and usage requirements of a cross-device interaction platform for controlling robotic systems in nursing care. Quantitative measures (SUS, TUI, TENS-Interface) and qualitative methods (think-aloud sessions and focus groups) were first analyzed separately and subsequently integrated in a mixed methods approach. The primary research question regarding overall platform feasibility was addressed through usability and interaction measures, while secondary questions concerning workflow integration and personalization were examined through combined TENS-Interface and qualitative feedback. The data were integrated both formatively, to inform iterative platform refinement, and summatively, to evaluate the platform's overall feasibility and value. This comprehensive approach allowed convergent and divergent findings to be interpreted in context.

Usability and Interaction

Caregivers demonstrated high levels of curiosity, perceived usefulness, and intention to use robotic technologies, accompanied by low levels of skepticism. Perceived usefulness emerged as the strongest predictor of intention to use robotic systems. These findings indicate that resistance among nursing staff is not the primary barrier to technology adoption. Rather, successful integration depends on whether technological solutions adequately address users' practical needs.

Although SUS scores revealed usability challenges—particularly for the Go1 robot and the PICO 4 headset—these issues largely reflect the constraints of iterative prototype development rather than fundamental rejection by users. These findings align with the qualitative findings. Early usability challenges were primarily related to complex interaction sequences, unclear system feedback, and inconsistent symbolic representations. Participants emphasized the need for intuitive, gesture- and voice-based input, streamlined workflows, and consistent symbolic representations. Iterative refinements, such as simplified step-by-step procedures and automated preparatory steps, directly addressed these usability challenges. Notably, acceptance and intention to use remained high even when usability temporarily declined.

The triangulated evidence demonstrates that high perceived usability and meaningful interaction design are critical enablers of platform adoption, supporting the primary research question regarding overall platform feasibility. This pattern is consistent with the Technology Acceptance Model, which emphasizes perceived usefulness as a stronger determinant of adoption than ease of use alone [50].

Personalization and Workflow Integration

Participants consistently emphasized the importance of tangible benefits, including automation of routine processes, integration into existing documentation systems, and the ability to tailor interventions to individual care recipients. Technology skepticism was mitigated when systems were intuitive, workflows were transparent, and benefits were clearly recognizable. These findings align with previous research demonstrating that technologies lacking practical relevance or workflow integration are unlikely to be adopted in nursing care [7,8,11]. The strong emphasis on personalization further supports existing evidence that user-centered and cocreative design approaches enhance acceptance, satisfaction, and care-related outcomes [21-24].

Training and Implementation Support

Training and implementation support were identified as critical enablers of successful adoption. Participants' feedback on instructional materials, step-by-step guidance, and protected environments for testing technologies was reflected in increasing TENS-Interface competence scores. Nursing staff reported growing confidence in their ability to use the platform safely and independently. These findings are consistent with Basic Psychological Need Theory, which posits that satisfaction with competence and autonomy fosters motivation and engagement [51]. In line with the Motivation, Engagement, and Thriving in User Experience model, improvements in autonomy and competence were associated with greater willingness to engage with robotic systems [38].

Structural Preconditions and Organizational Perspective

Although quantitative analyses did not directly capture organizational factors, qualitative findings underscored critical preconditions for successful implementation: stable technical infrastructure, access to technical support, compliance with privacy and data protection regulations, and cost-effectiveness. Participants with managerial responsibilities provided insights into resource allocation and long-term sustainability, emphasizing that organizational and structural factors must be addressed alongside usability and personalization to ensure successful adoption.

Limitations and Strengths

A major strength of this study is its iterative, user-centered development process, which systematically involved nursing staff through cocreative workshops and repeated prototype evaluations. The integration of qualitative and quantitative data enhanced the depth, credibility, and interpretability of the findings. Adherence to established methodological standards (GRAMMS, MMAT) and formal ethical approval further strengthen the study's rigor.

Several limitations must be acknowledged. The small and relatively homogeneous sample of 13 participants—many of whom held managerial roles and reported positive attitudes toward technology—limits generalizability and may reflect selection bias. Continuous involvement across multiple iterations may have influenced participants' evaluations, as familiarity with successive prototypes could lead to more favorable perceptions of improvement. Social interaction with the research team may also have increased the likelihood of socially desirable responses.

The absence of a control group restricts the ability to obtain independent, neutral assessments of usability and perceived benefit. In addition, participation was limited to two facilities with prior experience in research projects, potentially underrepresenting settings or individuals who are more skeptical of or burdened by technology. Finally, evaluations were conducted in simulated environments rather than routine clinical practice, limiting conclusions about long-term usability, scalability, and impact on care outcomes. The study also focused on a limited set of technologies and did not include perspectives of care recipients. Accordingly, the findings should be interpreted as exploratory rather than confirmatory.

Implications for Practice and Future Research

This study demonstrates that a unified, cross-device platform for robotic systems can be successfully developed through sustained end user involvement. Although the platform was initially designed to operate robotic technologies, needs articulated during the early requirements assessment led to the integration of VR content via the PICO 4 headset. This development illustrates the platform's extensibility beyond robotics to other digital assistive technologies. Such flexibility is essential for future-oriented nursing environments, as it enables the centralized control of multiple technologies through a single interface while preserving usability and opportunities for personalization.

Nursing staff expressed willingness and motivation to use robotic technologies; however, successful implementation depends on intuitive usability, meaningful personalization, seamless workflow integration, and structured training. Quantitative improvements in autonomy and competence were reflected in design features that support familiar interaction patterns, centralized control of multiple technologies, and adaptation to individual care needs. Qualitative findings further emphasized the importance of personalization, transparent workflows, and integration with existing documentation systems for both acceptance and actual use. Collectively, these results suggest that technological rather than human factors represent the primary barriers to the integration of robotics into nursing care. Such barriers can be mitigated through collaborative design, iterative refinement, and close alignment with everyday care practices.

Future research should complement participatory development approaches with evaluations conducted by independent user groups who were not involved in the design process. This would allow assessment from a more neutral perspective and reduce potential biases associated with repeated exposure or social desirability. Expanding participant diversity, including staff with lower digital affinity, will further strengthen generalizability. Testing the platform in real-world care settings with larger and more heterogeneous samples and incorporating the perspectives of care recipients will be essential to evaluate long-term acceptance, effectiveness, and impact. Given its open architecture, the platform provides a promising foundation for integrating additional assistive technologies and supporting broader digital transformation in nursing care.

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Data Availability

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

Conflicts of Interest

None declared.

Multimedia Appendix 1
Statistical analysis.
[XLSX File, 22 KB - nursing_v9i1e84118_app1.xlsx]

Multimedia Appendix 2
Qualitative evaluation.
[XLSX File, 15 KB - nursing_v9i1e84118_app2.xlsx]

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Abbreviations

EduXBot: Educational Exploration Robot Application Platform
GRAMMS: Good Reporting of a Mixed Methods Study checklist
ISO: International Organization for Standardization
MMAT: Mixed Methods Appraisal Tool
SUS: System Usability Scale
TENS: Technology-based Experience of Need Satisfaction
TUI: Technology Usage Inventory
VR: virtual reality

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Virtual Nursing Pilot in the Inpatient Setting: Qualitative Evaluation

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Abstract

Background: Global nursing shortages require innovative care delivery models. Virtual nursing is a cutting-edge model being explored.

Objective: This study aimed to examine the perspectives of clinical and administrative staff involved in a virtual nursing pilot on a medical-surgical unit and to identify best practices for future adoption.

Methods: We conducted a qualitative evaluation using individual semistructured interviews with virtual and bedside nurses, nurse executives, and IT project managers implementing a virtual nursing pilot program at a medical-surgical unit with 35 private and semiprivate beds at the Mount Sinai Hospital, a 1110-bed acute care hospital in New York, NY. Interviews took place in the spring of 2024 and were completed via phone or Zoom, audio recorded, and professionally transcribed. Participants were selected using purposive sampling. The authors applied an iterative thematic analysis to transcripts using Dedoose. Claude.ai was used to generate code summaries for select codes.

Results: Of 33 individuals approached, 16 (48.5%) consented to participate. Nine participants were clinical staff (virtual and bedside nurses and nurse managers), and 7 were executive leaders or managers in nursing and informatics. Our analysis identified the following themes: (1) staff attitudes toward virtual nursing shifted from resistance to acceptance over time, (2) direct communication channels between virtual and bedside nurses were critical for efficient care coordination and model adoption, (3) admission and discharge processes evolved throughout the pilot implementation, and (4) adaptable staffing allocations were necessary to accommodate fluctuating patient census and unit demands.

Conclusions: The main beneficiaries of this intervention, bedside nurses, found their virtual counterparts helpful following a few adjustments. Participants reported a perceived reduction in administrative burden, uninterrupted completion of clinical tasks, and they felt their overtime was reduced, which all increased their buy-in for this care model. There are several opportunities for improvement, such as real-time communication, unit-specific virtual nurse training, and flexible staffing for high-volume units. Our findings suggest that virtual nursing can address staffing challenges. Calculating the true return on investment for virtual nursing programs will require comprehensive mixed methods evaluations of such outcomes as care team and patient satisfaction, length of stay, readmission prevention, completion of nursing tasks, and reduction in overtime.

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KEYWORDS

virtual nursing; evaluation; qualitative; systems integration; change management; digital transformation; care delivery model; care coordination; staff satisfaction

Introduction

Technological advancements, staffing challenges, and evolving patient expectations are driving a digital transformation that is rewriting how we deliver health care. The COVID-19 pandemic accelerated the adoption of electronic communication platforms to help reduce the spread of the deadly virus. A workforce crisis has emerged globally with the United States facing a shortage of between 1.8 and 3 million nurses according to different projections [1,2]. The excessive workload placed on existing health care personnel has resulted in heightened stress, burnout, psychosomatic disorders, anger, and anxiety [1]. To address this challenge, health care leaders are exploring a variety of digital health tools and integrated care models. The use of telehealth for outpatient visits increased 38 times in the first 2 years of the pandemic [3]. The use of digital tools also increased in the inpatient setting [4]. The majority of these interventions have involved a physician connecting with a patient or bedside staff (a nurse) in a patient's home or a clinical setting [5,6].

The pandemic's toll on the health care workforce, nurses in particular, has put new pressure on hospitals to identify nursing tasks that could be completed remotely. Among these are administrative tasks such as admissions and discharges [7], patient education [8], and 1:1 sitting [9]. Of these, virtual sitting for fall prevention has the most evidence, with 12 studies conducted between 2009 and 2021 [9]. Using virtual nurses for admissions and discharges is more recent, with only three virtual nursing pilots on the topic published to date [7,8,10]. Other formats of virtual nursing have also been explored. For example, colleagues from the Mayo Clinic reported on an inpatient virtual registered nurse (RN) program, in which experienced nurses (often retired or nearing retirement) provided guidance to bedside RNs and proactively monitored patients, with no difference in patient safety and care outcomes [11,12].

In a collaborative effort to address staffing challenges and improve patient care, the Mount Sinai Hospital (MSH) partnered with Banyan Medical Solutions, a third-party vendor, to implement a virtual nursing platform on a selected inpatient unit. The implementation process involved installing compatible large-screen smart TVs, wall-mounted cameras, and pillow speakers, enabling virtual nurses to perform critical roles such as patient education, admissions, and discharges. This qualitative research study aimed to examine partner perspectives on this virtual nursing pilot at MSH with a focus on operational implementation and to identify best practices and recommendations for further refinement.

Methods

Setting

In January 2024, a virtual nursing pilot was initiated at a 35-bed medical-surgical unit at MSH. The fast-paced unit with high daily discharges accepts various postoperative patients. Virtual nurses, credentialed by the state but working remotely from a command center, have full access to the hospital's electronic health records. These nurses joined the company in 2021 2022, are relatively junior with experience in other settings, and chose virtual work for personal reasons. Privacy protocols included "virtual knock" protocol, verbal consent requirements, and headphone availability for patients in semiprivate rooms.

Study Design and Sampling

We conducted a qualitative study using semistructured interviews to examine staff and leaders' perspectives and experiences related to the virtual nursing pilot program. We used purposive sampling to recruit participants from diverse professional backgrounds, aiming to gain a comprehensive understanding of the program from the frontline to leadership viewpoints.

Recruitment and Participants

Between February and June 2024, we invited 33 individuals to participate through email outreach, in-person shadowing, distributing flyers in common areas, and collaborating with hospital leadership. Data saturation was reached after completing about two-thirds of the nurse interviews, when new interviews yielded little additional information, following accepted standards in qualitative research [13]. We continued to recruit nonclinical personnel to ensure diverse perspectives.

Data Collection

Semistructured interviews were conducted via Zoom using a MSH account, lasting about 30 minutes each. Topics included patient and staff safety, privacy, technology reliability, program acceptability and usefulness, and improvement opportunities. The interview guide was developed based on research team discussions, particularly input from nursing leaders attuned to staff hopes and expectations. Our interview guide did not specifically explore formal clinical governance structures, focusing instead on operational implementation experiences. Using an interview guide helped ensure consistency and reliability of collected data across participants [14]. Interviewers (JR, MB, KG) used probes for clarification and conducted clinical shadowing (JR, MB) with field notes.

Data Analysis and the Use of Artificial Intelligence

Interview data were professionally transcribed and analyzed using iterative thematic analysis [15]. The team used Dedoose [16] for data analysis and management, and Claude.ai [17] to generate drafts of data summaries for selected codes. Three researchers (KG, MB, JR) read and coded the transcripts manually, using both deductive and inductive codes, refining codes through weekly discussion. Two coders applied the final codebook to each transcript in Dedoose. Major codes included care coordination, impact on workload, opportunities for improvement, and inclusion in decision-making. Minor codes included staff satisfaction, timing, best practices, and limitations of virtual nursing. After coding, the team identified key themes, downloaded relevant excerpts, and used AI to generate comparative summaries for each subtheme. Three analysts (KG, JR, MB) combined, iterated, and edited these summaries to create drafts of Results sections for further team refinement.

Ethical Considerations

The study was determined to be exempt by the Program for Protection of Human Subjects at the Icahn School of Medicine at Mount Sinai on January 17, 2024 (STUDY-23-01378). Informed consent was obtained after the nature and possible consequences of the study were explained. The study adhered to local, national, regional, and international law and regulations regarding protection of personal information, privacy, and human rights. The study was deemed exempt by MSH's Human Subjects Protection Program, with all participants consenting to be interviewed and recorded, and receiving a US $25 gift card as compensation.

Results

Participants

Of the 33 individuals invited, 16 (48.5%) staff members consented and completed interviews (Table 1). The participants included 9 clinical staff (RNs, nurse managers, and virtual nurses) and 7 nonclinical personnel (executives in nursing and informatics, and IT managers). Based on the analysis of the data, we identified the following 4 major themes: (1) staff attitudes toward virtual nursing shifted from resistance to acceptance over time; (2) direct communication channels between virtual and bedside nurses were critical for efficient care coordination and model adoption; (3) admission and discharge processes evolved throughout the pilot implementation; and (4) adaptable staffing allocations were necessary to accommodate fluctuating patient census and unit demands.

Table . Participant characteristics and professional background (N=16).

Participant	Count, n
Professional background	
Registered nurse, including virtual nurses and executives with nursing background	12
Information technology or managers	3
Executives, including MSHS[a] executives and Banyan	2
Professional role	
Registered nurses at bedside	7
Virtual nurses	3
Information Technology	2
Operations personnel	2
Executives, including MSHS executives and Banyan	2
Gender	
Female	14
Male	2

[a]MSHS: Mount Sinai Health System.

Theme 1: Implementation Process: Staff Perspectives Adapt From Resistance to Acceptance

The implementation of virtual nursing revealed a clear evolution in staff attitudes, moving from initial skepticism to overall acceptance. Some of it had to do with the timing and depth of staff involvement in virtual nursing implementation decisions. Staff accounts indicate early concerns about role displacement and workflow disruption (Table 2, example 1a), which were exacerbated by the fact that early-stage participation was limited and staff were brought in late in the planning process. Staff identified missed opportunities for leadership to proactively engage frontline workers: "I would have loved to have had that interaction with Banyan earlier, because we had a bunch of questions that our people didn't have answers to" (Bedside RN, CL01; Table 2, example 1b). This delayed engagement led to accumulated questions and uncertainty among staff, though many issues were eventually resolved through concentrated information sessions. Nurse participants also reported that once the training was complete, they were relieved and realized that virtual nurses could be helpful (Table 2, example 1c).

Table . Key themes and representative quotes from participant interviews. Theme 1: Implementation process.

Example No.	Subtheme	Quote and participant role, ID
1a	Initial fears	“So there was a lot of trepidation. what is this actually going to look like. like physically how are they going to do this? And they’d be like, oh, we’ll get back to you.” (Bedside RN, CL01)
1b	Staff involvement	“.if the leadership is like. we’d like to go talk to the staff before we officially decide this so that we can let them know exactly how this works, maybe they’ll be a little bit more comfortable with it” (Bedside RN, CL02, Table 2, 1b).
1c	Relief	"We were thinking it was going to be a thing that we would have to worry about. But once you know all you have to do is a few clicks in the Banyan board, then I think that is definitely really helpful.” (Bedside RN, CL03)
1d	Decisions made at leadership level	“Because we are a union hospital, we did have to be very specific. That came from the CNO and the union.” (Nursing executive, NCL06)
1e	Leadership and change management	"It requires multiple conversations and sessions in advance of the model being implemented for people to first understand why we’re doing this. It's not for the heck of it. It's to help you" (Nursing executive, NCL07)
1f	Peer-to-peer learning	"I think if also there was an opportunity for people from [our unit] to go talk to the other units about it and how it worked, like to hear from peer-to-peer, that would be really helpful" (Bedside RN, CL03).

Several bedside nurses noted they wanted to be involved in technology evaluation and workflow decisions. This, however, was not always possible, as we learned from the interviews with nursing executives and nurse managers. One consideration was that the union leaders’ agreement on what tasks would be delegated to virtual nurses. Union considerations shaped decision-making authority, with decisions made at the leadership level (Table 2, examples 1c and 1d).

Our analysis also demonstrated real-world challenges in achieving meaningful staff participation while maintaining unit operations. Leaders described efforts to include staff while acknowledging limitations: "We do pull nursing staff off the floor to assist with any projects to get their insight, but we often know that they’re not able to stay every time for the whole hour, if at all” (Executive leader, NCL06). This resulted in a selective approach to staff involvement, with few staff members being able to go onsite to another hospital to observe Banyan operations.

During interviews, leaders emphasized their commitment to address staff concerns and support adoption of the new system. As one operations leader explained, "I would do anything I could to get leadership to the unit, to recognize that we appreciate you... we’re doing this as a resource for you” (Executive leader, NCL04). The implementation process required careful messaging and consistent support (Table 2, example 1e).

Finally, peer influence played a crucial role in shifting perceptions, particularly as floating nurses shared positive experiences across units: "When we get nurses from other units that float to us, they’re like oh my god, this is amazing. They all love it” (Bedside RN, CL06). Initial resistance transformed through hands-on experience and peer testimonials, with staff gradually recognizing virtual nursing as supportive rather than replacement technology (Table 2, example 1f).

Theme 2: Optimizing Technology Integration: Opportunities and Best Practices

System reliability and integration emerged as critical factors in implementing a virtual nursing platform. Here we describe *several operational opportunities for improvement* that can be used to establish best practices for implementation. These included technical integration to eliminate delays in communication, resolving audio quality issues, remote printing capability for virtual nurses, and volume control in shared rooms. These technical challenges collectively highlight the importance of robust infrastructure and seamless integration between systems for optimal integration into operational workflows.

Integration with existing hospital systems presented ongoing challenges. Multiple nurses noted issues with electronic health record connectivity and documentation access. These integration issues required bedside staff to navigate between multiple platforms, creating workflow inefficiencies (Table 3, example 2a). Bedside nurses desired a more nuanced communication tool with their virtual nurse partners in which they could specify discharge timing, for example, when transportation for the patient was already prearranged, and a direct communication line between virtual nurses and providers. This highlighted the need for systems that could accommodate real-time coordination between virtual and bedside teams.

Table . Key themes and representative quotes from participant interviews. Theme 2: Optimizing technology integration.

Example No.	Subtheme	Quote and participant role, ID
2a	Systems integration	"Opening a separate screen, it sounds crazy, but it's often a pain... We basically have to open up a separate page. We have to go out of our Epic and open up a separate page to move Banyan." (Bedside RN, CL04)
2b	Audio quality	"It's loud... depending on the age group, depending on how sedated the patient is... Some of it is a [local] issue, that some of the TVs aren't coming through the call bell." (Bedside RN, CL04)
2c	Printing connectivity	"...if [virtual nurses] have completed all the discharge… it's just… one extra button to print it. Whereas if we have to print it, we have to go in, we have to look at all the things, then print it, and then gather it again. So it just saves a couple extra minutes with it being like oh, you're already in that section, you press the button." (Bedside RN, CL02)
2d	Patients with special accommodations	“So at that point I would probably do the interpretive services myself in person because on top of it that there's a new barrier of virtual, we have to then find an interpreter, and then we have the technology issues of whether the phone in the room is actually working... But even when it is working, I've seen that admission, instead of taking probably like a half an hour, it takes like over an hour.” (Bedside RN, CL05)
2e	Workarounds	“And they themselves, taxi services, most of the time they’re rude… they’re like no, if they’re not here in the next two minutes I have to leave and pick up the next person. They don’t care. And then we’re like let’s just do the discharge ourselves and let’s just… like let’s not even wait for transport, let’s just roll the patient down in the wheelchair on our own before they lose their taxi.” (Bedside RN, CL05)

The interoperability challenges between the virtual nursing platform and the hospital’s EHR system affected *care plan documentation and continuity*. Virtual nurses documented within both the Banyan system and Epic, but the lack of seamless integration meant that care plan updates were not always immediately visible to bedside staff without actively switching between systems. When virtual nurses completed admission assessments or discharge education, bedside nurses reported needing to actively seek out these updates rather than receiving automatic notifications of completed tasks. Remote printing connectivity for virtual nurses represented another technical hurdle. Bedside nurses explained that efficiency could be gained through improved printing functionality (Table 3, example 2c). According to one nurse, “it just saves a couple extra minutes… [if] you’re already in that section, you press the button” (Bedside RN, CL02). While virtual nurses tried to send paperwork to print locally on the unit, this functionality did not work at the time of the interviews, making bedside nurses sign into the electronic medical record each time for the (virtually) discharged patient, find all the information, and send it to the printer again.

Audio quality issues particularly affected patients’ willingness to accept a virtual nurse and staff efficiency, with problems being more pronounced during night shifts. Volume control concerns in shared rooms further complicated the situation, creating potential privacy issues and patient dissatisfaction, highlighting the need for better audio privacy solutions such as mandatory headphone use or room-specific volume controls (Table 3, example 2b).

While adaptations in the virtual nursing program showed promise for standard patient interactions, additional complexities arose with specific patient populations. Extended processing times for patients requiring interpreter services emerged as a particular challenge. Our bedside nurse participants reported foregoing virtual support altogether to save time and ensure effective communication with patients who needed interpreter services (Table 3, example 2d).

In response to these challenges, staff developed various *workarounds* to maintain efficient patient care. For example, bedside nurses described how transportation constraints sometimes necessitated bypassing virtual nursing protocols.

One nurse explained that taxi drivers often gave ultimatums about immediate departure, stating they would leave if patients weren't ready. This led staff to expedite discharges independently rather than risk patients losing their transportation (Table 3, example 2e). This adaptive approach allowed staff to balance the benefits of virtual nursing with practical operational needs. Another workaround—the implementation of Epic's secure chat functionality—marked a significant improvement in real-time coordination, with staff reporting it helped them coordinate plans with their virtual counterparts. Developing clear communication protocols, particularly for urgent situations, proved essential for maintaining seamless patient care across virtual and bedside teams.

IT specialists in our study highlighted the importance of technical considerations, such as future *interoperability*, beyond the immediate virtual nursing pilot. One IT leader pointed out that it is important to consider the use/reuse of technology components, such as smart TVs, for new nursing workflows that could be covered remotely: "how do we utilize a single or a smaller set of devices?" (NCL03). This perspective underscores the importance of strategic planning for technology integration that considers both current needs and future applications.

Theme 3: Care Coordination: Benefits of Virtual Nursing on Teamwork

The implementation of virtual nursing transformed admission and discharge processes, creating new team dynamics between bedside and virtual nurses. This theme explores how these workflows evolved and the benefits that emerged from this collaborative approach.

Transformation of the Discharge Process

Before the virtual nursing pilot, discharges required bedside nurses to manage multiple competing priorities simultaneously. One nurse described the traditional discharge process prior to the virtual nursing pilot implementation that involved educating patients, who were often frightened, about their discharge, trying to be supportive, "all while maybe a call bell's ringing, you're trying to get somebody their meds, you're hopefully not getting an admission because your workload is full" (Bedside RN, CL04; Table 4, example 3a). With the introduction of virtual nursing, the process became more streamlined. The same nurse explained that now they just switch a certain setting and "Banyan will often just start doing the discharges" (Bedside RN, CL04), freeing bedside staff to perform other tasks.

Table . Key themes and representative quotes from participant interviews. Theme 3: Care coordination.

Example No.	Subtheme	Quote and participant role, ID
3a	Old workflows (previrtual nursing)	"…prior to Banyan, you waited for a discharge order… You printed out your paper and we went to the bedside… we're a postsurgical unit, many people are absolutely frightened about going home with a new hip… and you would spend a tremendous amount of time educating, and teaching, and explaining their discharge. Then we wait for transport. And this is all while maybe a call bell's ringing, you're trying to get somebody their meds, you're hopefully not getting an admission because your workload is full." (Bedside RN, CL04)
3b	Good catch	"The only time I remember that it didn't go well is we had a patient who needed… [Lovenox] education... And the only way I was able to figure that out is because he was leaving and then his wife came up to me and she was like we never got the Lovenox education… So I think the nurse should have picked it up, like oh, you're going home on Lovenox injection, do you know how to administer it?.. He could have just walked out, went home, and not know how to do it. Good thing his wife [asked]… And I was like oh, okay, let's go back into the room and we will go through the steps on how to administer the Lovenox injection." (Bedside RN, CL06)
3c	Division of patient education responsibilities	"Especially with our ortho patients, they are usually prescribed a certain blood thinner so that they don't develop any clots, and if they're already taking blood thinners at home, and there's an issue with the medication or any interaction, they could definitely help somebody, you know, prevent them from having an adverse reaction..." (Bedside RN, CL05) "The hands-on teaching, plus the discharge, can take a long time. So for the discharge paperwork to be reviewed, and then I come in and just have to do Foley teaching, for example, with the leg bag, that just takes a lot of time off of my plate for me to focus on other things." (Bedside RN, CL03)
3d	No direct communication with providers	"[Virtual nurses] are not able to communicate with the frontline providers, and if… the patient has any questions, and they can't answer, and then they'll message us, and then I have to message the doctor, and then I have to relay that information to the virtual nurse… So, you know what I mean, so she still has to go through me…" (Bedside RN, CL06)

The discharge process transformation remains a work in progress, particularly regarding the division of educational responsibilities between virtual and bedside nurses. This was evident when a patient nearly left without critical Lovenox self-injection education, discovered only when his wife proactively inquired as they were leaving (Table 4, example 3B). Following this learning opportunity, the nurse implemented a new protocol of personally reviewing the After Visit Summary before handoff, proactively identifying teaching responsibilities that fall within the bedside nurse's scope rather than the virtual nurse's capabilities, thus ensuring patients receive all necessary education before discharge.

Emerging Communication Patterns and Task Coordination

As the unit grew more comfortable with virtual nursing, new communication patterns emerged between bedside and virtual nurses. Bedside nurses noticed that virtual nurses began to proactively update them on task completion. Virtual nurses reported developing strategies for prioritization through communication with bedside staff. As one virtual nurse explained: "Communication is key. You just let the bedside nurse know what's going on… could you please… let us know the order that you want us to prioritize the patients, whose transportation is coming first… It makes all the difference in care" (Virtual RN, CL08). Virtual nurses reported initial lack of clarity about their role among patients, with one participant noticing an improvement in that respect: "the patients [are] just being educated more… regarding our services" (Virtual RN, CL07).

The division of educational responsibilities between virtual and bedside teams emerged as a key strength of the program. The system proved particularly valuable for complex cases, including newly diagnosed patients requiring extended education sessions. One bedside nurse highlighted the importance of virtual nurses' role in patient education, particularly for high-risk patients. She explained how orthopedic patients on blood thinners need to have their medications at home reviewed in case they were already taking blood thinners to prevent any interactions or adverse reactions (Table 4, example 3c).

A gap that remained unresolved at the time of the interviews had to do with virtual nurses' inability to message providers. For example, if a patient had a question during discharge that the virtual nurse could not answer, they had to message a bedside nurse who would then message a provider and report back to the virtual nurse who would relay it to the patient (Table 4, example 3d). Being unable to communicate directly with providers made this process unnecessarily involved and inefficient.

Time Efficiency and Focus on Direct Patient Care

A significant benefit reported by bedside nurses was how virtual nursing saved them time and allowed them to focus on hands-on teaching and direct patient care. One bedside nurse mentioned that discharges traditionally could take up to an hour and were now taken care of by their virtual counterparts (Table 4, example 3c). Another nurse echoed: "We're not stuck in a room for an hour doing admission questions and then having four other patients call on the Vocera and then get interrupted, going back and forth. That's what was happening before" (Bedside RN, CL06).

The ability to handle multiple tasks simultaneously was particularly valuable during busy periods. As one nurse explained: "Because if you're getting two admissions and you have a discharge, it's just a lot… So it's really helpful because then you're able to actually focus on hands-on patient care as opposed to…the paperwork aspect of it" (Bedside RN, CL03).

Improved Nursing Satisfaction and Work-Life Balance

The collaboration between virtual and bedside nursing staff resulted in positive outcomes for staff satisfaction and work-life balance. One nurse remarked, "It's nice to just like have that thought taken off your plate, as well as the admissions, just not having to stay late to do an admission when they come at… poor timing." (Bedside RN, CL02). Overall, the evolution of teamwork between virtual and bedside nurses created a more efficient workflow for admissions and discharges, allowing nurses to dedicate more time to direct patient care while ensuring comprehensive education and documentation.

Theme 4: Timing Is Key: Staffing Capacity and Patient Flow

Workflow integration and staffing alignment emerged as critical factors in the uptake and efficiency of virtual nursing, revealing the importance of proper coordination between virtual and bedside teams in managing patient flow.

Managing High-Volume Patient Movement

The partnership between virtual and bedside teams impacted patient workflow management, particularly during high-volume periods. One bedside nurse explained that their unit had "a colossal amount of movement… [with] 14 to 20 [daily] discharges and admissions" (CL04). Effective workforce distribution proved essential for managing such volume, as staff needed to adapt to fluctuating demands throughout the day. As another bedside nurse explained: "Sometimes they could say 10 [discharges], so they have, let's say, 5 [virtual] nurses on board, but then as the day goes on, the discharges do happen, so instead of having 10 we'll have 18" (Bedside nurse, CL06). This unpredictability highlighted the ongoing need to develop flexible staffing management strategies that could respond to rapidly changing conditions. Ascertaining the right staffing levels for virtual took some tweaking, as is evidenced by one bedside nurse report about initial challenges during the overnight shift, when there was only one virtual nurse available (Table 5, example 4A).

Table . Key themes and representative quotes from participant interviews. Theme 4: Timing is key.

Example No.	Subtheme	Quote and participant role, ID
4a	Initial insufficient staffing	"…it also comes down to how many people, how many nurses is Banyan hiring for our unit per shift... Because the thing is, [my supervisor] said oh, we noticed that things are running slow. [The virtual nurse said] I'm sorry, I apologize, it's just [I am] the only nurse with them at that shift… That was when Banyan was first implemented… I actually think Banyan can work in a fast-paced, but if there's enough staff, virtual nurse staff, and also to make things run faster." (Bedside RN, CL05)
4b	Impact on hospital throughput	"Once we discharge this patient we can pull more patients coming from the PACU and from the ED, so it helps them, like don't hold the OR schedule nor have a critical diversion in the ED" (Bedside RN, NCL05).
4c	Nurses more readily accept admissions at end of shift	"I think now that we have the Banyan nurses, nurses are not... reluctant on taking the admission from PACU. They'll just pick up because they know that when they come onto the floor that they don't have to deal with these admission questions, that they're going to be taken care of" (Bedside RN, CL06).

Impact on Hospital-Wide Operations

The virtual nursing system's impact extended beyond individual patient care to affect broader hospital operations. The most positive impact of the pilot, as perceived by our participants, was what they described as improved patient throughput. During peak periods, virtual nurses supported bedside teams, creating capacity to process patient admissions and discharges simultaneously. High volume peaks required different coordination compared to slower-paced environments, while night shift operations needed special adaptations to maintain patient comfort and prevent disruption during quiet hours. According to one nurse, by facilitating more efficient discharges, the system improved patient throughput across multiple departments (Table 5, example 4b).

This improvement in patient flow was also reflected in staff attitudes toward accepting new admissions. Nurses used to be reluctant to accept an admission from PACU, for example, if it meant they would have to stay longer after the end of their shift to complete it. According to several participants, this was no longer the case (Table 5, example 4c).

Time Investment in Patient Education

Virtual nurses reported dedicating significant time to patient education, highlighting the value of this investment despite its potential impact on short-term throughput. One virtual nurse reflected on the depth of engagement required: "I would say I think I'm long with discharges personally… I take a while. They have so many questions… The family's in there, the mom, the dad. So yeah, I feel like my discharges are long, like an hour… I feel bad. Some of them are newly diagnosed, so that's even longer, like an hour and a half" (Virtual RN, CL09). This time investment, while potentially extending the discharge process itself, ultimately supported more comprehensive patient education and potentially better postdischarge outcomes, demonstrating that flexibility in staffing and timing considerations needs to balance efficiency with quality of care.

Discussion

Principal Findings

This is the first qualitative evaluation of a virtual nursing pilot on an inpatient unit. Our findings demonstrate that virtual nursing implementation requires careful attention to technological infrastructure, operational readiness, and change management. We identified four major themes that characterized the virtual nursing implementation in our pilot: (1) achieving staff buy-in takes time and can benefit from earlier engagement strategies; (2) seamless technology integration, especially direct communication channels, is critical for smooth operation; (3) recognition of virtual nurses as integral team members, rather than auxiliary support, enhances collaborative care delivery; and (4) virtual nursing coverage must meet the demand to maintain relevance within the organizational or unit context.

Our study offers insights into implementing virtual nursing on inpatient units, which other hospitals can use when considering similar models. The unique unit or patient population characteristics—high volume, fast pace, surgical patients with diverse diagnoses—fit well with the virtual nursing pilot seeing benefits in admission or discharge support and patient education. If virtual support was unavailable or inefficient, the bedside nurses reverted to their traditional workflows. With the exception of some initial issues, the vendor was able to meet the challenge and provide sufficient support. Virtual nursing implementation on slower-paced units might prioritize functions like virtual sitters, which could be particularly useful on observation units.

Our findings highlight the critical importance of seamless EHR integration for virtual nursing models. The fragmented documentation workflow we observed, where staff navigated between multiple systems, created inefficiencies that could impact care continuity. The care plan coordination issues, exemplified by the Lovenox education incident, demonstrate how documentation gaps can directly affect patient safety. Virtual nursing programs must establish clear protocols for documenting care plan handoffs, particularly for complex patients requiring both virtual and bedside interventions and prioritize robust interoperability that allows direct documentation within the primary care record.

Technical and system reliability directly impacted operation readiness. The integration between EHR and the virtual nursing platform, audio quality, and physical environment considerations influenced staff adoption and clinical workflows. Virtual nursing adoption hinges on infrastructure investment that could be a barrier for smaller hospitals.

The pilot used out-of-state junior RNs. Other staffing models could be considered, such as floating bedside nurses as virtual for a fraction of their time. Implementers should weigh the efforts needed to educate new virtual staff vis-à-vis managing virtual nursing in-house.

Flexible staffing in response to patient flow emerged as one of the most critical factors for optimal operation. Implementation followed an overall positive trend—initial increases in workload during rollout, followed by productivity improvements once frontline staff adapted to their new workflow. Participants reported positive downstream effects such as reducing operating room holds and emergency department diversions through improved time to discharge and bed turnover.

This pilot aligns well with the cutting-edge innovations in health care operations. Our findings demonstrate that implementation depends on structured approaches to change management [18] while minimizing disruption to care delivery. Key insights from our analysis—albeit not new [19]—reveal the importance of early staff involvement in the decision-making process.

Staff adoption of the virtual nursing platform followed a progression from initial skepticism to approval. Clinical champions were powerful influencers of technology acceptance. Clear role separation created effective partnerships, particularly in educational delivery. Virtual nursing could leverage experienced nurses' expertise post COVID-19 pandemic, like programs at other institutions have shown [11,12].

Limitations and Strengths

Our study has the following limitations. We interviewed hospital personnel but not patients or caregivers. Understanding how both patients and caregivers view this intervention is essential for improving it further. Researchers need to examine not just how the interactions between patients and virtual nurses are designed to work, but also how patients and caregivers actually experience and respond to these interactions. It is a single-center pilot study in an academic medical center; our findings might not apply to a different health care setting or patient population. With about a 50% response rate, a nonrespondent bias is possible. Our study did not include quantitative data on reduced overtime, improved throughput, or quality indicators such as patient satisfaction, medication errors, or readmission rates. All comments related to these important metrics were based on the impressions of bedside and virtual staff and executive leaders. We also did not systematically examine formal clinical governance models or committee structures that may have guided the implementation process, nor did we evaluate preimplementation preparation or formal support models during rollout. However, this is the first published qualitative study of virtual nursing programs to our knowledge, capturing valuable nurse and leadership perspectives through its qualitative approach.

Recommendations for Planning Virtual Nursing Implementation

Based on our findings, implementation of virtual nursing requires attention across several domains. Organizations considering adoption should prioritize early infrastructure investment, unit-specific workflow design, clear governance structures, and intentional patient-facing communication. The following checklist sums up key considerations to guide planning and implementation.

- Technical infrastructure
- Invest in technical and communication infrastructure upfront to ensure seamless system integration between virtual and bedside nurses and between virtual nurses and providers
- Develop or adopt AI tools to support automatic patient prioritization for admission and discharge

- Workflow
- Implement dynamic staffing allocations responsive to patient volume fluctuations
- Adapt and optimize workflows to reflect specific demands of each unit
- Develop clear standard operating procedures for communication between virtual and bedside staff
- Conduct regular review of staffing allocations based on utilization patterns

- Clinical governance
- Establish formal governance structures with designated clinical champions

- Patient-facing communication
- Use nurses' insights to create standard messaging on introducing the virtual nursing program to patients and setting expectations
- Develop privacy standard operating procedures for shared rooms, including headphone distribution and consent procedures for virtual interactions

Conclusions

Virtual nursing is a cutting-edge care delivery innovation that goes beyond adoption of new technology. This virtual team model enhances care coordination, patient throughput, and staffing while keeping care patient-focused. Program success requires resources, technical infrastructure, and clear, unit-specific communication. Health care should see it as bedside care extension, with careful planning and ongoing adjustments based on data and feedback.

This study provides valuable insights for hospital leadership and management to understand the impact on clinical workload, staff acceptability and satisfaction, and patient care quality to support informed implementation decisions. Future research should explore several questions that emerged during this implementation: (1) How do virtual nursing models impact nurse retention and recruitment in a high turnover environment? (2) How might AI integration enhance the efficiency of virtual nursing documentation and communication? (3) How do patients perceive virtual nursing and how can their experience be improved? (4) What does virtual nursing affect quality and safety outcomes such as patient satisfaction, readmissions, and medication errors? Addressing these questions will further develop the evidence for this emerging care delivery model.

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Conflicts of Interest

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Abbreviations

MSH: Mount Sinai Hospital
RN: registered nurse

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Using Social Media Listening to Understand the Pressure Injury Experience: A Qualitative Descriptive Study

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Abstract

Background: Pressure injuries (PIs) are a common complication in people with reduced mobility or sensation and can be burdensome for individuals with PIs and their caregivers. Valuable insights and real-world challenges faced by individuals living with PIs can be captured through candid accounts posted on social media. Social media listening (SML) is a tool that can enhance the understanding of those with lived experience by offering firsthand accounts that are irreproducible from controlled studies.

Objective: This study aims to capture the candid experiences of individuals with PIs and caregivers through social media.

Methods: A noninterventional qualitative descriptive analysis was conducted using SML. Social media posts made on X (formerly Twitter), Reddit, and YouTube between January and December 2022 were compiled using SML tools X Pro (formerly TweetDeck) and Awario, and using Boolean search terms. Posts were manually screened for relevance, and duplicates were removed. Relevant posts were hand-coded by two independent reviewers. Inductive content analysis was used to analyze the posts.

Results: The search yielded 666 relevant posts from 498 unique social media users. Most posts were made in the United States (170/666, 25.5%), the United Kingdom (150/666, 22.5%), and Canada (62/666, 9.3%). Social media users provided detailed descriptions of the PIs, including the setting in which the PI occurred, the cause of the PI, and how the PI was managed. The majority of PIs (197/666, 29.6%) were reported to have occurred in the hospital setting due to a perceived lack of care from care providers, and local wound care was often cited (99/666, 14.9%) as a PI management strategy. Three key themes were developed regarding living with or caring for someone with a PI: (1) challenges experienced when living with or caring for a PI, (2) needs related to PI prevention and management, and (3) emotions experienced when living with or caring for a PI. Social media users frequently discussed challenges associated with living with a PI, including negative personal impacts and poor perceived treatment quality. Users also described a critical need for health care, education, and social support. Finally, users often expressed anger and/or sadness related to living with or caring for a PI.

Conclusions: SML captured candid insights into the experiences, challenges, and needs of individuals living with PIs and their caregivers globally that may not be gleaned from controlled studies. Individuals with lived experience and their caregivers often struggled with negative personal impacts regarding their physical health and daily functioning related to PIs, further highlighting the urgent need to address barriers to appropriate PI care. Clinicians and policymakers should consider practices and policies that optimize the delivery of person-centered PI care in order to overcome challenges and needs identified in this study.

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KEYWORDS

social media listening; social media; pressure injury; pressure ulcer; bedsore; caregiver

Introduction

Pressure injuries (PIs) occur due to damage to the integrity of the skin and underlying soft tissue resulting from severe and persistent localized pressure and shear, usually over a bony prominence [1-3]. Those at risk of developing PIs include older individuals and individuals with reduced mobility or sensation [1,3]. The global prevalence rate of PIs has remained stagnant at around 12% over the past few decades [4,5], which is notable because most PIs are avoidable if appropriate prevention techniques are applied [6]. This prevalence is especially troubling since PIs impose severe physical, mental, social, and emotional impacts on those living with or caring for them [7-11]. Individuals living with PIs often experience physical discomfort, social isolation, and challenges when performing daily activities [8]. Similarly, caregivers of individuals with PIs may experience a high caregiving burden and a low quality of life [12,13]. PIs also cause tremendous financial strain on affected individuals and the US health care system, with an estimated yearly expenditure of US $26.8 billion on hospital-acquired PIs [14].

The burdens and challenges of living with a PI may go unrecognized or unaddressed by the health care teams caring for individuals with PIs [8,11]. Patient-centered care, which incorporates patients' and caregivers' perspectives, preferences, needs, and goals, is essential for addressing patients' challenges and improving treatment adherence and patient outcomes [15,16]. An interventional study of hospitalized patients admitted for acute medical or surgical treatment comparing usual care with patient-centered interventions revealed that a patient-centered educational intervention resulted in greater confidence in medication adherence [17]. Similarly, an interventional study conducted in an inpatient ward specializing in care for patients with neurological, orthopedic, or musculoskeletal conditions revealed that the active involvement of patients and their colleagues during nursing clinical handovers resulted in a decrease in hospital-acquired complications [18]. Thus, understanding the perspectives of individuals living with PIs and their caregivers may provide insights into improving the delivery of patient-centered PI care [15,16].

Over the past few decades, social media has become a vital resource where communities of individuals living with health conditions and their caregivers from around the world share unfiltered opinions, seek health information, and connect with one another [19]. Social media platforms such as YouTube, X (formerly Twitter), and Reddit are popular forums for individuals to seek social support and health information or share their personal experiences with their health conditions and subsequent treatment [20]. The increasing use of social media by patient and caregiver communities presents a valuable opportunity for researchers to elucidate candid patient and caregiver perspectives and experiences as reported on social media sites [19]. This is made possible through social media listening (SML) [21,22], a research method that involves performing a systematic search of public social media platforms. SML uses tools such as Talkwalker, Salesforce Social Studio [23,24], and X Pro (formerly TweetDeck) to identify real-world, firsthand accounts of individuals' experiences with disease and treatment, quality of life, and unmet needs [23,25].

SML can be used as a complementary research method alongside traditional qualitative or quantitative studies and has been shown to yield several benefits [19]. Given that patient recruitment is not required, SML can reduce recall and reporting biases that may be present in interviews or retrospective data collection methods by removing the researcher from the discussion [19]. SML also allows researchers to collect data from patients without geographic restrictions, providing large-scale insight into a topic [19]. SML has been shown to be an effective method of understanding patient and caregiver perspectives, unmet medical needs, and adherence to treatment that may not have been previously identified in the literature [23-28]. For instance, Perić et al [23] explored the needs and lived experiences of patients with graft-versus-host disease by using Talkwalker to search for relevant posts on Twitter, Facebook, Instagram, and YouTube. Similarly, Kline et al [24] used Salesforce Social Studio and Talkwalker to understand unmet needs, barriers to treatment, patient journey, and treatment options for patients living with amblyopia. Other similar studies have investigated individuals' experiences with various medical conditions, providing critical insights into individuals' quality of life, treatment, and perception of their quality of care [27-30].

While previous studies have explored the challenges faced by individuals living with PIs and caregivers who provide support [8,11,13,31], their perceptions of their role in PI care [9,16,32], as well as their knowledge, information needs, and preferences for PI education [15,33-35], none have used an SML approach to explore their experiences. Given the benefits of SML and the pervasive use of social media in the present day, SML may provide important, unique, and unfiltered insights into the experiences, challenges, and needs of individuals with PIs and caregivers globally that may not be elucidated from traditional studies. Thus, our study aimed to capture the experiences, challenges, and needs of individuals with PIs and caregivers using SML, an emerging research method that could reveal aspects of the PI experience not easily observed in controlled research environments.

Methods

Study Design

This study implemented a noninterventional qualitative descriptive approach to analyze publicly available social media posts made on X (formerly Twitter), Reddit, and YouTube using SML software Awario and X Pro. The study design was conceived by postgraduate students and scientists with extensive experience in both qualitative and quantitative research. We used the SRQR (Standards for Reporting Qualitative Research) guideline [36] to draft this manuscript and the SRQR reporting checklist [37] when editing (Checklist 1).

Search Strategy

Overview

Between May and June 2023, comprehensive searches were conducted on Reddit and YouTube using Awario. Searches were simultaneously conducted on X using X Pro. Awario and X Pro enable users to search web-based platforms for phrases and keywords in public posts in a similar manner to a literature search [38,39]. Both Awario and X Pro identified English-language posts made between January 1 and December 31, 2022. X, Reddit, and YouTube were selected as popular open-access social media websites where users commonly share personal opinions and experiences, enabling us to feature the perspectives of a wide range of individuals. Predefined Boolean search strings were used to identify relevant posts on each social media platform, and Boolean operators (AND/OR) were used to combine each keyword within the strings (Multimedia Appendix 1). The search string included key terms related to pressure injury and alternate words for pressure injury, such as "bedsore" and "pressure ulcer," as well as care recipients' or caregivers' identities (ie, grandparents, parents, sister).

Definitions

A "user" or "social media user" referred to individuals with lived experience (ie, individuals who had experience living with a PI), caregivers (ie, individuals who provided direct, unpaid care to someone with a PI), or observers (ie, individuals who were not explicitly a caregiver but had witnessed someone else's PI experience as their friend or relative) who posted content on social media. Observers were distinguished from caregivers by their level of participation in providing PI care: caregivers explicitly provided care for someone with a PI, whereas an observer did not provide direct care for an individual with a PI but appeared to be actively involved in the life of an individual with a PI (eg, friend, colleague, or family member). A "post" was defined as any social media content identified through the search. A "mention" was defined as a reference to a specific topic within posts, which was used for coding in the analysis.

Inclusion and Exclusion Criteria

Social media posts from X, Reddit, and YouTube were included for analysis if they were written or recorded in English by individuals with lived PI experience, caregivers, or observers. In order to be included in the study, the social media post had to contain content relating to personal experiences with PIs (ie, experiences of living with a PI, caring for someone with a PI, or observations of another person's experience with PIs). There were no restrictions in terms of the user's geographic location.

Posts were excluded if they mentioned the development of a PI from medical masks or if the user did not fit the definition of an individual with lived PI experience, caregiver, or observer. Posts were also excluded if the user was a paid caregiver or health care professional (HCP) and if the post contained product endorsements or advertisements.

Data Screening

The results of each Boolean search were entered into a Microsoft Excel spreadsheet. Each X, Reddit, and verbatim transcript of the YouTube post was manually reviewed for relevance based on the inclusion and exclusion criteria before being input into a separate spreadsheet for content analysis. Any posts that did not meet the inclusion criteria or the exclusion criteria (eg, product endorsements) were removed. Duplicate posts that contained identical text were identified using the sort function of the spreadsheet and removed manually by researchers. To ensure interplatform data consistency, we applied common inclusion and exclusion criteria across platforms. Screening and verbatim transcription were performed in duplicate by two independent researchers to enhance trustworthiness.

Data Collection: Post Characteristics

Users' relationships with individuals living with a PI, geographic location, and intended audience were documented whenever such information was available from the users' social media profiles or could be inferred from the posts. Otherwise, users were classified as "unknown." Post details including the posting date, retrieval date, source platform (ie, X, Reddit, or YouTube), post format (ie, video, forum post, or tweet), and post hyperlinks were also documented on a Microsoft Excel spreadsheet.

Summative Content Analysis

Overview

Segments of text within each social media post were assigned a label (ie, code). Given that multiple segments of text within each social media post may have been present, social media posts were often assigned more than one code. Summative content analysis was used [40,41] through inductive coding; theme generation; and code, subcode, and theme frequency measurement.

Theme Generation

Inductive coding was used to formulate a comprehensive codebook. Primary codes, corresponding subcodes, example posts for reference, and code definitions were determined through an iterative process. The initial creation of codes and subcodes was performed independently by four research team members (PM, Pilar Tabuenca [PT], Uchechukwu Akunna [UA], and SG) based on post content, and the final codebook was developed following an exhaustive discussion by the team and the refinement of initial codes and subcodes. Disagreements were resolved through a discussion between coders or by an additional coder, if needed. Codes and subcodes were assigned to the relevant posts on a Microsoft Excel spreadsheet. Emotion codes were assigned to each post based on Plutchik's emotion wheel [42], which identifies eight primary emotion codes—joy, trust, fear, surprise, sadness, disgust, anger, and anticipation—along with their combinations. To ensure the reliability of the coding, these code assignments were later double-checked by four independent researchers (AI, AAO, IT, and JZS) and input into NVivo 12 (QSR International), a qualitative data management software.

The codes and subcodes were then consolidated into major themes representing the experiences of individuals with lived PI experience as reported on social media following further discussion by the research team. Posts were double coded under the same theme when they reflected multiple aspects of the theme; for instance, posts often described both personal impacts and perceived quality of treatment that were encountered while caring for a PI, which both fell under the theme of "Challenges experienced when living with or caring for a PI." As a result, the number of mentions (ie, codes) per theme surpassed the number of total posts in some cases.

Frequency Measurement

Code, subcode, and theme frequencies were calculated using NVivo 12. Frequency was similarly calculated and summarized for users' demographic information (ie, geographic location, intended audience, and relationship to the individual living with a PI).

Ethical Considerations

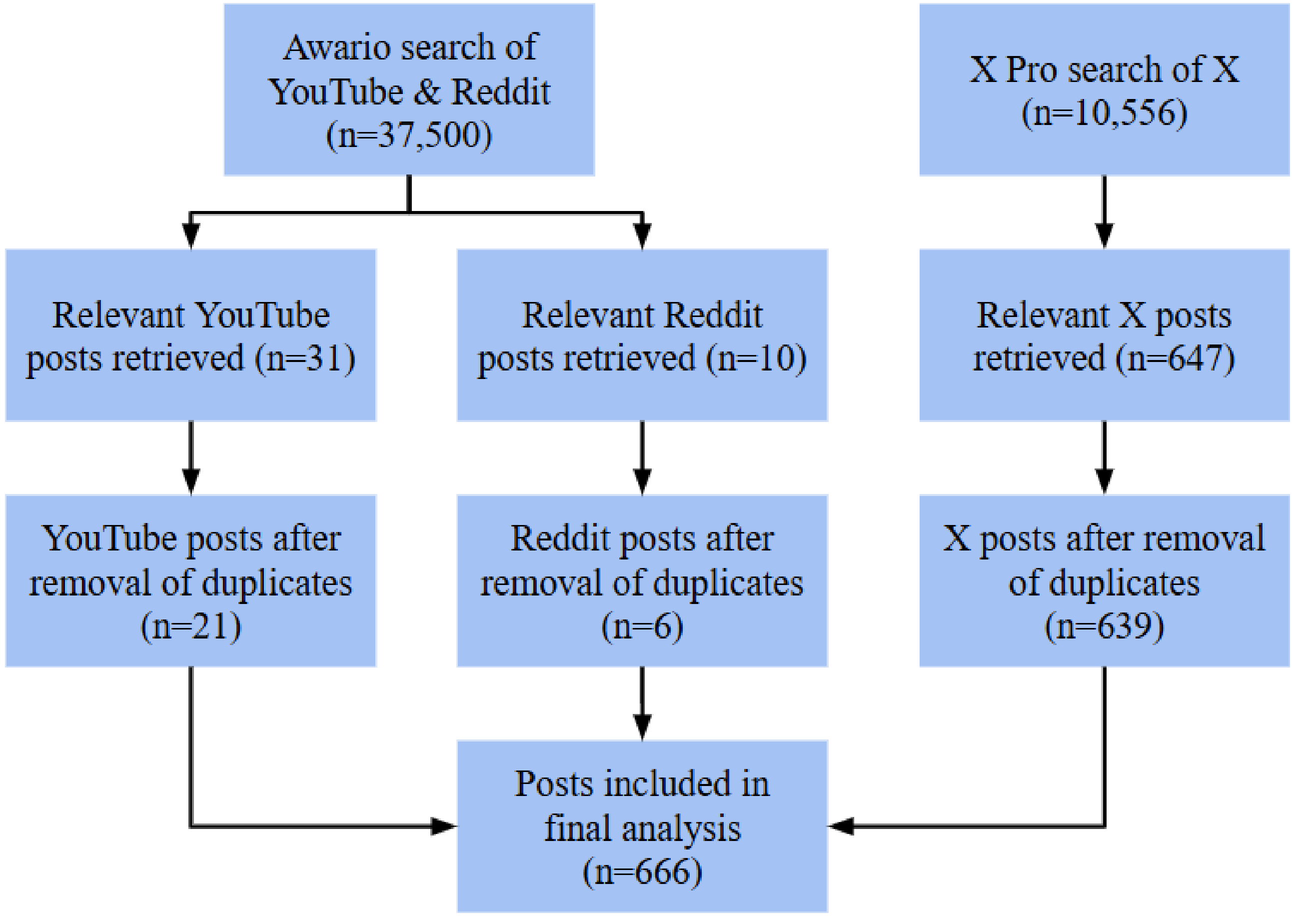
This study was exempt from human subject research ethics review because all data were obtained from public, internet-based sources, as per University Health Network [43] and University of Toronto [44] policies. No human participants were directly involved in this study, and as such, compensation was not provided. Study data were deidentified, and any identifiable information was removed from the study analysis, manuscript, figures, and tables.

Results

Search Strategy and Data Screening

The initial search retrieved 37,500 and 10,556 posts from Awario and X Pro, respectively (Figure 1). After three independent researchers (PM, PT, UA) manually screened the posts, 41 relevant posts were identified from Awario, and 647 relevant posts were identified from X Pro. Duplicate posts were then removed. Ultimately, 639 X posts, 6 Reddit posts, and 21 YouTube videos were identified as relevant to the study objectives.

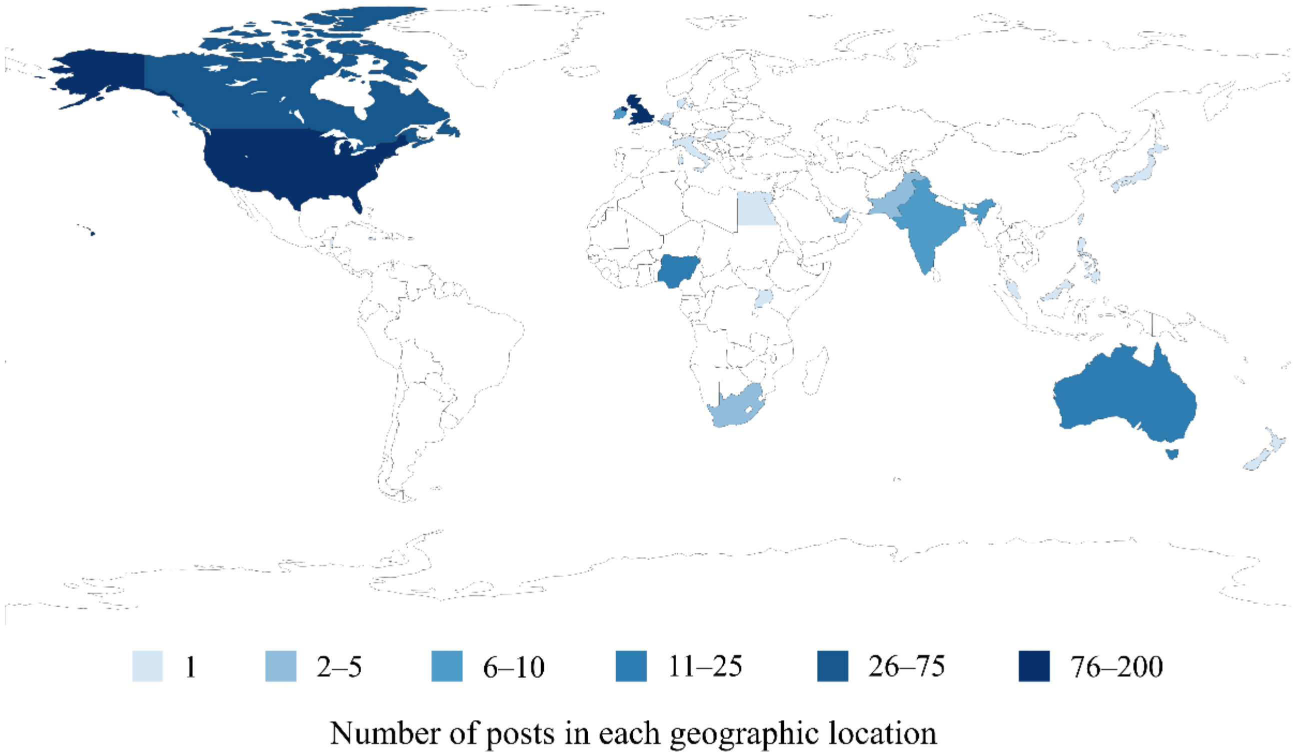
Figure 1. Flow diagram depicting the process of selecting relevant English-language social media posts made between January 1 and December 31, 2022, using social media listening (SML) software programs Awario and X Pro.



Post Characteristics

Our study identified 498 unique social media users across X, YouTube, and Reddit who generated a total of 666 posts. Of the 666 posts, 361 (54.2%) were posted by observers, 219 (32.9%) were posted by caregivers, and 86 (12.9%) were posted by individuals with lived PI experience. Caregivers and observers were often the child or other relative (eg, grandchild, sibling, parent) of the person with a PI. Most posts (n=631, 94.7%) were intended for the general public, although a few were targeted at specific health care institutions or other individuals (ie, governments, support groups). Most posts (n=481, 72.2%) were intended to share information about PIs with others (eg, warnings, knowledge about PI progression, causes, and complications), while some posts were intended to blame or advocate for others. Posts most frequently originated from the United States (n=170, 25.5%), the United Kingdom (n=150, 22.5%), or Canada (n=62, 9.3%), as seen in Figure 2.

Figure 2. Heat map displaying the distribution of social media posts according to geographic location.



Overview: The Pressure Injury Experience

Table 1 displays characteristics related to the PI experience, including the description of the PI, risk factors and causes of PIs, PI symptoms, the setting where the PI occurred, PI management, and commentary about PI healing. In posts (n=666), users frequently discussed the severity of the PI (n=120, 18%) and the location of the PI on the body (n=116, 17.4%). Several users described comorbidities (eg, dementia, obesity) as a risk factor for developing a PI (n=105, 15.8%), and many users cited a lack of care from HCPs or caregivers as the direct cause of their PI (n=156, 23.4%). Additionally, pain and discomfort were commonly reported symptoms (n=56, 8.4%). Many PIs were reported to have been hospital-acquired (n=197, 29.6%), and the most commonly reported PI management strategy was local wound care (n=99, 14.9%; eg, debridement, cleaning). A few users described the healing process of their PI (n=41, 6.2%).

Table . Frequency of posts that reported elements of the pressure injury (PI) experience, including PI description, risk factors, causes, symptoms, setting, management, and healing[a].

Topic	Posts, n	Relevant quotes
Pressure injury description		
Severity	120	"… my back, bottom & legs were a mass of pressure sores, two so severe that you could fit a large man's fist into the holes."
Location on body	116	"My Mum had a bedsore at the bottom of her spine right through to the spine. It killed her …"
Size	50	"… she had heel pressure ulcers the size of a silver dollar and deep ..."
Appearance	36	"… her bottom became an un-stageable bedsore. After surgery to remove [the] blackened and dead flesh, you could actually see her lower spine."
Number	34	"I'm alive, but I am dealing with three separate pressure ulcers …"
Duration	33	"Almost seven years of dealing with that pressure sore and it's finally healed …"
Risk factors of pressure injury		
Comorbidities	105	"She keeps getting UTIs and now she has a pressure sore that's slow to heal. She needs a hoist to get up. Her dementia is getting worse ..."
Immobility	50	"… She was essentially immobile, and fat. It took three hospital staff every time she needed to be repositioned to prevent bedsores."
COVID	15	"My mom got COVID… A few months later, she got an infection from a bedsore, got sepsis, and passed away. I believe COVID weakened her immune system …"
Body mass	15	"[He] was about 1200 pounds, bedridden, and ended up having a huge wound as a result of a bedsore."
Thin skin	7	"My mom went in hospital and got pressure ulcers like that within days ... Her skin was very thin."
Cause of pressure injury		
Lack of care	156	"She has two pressure sores on one foot as the carers in the home didn't move her when she was out of it for a couple of days."
Immobility	103	"... [My grandpa was] completely paralyzed. Ended up dying from a bedsore because of it."
Comorbidities	63	"…due to my spin a (sic) bifida and lack of sensation in some areas of my body I developed pressure ulcers on my sacrum and was hospitalized for wound care and sepsis."
Equipment-related	39	"I got a pressure sore on the back of my heel from my cast …"
Symptoms related to pressure injury		
Pain or discomfort	56	"My gran was constantly crying due to pressure ulcers …"
Bleeding or exudate	12	"… We are bringing my dad to see someone about some bedsores we are worried about because they're starting to bleed."
Odor	3	"… I could smell the infection as soon as I entered the room."

Topic	Posts, n	Relevant quotes
Setting where pressure injury occurred		
Hospital (ie, ICU[b], ER[c])	197	"... I've seen how they treated my mother in the hospitals ... She came home with a bedsore."
Care home	64	"Just like my loved one in LTC a couple of years back … She was yelling and crying out and the staff dismissed it as a regular dementia behavior … She ended up with a terrible pressure sore …"
Home	63	"Got my first pretty bad pressure sore since coming home, I do not want to go back to the spinal unit man."
Pressure injury prevention and management strategies		
Local wound care	99	"... [My dad] had surgery to debride bedsores."
Use of equipment (eg, cushion, mattress)	38	"... [My mom] had a scary bedsore & was given a gel pad for chair & bed. I have a gel mattress which is great for not getting bedsores …"
Offloading	21	"... You are the person who turns her over every 2 hours or she will get bedsores."
Bed rest	14	"[He] has been trying to heal a pressure sore by being on bed rest for nearly a year."
Inspection or assessment	14	"… I do skin checks every morning when I get up, every evening when I go to bed, and every time I go to the bathroom, I check the vulnerable areas."
Medication	14	"Just beginning my 3rd month in hospital as a result of a pressure sore. 9 weeks of IV antibiotics due to osteomyelitis."
Nutrition	11	"When I was recovering from severe damage related to my pneumonia/sepsis episode (stage 3 pressure ulcers, crushed immune system, etc.) they made me aim for 120 [grams of protein] every day. Three medical Ensures, special feeding tube formula ..."
Healing of pressure injury		
Healing process	41	"At the start the pressure sore needed 3 packing strings. Now, only half of 1 fits in."
Healing time	25	"My grandma (86) got a really bad bedsore … After nearly 20 months, it's finally almost healed."
Lack of healing	22	"I have a pressure sore right now that's been open for several months and not close to healing …"
Worsening	12	"My downfall was a pressure sore which rapidly went from bad to worse …"

[a]Some posts contained multiple constructs of the PI experience.

[b]ICU: intensive care unit.

[c]ER: emergency room.

Theme 1: Challenges Experienced When Living With or Caring for a Pressure Injury

Within the 666 posts, there were 807 mentions related to the challenges associated with living with a PI, caring for someone with a PI, or receiving care for a PI. A total of 423 out of 807 (52.4%) mentions identified the personal impact or impacts of living with a PI or caring for someone with a PI, with 221 out of 423 (52.2%) mentions discussing the challenges associated with PI complications, such as infection and death. A total of 158 out of 423 (37.4%) mentions related to the personal impact of living with a PI reported a negative impact of PI or caregiving on overall functioning (eg, work or employment, mobility, daily activities) and perceived quality of life. A total of 23 out of 423 (5.4%) mentions related to the personal impact of living with a PI reported negative financial impacts (ie, struggling to afford treatment), and 21 out of 423 (5%) discussed negative mental health impacts such as depression and social isolation.

> *My dad died from overwhelming sepsis due to osteomyelitis caused by his bedsores [and] of course everyone in the ICU had [pneumonia]. I checked his chart each day [and] it was sad to see signs of life slowly slipping away. Pressors couldn't keep him up.*

> *Mum has to stay in bed most of the day cause of pressure sore/open wound, we only transfer her to chair for a few hours.*

Additionally, there were 241 out of 807 (29.9%) mentions of the perceived quality of PI treatment received, with 205 out of 241 (85.1%) mentions describing poor care practices such as lack of care and misdiagnosis from HCPs that commonly led to PI complications for the individual. A total of 36 out of 241 (14.9%) mentions related to the perceived quality of treatment reported witnessing poor attitudes of caregivers and HCPs when treating the individual with a PI.

> *I had no idea [my mom] was suffering from a level 4 bedsore [because] the facility didn't tell me. The hospital told me. Shameful. This is the norm in most LTC facilities. This has to change. Now. #nursinghomeneglect.*

> *I haven't even mentioned some of the worst parts of this. My mom developed multiple new pressure ulcers at [healthcare facility]. I've had nurses and therapists privately tell me how bad things are at [healthcare facility]. I was told a nurse practitioner sighed in disappointment that my mom was improving.*

Furthermore, there were 102 out of 807 (12.6%) mentions related to perceived health care system issues when accessing services to treat PIs. Of these 102 mentions, 57 (55.9%) reported issues with accessing equipment or services (eg, difficulties obtaining pressure mattresses, long hospital wait times) and 26 (25.5%) mentions described prolonged hospitalization or inability to be discharged due to these challenges with health care access. Additionally, 19 out of 102 (18.6%) mentions related to perceived health care system issues described witnessing critical staffing shortages at health care facilities that contributed to the deterioration of the individual with lived PI experience.

> *Please help. Nobody will give us an air mattress for my elderly sick bed bound father! It's a disgrace when he is starting to get bedsores. He's under palliative care but without complex needs!!!!*

> *My poor dad ended up with a giant bedsore while on the barely staffed dementia ward at a [location] care home. He died of sepsis because of it. I was always stunned that there never seemed to be anyone up there working! So effed up!*

Finally, there were 41 out of 807 (5.1%) mentions related to a perceived lack of knowledge from HCPs, caregivers, or individuals with lived PI experience. Of these 41 mentions, 22 (53.7%) described a perceived lack of HCP's PI knowledge that contributed to the development or worsening of a PI. Moreover, 19 out of 41 (46.3%) mentions related to a lack of knowledge indicated the individual with lived PI experience or caregivers' lack of knowledge related to PIs or their prevention and management.

> *My mother had a horrendous [suppurating] bedsore on the back of her head after 8 weeks solid lying prone. We didn't know what it was but asked a nurse who shrugged and said, "Oh, that's weird. I don't know what it is" and walked off. It took 18 months to heal once home.*

> *I can't wait to look at my birthday messages, but [right now] I'm going to see my grandma [because] she's going to the hospital [for] bedsores that we don't know how to take care of.*

Theme 2: Needs Related to Pressure Injury Prevention and Management

There were 110 mentions about the users' needs related to PI prevention and management. Of these 110 mentions, 39 (35.5%) described a need for health care support. These mentions shared the users' need to receive PI care from HCPs, as well as the difficulty in accessing care.

> *[I have] infected pressure ulcers. Can't get ahold (sic) of family doctor. Virtual care clinics are booked up for multiple days—no way to get myself to a clinic.*

> *No, I had been trying to get treatment for pressure sores, but both my family members had covid at the time and couldn't take me to any appointments due to being covid positive.*

Moreover, of the mentions related to the user's needs related to PI prevention and management, 38 out of 110 (34.5%) mentions were related to a need for educational support. These mentions described users' need for advice from HCPs, health care organizations, or the general public related to PI prevention or management.

> *My dad is in a care home. He has dementia and now bad grade bedsores. Doctor said they are bad and could turn sepsis and [there is] nothing else they can do. Do I need a second opinion? Please help. Thanks.*

> *[My dad's] bedsores are bad which the Doctor has said could lead to sepsis. Any help or advice, please.*

In addition, there were 26 out of 110 (23.6%) mentions related to the need for social support. These mentions often described a need for spiritual guidance, prayers, or words of encouragement.

> *Please pray for me, I'm suffering with a pressure sore that won't go away.*

> *I've been dealing with a pressure sore for a [little] bit now. Today I found out it's infected. It's very triggering as pressure sores is how I lost my legs. Please send good vibes [or] distractions and stuff. I feel awful.*

Finally, there were 7 out of 110 (6.4%) mentions related to users' need for financial support. In these mentions, users requested assistance with medical bills related to PI prevention or management.

[Please] help my family to pay my mom's hospital bill. There's another 16 [days] left for surgery but yesterday my mom got admitted due to sudden bedsores and she's in pain right now. We [do not have any] income to buy the medication.

Please help me. I'm getting pressure ulcers from having to lay in bed a lot due to feeling unwell from my cancer. I started a [GoFundMe] a while ago and it hasn't got too much traction. I love you all and hope you'll take a second to boost this.

Theme 3: Emotions Experienced Related to Living With or Caring for a Pressure Injury

There were 478 mentions related to emotions when experiencing a PI, including primary emotions (ie, joy, trust, fear, surprise, sadness, disgust, anger, and anticipation) and a combination of these primary emotions (eg, anger and sadness, fear, and anger). Of the 478 mentions related to emotions experienced, negative emotions were frequently mentioned: 91 (19%) of the emotions included anger, 36 (7.5%) included sadness, and 68 (14.2%) included a combination of the two. Combinations of sadness with other primary emotions (eg, disgust, surprise, anticipation) were also frequently observed in 82 (17.2%) of the mentions. In total, 62 (13%) of the mentions included a combination of anger with other emotions. Combinations of fear with other emotions were also common in 54 (11.3%) of the mentions.

My mother is in aged care. Now transferring to palliative care after neglect. Massive bedsores despite instructions from doctor on how to position her. $600k plus daily fees for neglect and malnutrition that will ultimately see her out. We are beyond furious.

I am a mess, honestly. My sister and I take turns everyday feeding and hydrating her. She has a nasty bedsore, bone exposed … We can't even get her up to take her for a walk. I am just sad.

I've been TERRIFIED of getting pressure sores for a decade [and] half now, given my super low ability to move even in the bed I'm stuck in. I'm sitting or lying almost 24/7 … I'm super high risk [and] when it finally happens ... The [doctors] don't care.

Positive emotions were less frequently mentioned and included joy in 11 out of 478 (2.3%) mentions, anticipation in 5 out of 478 (1%) mentions, or both in 21 out of 478 (4.4%) mentions. Often, these emotions were expressed when describing appreciation for the kindness of others or anticipation related to the PI recovery process or prognosis.

My heart bleeds seeing my dad this way, bedsore has taken over but your donations kept him till this time. I can't thank you all enough but I know my God will reward you for your good deeds amen.

Today's goal: I'm hoping to take him on a wheelchair expedition outside his room--maybe even the hospital--for the first time in 2 months! Hopefully his pressure ulcer and spinal pain will allow it.

A good day! Nurse says pressure sore looking good, don't need to bandage it up with padding anymore. I should be able to pick up drugs at Tesco later [and] I think I can try get driving assessed and car adapted so I can drive with foot drop while it's healing! STOKED!!! #traumarehab

Discussion

Overview

To our knowledge, this is the first study investigating the experiences and perspectives of individuals with lived PI experience as shared through public social media posts. Using SML, we were able to capture the candid experiences and perspectives of individuals with PIs and caregivers that may not be easily gathered from controlled studies. Based on our findings, three major themes were developed: challenges experienced when living with or caring for a PI, needs related to PI prevention and management, and emotions experienced when living with or caring for a PI.

Principal Findings

Perceived Challenges of Living With or Caring for a PI

The most frequently mentioned perceived challenge related to PIs was the personal impact of living with a PI or caring for someone with a PI; most mentions involved challenges associated with complications of PIs, such as infection and death. Previous work notes that individuals living with PIs have an estimated two times higher risk of mortality compared with individuals living without PIs, often due to the development of severe infections [45]. Individuals with PIs are at high risk for bacteremia, which can cause a mortality of over 50% [46]. The findings from this work may help guide the development of strategies to help address this concern among those with lived PI experience.

Social media users frequently mentioned the negative impacts of PI on the daily, physical, occupational, or general functioning of individuals living with PIs. Previous studies on caregivers and those living with PIs identified similar experiences, with individuals reporting a reduction in mobility, independent movement, and quality of life [47-49]. A recent systematic review found that individuals living with PIs often demonstrated declines in physical function and activity, along with low quality of life scores [50]. These deficits are exacerbated by PI complications, such as pain and odor, which may impede the performance of physical and social activities [50]. In alignment with best practices for PI prevention and management, a holistic interprofessional approach should be used to address not only the PI but also the complications of living with a PI to help optimize outcomes.

Perceived poor quality of treatment related to PI management by HCPs or caregivers was reported by social media users. Posts often mentioned poor attitudes of HCPs and caregivers and neglect of the individual with lived PI experience, leading to increased pain experienced by the individual with lived experience, the development or worsening of a PI, infection, and even death. Other studies have highlighted negative attitudes of HCPs toward PI prevention and/or management as well as HCPs who engage in inadequate PI care practices [51-55]. These deficits in practice are potentially related to reported low levels of knowledge of HCPs related to PI prevention and management

[56-60]. This sentiment was shared by social media users in this study who reported a lack of HCP knowledge related to PI management.

According to the knowledge, attitudes, and practices model, knowledge may correlate with attitudes and health practices [61,62]. Thus, the reported lack of knowledge among HCPs may have also contributed to the reported negative attitudes and suboptimal care practices reported by social media users in this study. This is supported by previous studies investigating nurses' attitudes and perceived barriers toward PI prevention and management, which found that inadequate nurse training and knowledge were major obstacles contributing to their negative attitudes and inadequate practices [7,63,64]. Since low knowledge about PI may lead HCPs to adopt poor attitudes and health care practices, the need to ensure that HCPs receive sufficient training in PI prevention and management should be considered.

In addition to a lack of training and knowledge, HCPs have cited a lack of time and equipment (ie, pressure-relieving devices) as prominent perceived barriers to care delivery [51,65-67]. Other studies have found that staffing shortages and inadequate HCP training were persistent barriers to PI prevention practices [68-71]. These findings align with results from the present study, as social media users commonly identified health care system issues, including staffing shortages and lack of availability of equipment (eg, specialized mattresses). Health care system–related barriers appear to be shared globally, and future initiatives should ensure that equipment for PI prevention and management is accessible in order to optimize health outcomes for individuals living with PIs.

PI-Related Needs Among Those With Lived Experience

HCPs play a pivotal role in ensuring that the health care needs and goals of the person living with the PI are met [72,73]. Therefore, it is not surprising that the most frequently mentioned need identified by social media users was health care support related to managing PIs. Although best practice guidelines include self-management where people living with PIs assume responsibility for their PI [74], the frequent sentiment of social media users was the need for health care support, highlighting the limitations of self-management alone. Additionally, users often reported a continued need for HCP support, suggesting the need for ongoing provision of services. One potential contributor to the prevalent need for support may be the inaccessibility of PI resources. Previous studies have demonstrated that individuals seeking specialized medical care experience barriers related to long wait times and high treatment costs, making it exceptionally challenging to obtain relevant services [75,76]. Thus, these barriers may impact individuals' access to satisfactory PI care, driving their self-reported need for health care support.

Social media platforms provide a resource for individuals seeking guidance on managing their illnesses, allowing them to benefit from the advice and experiences shared by others [77,78]. As such, our study found that one of the most commonly expressed needs of individuals living with PIs was their request for advice and information regarding PIs. Social media can be beneficial as an educational resource because authentic accounts of an individual's illness can make medical information more relevant to the user's situation and help them to better understand it [78]. However, given the large volume of information available on the internet, the quality of information can vary widely [79] depending on its source and other post characteristics (eg, length of the post, author credentials). A study evaluating the quality of health information shared on online discussion forum websites, such as Reddit, found that posts shared by medical doctors were "of reasonably good quality" [80]. A recent study by Bang et al [81] that examined the quality of PI health information on YouTube found that longer videos produced by a physician and other health personnel contained more accurate and reliable information about PI prevention and management. In contrast, health information on X may not be reliable: a recent retrospective cohort study revealed that X users were approximately 974 times more likely to encounter inaccurate than accurate information about monkeypox [82]. Similarly, another study found that while authenticated authors on X with large followings were more likely to produce accurate posts about COVID-19, over 25% of the posts were inaccurate, indicating that this information may not be reliable for educational purposes [83]. Future studies should evaluate the quality of PI health information on various social media platforms and elucidate the factors impacting information quality to provide guidance for users regarding where and how to obtain reliable and accurate information.

Social media serves not only for sharing individual experiences but also for offering and receiving support [78]. In our study, social support emerged as a frequently mentioned need, which aligns with previous study findings that many caregivers of adults with cancer expressed a desire for social support in the form of prayers and patient visitation [84]. Individuals living with PIs are particularly vulnerable to social isolation due to the challenges associated with immobility and body image issues due to characteristics of PIs such as exudate and malodor [7,85]. Hence, social media may be a valuable resource for those living with PIs, allowing them to connect with others who can offer support. This notion is further supported by a study on social media use among adults during the COVID-19 pandemic, which highlighted how social media platforms can be major sources of social support amid isolation, ultimately aiding in the reduction of loneliness [86]. Future work should consider developing interventions to address the social isolation that individuals living with PIs may face.

Emotions Experienced as a Result of a Pressure Injury

In this study, anger, sadness, and a combination of the two emotions were the most frequently cited among social media users. This aligns with previous research findings that individuals with lived PI experience and caregivers often feel negative emotions such as anger, frustration, and sadness due to the lengthy healing process of PIs, lack of care received, and PI symptoms such as pain [7,32,50,87-89]. In the qualitative study of Latimer et al. [32] that explored the perceptions of individuals with PIs regarding their role in PI prevention, participants reported feeling angry and frustrated about failing to receive appropriate PI preventative care and experiencing negative interactions with HCPs. These findings suggest that the PI experience is often distressing and can incite intense negative emotions in those living with or caring for a PI. However, it is important to note that social media users tend to engage with and share negative emotions and experiences (eg, anger and distress) more frequently than positive ones on these platforms [90-95]. In addition, studies have shown that those in the online health community may be more likely to post negative content to seek emotional and informational support [96,97]. The platform X in particular has been associated with messages displaying highly negative emotions [92]. Given that X was our primary source of data, the potential likelihood of predominantly negative experiences reported on X was high, and as a result, our findings may be skewed. Nonetheless, our findings provide valuable insights into individuals' experiences living with or caring for a PI, highlighting the negative emotional impact of the pervasive challenges associated with preventing and managing PIs.

Implications for Digital Health

Our study identified the candid experiences, challenges, and needs of individuals with PIs and their caregivers, which have several actionable implications for digital health. In this study, individuals living with PIs and their caregivers frequently expressed a need for information and advice regarding PIs and PI care. Additionally, social media users often reported a continued need for HCP support throughout the PI journey, which they lacked access to. These findings suggest that researchers and clinicians should prioritize the development of accessible online PI educational materials or platforms for individuals with PI and caregivers. Online PI resources or platforms (eg, websites, mobile health apps, social media pages) could provide contact information for HCPs or health organizations, enabling individuals with PI and/or their caregivers to access PI information or support when needed. Disseminating critical health information in a centralized and accessible forum may help promote health literacy among individuals with PIs and caregivers who rely on social media sources to supplement knowledge gaps. In addition, given the widespread use of social media today, it may also be useful to develop social media campaigns to educate the general public about PIs to combat general misinformation.

SML allowed us to identify patterns in the experiences and struggles of individuals with PI and their caregivers, such as a perceived lack of adequate PI care received and lack of knowledge among HCPs. These issues may subsequently be targeted and addressed by relevant regulatory or health entities to improve patient experiences and outcomes. As such, we note that SML may be used in the future to complement digital health surveillance technology, as researchers may utilize SML to observe and track ongoing trends in the reported challenges and needs of individuals with PI and caregivers on social media. The information gathered by SML can generate important longitudinal insights into whether prevailing issues are being adequately addressed and what critical areas of health care improvement health care organizations and policymakers should focus on.

Limitations

While our study is strengthened by a rigorous screening and coding process to analyze and interpret social media data, we acknowledge several limitations. First, since researchers hand-coded all social media posts, it is possible that some codes were missed due to human error affecting the accuracy of the reported frequencies. However, this process was carried out through a meticulous process (ie, researchers held iterative discussions to determine codes and code definitions, with coding performed in duplicate), so this is not a notable concern. Additionally, we broadened search terms in our Boolean search strings to widen our search and maximize the number of relevant posts. However, we acknowledge that some of these search strings could be streamlined and improved upon in the future for optimal retrieval and efficiency in our analysis. Furthermore, only English-language posts were included, which largely limited our search results to content from English-speaking countries. Moreover, most of the posts included were created by users in the United States, meaning our findings may predominantly reflect the health care experiences of individuals living in this country. Another potential limitation is that we only searched YouTube, Reddit, and X; a broader range of social media platforms may have yielded more posts for inclusion. Additionally, we found that X yielded a disproportionately large number of posts compared with YouTube and Reddit, which may have skewed our analysis toward findings from X. Also, the format of posts across the selected platforms was very different and thus difficult to collectively analyze. As such, future research using SML may benefit from selecting more comparable social media platforms to facilitate analysis or analyzing posts from each platform separately. Additionally, we were unable to obtain a complete demographic profile of social media users (eg, age, gender, or sex) due to the limited demographic information available on social media user accounts. Since we analyzed posts from observers, caregivers, and individuals with lived experience as a homogeneous group, differences between the experiences, challenges, or needs of each subgroup were not elucidated. Future studies may benefit from subgroup analysis to identify unique findings for caregivers and individuals with lived experience. Finally, we acknowledge that there may be sampling bias present in our study, as social media users are often younger and more technologically literate [98]. Also, while we did not restrict our sample in terms of geographic location, we acknowledge that there are inequities in technology access and thus ability to use social media platforms [99]. These limitations may reduce the generalizability of our findings.

Conclusions

Our study used SML to explore the unfiltered experiences shared by individuals affected by PIs (ie, individuals with lived PI experience, caregivers, and observers) across social media platforms X, YouTube, and Reddit. We found that many users described challenges associated with PIs and PI care related to the negative personal impacts of living with a PI and receiving inadequate care from HCPs, highlighting the need to address these issues and identify barriers to appropriate PI care. Additionally, social media was often used to request or express a need for health care support and education, suggesting a critical need for supportive and educational resources for those affected by PIs. Finally, the most frequently observed emotion across posts was anger, consistent with previous findings that individuals with lived PI experience and caregivers often experience negative emotions about the PI experience. Our findings provide valuable insights into the candid experiences of individuals living with PIs, uncovering several gaps in care and research that require intervention to improve the well-being of these individuals. Clinicians, policymakers, and researchers should prioritize addressing the prominent challenges and needs identified from this work to optimize PI care delivery and patient outcomes.

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Data Availability

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

Conflicts of Interest

None declared.

Multimedia Appendix 1
Keywords, phrases, and Boolean operators used on social media listening software Awario and X Pro to identify relevant Reddit, YouTube, and X posts.
[DOCX File, 16 KB - nursing_v9i1e76682_app1.docx]

Checklist 1
SRQR checklist.
[DOCX File, 112 KB - nursing_v9i1e76682_app2.docx]

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Abbreviations

HCP: health care professional
PI: pressure injury
SML: social media listening
SRQR: Standards for Reporting Qualitative Research

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Health Care Professionals' Perspectives on the Use of a Wearable Device for Early Detection and Continuous Vital Signs Monitoring of Acute Respiratory Infections in Nursing Homes: Qualitative Study

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Abstract

Background: The growing aging population and staff shortages are placing pressure on Dutch nursing homes (NHs). These challenges have led to an increased interest in digital health technologies. Among these are wearable devices that allow for remote continuous monitoring of vital signs. An example is the Healthdot (smartQare), a wearable electronic device that continuously monitors heart rate, respiratory rate, and physical activity. In the context of acute respiratory infections (ARIs) in NHs, where initial symptoms can go unnoticed, continuous monitoring may aid in early recognition, timely intervention, and reduce staff workloads. However, little is known about how health care professionals perceive the use of continuous vital signs monitoring devices, such as the Healthdot, for this cause in NHs.

Objective: This study aims to explore the perspectives of healthcare professionals on the use of the Healthdot for early detection and monitoring of ARIs in NHs, to inform potential future implementation.

Methods: Semistructured interviews were conducted with 20 physicians, nurses, and certified nursing assistants from 4 NHs and 1 acute geriatric community hospital located in a NH. Interview transcripts were thematically analyzed to identify themes regarding their perspectives on the use of the Healthdot for monitoring ARIs in this setting.

Results: Five main themes were identified that related to the appropriate use of the Healthdot for NH clients and health care professionals: alignment of Healthdot use and NH clients' treatment policies, balancing safety and freedom, impact of the Healthdot on work processes, supporting rather than replacing care, and possible use during pandemics and in the future. Additionally, several preconditions for the use of the Healthdot were identified, including its usability, a support base among care staff, adequate training and guidance, communication with NH clients and their relatives, and a clear policy regarding its use.

Conclusions: Given the complexity of care in NHs, where clinical care is typically balanced against quality of life and a homelike environment, physicians generally expressed reserved attitudes toward the Healthdot, highlighting the need to consider multiple factors in its implementation. Care staff were generally positive about the device. Nevertheless, tailored assessment for each individual NH client remains essential, balancing treatment goals, safety, autonomy, and person-centered care. Additionally, clear communication and alignment between health care professionals in this setting are crucial, specifically regarding their expectations of the Healthdot's role in care processes. This study offers practical guidance that may inform future implementation efforts of continuous vital sign monitoring devices in NHs.

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KEYWORDS

wearable electronic devices; acute respiratory infections; nursing homes; continuous vital signs monitoring; health care professionals

Introduction

Nations across the globe are experiencing a demographic shift toward an older population [1]. The growth in aging populations, combined with a shortage of health care professionals [1,2], is placing a significant burden on Dutch nursing homes (NHs) [3]. In light of these challenges, digital health technologies, such as surveillance or vital signs monitoring devices, are increasingly being explored as promising tools to support care delivery in NH settings [4,5]. According to the Dutch central government, providing care digitally can not only provide older adults with more autonomy but can also support health care professionals by relieving their workload [6]. Implementing these technologies in NHs cannot only help address the issue of staff shortages but also has the potential to improve the quality of care [4,6,7].

One recurring health care problem frequently encountered in NHs involves acute respiratory infections (ARIs) [8]. Early recognition of ARIs and associated clinical deterioration in frail older adults remains challenging, as initial symptoms may go unnoticed, and NH clients with cognitive impairment often struggle to communicate their symptoms, leading to diagnostic and treatment delays [8,9]. Measurement of objective parameters possibly associated with ARIs, such as temperature, heart rate, respiratory rate, oxygen saturation, and reduced physical activity, could potentially be helpful for early recognition of ARIs and associated clinical deterioration [10]. One promising digital health device for remote vital signs monitoring is the Healthdot (smartQare), a wearable electronic patch that measures heart rate, respiratory rate, and physical activity (scored from 0 to 15, ranging from lying still to intensive movement such as sports) [11]. In the future, this application may be used by health care professionals in NHs to support them in making appropriate care choices regarding suspected ARIs, which can be focused on treatment and comfort. Additionally, automated monitoring of heart rate and respiratory rate by the Healthdot may reduce the workload for NH staff by obviating the need for these manual measurements.

While these prospects seem promising, little is known about how health care professionals in NHs perceive the use of wearable devices for continuous vital signs monitoring of ARIs. Insight into their views is essential to facilitate and inform potential future implementation and may help overcome both known and unknown challenges. This qualitative interview study, therefore, explores the perspectives of health care professionals on the use of the Healthdot for monitoring ARIs in NHs.

Methods

This interview study is part of the research project PRIMA (Plaster-Based Respiratory Infection Monitoring Assistant), which focuses on validating the Healthdot for recognizing clinical deterioration in NH clients with ARIs [12]. We used a qualitative research approach to gain a rich understanding of the perspectives of health care professionals on this topic. This study adhered to the COREQ (Consolidated Criteria for Reporting Qualitative Research) guidelines (Checklist 1) [13].

Recruitment and Study Population

Four NHs and 1 acute geriatric community hospital (AGCH) located in a NH were invited to participate in this interview study. These organizations were previously approached during the recruitment phase of the PRIMA project, in which only one of the NHs and the AGCH participated. Hereafter, the term "NH client" refers to both NH residents and AGCH patients located in a NH. In this interview study, all 5 organizations agreed to participate and invited health care professionals within their organizations to take part in the interviews. The invitation was broadly distributed by email, explicitly requesting representation from different professional groups, including physicians, nurses, and certified nursing assistants. A contact person from each organization provided the researchers with the contact details of health care professionals who were interested in participation.

Participants were included if they provided written informed consent and spoke the Dutch language. Participants were not expected to have knowledge of the Healthdot. Participants were purposively selected to create variation in the client population they cared for (ie, individuals with somatic and psychogeriatric conditions, individuals in short-term residential care, individuals undergoing geriatric rehabilitation, and individuals receiving acute geriatric care).

Data Collection

A semistructured interview guide (Multimedia Appendix 1) was developed by the research team (LCG, MCP, CMPMH, LMK, JS, and LWvB) and addressed the following topics: demographics, current practices regarding ARIs, digital health technologies in NH care, and the Healthdot. Prior to the discussion of the topic "Healthdot," participants received a short presentation explaining how the Healthdot is placed, how it is used for monitoring, and its intended use in nursing homes (ie, for early detection of ARIs and detection of clinical deterioration during an ongoing ARI). More information about the Healthdot can be found at the Philips smartQare website [14]. Formally trained PhD student LG performed a pilot interview with a nurse practitioner who was formerly employed in an NH. Adjustments were made to increase understandability, which were validated by the nurse practitioner.

Interviews were conducted by LG between May 2024 and December 2024 until data saturation was reached, defined as the point during data analysis at which no new information emerged. Depending on the participant's preference, interviews were held either via Microsoft Teams or in person at the NH. All interviews were audio-recorded. Verbatim transcripts were made, accompanied by field notes that included contextual information such as the setting, the relationship with the participant, the behavior of the participant, and reflections. The transcripts of the first 3 interviews were reviewed by senior researcher LWvB, who provided feedback to enhance the quality and consistency of subsequent interviews.

Data Analysis

Thematic analysis was used to analyze the data in accordance with the 6-phase approach described by Braun and Clarke [15]. Transcripts were read by researchers LG, MP, and LWvB themselves to familiarize with the data. Inductive coding was performed in MAXQDA 24 (VERBI Software) [16], using a bottom-up approach to allow themes to emerge directly from the data. Two researchers independently open coded nine interviews (LG and MP or LWvB), with an equal distribution of interviews with physicians and care staff. Discrepancies were discussed until agreement was reached, contributing to a shared understanding of coding and interpretation among the researchers. The remaining 11 interviews were open-coded by LG, guided by the coding decisions and interpretations agreed upon during the initial coding phase, after which the codes were reviewed and critically appraised by either MP or LWvB. Coding was conducted iteratively, with regular discussions between researchers LG, MP, and LWvB to review coding decisions, resolve uncertainties, and ensure consistency with earlier coding. Subsequently, axial coding was conducted to identify relationships between codes and organize them into categories. This process led to the identification of overarching themes that captured the main patterns in the data. Throughout the analysis, reflexive discussions among the research team (LG, MP, CH, JS, and LWvB) helped to validate interpretations.

Illustrative verbatim quotes were translated by LG and subsequently reviewed and corrected by 2 native English speakers.

Ethical Considerations

Upon review of the study protocol, the Medical Ethics Review Committee of the Amsterdam University Medical Center concluded that this study does not fall within the scope of the Medical Research Involving Human Subjects Act [17] (WMO; case 2024.0480). Participants provided written informed consent prior to the interview.

Results

A total of 20 participants were interviewed. Most participants were aged 36 to 50 years, and the sample included physicians (n=7), nurses (n=9), and other health care professionals (Table 1). Participants provided care for various NH client populations. The interviews lasted between 27 and 72 minutes (mean 47 , SD 9 min).

Table . Characteristics of participants (N=20).

Characteristics	Values, n (%)
Age (y)	
18 - 35	6 (30)
36 - 50	10 (50)
>50	4 (20)
Profession	
Physician	7 (35)
Nurse practitioner	1 (5)
Quality nurse	3 (15)
Nurse	6 (30)
Certified nursing assistant	3 (15)
Type of nursing home department[a]	
Psychogeriatric	9 (45)
Somatic	6 (30)
Short-term residential care	6 (30)
Geriatric rehabilitation	5 (25)
Acute geriatric care	5 (25)
Duration of employment at organization (y)	
<1	4 (20)
1 - 5	6 (30)
6 - 10	4 (20)
>10	6 (30)

[a]Multiple options possible.

Contextual Background

Current Practices in Monitoring ARIs

Participants stated that monitoring of ARIs and the frequency thereof are dependent on the treatment policies of NH clients. NH clients with a curative treatment policy (ie, full medical care including life-prolonging treatment) are monitored regularly, while NH clients with a palliative treatment policy (ie, care primarily focused on comfort, with optional life-prolonging treatment) or a symptomatic treatment policy (ie, care limited to symptom relief, no life-prolonging treatment) are monitored sporadically or not at all. Monitoring in cases of suspected ARI is performed by nurses or certified nursing assistants, either in consultation with or under the instruction of a physician, and consists of regular measurement of vital signs (ie, heart rate, respiratory rate, temperature, blood pressure, and oxygen saturation) and clinical observations (eg, clinical condition, bed confinement, and food and drink intake). For clinical observations, particularly in clients with psychogeriatric conditions, the continuity of care staff and their familiarity with NH clients were identified as critical factors, which are currently often lacking due to staffing shortages.

Organizational Perspectives on the Use of Digital Health Technologies

Differences were identified in how the participants described the perspective of their organization on digital health technologies. Some participants stated that their organization had no focus on digital health technologies at all, while other participants stated that their organization was actively implementing new technologies. In these latter organizations, digital health technology was considered a key focus area by management, with innovation teams and designated staff members embedded. Participants from some organizations mentioned that digital health technologies were being implemented, yet a clear and structured strategy was lacking, which limited sustainable implementation. Several organizations were already using digital health technologies to monitor vital signs, including bed sensors measuring respiratory and heart rate, vital signs monitors, or standalone devices.

Individual Perspectives on Digital Health Technologies

Participants' individual perspectives on digital health technologies were generally positive, provided that their implementation serves a clear goal that is beneficial for NH clients, health care professionals, or both. Most participants emphasized the need for technology to ensure future-proof health care, with fewer health care workers and more older adults. They noted that digital health technologies can offer possibilities to this end, and can help reduce workload. However, participants stressed that technology should not replace face-to-face care, but rather support it.

Perspectives on the Use of the Healthdot

Regarding the use of the Healthdot for monitoring ARIs in NHs, 5 main themes were identified: alignment of Healthdot use and treatment policy, balancing safety and freedom, impact of the Healthdot on work processes, supporting rather than replacing care, and possible use during pandemics and in the future.

Theme 1: Alignment of Healthdot Use and Treatment Policy

Participants emphasized the importance of having a clearly defined goal when using the Healthdot, aligned with the treatment policy of NH client. The Healthdot was generally considered suitable for NH clients with an active treatment goal, such as those receiving intermediate care after hospital admission or those with a curative treatment policy. It was also highlighted that the Healthdot could be of added value when monitoring ARIs in clients with psychogeriatric conditions, as this group often has difficulties expressing their symptoms. However, these clients tend to be fidgety and may intentionally or unintentionally pull off the Healthdot:

> *Yes, in residential care for people who still want a lot [in life]. And, for example, I think it [the Healthdot] would be very good for young people with dementia living in a group. That is often a group with quite a strong desire for treatment, but who are not eager for a monitoring visit.* [R2: physician]

Some physicians were hesitant about the Healthdot's actual impact on medical management, considering the limited treatment options for viral ARIs:

> *That's where my doubt lies with viral respiratory infections. Usually, you don't do very much, except for influenza. As you said, then you prescribe Oseltamivir. But if it's just a regular respiratory virus, it's a matter of support, symptom management, but beyond that I think: what more can you do?* [R20: physician]

Most participants perceived the Healthdot as less suitable for NH clients receiving palliative or symptomatic care, as vital signs are typically no longer routinely monitored, and deviations identified by the Healthdot would have limited or no consequences for clinical treatment. Physicians, in particular, voiced stronger reservations regarding its use in this context:

> *For example, someone who says: I don't really want any life-prolonging interventions anymore. If I don't wake up tomorrow, that's fine. What do you do with that in your system in terms of signaling? It is nice to know if someone is deteriorating, but you're not going to treat them because of that, you know.* [R8: physician]

Opinions varied concerning the potential added value of the Healthdot in providing comfort-focused care. While most physicians questioned whether earlier detection by the Healthdot would result in the earlier provision of care, care staff—including nurses and certified nursing assistants—mentioned that earlier identification of distress might enable more timely comfort measures:

> *It is useful to notice if someone is restless or becomes restless. Then you can go there and check to see: what does this person need? Really offering comfort.* [R12: quality nurse]

Several ethical dilemmas were raised regarding the potential contribution of the Healthdot to a focus on life-prolonging interventions, whereas it might be more appropriate in the NH population to focus on acceptance of the finiteness of life. In the latter case, one may not want to know and control everything regarding the clinical situation, as this is also accompanied by the burden of difficult decisions for professionals, NH clients, and their relatives:

> *On the one hand, I think: no, we really need to look [at possibilities regarding the Healthdot]. On the other hand, I think, is this truly the direction in which we should be heading, or should we also, at some*

> *point, simply accept that life is finite? And that sometimes, it's just the flu [you die of], so to speak. Of course, that's not a very politically correct thing to say, and it's very nuanced. I'm putting it quite bluntly now, but of course we're talking about people. There is also value in being ill in a nursing home, you know. Life is still meaningful then.* [R4: nurse practitioner]

> *Sometimes it is good to not always know, right? If someone significantly deteriorates without anyone noticing and then perhaps passes away, that can sometimes be a good thing. That not everyone knows, because if you know something, you also have responsibilities. […] For families it is often very difficult to have an opinion about this and it can be better if someone suddenly deteriorates rapidly and dies. Then it just is what it is.* [R6: physician]

Some participants mentioned the shift in Dutch NHs from a medical model toward a well-being and homelike model, which they perceived as conflicting with the implementation of the Healthdot. Nevertheless, other participants recognized that medical elements can still be necessary to support the well-being of NH clients:

> *The most important point is, then we're investing more in curative care, while I think that it should be more about well-being. So, I just wouldn't allocate more budget to further increase the intensity of curative care. We really need to realize that the average length of stay in a nursing home is only a few months, so what are we talking about? It's about making sure they have a good day, period.* [R1: physician]

Overall, a clear distinction emerged between physicians and care staff. Physicians tended to evaluate the Healthdot in terms of its relevance for treatment decisions and were, therefore, more critical in situations where monitoring was unlikely to influence clinical management. In contrast, care staff were generally more positive about its use, as they emphasized its potential to support the early recognition of changes in NH clients' conditions and to guide timely treatment- and comfort-focused care.

Theme 2: Balancing Safety and Freedom

Participants acknowledged that the Healthdot can influence both the safety and freedom of NH clients in positive and negative ways. They mentioned that the Healthdot could enhance safety by allowing earlier detection of deterioration and providing NH clients and their families with a sense of safety. At the same time, some NH clients may perceive this as a form of surveillance and a breach of their privacy. Additionally, restrictive measures taken in response to Healthdot alerts, such as isolating NH clients when an infection is suspected based on an elevated heart or respiratory rate, could be experienced as stressful and limit their freedom:

> *Yes, there is a strong view that no [restrictive] measures should be taken, because freedom is prioritized. That's really the tendency, more freedom, so we generally don't want restrictive measures.* [R6: physician]

Simultaneously, care staff identified potential benefits of the Healthdot in supporting NH clients' sense of freedom by reducing interference in daily life. Participants mentioned that the Healthdot could decrease the need for manual measurements, which are often experienced as burdensome, and eliminate nightly visits, thereby positively impacting sleep quality and recovery. For NH clients who are aggressive or refuse manual measurements, the Healthdot was seen as a less intrusive and more practical alternative.

> *You can't just keep opening doors all the time. People want to sleep, so how useful would it be if you just have a screen that allowed you to continuously monitor vital signs. That if there is an acute situation, you'd already be there before that acute situation.* [R17: nurse]

Altogether, both physicians and care staff acknowledged the potential impact of the Healthdot on safety and freedom. However, the perceived benefits in terms of reducing burden and supporting NH clients' freedom were primarily emphasized by care staff, whereas physicians did not explicitly highlight these aspects.

Theme 3: Impact of the Healthdot on Work Processes

Participants mentioned that the Healthdot could reduce the workload for care staff, by limiting the need for frequent manual measurements. This would also allow care staff to visit upon indication, for example, when an early warning signal is triggered by a prolonged elevated heart rate:

> *I think that it's efficient. I think that maybe you can say that you don't need to do checks 3 times a day, unless, for example, the dashboard of the Healthdot system shows abnormalities.* [R18: nurse]

Care staff expected that this would allow more time for other tasks and increase opportunities for personal interaction with NH clients. The Healthdot was particularly seen as valuable in intermediate care settings, where most monitoring takes place:

> *I think it [use of the Healthdot] also means more time for the clients. Sometimes you feel like you're just going from one client to the next, with multiple tasks. […] I think it would be really nice to have more time for a real conversation with someone, or to actually dive a bit deeper.* [R11: nurse]

Contrarily, some physicians expressed concerns that the Healthdot would increase their workload. They emphasized the large number of measurements and early warning signals generated by the device, along with the responsibility associated with interpreting and acting on these signals. They pointed out that, in medical practice, "measuring is knowing," and with that knowledge comes the responsibility to act. Additionally, concerns were raised about the potential for false-positive signals, particularly in this population where vital signs often deviate from the norm:

> *The more data you collect, the more you have to account for. Because all the data you receive, requires*

> *a response. As a physician, you have to relate to it. You're responsible for it. So, I don't want to know.* [R1: physician]

At the same time, participants acknowledged that the Healthdot could provide consistent, timely, and objective measures. These are often lacking, as measurements are regularly not or not adequately performed in practice. Respiratory rate was particularly regarded as a valuable addition, considering that there is currently no measurement equipment for this:

> *At least you're somewhat less dependent on whether care staff is going to do it [measuring vital signs] or not. So, that could be an advantage. Yes, so especially that you get more consistent and reliable input, whereas now it is often not consistent and also not always reliable.* [R8: Physician]

Nevertheless, participants highlighted that manual measurements would remain necessary, as the Healthdot does not measure all required vital signs, such as temperature, blood pressure, and oxygen saturation. It was stated that these parameters could be measured based on indications from the Healthdot, such as elevated heart or respiratory rates, instead of on a routine basis. Some physicians mentioned that the current level of monitoring by care staff is sufficient, suggesting that the Healthdot is not necessary.

The main difference between physicians and care staff within this theme concerned the perceived workload. While both groups agreed that the Healthdot would likely reduce the workload for care staff, physicians expressed concerns that their workload could increase. Care staff generally did not consider this potential impact on physicians.

Theme 4: Supporting Rather Than Replacing Care

Although participants recognized that the Healthdot could reduce workload, they emphasized that the device cannot replace care staff. Physicians, in particular, noted that observations made by care staff provide more valuable insights than measurements, especially when providing care focused on comfort:

> *Yes, then the question really is what … are they in pain at that moment? Is that why their respiratory rate is going up? Or is it actually the final phase [of their life]? Usually, the respiratory rate doesn't increase just like that. People will become restless, start moving, and that's often already a signal.* [R6: physician]

They also stressed the importance of ensuring that the Healthdot does not lead to a reduction in personal contact with NH clients, as this is often perceived as highly valuable. Care staff themselves generally did not share these concerns. Finally, costs were identified as an important factor. Participants noted that while the Healthdot is expensive, it cannot replace care staff. Therefore, the added value of the Healthdot must be substantial before an organization will consider its implementation.

Theme 5: Possible Use During Pandemics and in the Future

The possible use of the Healthdot during future pandemics or outbreaks was discussed in a few interviews. Although some participants viewed this as a promising application, others were hesitant, referring back to the balance between safety and freedom:

> *During COVID, it would have been nice if you could have seen in advance that someone's heart rate was rising. He develops fever, so he might have COVID, so you could have put him in quarantine earlier. But it's also a bit scary, because as soon as you, say, sneeze once, you might already have to go into quarantine, because that thing measures it all.* [R3: physician]

Moreover, some participants emphasized the potential value of the Healthdot in light of an anticipated future with fewer health care professionals available and a growing aging population. In this context, the Healthdot could support sustainable care delivery in NHs:

> *It's a necessity. It's an absolute necessity. We simply have no other choice, so I definitely think we should move in that direction. We shouldn't wait too long either, because if the statistics are correct, the staffing shortages will become very severe in the coming years.* [R14: quality nurse]

Preconditions for Using the Healthdot

One important precondition stated was the usability of the Healthdot. Participants mentioned that the device should be easy to use, allow monitoring from devices they currently use, be integrated into the electronic health records of NH clients, and be able to measure additional vital signs (ie, temperature, oxygen saturation, and blood pressure). It also needs to be trustworthy, and the early warning signal must be adjustable so that receiving too many false signals can be avoided. Moreover, participants pointed out that the Healthdot is single-use, suggesting that more sustainable alternatives should be explored.

Participants emphasized that successful implementation of the Healthdot requires a support base among care staff. They stated that this can be established by including them during the implementation process and incorporating their feedback. Several participants stated that it is essential to have enough care staff who are knowledgeable and skilled in using the Healthdot, suggesting that a dedicated team member could take the lead. Additionally, adequate training and guidance during the use of the Healthdot were emphasized as important, ensuring confidence for care staff.

Another precondition mentioned by several participants was the need for clear communication with NH clients and their families about expectations regarding the use of the Healthdot. Physicians stressed that it is crucial to prevent unrealistic expectations, for example, regarding how frequently the physician will review the data. They mentioned that some relatives may, at times, demand more than is feasible or preferable. Therefore, several participants recommended limiting NH clients' and relatives' access to the Healthdot data:

> *What I'm a bit worried about is that family members have unrealistic expectations. That you'll be at the*

> *bedside within 5 minutes. That you'll be held accountable for that, in a way.* [R3: physician]

Finally, a clear policy regarding the use of the Healthdot is needed, according to the participants. They noted that it should be clear for whom, when, and for what purpose using the Healthdot is appropriate. Moreover, clear instructions should be available that specify by whom early warning signals are followed up and which actions need to be taken. Participants also mentioned the need for clarifying roles and responsibilities, suggesting that care staff should be responsible for monitoring, while physicians provide clinical guidance and assess the progression of the infection.

Discussion

Principal Findings

This qualitative interview study provides valuable insights into health care professionals' perspectives on the use of the Healthdot for monitoring ARIs in NHs. While care staff were generally positive about the Healthdot, physicians' attitudes were mostly reserved, highlighting the need for careful consideration of the NH context and its associated complexities during potential implementation. Our findings show that implementing wearable continuous vital signs monitoring devices in this setting extends beyond clinical purposes and necessitates careful weighing of the NH client's treatment goals, ethical considerations, the balance of safety and freedom, its impact on care processes, and the importance of supporting rather than replacing personalized care.

Although perspectives of health care professionals on wearable continuous vital signs monitoring have been studied before in hospital settings, to our knowledge, we are the first to study these perspectives in the NH setting. A previous study by Weenk et al [18] found that hospital-based health care professionals were generally positive about continuous vital signs monitoring, whereas more reserved attitudes toward this were identified in our study. This difference might be explained by the context of NHs, where health care professionals must balance clinical care with NH clients' quality of life and a home-like environment. Participants raised ethical concerns regarding the use of the Healthdot, particularly in palliative care situations, as they expressed fears that the Healthdot might lead to life-prolonging care in these cases, instead of promoting comfort and well-being. Nevertheless, van der Steen et al. [19] emphasize that careful and timely recognition and management of symptoms are crucial for enhancing well-being in palliative care [19]. From this perspective, the Healthdot could potentially contribute to person-centered palliative care by supporting the timely recognition and relief of symptoms.

The balance between safety and freedom is a recurring topic in NH care that was also reflected in our findings. Participants noted that the Healthdot could enhance safety by enabling early detection of deterioration caused by ARIs and offering a sense of security, which is in line with findings from another study focusing on monitoring devices in NHs [20]. However, participants in our study also raised concerns about the impact of the Healthdot on NH clients' freedom, including feelings of being watched, privacy intrusion, and restrictive infection control measures. The COVID-19 pandemic demonstrated how such measures affected NH clients' autonomy and mental well-being [21]. Still, the relationship between freedom and care in NHs remains complex. It has been argued that some degree of intervention is always required in institutional care, making autonomy and freedom in this context not straightforward [22]. Haslam-Larmer et al [23] highlighted similar tensions in the context of location monitoring in dementia care, where privacy is often considered secondary to safety concerns [23]. Interestingly, participants also saw potential for the Healthdot to enhance NH clients' sense of freedom by reducing the need for manual measurements and nighttime disruptions. This aligns with findings from Emilsson et al [24], where NH staff reported that camera surveillance monitoring reduced unnecessary night-time visits [24]. To effectively balance safety and freedom, it is essential to consider the individual needs of each NH client, as the value placed on safety or freedom may differ for everyone.

A potential consequence of reducing manual measurements is a decrease in contact moments, which both physicians and care staff in our study considered essential for maintaining clinical insight and relationships. This concern is widely recognized across studies on both surveillance and vital signs monitoring in several care settings [18,24-26]. For instance, it was reported that continuous vital sign monitoring in hospitals may reduce bedside contact and compromise clinical judgment, as such systems cannot assess subjective experiences like pain [18,25,26]. Similarly, research on surveillance monitoring in NHs highlights the irreplaceable value of physical presence for both clinical observation and emotional reassurance [24]. However, Niemeijer et al [22] suggest that monitoring technologies do not necessarily reduce human contact, as during their study on surveillance technologies in residential facilities, nurses continued their rounds and maintained strong relationships [22]. In our study, participants also expected contact to remain necessary, as the Healthdot does not measure all vital signs needed for monitoring of ARIs and manual measurements are still required when indicated by the early warning signal. Moreover, both our findings and previous research suggest that time saved through monitoring may be reinvested in client-related tasks [18,22]. Nevertheless, with the expected increase in older adults in NHs and staff shortages [2,3], there is a risk that any time gained will be used to manage higher caseloads, potentially limiting opportunities for personal interaction.

Despite expectations that the Healthdot could save time for person-centered care, physicians in our study raised concerns about a possible increase in workload. Similar concerns have been reported in studies conducted in hospital settings, where the high frequency of measurements was found to burden physicians [18]. In line with our findings, several studies identified false-positive alerts as a contributor to "alarm fatigue," further adding to the workload [18,22]. Physicians in our study also expressed concerns about the increased burden of responsibility that comes with more measurements. NH clients and their relatives might have unrealistic expectations, assuming immediate intervention when measurements deviate. Previous research has shown that unrealistic demands from family members are a recurring challenge in NHs and can contribute to staff stress [27]. Managing expectations is, therefore, crucial for sustainable use.

Notably, our findings revealed differing perspectives between physicians and care staff regarding the use of the Healthdot. Across themes, we found that care staff were generally enthusiastic, viewing the device as a way to reduce workload, increase time for personal interaction, and enhance the freedom and well-being of NH clients. Physicians, however, expressed more critical views, raising concerns about the Healthdot's impact on clinical management, increased workload and responsibility, and potential implications for person-centered care. These differences may be explained by the distinct roles and responsibilities that physicians and care staff have within interprofessional collaboration, as described by Schot et al [28]. Whereas physicians may see the Healthdot primarily as a diagnostic tool requiring clinical action and interpretation, nurses may view it mainly as a support system in their caregiving routine, evaluating it in terms of practicality, efficiency, and NH clients' comfort. Recognizing these divergent perspectives is essential, as they may influence acceptance, integration into care routines, and overall effectiveness. This suggests that the successful implementation of the Healthdot will require clear communication, alignment on its intended purpose, shared understanding of its role in care practices, and active collaboration between health care professionals. Additionally, acceptance is influenced by the nursing home's organizational culture and leadership supporting innovation [29].

One limitation of this study is that the Healthdot is not currently used for monitoring ARIs in NHs, meaning that participants had to speculate about its potential use. This hypothetical context limited the extent to which their responses reflect real-world experiences or challenges and led some participants to reflect on the general use of the Healthdot in NHs rather than specifically for monitoring ARIs. Nonetheless, a strength of this study lies in its early involvement of end users, reflecting a growing emphasis in implementation research [30] and providing early insights, considerations, and key prerequisites for potential implementation. Additionally, our participants stressed the importance of including their perspectives to enhance acceptance and practical relevance, which aligns with evidence that such engagement fosters organizational readiness through an innovative culture and shared commitment [31,32]. Although some participants did have prior experience with the Healthdot in a research context due to their participation in the quantitative PRIMA study, this experience was limited to the placement of the Healthdot and did not involve monitoring with the Healthdot. No differences in responses were observed between participants with and without this prior experience.

Conclusions and Implications

Our findings demonstrate that implementing continuous vital signs monitoring devices, such as the Healthdot in NHs, involves multiple considerations and conditions, shaped by the complexity of this care setting. A tailored assessment is essential for each NH client, taking into account factors such as treatment goals, safety, autonomy, and person-centered care. Clear communication and alignment between physicians and care staff, as well as between NH staff and relatives of NH clients are crucial, particularly regarding expectations about the Healthdot's impact on care processes. Although this study focused on ARIs, many insights may be relevant to the broader application of monitoring devices in NHs. This study offers practical guidance and key considerations that may inform future implementation efforts of continuous vital signs monitoring devices in this setting.

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Data Availability

Due to the sensitivity of the data, the dataset will not be shared publicly.

Authors' Contributions

Conceptualization: LCG, LWvB, MCP, JS, CMPMH, LMK, MDdJ
Data curation: LCG
Formal analysis: LCG, LWvB, MCP
Funding acquisition: JS, MDdJ
Investigation: LCG
Methodology: LCG, LWvB, MCP, LMK
Project administration: LCG

Supervision: LWvB, MCP, JS, CMPMH
Validation: LWvB, MCP
Visualization: LCG
Writing – original draft: LCG
Writing – review & editing: LCG, LWvB, MCP, JS, CMPMH, LMK, MDdJ

Conflicts of Interest

None declared.

Multimedia Appendix 1
Interview guide.
[DOCX File, 42 KB - nursing_v9i1e84436_app1.docx]

Checklist 1
COREQ checklist.
[PDF File, 432 KB - nursing_v9i1e84436_app2.pdf]

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Abbreviations

AGCH: acute geriatric community hospital
ARI: acute respiratory infection
COREQ: Consolidated Criteria for Reporting Qualitative Research
NH : nursing home
PRIMA: Plaster-Based Respiratory Infection Monitoring Assistant

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Patients' Perceptions of the Role of Nursing in Substance Use Disorder Treatment Programs: Qualitative Study

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Abstract

Background: Substance use disorders are chronic conditions with significant personal and social consequences. Nursing care plays a key role in outpatient and community-based rehabilitation programs, yet patients' perspectives on this role remain underexplored.

Objective: This study aimed to explore how patients with substance use disorders perceive and interpret nursing care in community addiction treatment centers operated by the Spanish Red Cross in Madrid, Spain. Specifically, it sought to describe the organizational and care-related roles attributed to community addiction treatment centers and analyze patients' perceptions of nurses' technical and relational functions.

Methods: A phenomenological qualitative design was used. Fourteen in-depth, semistructured interviews were conducted with patients undergoing treatment at Red Cross centers. Participants were selected through purposive sampling to ensure diversity in age, gender, substance use, and treatment experiences. The data were analyzed using systematic text condensation and supported by the ATLAS.ti software.

Results: The center is perceived as a significant space not only for offering healthy leisure activities outside the context of substance use but also as a supportive environment that fosters a sense of belonging to a community. Patients valued the emotional support, empathy, and relational care provided by nurses, often highlighting their role in building trust and offering personalized attention. However, there was limited awareness of nurses' technical competencies.

Conclusions: These findings underscore the importance of holistic, patient-centered care and the need to enhance the visibility and recognition of nursing roles in addiction treatment settings.

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KEYWORDS
nurse's role; nursing staff; qualitative research; substance-related disorder; psychiatric nursing

Introduction

Background

Substance use disorders (SUDs) are defined by the *DSM-5* (*Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition*) as the "association of cognitive, behavioral, and physiological symptoms that indicate that the person continues to use a substance despite significant problems related to that substance" [1]. Globally, substance use represents a major public health concern and contributes substantially to the burden of disease, being associated with increased mortality, disability, and chronic conditions, such as liver disease, cancer, and infectious diseases [2-4]. SUDs commonly coexist with psychiatric disorders, particularly mood and anxiety disorders, which complicate treatment and worsen prognosis [3,5,6]. Consequently, SUDs can have a profound impact on a person's identity, causing individuals to lose their sense of self, which can manifest itself as a change in values and priorities, a deterioration of self-image, social disconnection, or a break with previous roles [5,6].

This individual impact underscores why SUDs represent a global challenge with serious consequences at the individual level. In 2025, there were 51,255 admissions to treatment for psychoactive substance dependence in Spain, representing an increase of 9.7% over the previous year [7]. Moreover, adherence to rehabilitation programs is often limited, with high dropout rates reported internationally and frequently linked to psychosocial vulnerability and difficulties in establishing therapeutic relationships with health care professionals [3].

Beyond physical and mental health consequences, SUDs also affect identity and social functioning, contributing to stigma, social disconnection, and loss of social roles [3]. In Europe, treatment demand continues to rise, with 51,255 admissions for psychoactive substance dependence recorded in 2025, representing a 9.7% increase compared with the previous year [7,8].

Although SUDs affect people of all genders, treatment-seeking populations in community addiction services are often predominantly male, which may lead to the underrepresentation of women's experiences in qualitative studies [6-8]. This is of relevance given the established role of gender in shaping pathways into substance use, the associated stigma, exposure to violence or trauma, caregiving responsibilities, and help-seeking behaviors. These factors might shape how nursing care is perceived and what forms of support are most beneficial. Therefore, incorporating a gender perspective might be essential when interpreting patients' accounts and designing nursing interventions in community addiction treatment centers [9].

Prior Work

Evidence-based rehabilitation programs have been shown to reduce the use of illegal opioids and improve patients' physical and mental well-being, as well as their quality of life [8]. These programs adopt a holistic approach, with a multidisciplinary team comprising nurses, psychologists, physicians, social workers, and occupational therapists. Furthermore, the centers where these programs are implemented administer substitution treatment and provide social support and nursing care [8,10]. The ideal outcome of substance use rehabilitation is a state of balance and control, where the person feels empowered to manage their life without relying on substances that alter their mental state [7,8]. This process involves a reconstruction of the individual's identity through a series of behavioral modifications, facilitated by health care professionals [7,9,10]. However, it is estimated that up to 40% of patients withdraw from these programs. In this context, the support and participation of a multidisciplinary team, including nurses, is an empowering element in addressing this condition [11].

The concept of care is understood as a natural phenomenon. The patient's world, vulnerability, health, and suffering form the core of this concept [12]. The science of care not only facilitates the treatment of disease but also addresses patients' emotional and social needs, thereby promoting their overall well-being. The quality of care is known to improve when health care professionals make a conscious effort to understand the world from the patient's perspective. This, in turn, strengthens the therapeutic relationship and promotes better care outcomes. A profound understanding of the experiences and perspectives of patients with SUDs is imperative for the development of patient-centered care. This knowledge facilitates the design of personalized interventions, tailored to the specific needs of this vulnerable population [13,14]. By exploring the subjective experiences of these patients in relation to their care, areas for improvement in health services can be identified, more empathetic and culturally sensitive practices can be promoted, and barriers to access and adherence to treatment can be addressed. This comprehensive strategy for addressing SUDs has the capacity to markedly enhance patients' quality of life, diminish the social disapproval associated with substance use, and ensure optimal long-term therapeutic outcomes [15].

Despite the presence of nursing in SUD rehabilitation programs, the literature indicates that its role continues to be invisible and poorly understood by both patients and society. In community and outpatient settings, nursing work tends to be diluted within the multidisciplinary team, making it difficult to identify its specific functions [13,14]. However, in addiction treatment centers (CATCs), nurses carry out key interventions that include comprehensive patient assessment, clinical follow-up, health education, administration and supervision of substitution treatments, early detection of relapses, crisis care, and, especially, the establishment of a therapeutic relationship based on trust and continuous support during the rehabilitation process [16]. This apparent contradiction between the relevance of care and the low social recognition of the nursing role justifies the need to explore how users themselves perceive and understand this care [13,17].

Study Objectives

However, there is a significant gap in the literature on the perception of patients with SUDs regarding the role of nurses in rehabilitation programs [16,17].

The primary aim of this study is to explore the experiences and perceptions of patients with SUDs regarding the nursing care they receive in outpatient and community settings in Spain. Specifically, the study seeks to analyze patients' perception of the role of nursing staff, considering both the technical and relational dimensions of nursing care as experienced by users and to describe the organizational and care role that users attribute to Red Cross CATCs in Madrid (Spain), including resources, routines, and processes involved.

Methods

The question of how the role of nursing is perceived in the context of patients with SUDs undergoing rehabilitation programs lends itself to a qualitative approach, specifically a phenomenological study. Qualitative research focuses on understanding the world of the participants [18].

Study Design

The researchers were interested in how patients recover from SUDs and how they perceive the role of nurses in this process. It was therefore determined that qualitative research would best meet the objective. To gain a deeper understanding of this experience, a phenomenological study was conducted, as in-depth interviews allow the emotional, social, and personal nuances of the rehabilitation process to be captured, as well as the importance of support from nurses [19-21]. This research was conducted based on the recommendations of the COREQ guide [22].

Participants

Patients diagnosed with SUDs according to the *DSM-5* [1] were selected.

Eligibility Criteria

The inclusion criteria established at the beginning of the study were as follows: participants had to be enrolled in a rehabilitation program, be over 18 years of age, and be able to speak Spanish. Patients who did not wish to participate in the study or who were physically and/or mentally unable to complete the interview properly were excluded from the study.

Study Sample

A sample of participants was intentionally selected to represent a range of age groups, socioeconomic backgrounds, recovery times, genders, and experiences regarding substance use and the impact of nurses during the rehabilitation process. Furthermore, the data were collated pertaining to the participants' date of birth, gender, marital status, substance of abuse, alcohol consumption, and number of prior admissions to rehabilitation programs (Multimedia Appendix 1).

Of the 15 participants, 14 were male, and 1 was female. The ages of the participants ranged from 32 to 78 years (Table S1 in Multimedia Appendix 1). The participants' demographic profile was as follows: 8 were unmarried, 4 were divorced, 2 were married, and none were widowed. The participants consumed a variety of substances, including alcohol, cannabis, cocaine, heroin, opioids, methamphetamines, ecstasy, ketamine, hallucinogens and magic mushrooms, spice, mephedrone, salvia, gamma hydroxybutyrate, and lysergic acid diethylamide. The substances most frequently used were cannabis, heroin, cocaine, and alcohol. The number of previous admissions to rehabilitation programs ranged from 1 to 10. All participants were enrolled in the Red Cross rehabilitation program in Madrid, Spain.

Access to the Population

Initially, the researchers identified the various support structures for treatment and posttreatment within the Red Cross organization. In-depth interviews were conducted at 2 Red Cross CATCs in Madrid (Spain).

The management team and the multidisciplinary team at the centers were contacted, and meetings were organized to discuss the research objective and obtain the help of the various professionals in identifying participants. Participants were recruited through purposive sampling, following a preliminary presentation of the study to patients at the Red Cross centers together with the center's management team. Factors that would facilitate a more nuanced categorization of the work were considered, particularly regarding the perception of the nursing role in individual interviews.

Data Collection

In-depth, individual, semistructured interviews were conducted in person with 15 participants. One participant decided to leave the interview after 14 minutes of recording, so a total of 14 patients completed the interviews. The average interview duration was 45 (SD 15.3) minutes, and the interviews were conducted in convenient settings, such as individual rooms at the CATCs, to ensure privacy. The interviews were conducted between January and April 2023. All interviews commenced with the following opening statement: "Please provide a brief overview of your professional background and the circumstances that led to your involvement in this field." The flexibility of this qualitative interview methodology enabled participants to share their experiences from their own perspective. Open-ended questions and prompts were strategically used to explore turning points, support, situations, and coping strategies when participants were reluctant to share them. The following questions and prompts were included: "Please find below a list of the key responsibilities that nurses in this institution typically have" (Multimedia Appendix 1). With the prior consent of the participants, the interviews were audio recorded. The data collection protocol for the interviews was consistent for all patients. Interviews were transcribed immediately after completion. Data collection ceased once sample saturation was reached [23].

Trustworthiness

The criteria used to ensure reliability, in accordance with Guba's contributions to naturalistic research, encompass credibility, transferability, dependability, and confirmability [24].

Credibility

All interviews were recorded, and the exact duration of each session was documented, with additional field notes providing further elaboration and complement.

Transference

The processes followed, both for data collection and subsequent analysis, have been described in detail.

Dependence

The data collection process and the instrument used for conducting the interview have been delineated and included (Multimedia Appendix 1). Furthermore, members have been added to the working team at different stages to carry out triangulation processes in the negotiation of meanings.

Neutrality

The saturation of messages and the inclusion of direct quotes in the final report ensure neutrality in the analysis of the data.

Analysis

The transcriptions of these recordings were then produced. Subsequently, a comparison was made between the recordings and transcripts to ensure accuracy. Thereafter, a systematic condensation of the text was carried out in the analytical process, with the following 4 steps [25]: first, the transcripts were read to obtain an overview and identify preliminary themes, with annotations made in the text. Second, a series of codes and code groups were developed. In the event of the emergence of divergent codes, the most appropriate ones were agreed upon to develop a shared understanding. Third, each code group was identified and condensed into categories, which were incorporated into the report, with relevant quotes selected for inclusion. Finally, the condensed subgroups were synthesized to generalize descriptions and concepts of the patients' experiences [26,27]. The data analysis was iterative and began concurrently with data collection, using the constant comparison method as described by Strauss and Corbin [23] to identify commonalities and variations across cases progressively incorporated.

The ATLAS.ti program (version 25.0.1) was used for the analysis, as were the Office suite and Microsoft Excel for descriptive data analysis, and Microsoft Teams for facilitating digital collaboration during coding.

Ethical Considerations

This study has been approved by the Ethics Committee of the Complutense University of Madrid (Reference: CE_20221215‐06_SAL). Furthermore, the study was conducted in accordance with the principles set out in the Declaration of Helsinki. In addition, to comply with the code of ethics for good practice in the collection of information for this research project, the resources provided by the Complutense University of Madrid have been accessed. The data have been anonymized, with all names appearing in the text being fictitious (Table S1 in Multimedia Appendix 1). Reasonable and appropriate physical, administrative, and technical measures have been taken to protect personal data from loss, misuse, unauthorized access, disclosure, alteration, or destruction. Participants were at liberty to accept or decline participation, and those who agreed to participate signed consent forms. It is important to note that no form of compensation was provided or offered to any of the participants.

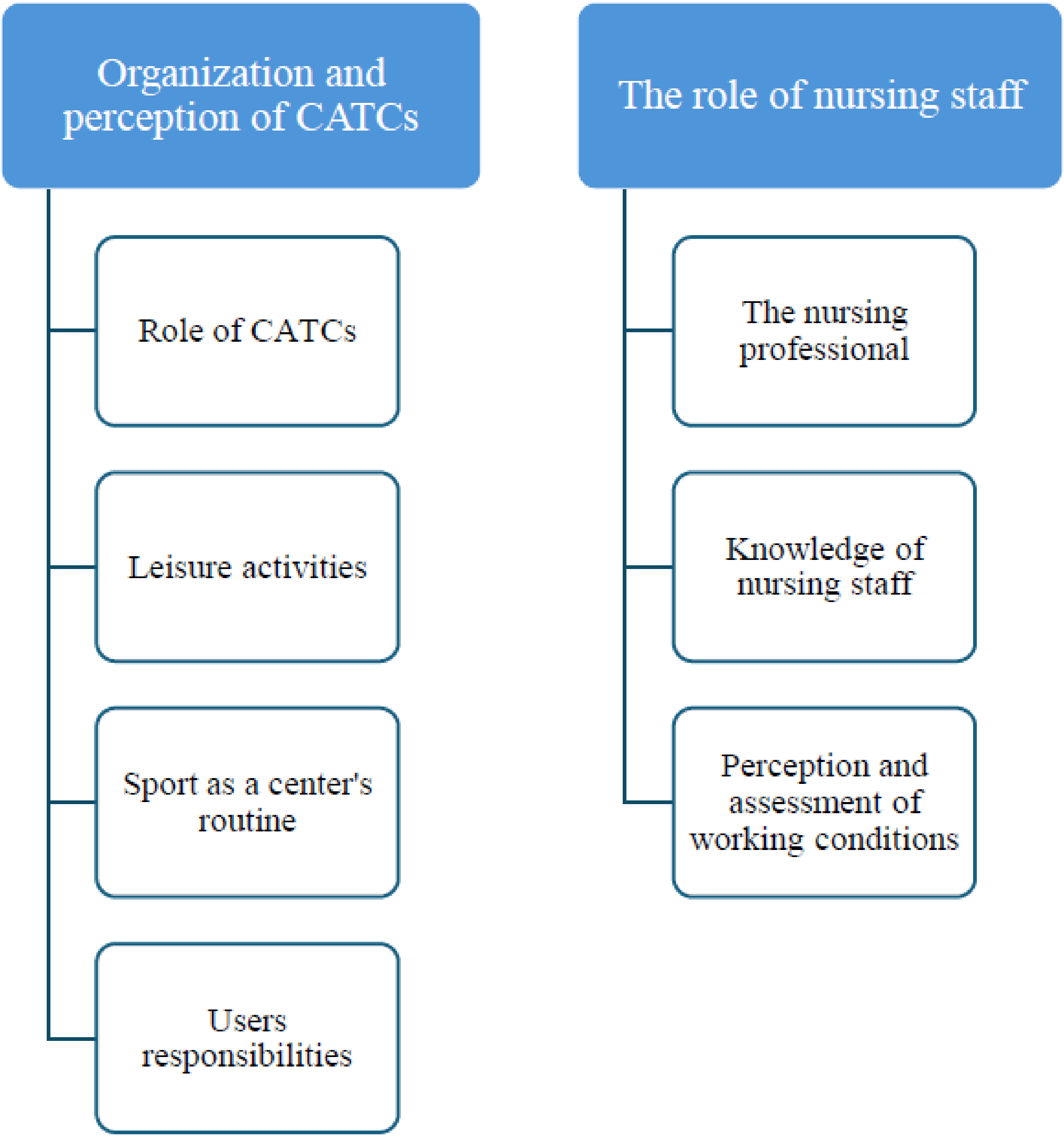
Results

Participant Characteristics

All participants had received a confirmed diagnosis of SUDs prior to the interview. Of the 15 participants, 14 were male, 8 (54%) were single, 5 (33%) were divorced, and 2 (13%) were married. The mean age of the subjects was 48.2 years (SD 9.28). The substances most frequently consumed were cocaine—used by 13 (86%) of the participants—cannabis and alcohol (Multimedia Appendix 2). The mean number of previous admissions to rehabilitation centers within the sample was 2.5 (SD 2.4).

In the following section, the results of the empirical investigation will be presented. The data obtained from the interviews have been organized into 2 overarching categories, which are related to the research objectives and questions (Figure 1). All these categories have been framed from the perspective of the users.

Figure 1. Emerging categories from patient narratives: organization of community addiction treatment centers (CATCs) and the nursing role.



The Role of CATCs

Key Functions of CATCs

The role of Red Cross CATCs is pivotal in helping participants to stop using substances. The interviews revealed several issues. First, these centers play a significant role in helping individuals stop using substances, particularly through measures such as prescribing methadone as a substitute for heroin: "This is how I became acquainted with the CATCs and the process of heroin substitution" (Óscar). It was also noted that the center offers users the possibility to have meals on-site and to receive support with various arrangements, including transport and mobility-related matters. "Additionally, my transport card is being loaded, which is a modest amount of four euros and a few cents" (Óscar).

The same user commented on the existence of these rehabilitation centers. He said that he had gone "to a hospital because I didn't know that the CATCs existed" (Óscar).

Leisure Activities

The importance of leisure activities in the daily lives of participants emerged as a recurring theme in the interviews, with all interviewees highlighting it as a central focus. Javier succinctly summarizes the routine of a typical day at the center, characterizing it as "attending therapy sessions." This assertion is corroborated by the observations of other participants, such as Oscar, who states: "At the Red Cross therapy centre (...) it helps me a lot because I was busy all day and I didn't have any nonsense going through my head." These centers, as a result, organize a variety of activities and "workshops on drugs, gender, reading ..." (Chema), which are emphasized in the interviews. Daniel elucidates the manner these centers provide support:

> *It's like, like, like a house where you can't just sleep. They also make us feel like this is our home. The Red Cross treats us very well and they really love us; they truly love us. I mean, it's not just a pat on the back and that's it. They are ... it's a complete embrace, from heart to heart.*

As well as the points raised by Chema, there have been repeated mentions of board games, music, and dance workshops. The latter has been of particular interest, given the work carried out by the volunteer running them:

> *She herself, who is not like all the other workshops that are all about that, about drugs, about you, about these, about others ... No, she plays music and says, "Now you do whatever you want" and "Now you dance, and now you ... and now everyone together here and now everyone there ... now everyone ..." I mean ... she makes you forget everything at that moment. No, you don't think about your problems, you don't have time to think about anything bad, or anything that could hurt you, that could ... She doesn't give you time, she doesn't let you. She's full of life.* [María]

Sport in the Center's Routines

Sport has also been mentioned in numerous interviews, often referred to as "sports activities in the morning" (Paco). To that end, the following activities have been outlined:

- "Playing table tennis or cycling or exercising." (Rodolfo)
- "Some days it's Tai Chi, other days they go walking." (Maria)
- "I played volleyball, which I hadn't played in years." (Roberto)
- "Now we are cycling." (Antonio)

In addition, sport has been referenced on a single occasion as a concomitant treatment for other conditions: "I come walking to get some exercise because of my diabetes" (Chema).

Users' Responsibilities in the Centers

Leisure time is also spent carrying out different responsibilities assigned by the center:

> *Oh, and if it's your turn to do the office work, you have to set the table. If it's your turn to wash up, you have to wash up too, and so on.* [Fulgencio]

> *"As for routines ... we have a plan too ... there's a ... a notebook where they write down when we have to prepare meals, wash the dishes ... That's how we keep busy. .. the manager of the centre writes it down for everyone. And on days when it's my turn, it's someone else's turn ... When it's my turn, I have to serve the tables, then clear the dishes, take out the rubbish bins ... and so on, routine stuff ... To clean the dishes, then dry them ... That's how it works, I don't know, to keep us busier."* [Óscar]

> *Then one day it's your turn to wash the dishes and another week you're in charge. You're responsible for distributing the food and so on, but hey, they're supervising you.* [Rodolfo]

Functions of the Nursing Professional

Role of Nurses in CATCs

A variety of professionals are employed in these centers, including nurses, doctors, psychiatrists, psychologists, and occupational therapists. Nurses have been the central focus of the work, and they have taken up a large part of the interview time. The functions of nursing staff are those that have been most frequently mentioned in the coding process, in relation to the perception of this group. It is generally understood that the profession is held in high regard by its users. There are some very compelling testimonials in this regard:

> *At the Jiménez-Díaz Foundation, nurses treat you excellently. I can't say anything bad about healthcare here in Spain or about the nurses, they are all lovely and very professional.* [Roberto]

These comments are not isolated, as they are reinforced by other comments that echo the same sentiment.

For example, Roberto stated:

> *The nurse who works with the doctor [at the CATC] (...) is a lovely girl, she is super friendly, she is a sweetheart. Professionally, she is excellent, as they say. And also, she was very concerned and asked me: are you okay?*

Daniel also commented that "the treatment by the nursing staff [at the CATC] was very good, very good, very good." He particularly highlighted the treatment by the nurse above all others. When asked about the care that had meant the most to him, he pointed to the emotional support provided by a nurse:

> *I'm very clear about this. It's (...) a nurse I had at the shelter [at the CATC] (...), accompanying me to an ambulance because I have tinnitus. Then they were saying bad things to me, and she was the first person I talked about it. And that, and how she accompanied me and went down the stairs with me ... I was shaking because I didn't want to go to the ambulance, I didn't want to go there. I was terrified of being alone for even a second with the voice. And that's the most the nurses have done for me.* [Daniel]

On occasion, this positive perception was intertwined with the work of the entire team, as Antonio noted:

> *Here [at the CATC] we have a psychologist, a social worker, a nurse, the manager, very good people, the workers too. They get angry, which is normal sometimes, but they are people.*

The testimonies are intricately interwoven throughout the interview, thereby underscoring the human dimensions of the nursing professional. Various statements highlight the staff's attentiveness and their provision of empathetic listening and support, in response to the most useful care they have received:

> *Therapies where you can talk, like two people. You know what I mean? Being able to sit down, two people. You, with a therapist, being able to sit down and have .. him being able to tell you about his problems and you being able to tell him your problems, having someone there to talk to unburden yourself. Telling him, "Look, I got out of bed and cried." I cried because of this, because of this and because of this, and being able to tell you ... your things and him being able to tell you his things.* [Jorge]

> *This girl … the girl on the other side, at the Red Cross [at the CATC]. She ... I saw that she was concerned about my situation the first day I went there. I ... I thought she was a psychologist rather than a nurse, from the time I spent talking to her and expressing my feelings, my experiences, where I came from, where I was going, and why I found myself where I was. I was there for, I don't know, two hours, three hours, talking to her, and she was a nurse, not a psychologist. And she was concerned about ... about how I was doing.* [Jero]

Even when pointing out other functions, Paco considered that

> *the way the staff [at the CATC] treat you is what matters most ... because that's what affects you the most. But then, of course, each person ... the pills and so on ... also have an influence. But ... the way they treat you is what attracts you the most.*

Rehabilitation programs were also identified as particularly valuable forms of care, with participants citing the significance of being listened to in difficult situations:

> *My nurse [at the primary care centre], who has helped me to trust her a little, weigh myself, tell her when I have used drugs and when I haven't, give thanks, I am grateful to the people who have been helping me since 2015. And even though I messed up and stuff, they did everything they could to help me (...) see what we needed.* [Óscar]

In other words, the same patient insisted:

> *She was teaching nursing classes here, for everyone. That was very positive because there were classes on all kinds of illnesses, how to use pills ... There were also classes on quitting smoking, how to quit smoking ... There are workshops for people who want to quit smoking too. These workshops are run by nurses. That's all I can say for now because I can't remember anything else.* [Óscar]

María was very clear on this point: "They [at the primary care center] ... do a bit of psychology and nursing, kind of combining the two." Another user, Jero, who had already pointed out the importance of nursing staff's ability to listen, emphasized the importance this can have in other therapeutic aspects, such as methadone use:

> *Well, if this is the first day—I said—"it shouldn't take too long." He [at the CATC] offered me something ..., which was methadone, and I said, "Look, I don't want that, I've never taken that in my life, but I'm afraid, because I've heard that there are people who spend their whole lives taking that crap." I said, "Well, let's start with a very, very small amount. Let's see if that's enough for you and then we'll reduce it." "Okay, I'll accept it, because of the way you've treated me, because I can see that you're someone who cares about the situation I'm in without knowing me at all, and because I've ... I've opened up to you and told you about ... my plans." It was really good, to be honest, that's the part I'm most grateful for.* [Jero]

Knowledge of Nursing Staff

During the interviews, references to the work of nurses were particularly prevalent, especially in discussions of more general topics and when the work functions of the entire team were intertwined. There are numerous examples of this phenomenon, particularly in relation to the role of the doctor. For instance, when asked about the duties of a nurse, Paco replied:

> *Well, we ... I, for example, go up to cognitive workshop, which was today ... to the girl in cognitive workshop [at the CATC]. And then, in case you have ... there's the doctor, the doctor in case something happens to you. I have a toothache and I ask him for ... a pill for toothache because it hurts and I still haven't ... I go to the medical centre by bus and I always forget to stop at medicine.*

Another patient intermingled the roles of different professionals in his reflections:

> *I haven't had much … much … much experience with nurses, because as I'm new, I haven't had much time. What I do have is a good day centre, which I've had for two days now, OK? And I only have experience with Susana, who is my psychologist, and with Dr. Felipe, I don't know if you know him. They are the only ones I have experience with.* [Roberto]

Comparisons were even drawn between nurses and doctors:

> *You know more. You are not doctors, but we can trust you more than doctors. I am quite bold, having been a salesperson all my life, so I don't mind, but ... I think a doctor can be more reserved than a nurse.* [Eduardo]

These relationships and role confusions are not exclusive to CATCs, as they also mentioned past experiences in which they highlighted the importance of nurses in primary care centers:

> *At the mutual insurance company, for example, this leg that I told you I hurt while cleaning ambulances, they treated me like a queen. Both in physiotherapy and in ... when it came to medication, creams, everything, and all for free.* [María]

> *Not everyone knows about nursing. There are things that if you have, if you have a wound here, you put*

> *Betadine on it or whatever and that's it. But there are things that they have to give you. They have to tell you, "Look, the stretch consists of squats, this, that and the other, OK?" (...) Well then, I think that time should also be used to ... I see that they devote a lot of time to older people [at the primary care centre].* [Maria]

Perception and Assessment of Working Conditions

Another noteworthy aspect that emerged from the interviews was related to working conditions, including issues of overburden:

> *Well, I can see that he's a bit overworked, but even so, he's always available [at the CATC]. Yes, if I could add something ... a little help, give him some assistance. Because he does tests, dispenses medication, sees patients ... You don't have to make an appointment with him. Because you talk to him beforehand and Julián is immediately available.* [Chema]

> *Appointments take a long time. For example, those at the public centre and at the outpatient clinics too. Sometimes they can't see you, even if it's an emergency, because they have someone else who maybe ... well, you say it yourself ... I mean, I don't pay for my medication, do I? Because I earn very little. So there are times when I've had to buy the medication because I needed it at that moment because they don't have enough nurses [referring to nurses in outpatient/primary care consultations]. They keep cutting back instead of ... providing more for the population.* [María]

This same patient, María, concluded very clearly: "I think people should be given more permanent jobs."

Discussion

Principal Results

Patients with SUDs perceive nursing care positively, although they predominantly highlight relational aspects, such as accompaniment, active listening, and trust. In some cases, there appears to be a lack of awareness regarding nursing functions, particularly those within the scientific and technical domains. The results of this study provide valuable insight into how patients with SUDs value and interpret the nursing care they receive in outpatient and community-based rehabilitation programs in Spain.

From a phenomenological perspective, understanding patients' perceptions of the role of nursing requires first delving into their personal history of substance use. This is not merely a chronological account of events; it is a complex network of lived experiences, emotions, social relationships, and meanings attributed to the substance and its effects [28]. The mean number of previous admissions to rehabilitation centers in the sample was 2.5 (SD 2.4). This aspect also frequently features in patients' accounts, highlighting the chronic nature of SUDs and the difficulties in achieving sustained rehabilitation over time [4,7,28].

Participants offered a largely favorable evaluation of the center, regarding it as a vital asset in their rehabilitation process. This positive perception appears to be associated with the multidisciplinary team, comprising doctors, psychologists, social workers, occupational therapists, and nurses. The team's role is to address both the physical and psychological aspects of treatment and provide comprehensive support that extends beyond a purely clinical approach [12,13,15]. In their testimonies, participants highlight the professional and emotional support they received, as well as the feeling of belonging to a safe and structured environment that not only distances them from problematic consumption environments but also provides for their basic needs and offers opportunities for improvement in various areas.

On the other hand, participating in a variety of group activities, such as physical exercise, healthy leisure initiatives, and workshops focusing on integrating patients into the workplace and fostering personal relationships, was considered vital for sustaining abstinence. Physical exercise is widely used as a complementary therapy in SUD treatment. It is considered a healthy practice, as well as a meaningful and socially integrative activity [29,30]. Similarly, the other leisure workshops offered at the center are seen as potentially transformative by providing entertainment in environments unrelated to substance use and fostering a sense of belonging to a social group [28,29]. One possible explanation for these findings is that the center is perceived not only as a protective factor against relapses, but also as a safe resource for well-being and ongoing support. This finding is consistent with other studies addressing this issue but contrasts with previous studies documenting experiences of stigmatization and discriminatory treatment in hospital settings. The role of the multidisciplinary team could be pivotal in generating a positive overall experience that encourages adherence to the rehabilitation program and social integration [30,31]. This approach is consistent with the Schlossberg transition process model, in which the authors recommend that, to effectively cope with a transition—namely, rehabilitation from SUDs—people need access to diverse types of support [32]. These support categories can range from interpersonal relationships (such as sponsors and spouses) to more distant support systems (such as institutions and communities), including rehabilitation centers [33]. Consequently, rehabilitation programs that adopt a holistic perspective—combining respect for patient autonomy with a flexible and adaptable support structure—align not only with international standards but also with a patient-centered approach [7,10].

Regarding nursing care, the participants in our study recognize nurses as key figures in the rehabilitation programs of the Red Cross CATCs. Most of the nursing practices identified as beneficial by the participants in this study pertain to relational care interventions. They emphasize their close working relationships, active listening skills, and emotional support as key differentiating factors compared to other health care professionals in the multidisciplinary team. Furthermore, they place a high value on the involvement of nursing staff, particularly in health education, support in times of crisis, and management of withdrawal symptoms. This finding aligns with the results of other studies, which indicate that patients with SUDs perceive increased support and reduced judgment from nursing professionals [34,35]. As demonstrated in previous research, the provision of compassionate care is of paramount importance, even in relation to other populations [36,37].

Comparison With Prior Work

This evidence indicates that the therapeutic relationship is fundamental for patients, regardless of their age or care setting. Skills, such as listening, communicating, and providing reassurance, are valued and recognized as essential, not as inferior or merely technical skills [38]. In addition, other studies have shown that relational interventions generate a wide variety of positive health outcomes. Research has demonstrated that effective therapeutic relationships can enhance treatment adherence and rehabilitation and reduce perceptions of stigma, as outlined in Parkhideh et al [39]. As demonstrated in the literature and as evidenced by our own findings, there is clear evidence of the importance that patients attach to being treated with respect and as people rather than as problems or diseases [40].

Among the recommendations expressed by users, the one that stands out is the suggestion that health care personnel show greater patience during care. This demand reflects a need for more humane and empathetic treatment and highlights the importance of the therapeutic relationship component. Patience is seen as a sign of understanding, respect, dignity, and a willingness to listen, which are all basic elements in building an effective working relationship. This is particularly relevant in contexts involving vulnerable populations, such as individuals with SUDs. Integrating this perspective into clinical practice has the potential to enhance the quality of care and ensure adherence to treatment [35,38].

However, there is a lack of knowledge regarding the roles performed by each member of the health care team. Although the role of the nurse remains constant within the team, participants confuse their role with those of doctors and social workers during the discussions. This is also evident from the absence of any codes or categories relating to other areas of nursing care. One potential explanation for these findings is that patients may not have had sufficient time to comprehend the nature of nursing work. However, it should be noted that all participants had previously been admitted to at least 1 other rehabilitation program. Therefore, the lack of knowledge about nursing work may not be attributable to a lack of contact with nursing staff, but rather to the invisibility of care. The extant literature supports this assertion. In both this population and the general population, care is often not directly associated with nursing. This may mean that the specific and specialized role of nurses in various contexts is not fully recognized. This lack of knowledge about nursing care reflects an underlying problem, which contributes to its social and professional devaluation [41,42].

The participants' accounts also allow us to infer a structural reality that affects the professional practice of nursing: the low institutional and social value placed on this group. This situation is evident in working conditions that often fail to reflect the complexity of the care required by patients with SUDs. These conditions include a lack of financial recognition, excessive workloads, a shortage of adequate rest areas for staff, and limited participation by nurses in decision-making spaces. This invisibility stands in stark contrast to the pivotal role that patients themselves ascribe to nurses in their recovery processes, particularly regarding human support, active listening, and the establishment of long-term therapeutic bonds [43]. This structural invisibility might help explain why some participants were uncertain about the specific responsibilities of each professional, occasionally mixing up nursing functions with those of other team members. This confusion may also arise from overlapping interdisciplinary tasks, inconsistent role introductions—particularly at admission or during care-plan changes—and contextual factors in SUD care, such as time pressure, staff turnover, and psychosocial vulnerability. Therefore, strengthening role communication and increasing the visibility of nursing responsibilities might enhance patients' understanding and recognition of nursing care within community addiction services [41]. Role ambiguity may also limit patients' ability to actively seek nursing support. Brief standardized introductions at admission, visible role identification, and, when feasible, assigning a reference nurse may improve clarity. Future research should further explore patients' perspectives on strategies to enhance understanding of nursing roles in care [41,44].

Limitations

This study is one of a limited number of research projects conducted in Spain that address the perceptions of a particularly challenging-to-reach demographic, such as patients with SUDs. However, it is vital to understand the experiences of individuals with SUDs and their interactions with nursing care in order to improve and personalize interventions and establish effective improvement strategies within this particularly vulnerable population. Nevertheless, this study presents some limitations. Most of the participants in the sample are male, and most of them self-identify as such. This finding is consistent with the available evidence, which points to a higher prevalence of substance use among men [2]. From a gender perspective, this pattern may be influenced by social constructs associated with masculinity. These constructs include the normalization of risk, pressure to demonstrate strength or autonomy, and perceived lower access to emotional support networks [4]. These factors may facilitate the initiation and maintenance of use and therefore bias the findings. Conversely, the participants were members of merely two centers belonging to the same rehabilitation Red Cross program, which may have exerted an influence on the results due to the absence of variety in the care received. Furthermore, no distinction was made between different types of nursing care (specialized, hospital-based, or based on the years of experience of the professionals). To expand the knowledge base regarding this population's perceptions of the nursing role, future studies involving samples of patients from diverse rehabilitation programs and incorporating a gender perspective are essential. Women's perspectives may be insufficiently captured in this study, and future research should purposively recruit more women (and gender-diverse participants when possible) to better inform gender-responsive nursing care in community addiction services.

Conclusions

This study demonstrated that SUD is a chronic condition, with multiple admissions to rehabilitation programs. Participants have provided a positive evaluation of the rehabilitation center, emphasizing the comprehensive support provided by the multidisciplinary team and the safe environment it offers, beyond clinical treatment. Group activities and ongoing support are key factors in maintaining abstinence and promoting social integration.

Patients with SUDs place a high value on the role of nursing, particularly relational interventions over technical interventions. However, this assessment contrasts with a lack of knowledge about certain functions of the nursing profession, which limits their ability to recognize and take advantage of their capacity for action in community settings.

These findings emphasize the necessity to enhance care models through a holistic approach, considering patients' life contexts and recognizing both individual care and structural conditions. Nurses can play an essential role in designing patient-centered interventions to achieve sustainable recovery and a positive therapeutic experience.

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Data Availability

No additional data are available due to data protection requirements.

Authors' Contributions

CLG, MGdQC, and BGT led the design of the study, its analysis, and the preparation of the study. BGT contributed to the data analysis, identification of codes, and categories and selection of relevant quotes. CLG, MGdQC, BGT, NMG, and GGN have contributed to preparing the study. All authors have read and approved the final study.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Sociodemographic data, participant information, and interview guide.
[DOCX File, 16 KB - nursing_v9i1e82401_app1.docx]

Multimedia Appendix 2
Most used substances among interviewed participants enrolled in the rehabilitation program.
[PNG File, 75 KB - nursing_v9i1e82401_app2.png]

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Abbreviations

CATC: community addiction treatment center
***DSM-5*:** *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition*
SUD: substance use disorder

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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.

All authors did not agree with retraction.

Reference

1. Hamarash MQ, Ibrahim R, Yaas MH, Abdulghani MF, Al Mushhadany O. Comparative effectiveness of health communication strategies in nursing: a mixed methods study of internet, mHealth, and social media versus traditional methods. JMIR Nurs 2024 Nov 19;7:e55744. [doi: 10.2196/55744] [Medline: 39622705]

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Performance of Large Language Models in the Japanese Public Health Nurse National Examination: Comparative Cross-Sectional Study

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Abstract

Background: Large language models (LLMs) have shown promising results on Japanese national medical and nursing examinations. However, no study has evaluated LLM performance on the Japanese Public Health Nurse National Examination, which requires specialized knowledge in community health and public health nursing practice.

Objective: This study aimed to compare the performance of multiple LLMs on the Japanese Public Health Nurse National Examination and evaluate their potential utility in public health nursing education.

Methods: Three LLMs were evaluated: GPT-4o, Claude Opus 4, and Gemini 2.5 Pro. All 110 questions from the 111th Public Health Nurse National Examination were administered using standardized prompts. Questions were classified by format (text vs figure or calculation), content (general vs situational), and selection type (single vs multiple choice). Accuracy rates and 95% CIs were calculated, with statistical comparisons performed using chi-square tests.

Results: All LLMs exceeded the passing criterion (60%). The accuracy rates were as follows: 85.5% (94/110) for GPT-4o (95% CI 77.5% - 91.5%), 91.8% (101/110) for Claude Opus 4 (95% CI 85.0% - 96.2%), and 92.7% (102/110) for Gemini 2.5 Pro (95% CI 86.2% - 96.8%). No significant differences were found among the LLMs (*P*>.99). However, all models showed lower accuracy on multiple-choice questions than on single-choice questions, with significant intramodel differences observed for GPT-4o (10/16, 62.5% vs 82/92, 89.1%; *P*=.01) and Claude Opus 4 (12/16, 75% vs 87/92, 94.6%; *P*=.03).

Conclusions: LLMs demonstrated high performance on a public health nursing examination but showed limitations in complex reasoning requiring multiple-choice selection. These findings suggest the potential for LLM use as educational support tools while highlighting the need for cautious implementation in specialized nursing education.

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KEYWORDS

large language models; public health nursing; licensure; nursing; artificial intelligence; AI; education

Introduction

With advances in artificial intelligence (AI), large language models (LLMs) have gained attention in various fields. High-performance LLMs have been developed, including GPT-3.5, GPT-4, Anthropic's Claude, and Google's Gemini [1-3], which have demonstrated their ability to generate contextually appropriate responses to complex questions. In Japan, the capabilities of these models have been evaluated using questions from the national medical and nursing examinations. Liu et al [4] compared GPT-4o, GPT-4, Claude Opus 3, and Gemini 1.5 Pro using Japan's national medical examinations and found that GPT-4o achieved the highest accuracy rate (89.2%) and intermodel performance depending on the subject area and question format. Takagi et al [5] also found that GPT-4 significantly outperformed GPT-3.5 in national medical examinations (79.9% vs 50.8%), revealing significant performance gaps between model generations. Taira et al [6] reported that LLM accuracy declined for questions about pharmacology, social welfare, and related legal regulations on national nursing examinations, suggesting limitations in responding to questions requiring specialized knowledge and institutional understanding. These findings demonstrate LLM utility and associated challenges in Japanese language processing and professional examinations.

However, no study has compared the performance of multiple LLMs on the Japanese Public Health Nurse National Examination, which assesses the knowledge and skills necessary for public health nursing practice. The Public Health Nurse National Examination comprises content addressing community-based health issues, multidisciplinary collaboration, and public health nursing activities, requiring not only medical knowledge but also an understanding of Japan's community health systems [7]. Compared to clinical medicine, public health nursing presents unique challenges for LLMs. While medical examinations primarily assess biomedical knowledge and clinical reasoning, public health nursing requires the integration of social determinants of health, public health policy knowledge, community-level interventions, and understanding of local health systems. These multifaceted aspects demand complex reasoning that simultaneously considers multiple factors, which may pose greater challenges for current LLMs. Therefore, this study aimed to compare and evaluate the performance of GPT-4o (Open AI), Claude Opus 4 (Anthropic), and Gemini 2.5 Pro (Google AI) on questions from the Japanese Public Health Nurse National Examination to clarify the extent to which AI can respond to the specialized knowledge and skills necessary for public health nursing. We believe our work has significance for examining the potential for AI use in future public health nursing education.

Methods

Study Design

This comparative cross-sectional study evaluated the performance of 3 LLMs on the Japanese Public Health Nurse National Examination. We used a census sampling approach, analyzing all questions from the examination to compare accuracy rates across different LLMs and question types.

Tested LLMs

Three representative LLMs were selected: OpenAI's GPT-4o [1], Anthropic's Claude Opus 4 [2], and Google's Gemini 2.5 Pro [3].

Japanese Public Health Nurse National Examination

The Japanese Public Health Nurse National Examination is conducted based on the Act on Public Health Nurses, Midwives, and Nurses to assess the knowledge and skills necessary for public health nurses [8]. It includes 110 questions. The questions are classified as general and situational. General questions are worth 1 point each, whereas situational questions are worth 2 points each. The passing criterion is 60% correct answers for general and situational questions combined, although the percentage may be adjusted when inappropriate questions are excluded. The questions are in multiple-choice format, and the participants must select one or more correct answers from 4 to 5 options. The pass rate is 90% to 95%.

Study Population and Question Selection

This study used a census sampling approach, including all 110 questions from the 111th Public Health Nurse National Examination administered in February 2025 [9]. No sampling was conducted as the entire population of examination questions was analyzed. For questions containing figures and tables, figures were processed as image data, whereas the question text was handled as text. No questions were designated as inappropriate by the Ministry of Health, Labour and Welfare; the passing criterion was 60% [9]. The examination questions were classified according to format (text questions and figure or calculation questions), content (general and situational questions), and selection type (single- and multiple-choice questions).

Prompt Engineering

Because prompt engineering significantly affects the generated output, the question input formats were standardized. On the basis of previous research [4-6], 6 prompts corresponding to different types of questions were created (Table 1).

Table . Standardized prompts for different question types in the Japanese Public Health Nurse National Examination. Template placeholders (“<” and “>”) indicate where specific content was inserted for each question type.

Prompt type	Prompt template
Prompt 1: general questions	“Japanese Public Health Nurse National Examination questions are presented. Please answer the following question in brief by selecting an option. Select one option unless otherwise specified. Question: <Question content> 1. <Option 1> 2. <Option 2> 3. <Option 3> 4. <Option 4> 5. <Option 5> (if applicable)”
Prompt 2: situational questions	“Japanese Public Health Nurse National Examination questions are presented. Based on the following situational setting, please answer the question in brief by selecting an option. Select one option unless otherwise specified. Situation: <Situational content> Question: <Question content> 1. <Option 1> 2. <Option 2> 3. <Option 3> 4. <Option 4> 5. <Option 5> (if applicable)”
Prompt 3: image questions	“Japanese Public Health Nurse National Examination questions are presented. Please review the following image and answer the question in brief by selecting an option. Select one option unless otherwise specified. Question: <Question content> 1. <Option 1> 2. <Option 2> 3. <Option 3> 4. <Option 4> 5. <Option 5> (if applicable)”
Prompt 4: situational questions with images	“Japanese Public Health Nurse National Examination questions are presented. Based on the following situational setting, please review the image and answer the question in brief by selecting an option. Select one option unless otherwise specified. Situation: <Situational content> Question: <Question content> 1. <Option 1> 2. <Option 2> 3. <Option 3> 4. <Option 4> 5. <Option 5> (if applicable)”
Prompt 5: calculation questions	“Japanese Public Health Nurse National Examination questions are presented. Please read the following question, review the mark sheet format in the image, and answer the question in brief by selecting an option. Provide your answer as a numerical value in brief. Question: <Question content>”
Prompt 6: situational calculation questions	“Japanese Public Health Nurse National Examination questions are presented. Please read the following situational setting and question, review the mark sheet format in the image, and answer the calculation question. Provide your answer as a numerical value in brief. Situation: <Situational content> Question: <Question content>”

Data Collection Procedures

Questions were input from June 25 to 26, 2025. The question text and images were directly inserted into each LLM’s chat window. Each question was input in a new independent chat window to avoid potential influence from previous responses. All questions were administered in Japanese using standardized prompts.

The definition of “correct” answers was based on the official answers published by the Ministry of Health, Labour, and Welfare [9]. Only answers that clearly matched the official correct answers and followed the instructions provided in the question text were considered “correct.” Ambiguous answers, evident mistakes, unclear responses, and responses with an excessive number of answer choices were considered incorrect. All responses from the LLMs were independently reviewed and scored by 2 authors (YT and RK), with any discrepancies resolved through discussion.

Data Analysis

For each LLM, the number of correct answers, accuracy rates, 95% CIs, total scores, and score rates were calculated. Accuracy rates were compared across question format (text vs figure or calculation), question content (general vs situational), and selection type (single vs multiple choice) both between LLMs (inter-LLM comparison) and within each LLM (intra-LLM comparison). Numerical input calculation questions were excluded from the selection type analysis.

Statistical comparisons were performed using chi-square tests for expected cell frequencies of ≥5 and the Fisher exact test when expected cell frequencies were <5. For multiple pairwise inter-LLM comparisons, the Bonferroni correction was applied to control for type I error. Statistical significance was set at $P \leq .05$ (2 tailed). All statistical analyses were conducted using Stata (version 18.0; StataCorp LLC).

Ethical Considerations

Ethics approval was not required because only data from a published database were analyzed.

Results

Detailed results are presented in Table 2. The accuracy rates for each LLM for all 110 questions were as follows: 85.5% (n=94) of the questions for GPT-4o (95% CI 77.5% - 91.5%), 91.8% (n=101) of the questions for Claude Opus 4 (95% CI 85.0% - 96.2%), and 92.7% (n=102) of the questions for Gemini 2.5 Pro (95% CI 86.2% - 96.8%). The corresponding scores were 86.2% (125/145), 91.7% (133/145), and 93.1% (135/145), respectively, all of which exceeded the passing criterion (60%). In terms of question characteristics, the accuracy rates for general questions (n=75) were as follows: 84% (n=63) for GPT-4o, 92% (n=69) for Claude Opus 4, and 92% (n=69) for Gemini 2.5 Pro. The corresponding rates for situational questions (n=35) were 88.6% (n=31), 91.4% (n=32), and 94.3% (n=33), respectively.

Table . Performance of large language models (LLMs) on the 111th Public Health Nurse National Examination.

Category	GPT-4o		Claude Opus 4		Gemini 2.5 Pro		LLM comparison *P* value		
	Correct answers, n (%)	*P* value	Correct answers, n (%)	*P* value	Correct answers, n (%)	*P* value	GPT-4o vs Claude Opus 4	GPT-4o vs Gemini	Claude Opus 4 vs Gemini
Overall accuracy rate (n=110)	94 (85.5)	—[a]	101 (91.8)	—	102 (92.7)	—	>.99	>.99	>.99
Overall score (n=145)	125 (86.2)	—	133 (91.7)	—	135 (93.1)	—	>.99	>.99	>.99
By question content		.53		>.99		>.99			
General questions (n=75)	63 (84.0)		69 (92.0)		69 (92.0)		>.99	>.99	>.99
Situational questions (n=35)	31 (88.6)		32 (91.4)		33 (94.3)		>.99	>.99	>.99
By question format		.69		>.99		.60			
Text questions (n=98)	84 (85.7)		90 (91.8)		90 (91.8)		>.99	>.99	>.99
Figure or calculation questions (n=12)	10 (83.3)		11 (91.7)		12 (100.0)		>.99	>.99	>.99
By selection type		.04		.03		.09			
Single-choice questions (n=92)	82 (89.1)		87 (94.6)		87 (94.6)		>.99	>.99	>.99
Multiple-choice questions (n=16)	10 (62.5)		12 (75.0)		13 (81.3)		>.99	>.99	>.99

[a]Not applicable.

In terms of question format, the accuracy rates for the text questions (n=98) were as follows: 85.7% (n=84) for GPT-4o, 91.8% (n=90) for Claude Opus 4, and 91.8% (n=90) for Gemini 2.5 Pro. The corresponding rates for figure or calculation questions (n=12) were 83.3% (n=10), 91.7% (n=11), and 100% (n=12), respectively. The accuracy rates for single-choice questions (n=92) were as follows: 89.1% (n=82) for GPT-4o, 94.6% (n=87) for Claude Opus 4, and 94.6% (n=87) for Gemini 2.5 Pro. However, for the multiple-choice questions (n=16), all LLMs showed decreased accuracy, and the corresponding rates were 62.5% (n=10), 75% (n=12), and 81.3% (n=13), respectively.

Statistical comparisons among the LLMs showed no significant differences. Intra-LLM comparisons revealed significant differences between single- and multiple-choice questions for GPT-4o (*P*=.01) and Claude Opus 4 (*P*=.03), with the accuracy rates for multiple-choice questions being significantly lower.

Discussion

Principal Findings

This study compared and evaluated the performances of multiple LLMs on the Japanese Public Health Nurse National Examination. All the LLMs significantly exceeded the passing criterion of 60%. These results indicate that LLMs have acquired considerable specialized knowledge, with the performance of GPT-4o (94/110, 85.5%) being comparable to that of LLMs in previous medical examinations [4] and superior to that of older-generation models [6].

While all LLMs showed high overall accuracy rates, a clear performance decline was observed for multiple-choice questions. This contrasts with the high accuracy rates for single-choice questions, with significant differences found for GPT-4o and Gemini 2.5 Pro. This phenomenon demonstrates the current limitations of LLMs in complex reasoning, which requires the simultaneous evaluation of multiple concepts. As public health nursing practice requires comprehensive judgment considering multiple factors such as regional characteristics, residents' needs, social resources, and multidisciplinary collaboration, the performance decline on multiple-choice questions indicates that LLMs have limitations in the complex decision-making faced in actual public health nursing practice.

The accuracy rates of the LLMs evaluated in this study (94/110, 85.5% to 102/110, 92.7%) and their scores (125/145, 86.2% to 135/145, 93.1%) substantially exceeded the passing standard (60%). The pass rate for the 111th Public Health Nurse National Examination was 94% [9]; however, this represents the proportion of examinees who exceeded the passing standard, and the overall mean score for all examinees is not publicly available. Therefore, a direct comparison between the overall academic performance of examinees and LLM performance is challenging.

In the field of medical education, multiple studies comparing LLM and student performance have been reported. A study comparing final-year emergency medicine students with AI models [10] demonstrated that students achieved a 79.4% accuracy rate, outperforming ChatGPT (72.5%) and Gemini (54.4%). The superiority of students was particularly pronounced in image-based questions, highlighting current limitations in AI models' visual information processing capabilities. Additionally, a study using 1070 medical imaging questions [11] found that GPT-4 correctly answered 67.8% of the questions it attempted, whereas the students' passing mean was 63%. However, the student majority vote achieved a 94.5% accuracy rate, substantially surpassing the AI. This demonstrates that even when individual students' abilities may be equal to or slightly inferior to those of AI, collective student judgment significantly exceeds AI performance.

In our study, while LLM performance on figure or calculation questions was high (10/12, 83.3% to 12/12, 100%), the small number of questions (n=12) necessitates larger-scale validation. More importantly, the learning processes of LLMs and humans are fundamentally different. LLMs learn patterns from large volumes of text data, whereas public health nurses acquire decision-making capabilities by integrating practical experience with theoretical knowledge. Furthermore, human public health nurses possess essential practical competencies that are not measurable through written examinations, including ethical judgment, empathy, and interpersonal communication skills. As these previous studies [10,11] demonstrate, while AI shows potential as a supplementary educational tool, it cannot replace human capabilities, particularly in areas requiring visual interpretation, clinical reasoning, and collective judgment. Therefore, LLMs should be appropriately positioned as educational and learning support tools rather than as replacements for human public health nurses.

The results of this study have important implications from the perspective of competency development in public health nursing education. The "Practical Competencies Required of Public Health Nurses and Achievement Goals and Levels at Graduation" document by the Japanese Ministry of Health, Labour and Welfare [12] classifies public health nurse competencies into five domains: (1) ability to clarify community health issues and develop plans; (2) ability to provide continuous support and collaborative organizational activities for individuals, families, groups, and organizations to enhance community health promotion capacity and evaluate these activities; (3) community health crisis management capacity; (4) ability to develop projects, policies, social resources, and systems to enhance community health levels; and (5) professional autonomy and continuous quality improvement capacity. LLMs may be particularly effective in providing learning support during information gathering and assessment stages within domain 1. This competency includes information collection for clarifying community health issues, community diagnosis, and prioritization of health issues, where LLMs are expected to play a supplementary role in confirming foundational knowledge and organizing information.

For domain 1, the achievement level at graduation is set at either level 1 ("able to implement independently with minimal guidance") or level 2 ("able to implement under supervision [from supervising public health nurses or faculty]") [12]. As revealed in this study, LLMs demonstrated a performance decline in multiple-choice questions and have limitations in complex judgment tasks. Therefore, when using LLMs as educational tools, it is crucial to cultivate students' ability to critically evaluate LLM outputs and maintain practical judgment skills based on community characteristics to reach these achievement levels.

Several ethical considerations must be addressed when using LLMs in public health nursing education. The Japanese Ministry of Education, Culture, Sports, Science and Technology guidelines [13] indicate that directly using generative AI outputs does not deepen students' own learning, that differences in generative AI types (paid vs free versions) may create disparities in student outcomes leading to unfairness, and that confidential and personal information may be unintentionally leaked or disclosed. A survey of Japanese medical students [14] found that while 41.9% had experience using ChatGPT, only 10.2% had used it for medical assignments and 47% held negative views about its use for medical reports. Many students felt that, considering the time required to verify AI responses, independent learning would be more efficient, highlighting the essential need to cultivate critical evaluation skills for LLM outputs. A narrative review on chatbot integration in nursing education [15] also emphasizes the importance of ethical considerations, indicating the urgent need to establish ethical frameworks for AI use across nursing education.

The results of this study revealed that while LLMs demonstrated high accuracy rates on the Public Health Nurse National Examination, performance declined on multiple-choice questions. This finding has important implications for using LLMs as learning support tools in public health nursing education. Given the demonstrated limitations of LLMs in complex judgment requiring simultaneous consideration of multiple factors, LLMs are suitable for supplementary roles such as confirming foundational knowledge and gathering information, whereas faculty instruction remains crucial for learning scenarios requiring complex judgment. The Ministry of Education, Culture, Sports, Science and Technology has issued guidelines [13] on the educational use of generative AI at universities and colleges of technology, and public health nurse training institutions are also called upon to develop guidelines that clearly specify appropriate use scenarios and limitations for LLMs. A nationwide survey on information and communications technology (ICT) use among public health nurses in local governments [16] found that 82.8% responded that they did not know the procedures for promoting ICT use, indicating challenges in adapting to digital technology even among practicing public health nurses. This suggests the importance of providing systematic digital literacy education from the public health nurse training stage.

A detailed examination is needed regarding curriculum integration and faculty training. For example, development of specific implementation strategies is required, including in which courses and how LLMs should be introduced, how to design a phased introduction process, and how faculty should learn appropriate LLM use methods. In particular, establishing organizational training systems for enhancing faculty AI literacy and developing assessment methods premised on LLM use are important future challenges. To accumulate knowledge regarding these strategies, pilot program implementation and evaluation will be necessary.

As practical implications, there is potential for the use of LLMs as continuing education and self-directed learning support tools for practicing public health nurses. A concept analysis of LLMs in nursing education [17] positions LLMs as transformative tools that provide accessible and personalized learning support and promote cognitive and skill development. In public health nursing education as well, use is anticipated for responding to new public health issues and during information gathering stages in community diagnosis. Additionally, there is potential for the use of LLMs as an auxiliary tool in situations requiring rapid information organization, such as during disasters or emerging infectious disease outbreaks. However, a survey on ICT use among public health nurses in local governments [16] found that 89.1% of municipalities expressed concerns about individuals who have difficulty adapting to digital technology, necessitating careful introduction that considers the essence of interpersonal support in public health nursing work. Furthermore, while 55.9% in the same survey actively promoted ICT use, only 26.7% perceived progress as smooth, indicating challenges in digital literacy education for practicing public health nurses and establishing organizational support systems. As noted in the aforementioned concept analysis [17], careful attention must be paid to LLM limitations and ethical implications, ensuring that LLM integration aligns with the values and goals of nursing education. Therefore, when using LLMs in practical settings, it is essential to critically evaluate LLM outputs and integrate them with community characteristics and practical knowledge, considering the limitations in complex judgment revealed in this study.

The findings of this study occupy an important position within the broader context of AI use in health profession education. A narrative review on chatbots in nursing education [15] demonstrated a surge in related research from 2021 to 2023 (with 2023 accounting for 70% of publications), indicating growing scholarly interest in this field. Together with LLM evaluation studies on medical licensing examinations [4,5], it is becoming increasingly clear that LLMs demonstrate high performance across medical licensing examinations generally. However, the performance decline on multiple-choice questions demonstrated in this study indicates the existence of LLM limitations in complex judgment unique to public health nursing, such as integration of social determinants of health and planning of community-level interventions. This is consistent with findings from previous studies in medical education [10,11] showing that collective student judgment far exceeds that of AI, supporting the appropriate positioning of LLMs as educational and learning support tools rather than replacements for human health professionals. Additionally, a survey of medical students [14] showed that 47% held negative views about LLM use for medical assignments, indicating the recognition of the need for verification. A concept analysis in nursing education [17] also pointed out the need for careful consideration of LLM limitations and ethical implications. Furthermore, the aforementioned review on chatbot integration in nursing education [15] emphasizes the importance of ethical considerations and the urgency of original research while acknowledging it as a promising field. Collectively, these findings suggest that across health profession education generally, while LLMs have potential as useful auxiliary tools, cultivating the ability to understand their limitations and use them critically is a common challenge across all types of health profession education.

Limitations and Future Directions

This study has the following strengths. First, this is the first study to evaluate the performance of multiple LLMs on the Public Health Nurse National Examination. While LLM evaluations have been conducted on medical and nursing licensing examinations, this study represents the first systematic evaluation in the public health nursing field. Second, reproducibility was ensured through the use of standardized prompts. Six prompts were created according to question types, achieving consistent evaluation. Third, detailed analysis by question format revealed the important finding of performance decline on multiple-choice questions. This discovery demonstrates LLM limitations in complex reasoning requiring the simultaneous consideration of multiple factors, with important implications for future educational implementation.

This study has several limitations. First, as a cross-sectional evaluation of a single year, temporal changes in LLM performance and reproducibility across different examination years could not be evaluated in this study. Second, accuracy rates alone do not clarify the quality of reasoning processes or correlation with actual public health nursing practice competencies. Third, while LLM versions and settings may influence results, this study was limited to evaluation using specific versions (GPT-4o, Claude Opus 4, and Gemini 2.5 Pro). Fourth, results may vary depending on prompt expression methods, and there is no guarantee that the standardized prompts used in this study are optimal. Fifth, because the overall mean score for examinees is not publicly available, direct performance comparison between LLMs and human public health nurse examinees is difficult. Furthermore, this study verified LLM performance in the educational evaluation context of a national examination and did not evaluate their utility or safety as decision support tools in actual public health nursing practice. Future research should include continued evaluation over multiple years, qualitative analysis of reasoning processes, validation of utility in practical settings, comparative studies with human public health nurses, and examination of applicability to decision support in actual practice.

Conclusions

The LLMs evaluated demonstrated high performance on the Public Health Nurse National Examination; however, they also had limitations in solving problems requiring complex judgment. These findings provide important foundational data showing the possibilities and challenges of AI use in public health nursing. On the basis of these results, LLMs should be cautiously used as supplementary tools in public health nursing education.

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Data Availability

The data supporting the findings of this study are available from the corresponding author (YT) upon request.

Authors' Contributions

YT contributed to conceptualization, methodology, investigation, funding acquisition, supervision, and manuscript review and editing. RK contributed to methodology, investigation, data curation, formal analysis, and writing of the original draft. RO and SO contributed to manuscript review and editing.

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence
ICT: information and communications technology
LLM: large language model

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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.

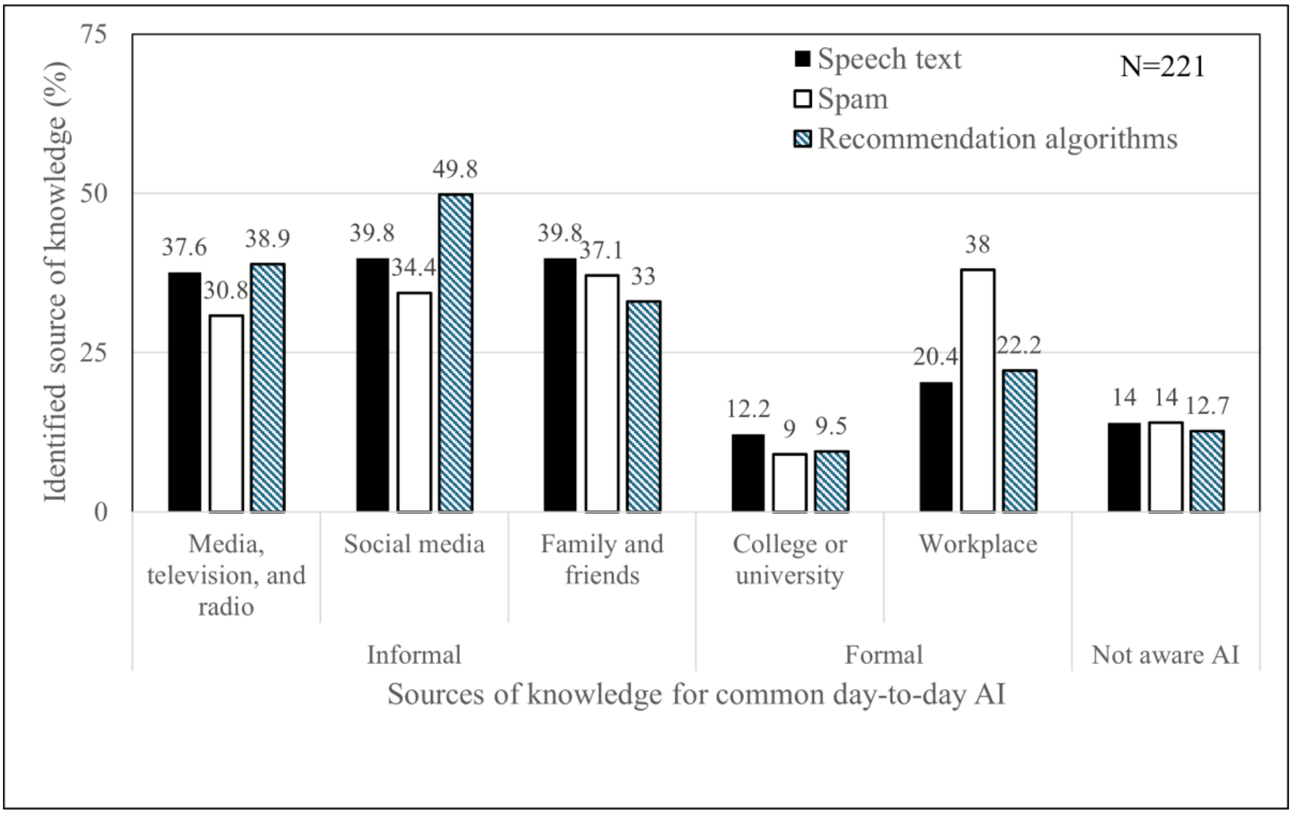
CHNs' Awareness of the Emergence of AI, Including ML Applications, in Nursing

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.

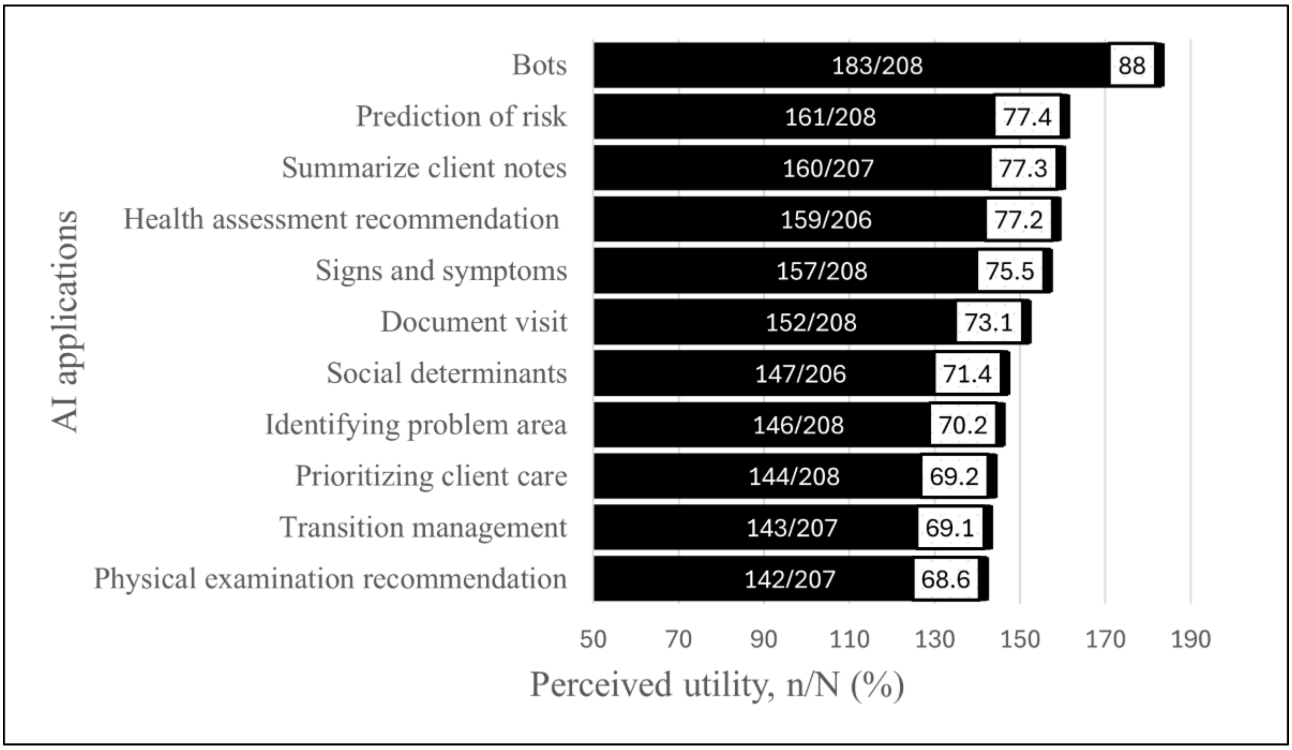


Table . Respondents' perception of the utility of AI[a] applications related to their level of AI knowledge.

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)				

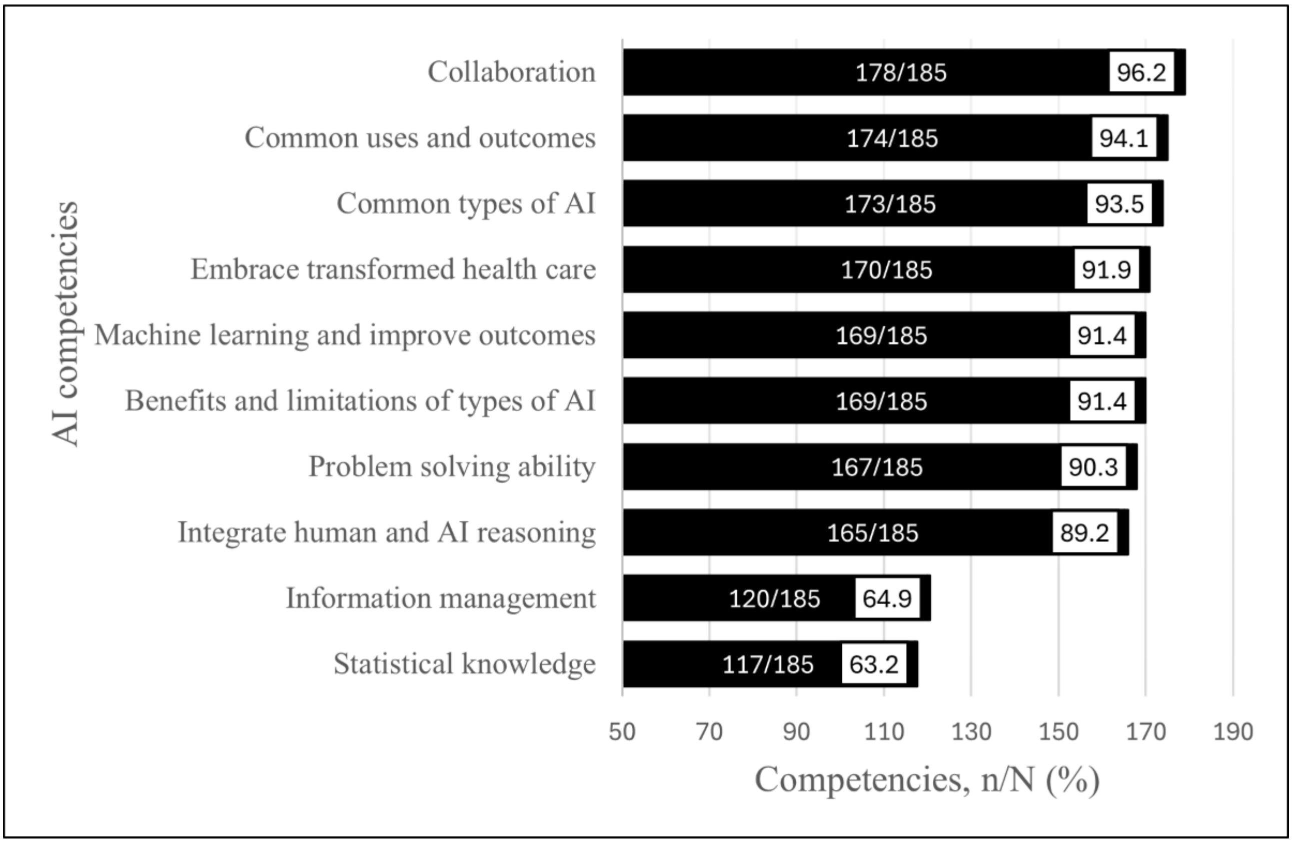
[a]AI: artificial intelligence.

[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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Development of Telenursing Guidelines to Improve the Quality of Services in Diabetic Wound Care in a Hospital in Thailand: Case Study

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Abstract

Background: The majority of patients with diabetic wounds living in Mae Chan District, Chiang Rai Province face challenges such as a shortage of nurses, limited access to health care, and insufficient resources. Strategies such as specialist networks, patient monitoring, and online care platforms are crucial to improving diabetic wound management in the community.

Objective: This study aims to develop telenursing guidelines for caring for patients with diabetic wounds and foot ulcers, and to investigate the effects of telenursing on wound healing among patients.

Methods: Participatory action research was conducted in three cycles: (1) assessing the current situation and feasibility of telenursing; (2) evaluating telenursing guidelines for wound healing; and (3) examining the effects of telenursing on wound healing, amputation rates, and patient satisfaction.

Results: The mean diabetic wound severity scores decreased after receiving telenursing care at weeks 2, 4, 6, and 8 (P<.001). No patients were found to have foot or leg amputations. The patients in the group who received telenursing care showed that their wounds healed in an average of 8.6 (SD 4.3) weeks. The satisfaction score for telenursing care was 4.7 out of 5 (SD 0.2).

Conclusions: Telenursing guidelines were developed to enhance access to wound care, reduce amputation rates, and promote wound healing, resulting in a significant reduction in wound severity and the absence of amputations. The study further demonstrated that telenursing not only expedited healing times but also reduced health care costs and improved patient satisfaction.

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KEYWORDS

telenursing; diabetic ulcers; wound care; nursing guideline; quality of service

Introduction

Diabetes is one of the serious chronic diseases strongly associated with health complications, including macrovascular disease, microvascular disease, peripheral vascular complications, and neuropathy, leading to serious health problems such as coronary heart disease, stroke, kidney disease, and retinal abnormalities. In addition, patients with diabetes are at risk of having foot ulcers, which are the most common complications causing disability, amputation, or premature death. This is one of the most critical public health problems. Diabetic foot ulcers are among the most common complications in persons with diabetes who have problems with uncontrolled blood sugar [1]. The incidence shows that patients with diabetes develop foot ulcers at 19% to 34% and have recurrence symptoms within 3 to 5 years at 65%; moreover, foot or leg amputation is found to be shared among patients with diabetes compared to the general population at 50% to 70%, and they have a chance of premature death within 5 years [2]. Foot ulcers among persons with diabetes take longer to recover than those of normal people, taking an average of 11 to 14 weeks. This could affect the lifestyles of the patients because it causes physical, mental, and social limitations. According to a study of health expenses for caring for patients with foot ulcers in a tertiary university hospital in Singapore between 2013 and 2017, the average cost of wound care alone was US $3368 per patient per year; the cost of minor amputation below the ankle was US $10,468 per patient per year; and the cost of major amputation above or below the knee was US $30,131 per patient per year [3].

Foot ulcers [4,5] can be classified into the following types of wounds. First, infected ulcers are where the wound is infected and becomes inflamed. The area around the wound is red and spreading from the original site. Symptoms of infected wounds are redness, swelling, pain, and pus. Second, neuropathic ulcers are the most common complication of uncontrolled diabetes. The wound is usually round in shape, with a deep hole in the middle part and thickened skin on the edges. It is found at the base of the big toe and pinky toe. Neuropathic ulcers develop from smaller wounds with symptoms of redness, swelling, numbness, or inflammation around the affected area. Third, ischemic ulcers are wounds that develop when the arteries do not deliver enough blood flow to a specific area, causing local ischemia in the skin and the underlying tissues. Initially, these ulcers manifest as blue discoloration, necrosis, or gangrene. They are painful wounds often found on the tips of the toes, especially the big and pinky toes. The characteristics of the wounds are pale, yellow, and cold, with a weak or absent pulse. They often start at the fingertips and pose an increased risk of amputation if left untreated. Diabetic ulcers are complex and chronic wounds that cannot follow the normal wound-healing process. When the wound is infected, dead tissue (sloughing or shedding) and purulent exudate from inflammation of the wound. There is no new tissue formation, and it does not heal within 4 weeks. Diabetic wounds heal slowly, and sometimes they do not heal. If the wounds are left without proper care, they will cause an infection that will spread to the bone layer (osteomyelitis), requiring organ removal (amputation). If a severe infection enters the bloodstream (septicemia), it can cause death. The essential goals in caring for patients with diabetic ulcers are to prevent disability from the wound spreading to the point where it is necessary to amputate the involved organ, to prevent new wounds from forming after treatment, and to increase the quality of life of the patients.

Diabetic wound care is integral to medical practice to heal wounds better and faster. To promote wound healing faster, (1) clean the wound to prevent infection and promote the wound healing process, (2) keep the wound elevated to reduce fluid accumulation and promote blood circulation, (3) provide adequate knowledge regarding nutrition to promote the wound healing process, (4) have enough rest because resting will reduce the metabolic process inside unnecessary cells and tissues and can carry enough oxygen and nutrients to the wounds, and (5) promote personal hygiene [6]. Diabetic wound care should be supervised by a nurse with clinical expertise who can collect, evaluate, analyze, and identify the needs and problems of patients. Expert nurses should be able to manage options for care and use medical supplies and equipment correctly and appropriately, obtain communication skills to coordinate with the treatment team and encourage family members to participate in care, identify health services and resources, protect patients' rights and privacy, and preserve patient safety and prevent harm during care [7-9]

Despite a community point prevalence of approximately 1.5% to 5% for diabetic foot ulcers, the lifetime incidence risk reaches 19% to 34% [1]. This elevation is frequently linked to suboptimal foot self-care practices; however, there are not enough nurses to meet the increasing demand for care and other issues in Mae Chan District, Chiang Rai Province, such as a lack of health equipment; resources; and access to health services, communication channels for health care advice, and continuity of care rehabilitation. Therefore, strategies for caring for diabetic wounds are necessary, such as creating a network of channels for giving advice from specialists to nurses, caregivers, and patients in the community, monitoring and following up with patients, and providing quality of service through online channels. Various health care advice channels could increase access to services, reduce waiting time, and facilitate patients in a new way of life (New Normal). Moreover, the use of digital technology systems to provide health services for continuous care and referral to primary care units with the best practice guidelines, The Nursing and Midwifery Council has announced telenursing strategies to provide health care advice and to find solutions related to health within the knowledge framework of the nursing and midwifery profession [10].

Telenursing uses information and communication technologies to develop all fields of nursing care, education, and research at a distance [11]. In Thailand, the Nursing and Midwifery Council provides advice and solutions related to health within the knowledge framework by using this digital technology system to provide services and support all forms of nursing care, including continuous care, quality of care, equal access to health, and allowing people to manage their health through online services [10]. Telenursing care increases channel access to health services, covers health care in remote areas, especially in areas with travel restrictions, and maintains professional standards and quality. Patients also do not need to commute to the hospital, which helps reduce the cost of hospital admission and other related expenses while still allowing monitoring and following up on patients' conditions through online channels.

The Mae Chan Hospital is located in the Chiang Rai Province. It is a middle-level hospital that can host up to 120 beds and support referrals from community hospitals in the joint service network of 4 districts: Mae Chan District, Mae Fah Luang District, Doi Luang District, and Chiang Saen District. The Mae Chan Hospital is responsible for caring for patients referred from community hospitals when the capacity of those hospitals in the 4 districts reaches the limit. The hospital helps increase access to treatment for service users in the area, reduces referrals to regional hospitals (advanced-level hospital), and supports primary service units in each district. The Wound and Ostomy Care Clinic, Mae Chan Hospital, provides services for patients with chronic wounds, bedsores, general wounds, penetrating wounds, drains, and ostomy care. Some nurses specialize in diabetic wounds, one specialist in ostomy care, and one in general care for patients. There were a number of people who received services from 2020 to 2022, including a total of 2142, 1571, and 1675 patients, representing 3725, 4931, and 6239 visits, respectively. There were 114, 70, and 67 patients with diabetic ulcers, accounting for 405, 281, and 291 visits, respectively. The average cost of commuting to the hospital for patients to receive wound care is US $10 per time. The average number of days to receive wound care services is 14 to 45 days per person. In general, the travel distance for patients to visit the wound care and ostomy clinic is 1 to 40 km. Due to travel distance and expenses involved in wound care at the hospital, some of the patients are unable to receive treatment regularly and continuously, so many patients experience wound spreading and recurrence of wound infection, leading to foot or leg amputation in some cases.

According to literature reviews, telenursing is important in assisting patients to access standard care for chronic wounds. Telenursing care helps reduce complications and the number of patients admitted to the hospital, which encourages participation among patients, caregivers, and nurses in self-care practices, and increases patient satisfaction because it reduces travel time, traveling costs, and other related expenses of going to the hospital. Therefore, the research team was interested in studying the development of telenursing guidelines for caring for patients with diabetic wounds and foot ulcers, and the effects of telenursing on wound healing in patients to provide quality service and prevent the spread and recurrence of wound infections and foot and leg amputations in patients.

Methods

Study Design

This was participatory action research [12], which divided the study into 3 cycles.

Cycle 1

The current situations, problems, and needs of patients with diabetic wounds and the feasibility of using telenursing guidelines in the context of the Mae Chan Hospital, Chiang Rai Province, and community networks in the research area were studied. The researcher used lessons learned from the study to conclude the issues and needs of developing and drafting telenursing guidelines for diabetic wound care. Informants and participants in the design of diabetic wound care guidelines and telenursing system were purposively selected, consisting of (1) patients with diabetic wounds and/or their caregivers who received care in the Wound and Ostomy Care Clinic, totaling 10 persons; (2) the multidisciplinary team including a surgeon, a pharmacist, a nutritionist, and 9 registered nurses at subdistrict health-promoting hospital in the Mae Chan Hospital networks, totaling 12 people; and (3) a computer technical officer.

The interprofessional team plays a critical role in providing comprehensive care for patients with chronic diabetic wounds. The surgeon is central to diagnosing the underlying causes of chronic wounds, determining their etiology, and formulating an integrated treatment plan. In collaboration with the health care team, the surgeon ensures the effective implementation of telenursing guidelines, addressing the needs of patients who face barriers to in-person health care access. The pharmacist works closely with the physician and nursing staff to select appropriate topical treatments that promote wound healing and minimize the risk of infection. In addition to this, the pharmacist is responsible for educating both patients and their families on the proper use of medications and wound care techniques. The nutritionist plays a vital role by recommending dietary strategies that support wound healing, promote tissue regeneration, and address underlying risk factors such as poor circulation or diabetes. Their tailored nutritional guidance is designed to strengthen the immune system and accelerate recovery. Finally, the computer technical officer ensures the seamless operation of the telemedicine system, facilitating smooth communication via platforms like the "Wound Care Mae Chan" LINE app. They provide technical support, enabling real-time updates and enhancing the overall telehealth experience for both health care providers and patients.

Cycle 2

Telenursing guidelines toward diabetic wound healing were studied. Participants recruited in the study were patients with diabetic wounds and professional nurses from subdistrict health-promoting hospitals under the Mae Chan Hospital network, totaling 20 persons. A sample size calculation was done using G*Power software version 3.1.9.4 (Fual et al), with test power set at 0.70, confidence value at 0.05, and influence value (effect size) at 0.30. The number of samples obtained from the calculation was 13. An additional 50% was added to the sample size, so the total number of participants in this cycle was 20.

Cycle 3

The effects of telenursing on diabetic wound healing were studied by evaluating the wounds, foot or leg amputation, and satisfaction with using telenursing guidelines. A quasi-experimental one-group pretest-posttest design was employed in this stage of the study.

Research Instruments

The tools used for data collection are given below:

1. General information on characteristics was collected, including gender, age, education level, occupation, history of smoking, history of diabetes and duration, and types of diabetic wounds.
2. Bates-Jensen Wound Assessment Tool (BWAT): the BWAT consists of 13 wound characteristics: size, visible depth, wound edges, undermining and tunneling processes, necrotic tissue type and amount, exudate type and amount, surrounding skin discoloration, peripheral tissue edema, peripheral tissue induration, granulation tissue, and epithelialization [13]. The scores range from 13 to 65, and content validity and concurrent validity are both equal to 0.91. The assessment tool was used in a tryout among 10 patients with similar characteristics to find reliability using the Cronbach α coefficient formula, and the reliability value was 0.88. The cutoff scores of BWAT are the following: minimal scores are 13 to 20, mild severity scores are 21 to 30, moderate severity scores are 31 to 40, and critical severity scores are 41 to 65.
3. The questionnaire on satisfaction with the telenursing guidelines consists of 7 items rated on a 5-point Likert scale measuring satisfaction, with response options ranking from 5 (very satisfied), 4 (satisfied), 3 (neutral), 2 (dissatisfied), and 1 (very dissatisfied).

The tools used to conduct the study included the following:

1. Guidelines for diabetic wound care: the researcher developed the guidelines based on the existing literature review by specifying keywords to search for papers and related documents, including diabetic wounds, chronic wounds, guidelines for wound care, and wound care. The

literature review search period was set from 2014 to 2023. Information was also obtained from cycle 1, which involved studying the current situations, problems, and needs of patients with diabetic wounds and the feasibility of using telenursing guidelines. The researcher presented a draft of telenursing guidelines to 3 experts in the fields of surgery, preventive medicine, and wound and ostomy care. These experts reviewed the guidelines to ensure they were consistent with the research objectives. Content validity was performed by measuring the Index of Item Objective Congruence, which was equal to 0.80.

2. LINE app "Wound Care Mae Chan"
3. Telemedicine Service System (Telemedicine; ITELE) of Mae Chan Hospital

Ethical Considerations

The Human Research Ethics Committee at Chiang Rai Provincial Public Health Office approved this research study under approval 37/2023, with certification granted on April 1, 2023. The researcher adhered strictly to ethical principles throughout the study. Before participation, the researcher clearly communicated the objectives of the study, the research process, the expected duration, and the anticipated benefits to ensure a full understanding; subsequently, written informed consent was obtained from all participants before any data collection commenced. Informants and participants were informed that communication regarding wound care would be conducted via the LINE application, specifically designated for this research group. They were also informed of their right to withdraw from the study at any time, without any impact on their current treatment or benefits received from the hospital.

Participants received a remuneration of US $6 for each completed data collection session. The researchers were committed to protecting the participants' rights and privacy. As such, all data were recorded using codes instead of real names, ensuring anonymity. All participant information was kept confidential and could not be traced back to any individual. The findings of the study were presented as aggregated data to protect participant identity. Furthermore, all recorded data, including images, would be destroyed 1 year after the publication of the research results.

Results

As per the study objectives, we developed telenursing guidelines for caring for patients with diabetic wounds and foot ulcers, and studied the effects of telenursing on wound healing, using participatory action research.

In cycle 1, to study the current situations, problems, and needs of patients with diabetic wounds and the feasibility of using telenursing guidelines, we recruited 10 informants who were patients with diabetic wounds and foot ulcers aged between 30 and 74 years (average age 62.6, SD 12.4 years; duration of diabetes 1-10 years; average duration of diabetes 4.9, SD 3.5 years; average wound assessment score 51.3, SD 3.3); additional informants included a surgeon, a pharmacist, a nutritionist, 9 registered nurses at the subdistrict health-promoting hospital, and a computer technical officer. The following needs and problems were found.

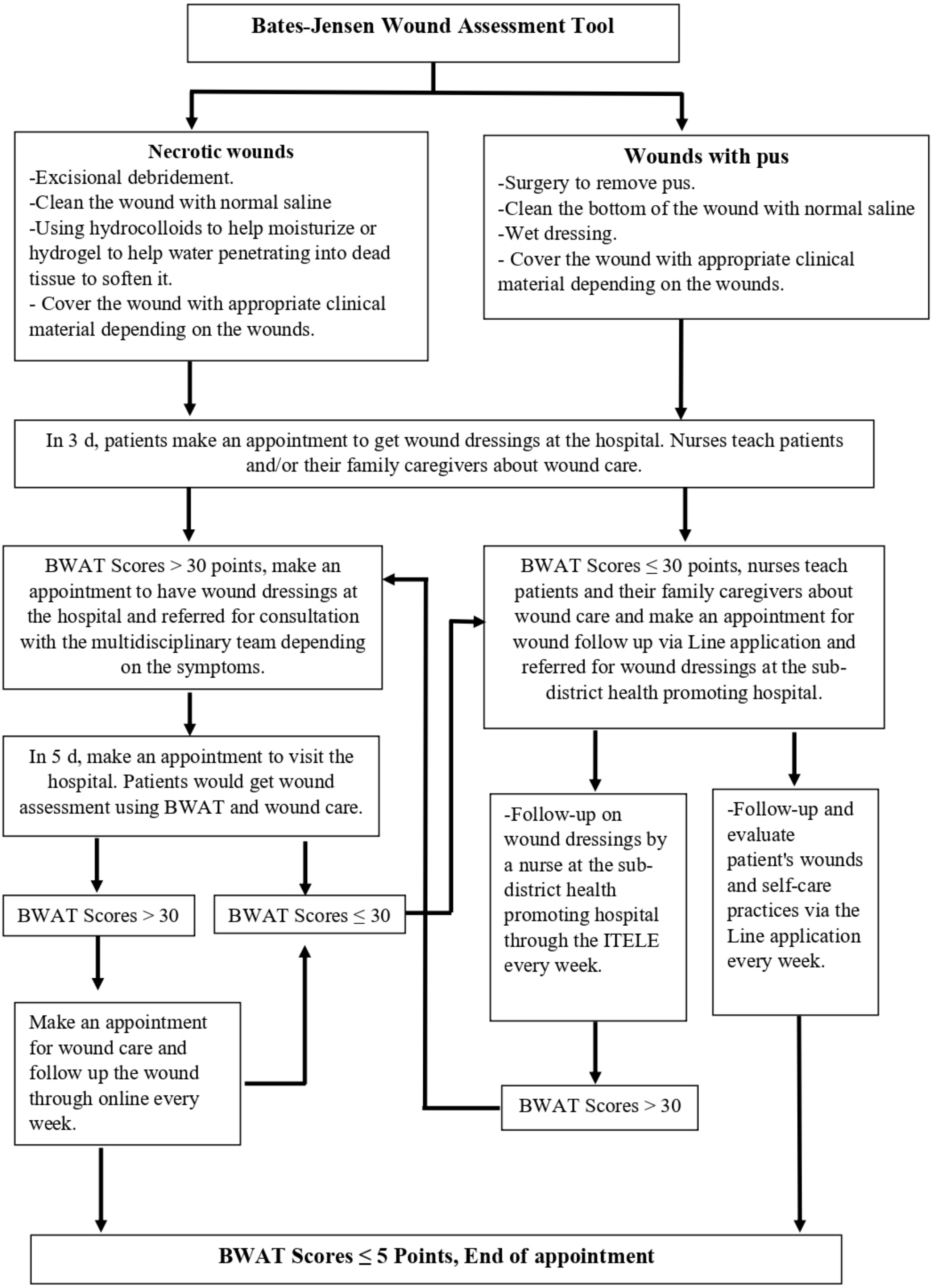
Some patients could not receive wound care regularly and continuously because of the distance to the hospital, traveling difficulties, expenses for transportation, food, medical care, and related costs. Findings showed that some patients live far from the hospital. It costs them a lot of money per hospital visit. In some cases, patients have no one to take them to the hospital because family members have to work, and if they have to accompany the patients to the hospital, they have to miss their work and lose income. Moreover, they must spend extra money on transportation and food while waiting for patients to receive wound care. The cost of traveling to the hospital to receive wound care services is approximately 100 to 1000 Baht (US $2.85-$28.50) per visit, which is too much for them to spend, especially for patients and their family members who live in a remote community area.

Lack of knowledge about diabetic wound care is one of the problems. Patients lack adequate knowledge of wound care, nutrition, and control of blood sugar levels. These are factors for wound healing. In some cases, patients did not follow up on the appointment, which could also affect their physical health. Because of this, many patients experienced wound spreading and recurrence of wound infection, and in some cases, may experience foot or leg amputation.

Treating severely infected wounds requires skills and expertise in advanced wound care, which exceeds the potential of community nurses working in subdistrict health-promoting hospitals, and patients did not have access to or resources for advanced wound care, such as hydrocolloid, hydro fiber, alginate, hydrogel, foam, and film dressings.

Nowadays, the majority of patients and their family caregivers have smartphones that can be used to communicate via the LINE app. Introducing telenursing for diabetic wound care among patients could help reduce barriers to receiving health care services. Based on the study of situations, needs, and problems among patients with diabetic wounds, telenursing guidelines for diabetic wound care are summarized as shown in Figure 1.

Figure 1. Telenursing guidelines for diabetic wound care. BWAT: Bates-Jensen Wound Assessment Tool; NSS: normal saline solution.



In cycle 2, the telenursing guidelines for diabetic wound healing were evaluated.

The study sample included 20 patients with diabetic wounds and foot ulcers, and half of them were female (n=10, 50%) and aged 30 to 81 years, with an average age of 47.6 (SD 9.4) years and an average duration of diabetes of 7.6 (SD 6.4) years. Studies showed that the wounds were found most on the leg, foot, and toe (n=15, 75%). The average assessment wound severity score was 50.8 (SD 4.4), indicating that patients had wound critical severity (BWAT=41‐65 points represents critical severity), and the results are shown in Table 1.

Table . Attributes of the sample.

Items	Value
Sex, n (%)	
Male	10 (50)
Female	10 (50)
Age (y)	
30 - 49, n (%)	2 (10)
50 - 59, n (%)	3 (15)
60 - 69, n (%)	9 (45)
≥70, n (%)	6 (30)
Mean (SD)	62.6 (12.4)
Duration of diabetes (y), n (%)	
0 - 2	4 (20)
3 - 5	6 (30)
6 - 10	7 (35)
≥10	3 (15)
Wound location, n (%)	
Head and neck	1 (5)
Arm, hand, and fingers	4 (20)
Legs, feet, and toes	15 (75)
Pain, n (%)	
Pain occurs during wound dressing	7 (35)
Pain is present at all times	8 (40)
Intermittent pain	5 (25)
Wound status score	
Mean (SD)	50.8 (4.35)
Critical severity (BWAT[a]=41 - 65 points), n (%)	20 (100)
Wound characteristics, n (%)	
Size (length × width) (cm^2)	
<4	3 (15)
4-16	11 (55)
16.1-36	2 (10)
36.1-80	3 (15)
>80	1 (5)
Depth	
Obscured by necrosis	5 (25)
Full-thickness skin loss with extensive destruction, tissue necrosis, or damage to muscle, bone, or supporting structures	15 (75)
Wound edges	
Indistinct, diffuse, and none clearly visible	19 (95)
Distinct, outline clearly visible, attached, and even with wound base	1 (5)
Undermining	
<2 cm in any area	14 (70)
2 - 4 cm involving <50% wound margins	6 (30)

Items	Value
Necrotic tissue type	
Loosely adherent yellow slough	3 (15)
Adherent, soft, and black eschar	17 (85)
Necrotic tissue amount	
>50% and <75% of wound covered	14 (70)
75%-100% of wound covered	6 (30)
Exudate type	
Serosanguineous: thin, watery, and pale red or pink	1 (5)
Serous: thin, watery, and clear	7 (35)
Purulent: thin or thick, opaque, tan or yellow, and with or without odor	12 (60)
Exudate amount	
The amount of secretion is ≤25%	1 (5)
The amount of secretion is more than 25% - 75%	7 (35)
The amount of secretion is more than 75%	12 (60)
Skin color surrounding the wound	
Bright red and/or blanches to touch	16 (80)
Black or hyperpigmented	4 (20)
Peripheral tissue edema	
Pitting edema extends <4 cm around the wound	9 (45)
Crepitus and/or pitting edema extends >4 cm around the wound	11 (55)
Peripheral tissue induration	
None present	1 (5)
Induration, <2 cm around the wound	2 (10)
Induration 2 - 4 cm extending <50% around the wound	6 (30)
Induration 2 - 4 cm extending >50% around the wound	11 (55)
Granulation tissue, n (%)	
Bright, beefy red; <75% and >25% of wound filled	3 (15)
Pink and/or dull, dusky red and/or fills <25% of wound	17 (85)
Epithelialization, n (%)	
50% to <50% wound covered	3 (15)
<25% wound covered	17 (85)

[a]BWAT: Bates-Jensen Wound Assessment Tool.

The researcher prepared workshops and set up a meeting to explain the task of developing telenursing guidelines to the committee and those responsible for the continuous care, advanced wound care, and training program using the ITELE.

In cycle 3, mean wound severity scores were compared before and after receiving telenursing guidelines for diabetic wound care at week 2, week 4, week 6, and week 8 using 1-way repeated measures (ANOVA) statistical analysis; the results are shown in Table 2. The mean scores for wound severity were significantly different at the .001 level. A comparison of the wound severity scores before and after receiving telenursing nursing care guidelines for wound care at week 2, week 4, week 6, and week 8 using *t* test (1-tailed) statistical analysis is shown in Table 3.

Table . Comparison of the wound severity scores before and after receiving telenursing guidelines toward diabetic wound care using repeated measures of 1-way ANOVA statistics.

ANOVA	Sum of square	*df*	Mean square	*F* test	*df*	*P* value
Between-group	15,379.4	4	3844.8	401.7	4	<.001
Within-group	3360.2	95	35.4	—[a]	95	—
Total	18,739.6	99	—	—	99	—

[a]Not applicable.

Table . Comparison of the wound severity scores before and after receiving telenursing guidelines towards diabetic wound care at week 2, week 4, week 6, and week 8.

	Wound severity scores, mean (SD)	*t* test (*df*)	*P* value
Before and after receiving telenursing care guidelines for diabetic wound care in the second week	23.7 (5.3)	20.0 (19)	<.001
Before and after receiving telenursing care guidelines for diabetic wound care in the fourth week	29.6 (3.9)	34.3 (19)	<.001
Before and after receiving telenursing care guidelines for diabetic wound care in the sixth week	32.0 (4.0)	35.3 (19)	<.001
Before and after receiving telenursing care guidelines for diabetic wound care in the eighth week	34.0 (4.7)	36.1 (19)	<.001
After receiving telenursing care guidelines for diabetic wound care in the week 2 and week 4	5.9 (3.9)	6.8 (19)	<.001
After receiving telenursing care guidelines for diabetic wound care in the week 2 and week 6	8.3 (5.0)	7.4 (19)	<.001
After receiving telenursing care guidelines for diabetic wound care in the week 2 and week 8	10.3 (6.5)	7.1 (19)	<.001
After receiving telenursing care guidelines for diabetic wound care in the week 4 and week 6	2.4 (2.6)	4.1 (19)	<.010
After receiving telenursing care guidelines for diabetic wound care in the week 4 and week 8	4.4 (3.9)	5.1 (19)	<.001
After receiving telenursing care guidelines for diabetic wound care in the week 6 and week 8	2.0 (2.3)	3.8 (19)	<.010

According to Table 3, the wound severity scores after receiving telenursing care in the 2nd, 4th, 6th, and 8th weeks had decreased statistically (*P*<.001). The scores after receiving telenursing care in weeks 4, 6, and 8 had decreased statistically from week 2 (*P*<.001). The scores after receiving telenursing care in weeks 6 and 8 had decreased statistically from week 4 (*P*<.001), and the scores after receiving telenursing care in week 8 had decreased statistically from week 6 (*P*<.001).

Discussion

Principal Findings

The findings of this study showed that samples had a mean age of 62.6 (SD 12.4) years, an average duration of having diabetes for 4.9 (SD 3.5) years, and high levels of wound severity on average (BWAT=50.8, SD 4.3). This indicates that the majority of the sample were older people, who have a high risk for critical wound severity. First, the factors affecting the wound healing process include infection, high blood sugar levels, and nervous system disorders. This is consistent with the study by Burgess et al [14], which found that the pathophysiology related to the diabetic wound healing process includes hyperglycemia, neuropathy, microvascular complications, infection, inflammation, and immune system deficiency in chronic wounds, and the psychological impacts of diabetes mellitus. Second, the factors preventing patients from receiving wound care continuously include financial limitations, distance to the hospital, no caregivers taking them to the hospital, and so on.

From the in-depth interviews, it was found that the majority of patients live far from the hospital. Distance is one of the barriers to accessing health services. Some patients do not have anyone to care for because family members have to work. Due to this reason, some of the patients are unable to go to the hospital by themselves. If a caregiver comes to the hospital, it would cost more money for traveling expenses, which is more than the net income received each day. The average cost is US $6 to US $10 per time, which is considered a high expense. Third, the knowledge factors where the patient does not have enough knowledge regarding blood sugar control and nutrition, which are important factors to promote wound healing. The problems and needs of patients led to the development of telenursing guidelines to provide patients with access to wound care services to prevent leg or foot amputation, increase the rate of wound healing, reduce wound healing time, reduce inequality, and distribute opportunities to access advanced wound care and resources for wound healing.

A study of the development of using telenursing guidelines on diabetic wound healing found that the mean wound-based severity scores had decreased significantly after receiving telenursing guidelines for diabetic wounds in week 2, week 4, week 6, and week 8 (P<.001). Moreover, no patients were found to have foot or leg amputation. This can be explained by the fact that the samples in this study received baseline assessment, including illness history, duration of the wound, history of received medicine, financial status, nutrition, and wound assessment using the BWAT. Patients also received wound assessment every week from the beginning throughout the study. Having regular wound assessments is important for effective wound care. Understanding factors affecting wound healing helps nurses make appropriate decisions in wound care [15]. This allows the wound healing process to proceed normally, and it works well together by preparing the wound to be in an appropriate state according to the principles of wound bed preparation [16]. Wound management consists of three phases. First, the debridement of the wound is when dead or unhealthy tissue is removed from a wound. It stimulates wound healing to the proliferative phase, causing re-epithelialization of the wound to be smaller, which prevents or reduces the amount of infection by removing pathogenic parts such as foreign bodies. Second, the wounds are made moist by dealing with secretions, making the wound healing more effective and causing angiogenesis, the formation of granulation tissue, and the process of re-epithelialization. Third, the wound infection is controlled by cleaning the wound to reduce the number of germs and giving topical antibiotics [17,18].

Information for developing telenursing guidelines was obtained from studying the situations, problems, and needs of patients with diabetic wounds and foot ulcers, as well as from reviewing the existing literature. Based on the information, self-care behaviors are important for promoting wound healing among patients, such as controlling blood sugar levels, taking care of the wound by cleaning and getting wound care regularly and continuously, and eating proper food with good nutrition. According to this study, the patients in the group that received telenursing care could heal wounds in an average of 8.6 (SD 4.3) weeks. The patients in the group that received advanced wound care and normal wound care could heal their wounds in an average of 10.2 weeks. The patients in the group that received wound care every day (conventional wound dressings) and normal wound care could heal in an average of 11.72 weeks. The average cost of wound care for the group receiving telenursing guidelines was 11,772 Baht (US $336.34) per person, receiving advanced wound care and normal care was 14,772 Baht (US $422.06) per person, and receiving wound care and normal care every day was 22,740 Baht (US $649.71) Baht per person. In terms of the average score of satisfaction using telenursing guidelines, it was 4.7 out of 5 (SD 0.2). This is consistent with many studies stating that self-care behaviors, blood sugar level control, and continuous use of medication among patients with diabetes were better after telenursing care [19-22], and this reduces the use of resources for treating diabetic wounds, hospital admissions, and patient expenses while maintaining service quality [19,23-26].

This research is in alignment with both national and international policies that promote the incorporation of digital technology as a tool for enhancing health care services. It also functions as a conduit, bridging the gap between communities and health care systems, thereby mitigating geographical and relational disparities between the public and health care providers. Moreover, digital technology empowers individuals to stay informed about evolving health conditions, understand their rights to access high-quality, equitable, and safe health care, and fosters public awareness and collaboration in improving personal and community health outcomes [27,28].

Suggestions for Using Research Results

To continuously produce good results when implementing telenursing guidelines for improving the quality of services in diabetic wound care, those involved in the development process, including community people, patients, health care providers, nurses, health staff, and family caregivers, must be prepared in terms of knowledge in the field of diabetic wound care such as advanced wound care, the ITELE program, community nursing, self-care practices and knowledge regarding the use of remote technology in accordance with the steps of the nursing process, and health assessment, including defining problems, planning, practice, and evaluation.

There must be supervision, monitoring, and evaluation of the use of telenursing guidelines to improve nursing practices suitable to the community context and in accordance with knowledge about advanced wound care, diabetic wounds, chronic wounds, and remote technology.

Limitations

The small sample size limits the ability to generalize the findings to a broader population.

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Conflicts of Interest

None declared.

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Abbreviations

BWAT: Bates-Jensen Wound Assessment Tool

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