JMIR Nursing

Journal Impact Factorâ ¢ (JIF) (2023): 5.8
Volume 7 (2024) ISSN 1438-8871 Editor in Chief: Gunther Eysenbach, MD, MPH

Contents

Viewpoints

Reviews

Original Papers

Advancing AI Data Ethics in Nursing: Future Directions for Nursing Practice, Research, and Education

Patricia A Ball Dunlap[1,2], MS, MSN, RN, NI-BC, CPHIMS; Martin Michalowski[1], PhD

[1]School of Nursing, University of Minnesota, 5-140 Weaver-Densford Hall, 308 Harvard Street SE, Minneapolis, MN, United States

[2]Center for Digital Health, Mayo Clinic, Rochester, MN, United States

Corresponding Author:
Patricia A Ball Dunlap, MS, MSN, RN, NI-BC, CPHIMS
School of Nursing, University of Minnesota, , 5-140 Weaver-Densford Hall, 308 Harvard Street SE, Minneapolis, MN, , United States

Abstract

The ethics of artificial intelligence (AI) are increasingly recognized due to concerns such as algorithmic bias, opacity, trust issues, data security, and fairness. Specifically, machine learning algorithms, central to AI technologies, are essential in striving for ethically sound systems that mimic human intelligence. These technologies rely heavily on data, which often remain obscured within complex systems and must be prioritized for ethical collection, processing, and usage. The significance of data ethics in achieving responsible AI was first highlighted in the broader context of health care and subsequently in nursing. This viewpoint explores the principles of data ethics, drawing on relevant frameworks and strategies identified through a formal literature review. These principles apply to real-world and synthetic data in AI and machine-learning contexts. Additionally, the data-centric AI paradigm is briefly examined, emphasizing its focus on data quality and the ethical development of AI solutions that integrate human-centered domain expertise. The ethical considerations specific to nursing are addressed, including 4 recommendations for future directions in nursing practice, research, and education and 2 hypothetical nurse-focused ethical case studies. The primary objectives are to position nurses to actively participate in AI and data ethics, thereby contributing to creating high-quality and relevant data for machine learning applications.

(JMIR Nursing 2024;7:e62678) doi:10.2196/62678

KEYWORDS

artificial intelligence; AI data ethics; data-centric AI; nurses; nursing informatics; machine learning; data literacy; health care AI; responsible AI

Introduction

Artificial intelligence (AI) has become increasingly popular in the United States and globally. Major US media outlets frequently report on AI, covering topics from job displacement concerns to its diverse and innovative applications across various industries. In the health care sector, where there is a vast amount of electronic administrative and clinical data, the adoption and application of AI technology are expected to grow significantly, with projections suggesting a market increase to approximately US$208 million by 2030 and a compounded annual growth rate of 38.5% worldwide [1]. Moreover, AI ethics has gained more recognition due to the negative outcomes and ethical issues related to algorithmic bias, lack of transparency, trust issues, data security, and fairness. A preliminary examination of a global AI ethics case registry indicates that AI incidents proliferate across multiple industry sectors [2].

Machine learning algorithms, particularly those featured in headlines or academic papers about ethical violations, are often central to these discussions. For instance, large language models and other machine learning algorithms have been reported to generate incorrect medical results [3-5], exhibit bias [5,6], and fail to identify chronically ill Black American patients who require high-risk care management [5,7]. These reports effectively draw attention to the malfunctioning of AI technologies. However, deeper analysis reveals that the underlying root cause of these failures often lies in the data used by these algorithms. Data integrity is fundamental to AI technology, as it powers these influential systems [8-10].

Poor quality or unrepresentative data in developing AI technologies can lead to significant issues, such as generative AI algorithms producing incorrect responses (known as “hallucinations”) and the degradation of machine learning model performance when encountering new data. These problems can disrupt operations and damage the public reputation of organizations, particularly in high-stakes environments like health care, thereby endangering patient outcomes and safety. Thus, data must be prioritized and scrutinized in discussions about AI, emphasizing the importance of ethical data collection, processing, and usage. Data ethics are critical for developing well-designed AI solutions and achieving responsible AI in health care, especially in technologies tailored for nursing.

Progressing from the existing literature, this viewpoint paper explores the principles of data ethics and their critical role in achieving responsible AI in health care and nursing. It also presents existing ethical data frameworks and strategies, emphasizing how data operations and usage contribute to generating high-quality data sets. These data sets are essential for training AI technologies to meet their intended performance and value objectives. The objectives of our viewpoints are to (1) introduce the principles of data ethics and relevant frameworks within the health care context; (2) examine how data-centric AI methodologies uphold the principles of data ethics by fostering the creation of high-quality data sets for machine learning; and (3) discuss the importance of AI data ethics, data-centric AI, and data quality for nursing practice, education, and research, including offering recommendations for future directions. We advocate further exploration and discussion of AI data ethics among nurses and nurse informatics researchers. With an effective organizational data governance structure and committed data-centric culture, we hypothesize that data ethics will significantly enhance AI development quality, thereby facilitating ethical and responsible AI solutions in practice, education, and research.

Responsible AI

Before discussing AI data ethics in depth, it is pertinent to introduce the concept of responsible AI, as its principles greatly influence those of AI data ethics. Responsible AI aims to ensure that AI systems are designed, developed, and deployed in ethical, fair, transparent, accountable, and beneficial ways to all intended users [11]. It is a multidimensional approach aiming to establish standards and values that prevent security issues, biases, and discrimination [12]. Five principles underpin the creation of responsible AI solutions and they are (1) accountability; (2) sustainability; (3) bias, fairness, and privacy; (4) transparency and explainability; and (5) robustness, security, and safety [13,14]. These principles also inform the principles of AI data ethics.

AI Data Ethics

About AI Data Ethics and Its Role in AI

Data ethics is a critical aspect of responsible AI focusing on the ethical aspects of data operations, including data collection, processing, and use. It encompasses a broad range of ethical issues related to data handling, whether the data are structured or unstructured, across various modalities [15-17]. Existing research indicates that poor data ethics can have significant consequences. For instance, 57% of consumers reported they would stop doing business with companies that breached their trust through irresponsible data practices [15]. Moreover, using suboptimal data to train machine learning algorithms can result in harmful outcomes for patients, such as misdiagnosis [18], misidentification [18,19], or data privacy breaches, even if the data were deidentified before use in machine learning algorithms [8].

In the context of this viewpoint report, it is crucial to analyze data independently from the machine learning algorithms that process it. This separation underscores the need for strategies, governance, a data-literate organizational culture, and ethical principles that ensure the creation and use of high-quality data for AI technologies. As Radziwill [20] noted, human error is often the root cause of bad data. Data may also reflect historical human biases embedded during their production, consumption, curation, and management. Therefore, data ethics is essential for addressing issues and unintended consequences stemming from poorly managed data.

Furthermore, there is a growing recognition of the importance of distinguishing data ethics from AI ethics, allowing for ethical decisions, specifically in data handling and the AI algorithms that use this data [16,17,21]. This approach emphasizes a data-centric perspective that focuses on the moral dimensions of data [16] and the ethical principles governing real-world and synthetic data [22].

Ethical Concerns Around Real-World and Synthetic Data in AI

Generative and predictive machine learning algorithms require extensive data sets to achieve performance objectives. Data scarcity has emerged as a significant concern within the AI and research communities, primarily due to the depletion of real-world training and validation data sets necessary for AI development. Several factors contribute to this issue, such as website owners increasingly protecting their data by enforcing data consent requirements [23]. It is projected that data scarcity could become a critical issue between 2026 and 2032 [24]. Additionally, the use of real-world data for AI development encounters problems such as missing data, which demands either imputation or deletion.

The generation of synthetic data is being accelerated to address issues related to data scarcity, privacy, and consent [22]. Synthetic data are expected to surpass real-world data by 2030 [22,25]. In the health care sector, synthetic data are used for simulation and prediction research, health IT development, education, and training [22,26]. Despite its benefits, generating synthetic data for AI development presents ethical dilemmas and risks, especially in high-stakes areas such as health care. For instance, although synthetic data can help represent diverse populations and reduce algorithmic biases, overreliance on such data can lead to challenges and unforeseen long-term effects of converting unrepresentative data into representative data [22]. Thus, ethical concerns arise regarding the non-maleficence and fidelity of synthetic data—whether it can address real-world disparities or prevent the dissemination of misinformation [22].

Principles of AI Data Ethics

Rhem [8] identified eight principles of AI data ethics, which are summarized as (1) transparency: is there clarity regarding the use, purpose, storage, and protection of the collected data? (2) Fairness: does the data collection and usage avoid exacerbating existing inequalities or biases? (3) Privacy: does the data collection process respect individuals’ privacy and autonomy, potentially through informed consent? (4) Responsibility: are data collectors and users accountable for ethical data collection and usage, including any harm resulting from these processes? Are mitigation steps in place? (5) Security: are data stored and transmitted securely to prevent unauthorized access, use, or disclosure? (6) Inclusivity: does the data collection and usage process ensure the inclusion of diverse perspectives and experiences, especially those that are underrepresented? (7) Transparency in decision-making: are decisions based on explainable and interpretable data? (8) Continual assessment: does the organization continuously monitor and assess its data practices to ensure they align with ethical principles [8]?

Shanley et al [22] were inspired by the five principles of responsible AI to initiate discussions on data ethics and synthetic data in AI. They proposed five principles to govern synthetic data (1) responsibility; (2) non-maleficence; (3) privacy; (4) transparency; and (5) justice, fairness, and equity [22]. These principles closely align with the globally recognized principles of AI—responsibility, non-maleficence, privacy, transparency, and justice and fairness [27]. Moreover, the ethical principles suggested by Shanley et al [22] and their associated questions correspond with Rhem's [8] AI data ethical principles. This alignment is detailed in Table 1, which includes an adaptation of Rhem's [8] principle of fairness.

Table . Summary of data ethical principles for AI[a].

Principles of AI data ethics	Rhem [8] questions	Shanley et al [22] questions	New addition
Transparency	Transparency: is there clarity regarding the use, purpose, storage, and protection of the collected data?	Transparency: how well does the synthetic data capture the phenomena it supposedly represents? How does the synthetic data deviate from the “real” data? What were the considerations when mitigating biases and how were they mitigated?	N/A[b]
Just, fair, and equitable data operations (DataOps)	Fairness: does the data collection and usage avoid exacerbating existing inequalities or biases?	Justice, fairness, and equity: are the underrepresented group’s diversity and emerging novelties adequately considered? How are the developers held accountable for watching new characteristics, traits, or phenomena emerging within the synthetic data set? What is the process of alerting developers of overreliance on synthetic data for groups or populations where data collection is more challenging or costly?	N/A
Privacy	Privacy: does the data collection process respect individuals’ privacy and autonomy, potentially through informed consent?	Privacy: what data privacy policies need to be used for synthetic data set generation and use, including who is responsible for the policies? How do we obtain meaningful consent from the individuals and communities impacted by using their data for synthetic data set generation? What notions of data ownership should pertain to synthetic data set creation?	N/A
Responsibility	Responsibility: are data collectors and users accountable for ethical data collection and usage, including any harm resulting from these processes? Are mitigation steps in place?	Responsibility: who decides when and for what purpose synthetic data set generation is justified? When are real-world data necessary, and when is it appropriate to partially apply synthetic data sets? Suppose synthetic data entails accounting for additional considerations during the decision-making process. Does its use imply new or different responsibilities for those involved in the AI supply value chain? What does this mean for the roles, responsibilities, and decision-making processes of those involved in generating and using the synthetic data?	N/A
Security	Security: are data stored and transmitted securely to prevent unauthorized access, use, or disclosure?	N/A	N/A
Inclusivity	Inclusivity: does the data collection and usage process ensure the inclusion of diverse perspectives and experiences, especially those that are underrepresented?	Non-maleficence: what is the gap between the real world in which the AI is intended to operate and the synthetic world in which it was trained? What means and measures can we use to describe the gap adequately? And what vocabulary can we use to make sense of the uncollected data in the real world regarding its status vis-à-vis knowledge or truth claims? What is the potential for intentional or unintentional misuse of synthetic data?	N/A

Principles of AI data ethics	Rhem [8] questions	Shanley et al [22] questions	New addition
Transparency in decision-making	Transparency in decision-making: are decisions based on explainable and interpretable data?	Transparency: see the transparency principle that is provided at the beginning of the table.	N/A
Continual assessment	Continual assessment: does the organization continuously monitor and assess its data practices to ensure they align with ethical principles?	N/A	N/A
Safety	N/A	N/A	Do data operation activities and processes consider, identify, and mitigate risks associated with preventing danger, risk, or injury to individuals (patients)?

[a] AI: artificial intelligence.

[b] N/A: not applicable.

Patient safety is paramount in health care and nursing, encompassing the protection of patients from events such as danger, risk, or injury. Security concerns freedom from danger or threats, whereas privacy analyzes the unauthorized access or use of patient data. We suggest incorporating a ninth principle, safety, into Rhem's [8] 8 principles of AI data ethics, as outlined in Table 1. A pertinent question for this new principle is "Do data operation activities and processes consider, identify, and mitigate risks associated with preventing danger, risk, or injury to individuals (patients)?" There is a dearth of consensus in the scientific and industrial literature from AI and health informatics research communities regarding definitions and practices that would guide AI data ethics. These definitions and shared principles are crucial for guiding the implementation and assessment of data ethics in clinical practice. As noted by Panai [21], data ethics represents an underdeveloped area within organizations and lacks a clear definition. Similarly, AI data ethics is a latent or underexplored area in health care and nursing informatics scientific research.

Ethical Data Frameworks

Numerous proposals exist for ethical data frameworks that support these principles. Floridi and Taddeo [16] advocate for a macroethical data ethics framework, which aims to avoid narrow, ad-hoc approaches and enables organizations to develop solutions that optimize the societal benefits of data science. Furthermore, Marcovitch and Rancourt [17] endorse standardized tools that facilitate the integration of data ethics accountability mechanisms, such as disclosure and transparency processes, at the organizational level. This is particularly important given the variations in legal frameworks across countries. Their proposed tools include the integration of data ethics into organizational culture, the establishment of data processes or management systems, a data governance structure, organizational transparency in ethical decision-making regarding the data supply chain, and a consistent method for demonstrating and verifying ethical data practices [17].

Note that the frameworks proposed by Floridi and Taddeo [16] and Marcovitch and Rancourt [17] are not specifically tailored to the context of health care or nursing. The absence of a verifiable theoretical or conceptual AI data ethics framework that supports research, alongside a practical evaluation framework that translates effectively into practice, represents a significant gap in health and nursing informatics research. The ideas presented by Floridi and Taddeo [16] and Marcovitch and Rancourt [17] could serve as a foundation for developing such frameworks within the nursing field.

Ethical Data Frameworks Challenges

Without a shared organizational data vision, strategy, and policies, implementing aspects of the proposed data ethical frameworks may be challenging, including risking data integrity. There needs to be clarity and knowledge about the responsibilities and liabilities of the people in charge of the data processes. The accountability and culture change should begin with the organization's executive team. Then, the executive team members intelligibly communicate the data cultural expectations, and policy changes to their departments, units, and teams. There is clarity about the responsibilities and liabilities of people who produce and consume the organizational data assets.

Nurses are producers and consumers of organizational data assets. For instance, they produce electronic health record (EHR) data and use them for nursing quality improvement initiatives. Positive deviance in effective data practices could be the impetus for remarkable cultural changes when poor data management practices are in place due to the absence of an organizational-level data vision, strategy, and policies. Suppose a nurse leader is passionate about the societal benefits of data science and AI, including taking the initiative to understand the importance of data quality. This individual becomes a change agent for their team. Their team's culture becomes data-centric, with patient safety and outcomes at the forefront. The team develops policies and standardized procedures that facilitate improved EHR data entry processes, which are less burdensome for the nurse but help them be accountable to the principles of AI data ethics. The team expresses knowledge about how data quality impacts patient care and the technologies they use in clinical settings. They observe technology as a mechanism to provide quality nursing care. Their attitudes and behaviors result in improved data quality for the nursing unit. This team is now a data vanguard. Other departments and nursing teams notice that this nursing unit outputs high-quality data, leading to improved insights for the unit. This "positive deviant" team's data practices led to informative unit-level reports, fewer data-related errors, and enhanced patient outcomes. Other nursing teams are curious and want to model this team's effective data procedures and practices. This influence could motivate the organization's nursing departments to follow suit.

Data-Centric AI

Model-Centric and Data-Centric AI Paradigms

AI technologies that leverage machine learning require substantial data for effective functioning. Machine learning is a subset of AI that enables computers to learn and adapt autonomously through algorithms and statistical models, with minimal or no human intervention. These systems demand extensive data volumes, with generative AI requiring even larger data sets and greater computing power to discern underlying patterns in the data. Historically, the development of prevalent AI technologies has adopted a model-centric strategy, prioritizing the machine learning algorithm or model as the primary focus for enhancing performance [28]. In this approach, data-related activities such as curation, collection, and labeling are often deprioritized and occur only once, leading to potential ethical issues such as algorithmic bias and mispredictions.

The model-centric approach does not adequately address the principles of data ethics, as it overlooks the complexity, nuances, challenges, and accuracy of data, which are vital for improving the behavior of machine learning models [29]. Recognizing these limitations, the AI industry is shifting toward a data-centric strategy, which places data—the "fuel" of AI—at the core of the development process [28-30]. This strategy emphasizes the importance of data quality to achieve high-performance machine learning models [9,29]. Unlike the model-centric approach, data activities in the data-centric strategy are iterative, while model optimization remains static [9,29]. This approach also promotes the involvement of domain experts to secure relevant, high-quality data sets for machine learning [30].

Data-Centric AI Role in Achieving Data Ethics and Responsible AI

The data-centric AI methodology involves developing, iterating, tracking, and maintaining the quality and integrity of AI systems' data. It focuses on creating adequate training data, designing appropriate inference data, and ensuring data sustainability (establishing data lineage) [29]. Given the importance of high-quality data, the data-centric approach aligns with the principles of data ethics and responsible AI. For instance, meticulous data curation and collection support ethical principles of fairness, responsibility, and transparency. The involvement of domain experts such as clinicians, clinical informaticists, and regulatory and privacy specialists promotes inclusivity, transparent decision-making, and privacy protection. These diverse perspectives help safeguard patient data privacy and prevent harm from substandard data. Considering data sets as a distinct and valuable product separate from the machine learning model also encourages health care organizations to establish continuous assessment protocols for their data collection and usage practices.

Significance of Data-Centric AI and AI Data Ethics in Nursing

In the broader health care context, we integrated the principles of data ethics and related data-centric AI strategies into nursing practices, emphasizing their role in creating high-quality data sets for machine learning. We now explore the significance of these concepts in nursing. First, AI has become increasingly prevalent in both nursing research and practice. A recent scoping review highlighted various AI activities and applications within nursing [31]. Nurse researchers and informaticists need to understand the distinctions between model-centric and data-centric AI [32] and their impacts on developing safe and effective AI technologies in health care settings, which influence care processes and workflows. This paper aims to establish a consensus on AI data ethics in nursing and motivate nurse informatics researchers to investigate further and discuss this crucial topic.

Second, numerous machine learning algorithms in health care use data from EHRs. Nurses, who are primary users of EHRs [33,34], generate various electronic clinical documents detailing different aspects of patient care and progress (eg, admission assessments, nursing care plans, nursing education, and medication administration). We hypothesize that most frontline nurses are unaware of how their EHR data influences the performance and use of AI technologies. There is an existing awareness of the negative consequences of poorly designed EHR user interfaces on data quality in research and practice [35-38]. To effectively use EHR data in developing AI-driven clinical decision support systems, data collection and processing by the EHR user community must be optimized [35]. Integrating AI data ethics into both practice and academic nursing curricula could enhance awareness about how EHR data are used by downstream systems and the role nurses play in generating high-quality EHR data for AI technologies. This approach introduces new research opportunities, such as examining the relationships between nurses' data literacy and AI-related data quality.

Third, nurses who are more aware of data-centric AI and the principles of data ethics could increase their confidence in collaborating with data scientists, engineers, and other AI specialists on data-centric projects to produce meaningful, high-quality data and data sets. These efforts lead to development of high-performance machine learning models that align with nurses' workflows. This applies to both real-world and synthetic data used in machine learning. Nurses provide valuable insights into patient safety and privacy and understand data collection at the point of care. Their contributions are crucial in helping health care organizations adhere to the principles of AI data ethics, develop responsible AI technologies that enhance their workflows, and support safe patient care.

Nursing Practice and Research Implications

Machine learning algorithms, such as generative AI algorithms trained on poor-quality and unrepresentative data sets, can create significant political consequences in health care, such as exacerbating bias and health disparities. AI data ethics and data-centric AI represent emerging concepts in nursing. The nursing literature on these topics is limited, including discussions on the implications of using synthetic data to develop AI technologies tailored for nursing.

Finally, fictional nurse-oriented ethical case studies are presented in Textboxes 1 and 2. They illustrate potential ethical data breaches in real-world scenarios. These case studies can help nurses become informed about why AI data ethics should matter to them and examine their data practices, ensuring they perform their best in not becoming unknowingly enablers of data issues but high-data quality contributors and problem-solvers.

Textbox 1. Fictional nurse-specific case study #1: real-world data.

Electronic health record (EHR) burnout leading to poor data entry with adverse data cascade effects

Ava is a new graduate nurse in her fourth month of orienting on a busy adult medical-surgical unit. Six hours into her third consecutive 12-hour night shift, she must complete electronic clinical documentation for 4 patients in the EHR. Ava is sleep-deprived and highly stressed as she adjusts to becoming a competent med-surg nurse who can function without the supervision of a nurse preceptor. Additionally, her patient load was intense during this shift. She received a new admission from the telemetry floor about a few hours ago, a 70-year-old male patient named Carl. Carl arrived at Ava's unit moderately agitated and had a newly placed trach. Ava is ready to end her shift and get the much-needed respite. She must complete assessment documentation for Carl before the shift changes. The copy-forward feature was leveraged to accelerate Carl's assessment documentation, essentially copying some data elements previously documented by a telemetry nurse in the EHR. A data entry error embedded in the previous admission note is unknown to Ava. There is a mistake concerning Carl's medical history. In the telemetry admission note, the patient's smoking status was mistakenly documented as "Non-smoker," although a relative communicated that Carl currently smokes. This incorrect value was pulled into Ava's shift assessment note via the copy-forward function. Moreover, due to exhaustion, Ava did not realize her assessment notes became bloated with irrelevant and duplicate data because of the copy-forward option. The shift assessment documentation copy-forward action occurred repeatedly by subsequent nurses caring for Carl during his hospitalization.

A few years later, a data scientist is requested to build a new machine learning model that will predict patients having a history of smoking and at risk for moderate to severe mental instability during their hospitalizations because of nicotine withdrawal and other socioeconomic factors. Furthermore, the final artificial intelligence (AI) solution will generate nursing care plans and patient education recommendations. This project was inspired by nurses' desires to provide equitable care, taking precautionary steps to ensure these patients are comfortable and safe during their hospital stays. The erroneous data tied to Carl's previous hospital encounter were included in the training data set. An expert nurse was not engaged in the data collection and the data set validation processes.

AI data ethical principle breach and brief commentary:

- Responsibility: which data owners or consumers are accountable for the insufficient EHR data used to develop the machine learning model? What are the mitigation steps for mispredictions or generative AI hallucinations that may result in patient harm?
- Inclusivity: how are we assured that the data sets represent the use case and intended patient population? This case study presents missing perspectives from nurse stakeholders, patient advocates, and critical decision makers.
- Safety: a patient encounter with characteristics like Carl's data is predicted to be low risk, and hence, no recommendations were made by the AI solution. An expert nurse may catch the misprediction and take corrective steps. However, an inexperienced nurse may trust the prediction. This is a missed opportunity, and the proper treatment may be delayed or denied, potentially leading to an adverse patient outcome and reputational harm for the organization.

Textbox 2. Fictional nurse-specific case study #2: synthetic data.

Generating synthetic data for health equity machine learning

A data scientist is developing a nurse-specific machine learning model to predict whether patients are at risk of nonadherence to cardiac care at-home instructions, increasing their readmission risks. The discharge nurse provides and discusses these instructions with the patient before they are discharged from the hospital to home. The anonymized training and validation data sets have 500 and 300 observations, respectively, derived from the hospital's electronic health record (EHR) data. The data sets are not representative of a diverse patient population. This concern is significant to the data scientist because the data sets incorporate social drivers of health data elements (SDOH). After all, the project is funded by a federal grant with an initiative to improve health equity among disadvantaged patients in the United States. So, the data set must represent a diverse patient population. No formal organizational artificial intelligence (AI) data ethical policies or data ethics oversight committee exists to guide synthetic data creation. The data scientist does their best to add between 30 and 50 fictional observations, using the available training and validation data sets to guide the synthetic data modeling.

AI data ethical principle breach and brief commentary:

- Just, fair, and equitable data operations: the data scientist worked alone to create an assumable diverse data set. This decision should involve multiple key stakeholders and a vetting process to ensure the organization does not experience reputational harm and to protect patients from adverse outcomes. The potentially biased data set used to train the machine learning model may result in unforeseen algorithmic bias.
- Responsibility: if an adverse patient outcome occurs because a nurse trusted the predictions made by this machine learning model, who is held responsible? What does the root cause analysis process look like?
- Inclusivity: the "diverse" data set the data scientist developed may be insufficient and unrepresentative of the intended target population. What policies are guiding the decision around what is considered inclusive data? There are missing perspectives from key stakeholders.
- Transparency in decision-making: can the data scientist adequately explain the decisions behind developing the data sets to nontechnical users? After making a prediction, does the AI solution provide interpretable results that could guide nurses about how it arrived at its conclusion?
- Safety: has the data scientist documented the data activities, including the identified risks to nurses and their patients and the risks' mitigation plans?

Recommendations for Nursing

We present 4 recommendations to enable nurses to engage with and contribute to developing responsible AI technologies that align with their workflows and adhere to the principles of AI data ethics. Implementation of the recommendations could transform nursing care, practice, and education around data. They aim to prepare nurses for their future in practicing and learning in health care AI. Transformations include (1) AI technologies effectively reduce nurses' burdensome documentation, (2) AI and data-literate nurses experiencing a reduction in technological fears like job displacement—rather than fearing the technology, learn and use it to their advantage, (3) nurses advocating for their profession and patients by getting involved in the design of AI technologies, and (4) nurses' improved data knowledge and management practices leading to insights that positively impact patient outcomes and the service they provide to their patients.

Recommendation 1: Data Ethics Engagement Necessitates Data Literacy in AI

As AI becomes increasingly integral to the daily responsibilities of nurses across various clinical and administrative settings, nurse leadership must promote a data-centric culture within the nursing profession. Leaders should serve as role models, emphasizing the importance of data quality in nursing practice. One approach to achieving this is by enhancing nurses' understanding of AI and data. Nurses need to comprehend how downstream systems use the data they produce in EHR. It is crucial to reflect, correct, and evolve from the existing cultural norms and power dynamics that hinder effective EHR data collection, establishing a new culture that recognizes the importance of maintaining data quality at the point of care.

Additionally, nurse educators and researchers should strive to improve their AI and data literacy skills and develop new curricula to bridge the knowledge gap in AI and data among nursing students, particularly those enrolled in nurse informatics programs or those pursuing research in informatics. Data literacy is the ability to explore, read, write, understand, and communicate meaningfully within a specific context [39,40].

Improved data literacy facilitates discussions regarding data usage and ethics in AI. Establishing a common language that clearly defines data literacy and ethics in nursing is necessary, including the principles of AI data ethics to guide the development of nurse-specific AI technologies. Furthermore, a shared language and a solid foundation in data knowledge equip nurses to act as data stewards, engage in ethical discussions, innovate in data management, and collaborate with AI specialists to develop responsible, nurse-specific AI technologies. These initiatives align with the principles of inclusivity and responsibility in AI data ethics.

Recommendation 2: Data-Oriented Culture Motivates Ethical Accountability Mechanisms

Creating and nurturing a data-oriented culture among nurses can enhance their involvement in ethical accountability mechanisms for AI data, as outlined by Marcovitch and Rancourt [17]. However, the concept of data ethics remains poorly defined, leading to overlapping responsibilities and ambiguous accountabilities. This lack of clarity can hinder the effective detection of ethical violations in data use, as data ethics often merges into broader ethical principles that are insufficient at the granular level of data abstraction [21]. Consequently, there is a need for specific job roles focused on how data ethics can inform ethical decisions regarding data and the machine learning algorithms that process it. These roles would involve establishing relevant policies and practices and advocating for the consumer—here, the patient. Thus, the recommendation to establish a Chief Data Ethics Officer role emerges [21,41]. The mandate of this officer is ethical rather than legal [41], focusing on leading a support team responsible for drafting a code of data ethics, forming and managing a data ethics committee, and overseeing data-oriented ethical issues [21].

With a data-centric organizational culture, data governance, and a Chief Data Ethics Officer, nurse leaders and researchers can explore and implement innovative, nursing-centric data roles. These roles are crucial for upholding the principles of AI data ethics in nursing practice and creating standardized data accountability tools, policies, and processes that effectively evaluate and measure AI data ethics in nurse-specific AI technologies. Job roles such as Chief Nurse Data Ethics Officer and Nurse Data Steward should be explored further.

Nurse educators should implement courses that prepare nurses for data-oriented roles in AI. Nursing degree programs at both undergraduate and graduate levels should be adapted to include relevant courses on AI, data ethics, foundational data science, and data literacy. Nurse scientists are encouraged to explore novel approaches, frameworks, and instruments that enable the integration of ethical accountability mechanisms and effectively assess the principles of AI data ethics reinforced by scientific evidence.

Recommendation 3: Optimal Data Quality Is Conditioned on Domain Expertise Participation

Domain expertise is essential for generating high-quality data [32], and human involvement is critical to successfully executing data-centric AI tasks [29]. Nurses can use their knowledge of data-centric AI and data ethics to actively engage in all phases of AI development and positively leverage their expertise. Specifically, nurse informaticists have opportunities to participate in activities such as data annotation, labeling, and the verification and validation of data elements used in AI data sets. Furthermore, throughout the AI development lifecycle, nurses can play a pivotal role in identifying and addressing opaque data decisions that may affect frontline clinicians' trust and usage of AI technologies, thereby enhancing transparency in decision-making processes. The active involvement of nurses in these data-centric AI activities, combined with their commitment to patient advocacy, supports the ethical principles of data privacy and promotes accountability and ownership of data collection, processing, and use.

Recommendation 4: High-Quality, Ethical Data Curtails Health Care Political Consequences

Nurse leaders, educators, and researchers must recognize that implementing responsible AI technologies and initiatives in health care is complex and challenging, despite significant interest in AI ethics [5]. This statement is not intended to deter nurses from exploring methods to develop ethical AI technologies that use high-quality, representative clinical data. Instead, it aims to raise awareness and encourage nurses to persevere through challenges, including maintaining patience and resilience during the change management process. AI technologies are often politically influenced, reflecting their designer's values, beliefs, and norms, as well as the data and data sets used to train them [5,42]. Political consequences may arise from data operations such as selection, labeling, preprocessing, and transformation [42]. Nurses, working at various touchpoints across diverse settings in the health care ecosystem, bring unique perspectives to the AI discussion, which can help promote and advocate for the principles of AI data ethics.

Conclusions

Working with data is time-consuming and challenging and often perceived as less exciting than developing machine learning models or AI technologies. Despite this, the foundational role of data in AI systems cannot be overstated; high-quality data are crucial for the performance and value of AI technologies in health care. The principles of AI data ethics aim to promote responsible AI and the creation of ethical AI technologies [8]. The methods used to collect, store, use, and share data have profound implications for individuals, organizations, and society [8].

Conflicts of Interest

None declared.

References

1. AI in healthcare market size, share & trends analysis report by component (hardware, services), by application, by end-use, by technology, by region, and segment forecasts, 2024 - 2030. Grand View Research. 2023. URL: https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-healthcare-market [accessed 2023-10-14]
2. AI ethics case studies & AI incident registries. AI Ethicist. URL: https://www.aiethicist.org/ethics-cases-registries [accessed 2023-12-28]
3. Bhattacharyya M, Miller VM, Bhattacharyya D, Miller LE. High rates of fabricated and inaccurate references in ChatGPT-generated medical content. Cureus 2023 May;15(5):e39238. [doi: 10.7759/cureus.39238] [Medline: 37337480]
4. Emsley R. ChatGPT: these are not hallucinations - they're fabrications and falsifications. Schizophrenia (Heidelb) 2023 Aug 19;9(1):52. [doi: 10.1038/s41537-023-00379-4] [Medline: 37598184]
5. Siala H, Wang Y. SHIFTing artificial intelligence to be responsible in healthcare: a systematic review. Soc Sci Med 2022 Mar;296:114782. [doi: 10.1016/j.socscimed.2022.114782] [Medline: 35152047]

6. Mittermaier M, Raza MM, Kvedar JC. Bias in AI-based models for medical applications: challenges and mitigation strategies. NPJ Digit Med 2023 Jun 14;6(1):113. [doi: 10.1038/s41746-023-00858-z] [Medline: 37311802]
7. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science 2019 Oct 25;366(6464):447-453. [doi: 10.1126/science.aax2342] [Medline: 31649194]
8. Rhem AJ. Ethical use of data in AI applications. In: Miroslav R, editor. Ethics - Scientific Research, Ethical Issues, Artificial Intelligence and Education, 1st edition: IntechOpen; 2023. [doi: 10.5772/intechopen.1001597]
9. Budach L, Feuerpfeil M, Ihde N, et al. The effects of data quality on machine learning performance. arXiv. Preprint posted online on Jul 29, 2022. [doi: 10.48550/arXiv.2207.14529]
10. Ng A. A chat with Andrew on mlops: from model-centric to data-centric AI. YouTube. 2021. URL: https://www.youtube.com/watch?v=06-AZXmwHjo [accessed 2022-10-08]
11. Zhang R, Zhang Z, Wang D, Liu Z. Editorial: responsible AI in healthcare: opportunities, challenges, and best practices. Front Comput Sci 2023;5. [doi: 10.3389/fcomp.2023.1265902]
12. Merhi MI. An assessment of the barriers impacting responsible artificial intelligence. Inf Syst Front 2023 Jun;25(3):1147-1160. [doi: 10.1007/s10796-022-10276-3]
13. OECD AI principles overview. OECDAI Policy Observatory. URL: https://oecd.ai/en/ai-principles [accessed 2024-08-22]
14. Frequently asked questions: what is responsible artificial intelligence (rAI)? Responsible Artificial Intelligence Institute. URL: https://www.responsible.ai/faq/ [accessed 2024-08-22]
15. Data ethics: what is data ethics? Cognizant. URL: https://www.cognizant.com/us/en/glossary/data-ethics [accessed 2023-11-28]
16. Floridi L, Taddeo M. What is data ethics? Philos Trans A Math Phys Eng Sci 2016 Dec 28;374(2083):20160360. [doi: 10.1098/rsta.2016.0360] [Medline: 28336805]
17. Marcovitch I, Rancourt E. A data ethics framework for responsible responsive organizations in the digital world. Statistical J IAOS 2022;38(4):1161-1172. [doi: 10.3233/SJI-220067]
18. Roberts M, Driggs D, Thorpe M, et al. Common pitfalls and recommendations for using machine learning to detect and prognosticate for COVID-19 using chest radiographs and CT scans. Nat Mach Intell 2021;3(3):199-217. [doi: 10.1038/s42256-021-00307-0]
19. Heaven WD. Hundreds of AI tools have been built to catch covid. None of them helped. MIT Technology Review. 2021. URL: https://www.technologyreview.com/2021/07/30/1030329/machine-learning-ai-failed-covid-hospital-diagnosis-pandemic/ [accessed 2023-12-02]
20. Radziwill NM. Data, Strategy, Culture & Power: Win with Data-Centric AI by Making Human Nature Work for You, 1st edition: Lapis Lucera; 2024.
21. Panai E. The latent space of data ethics. AI & Soc 2023. [doi: 10.1007/s00146-023-01757-3]
22. Shanley D, Hogenboom J, Lysen F. Getting real about synthetic data ethics: are AI ethics principles a good starting point for synthetic data ethics? EMBO Rep 2024 May;25(5):2152-2155. [doi: 10.1038/s44319-024-00101-0] [Medline: 38388694]
23. Longpre S, Mahari R, Lee A, et al. Consent in crisis: the rapid decline of the AI data commons. Data Provenance Initiative. URL: https://www.dataprovenance.org/consent-in-crisis-paper [accessed 2024-08-22]
24. Villalobos P, Sevilla J, Heim L, Besiroglu T, Hobbhahn M, Ho A. Will we run out of data? An analysis of the limits of scaling datasets in machine learning. arXiv. Preprint posted online on Oct 26, 2022. [doi: 10.48550/arXiv.2211.04325]
25. Linden A. Is synthetic data the future of AI. Gartner. URL: https://www.gartner.com/en/newsroom/press-releases/2022-06-22-is-synthetic-data-the-future-of-ai [accessed 2024-08-22]
26. Gonzales A, Guruswamy G, Smith SR. Synthetic data in health care: a narrative review. PLOS Dig Health 2023 Jan;2(1):e0000082. [doi: 10.1371/journal.pdig.0000082] [Medline: 36812604]
27. Jobin A, Ienca M, Vayena E. The global landscape of AI ethics guidelines. Nat Mach Intell 2019;1(9):389-399. [doi: 10.1038/s42256-019-0088-2]
28. Hamid OH. From model-centric to data-centric AI: a paradigm shift or rather a complementary approach? 2022 Presented at: 2022 8th International Conference on Information Technology Trends (ITT); May 25-26, 2022; Dubai, United Arab Emirates. [doi: 10.1109/ITT56123.2022.9863935]
29. Zha D, Bhat ZP, Lai KH, et al. Data-centric artificial intelligence: a survey. arXiv. Preprint posted online on Mar 17, 2023. [doi: 10.48550/arXiv.2303.10158]
30. Data-centric AI vs. model-centric AI - everything you need know. Artificial Intelligence Board of America. 2022. URL: https://www.artiba.org/blog/data-centric-ai-vs-model-centric-ai-everything-you-need-know [accessed 2022-12-14]
31. Hwang GJ, Chang PY, Tseng WY, Chou CA, Wu CH, Tu YF. Research trends in artificial intelligence-associated nursing activities based on a review of academic studies published from 2001 to 2020. Comput Inform Nurs 2022 Dec 1;40(12):814-824. [doi: 10.1097/CIN.0000000000000897] [Medline: 36516032]
32. Ball Dunlap PA, Nahm ES, Umberfield EE. Data-centric machine learning in nursing: a concept clarification. Comput Inform Nurs 2024 May 1;42(5):325-333. [doi: 10.1097/CIN.0000000000001102] [Medline: 38241753]
33. Collins S, Couture B, Kang MJ, et al. Quantifying and visualizing nursing flowsheet documentation burden in acute and critical care. AMIA Annu Symp Proc 2018;2018:348-357. [Medline: 30815074]

34. Sutton DE, Fogel JR, Giard AS, Gulker LA, Ivory CH, Rosa AM. Defining an essential clinical dataset for admission patient history to reduce nursing documentation burden. Appl Clin Inform 2020 May;11(3):464-473. [doi: 10.1055/s-0040-1713634]
35. Madandola OO, Bjarnadottir RI, Yao Y, et al. The relationship between electronic health records user interface features and data quality of patient clinical information: an integrative review. J Am Med Inform Assoc 2023 Dec 22;31(1):240-255. [doi: 10.1093/jamia/ocad188] [Medline: 37740937]
36. Diaz-Garelli F, Strowd R, Lawson VL, et al. Workflow differences affect data accuracy in oncologic EHRs: a first step toward detangling the diagnosis data babel. JCO Clin Cancer Inform 2020 Jun;4:529-538. [doi: 10.1200/CCI.19.00114] [Medline: 32543899]
37. Johnson CM, Johnston D, Crowley PK, et al. EHR usability toolkit: a background report on usability and electronic health records. Agency for Healthcare Research and Quality, US Department of Health and Human Services. 2011. URL: https://digital.ahrq.gov/sites/default/files/docs/citation/EHR_Usability_Toolkit_Background_Report.pdf [accessed 2024-08-25]
38. Staggers N, Elias BL, Makar E, Alexander GL. The imperative of solving nurses' usability problems with health information technology. J Nurs Adm 2018 Apr;48(4):191-196. [doi: 10.1097/NNA.0000000000000598] [Medline: 29570144]
39. Panetta K. A data and analytics leader's guide to data literacy. Gartner. 2021. URL: https://www.gartner.com/smarterwithgartner/a-data-and-analytics-leaders-guide-to-data-literacy#:~:text=What%20is%20data%20literacy%3F,case%2C%20application%20and%20resulting%20value [accessed 2024-01-13]
40. Stobierski T. Data literacy: an introduction for business. Harvard Business School Online. 2021. URL: https://online.hbs.edu/blog/post/data-literacy [accessed 2024-01-13]
41. Ray B. Why marketers need a chief data ethics officer now. AiThority. 2023. URL: https://aithority.com/technology/why-marketers-need-a-chief-data-ethics-officer-now/ [accessed 2024-08-27]
42. Faraj S, Pachidi S, Sayegh K. Working and organizing in the age of the learning algorithm. Inf Org 2018 Mar;28(1):62-70. [doi: 10.1016/j.infoandorg.2018.02.005]

Abbreviations

AI: artificial intelligence
EHR: electronic health record

Edited by E Borycki; submitted 28.05.24; peer-reviewed by CSY Park, L He; revised version received 08.09.24; accepted 13.09.24; published 25.10.24.

Please cite as:
Ball Dunlap PA, Michalowski M
Advancing AI Data Ethics in Nursing: Future Directions for Nursing Practice, Research, and Education
JMIR Nursing 2024;7:e62678
URL: https://nursing.jmir.org/2024/1/e62678
doi:10.2196/62678

Viewpoint

Software Testing of eHealth Interventions: Existing Practices and the Future of an Iterative Strategy

Oyinda Obigbesan[1]; Kristen Graham[2], BSc, MBA; Karen M Benzies[1,3], RN, PhD

[1]Cumming School of Medicine, University of Calgary, Calgary, AB, Canada
[2]Haskayne School of Business, University of Calgary, Calgary, AB, Canada
[3]Faculty of Nursing, University of Calgary, Calgary, AB, Canada

Corresponding Author:
Karen M Benzies, RN, PhD
Faculty of Nursing
University of Calgary
2500 University Drive NW
Calgary, AB, T2N 1N4
Canada
Phone: 1 403 220 2294
Email: benzies@ucalgary.ca

Abstract

eHealth interventions are becoming a part of standard care, with software solutions increasingly created for patients and health care providers. Testing of eHealth software is important to ensure that the software realizes its goals. Software testing, which is comprised of alpha and beta testing, is critical to establish the effectiveness and usability of the software. In this viewpoint, we explore existing practices for testing software in health care settings. We scanned the literature using search terms related to eHealth software testing (eg, "health alpha testing," "eHealth testing," and "health app usability") to identify practices for testing eHealth software. We could not identify a single standard framework for software testing in health care settings; some articles reported frameworks, while others reported none. In addition, some authors misidentified alpha testing as beta testing and vice versa. There were several different objectives (ie, testing for safety, reliability, or usability) and methods of testing (eg, questionnaires, interviews) reported. Implementation of an iterative strategy in testing can introduce flexible and rapid changes when developing eHealth software. Further investigation into the best approach for software testing in health care settings would aid the development of effective and useful eHealth software, particularly for novice eHealth software developers.

(JMIR Nursing 2024;7:e56585) doi:10.2196/56585

KEYWORDS

eHealth; health system; digital health; mHealth; mobile health; app; software testing; alpha testing; beta testing; usability testing; agile development; health applications; software; usability; literature review; narrative review; testing; ICT; information and communication technology; reliability; safety

Introduction

eHealth interventions are becoming a part of standard care, with mobile apps or software solutions being created for patients and health care providers. For example, we designed a digital audit software for a new model of care called Merge (which is better known in research and development as Alberta Family Integrated Care) that improves outcomes by integrating families of newborns with critical illness into the neonatal intensive care unit (NICU) team [1]. Merge was adopted in all 14 NICUs in Alberta, Canada, through a process that involves quarterly fidelity audits, which are central to implementation success and sustainability. We replaced the manual and labor-intensive audits with this fidelity audit software to increase efficiency and reduce personnel costs.

Appropriate software testing is important to ensure that an eHealth intervention realizes its goals, which may include improving access, efficiency, and quality of care [2]. Software testing, which includes alpha and beta testing, is critical to establish the effectiveness and usability of an eHealth software. In this viewpoint, we define alpha testing in accordance with the Guide to the Software Engineering Body of Knowledge [3], as internal software testing, which occurs first and is often performed within the development team [4]. Subsequently, beta testing is performed, which is external and involves a larger testing sample representative of the end-user population [3,4].

When we set out to test the Merge fidelity audit software, we wanted to identify software testing practices for novice eHealth software developers. Thus, we performed an exploratory scan of the literature to understand and identify existing methods for testing software in health care settings.

For our exploratory scan, we used Google Scholar and search terms related to eHealth software testing (eg, “health alpha testing,” “eHealth testing,” and “health app usability”). We included research articles that described their process of either alpha or beta testing and were either patient- or health care provider–facing. We excluded articles if they were nonpeer-reviewed literature published before 2015 from a non-Organisation for Economic Co-operation and Development member country because we were interested in recent practices conducted in similar health care contexts. We identified 34 articles that met our inclusion criteria; among these, we selected 7 articles for this viewpoint about software testing practices (Multimedia Appendix 1), including 5 primary research articles [5-9], 1 review article [10], and 1 framework [11].

Lack of a Standardized Testing Framework

There was not a single standardized framework for software testing that was used across the 5 primary research articles [5-9]; 2 articles [7,8] cited two different frameworks, while the other 3 articles did not cite any. Fishbein et al [8] used Darlow and Wen’s [12] best practices to guide the development of their mobile health (mHealth) intervention. The practices relevant for software testing included using mixed methods (eg, questionnaires, semistructured interviews), engaging stakeholders (eg, software designers, subject matter experts, health professionals, patients), and publishing the results of testing to facilitate learning from successes and difficulties [12]. Cho et al [7] used the 3-level stratified view of health IT usability evaluation [13]. Levels of testing, as defined by this framework, consisted of (1) a user-centered design, which incorporated users’ needs in the development phase; (2) a usability evaluation in a laboratory setting, where testing occurred in a regulated environment; and (3) usability in a real-world setting, which assessed user experience in practical applications [7,13]. In Cho et al [7], levels 2 and 3 most closely correspond to beta testing, as testers are representative of the end-user population [7]. While Darlow and Wen’s [12] best practices provide guidelines regarding what the testing should include, the stratified view of health IT usability evaluation [13] provides more specific guidance on how to conduct testing and what each phase may entail. However, both frameworks involve multiple methods of testing to gain comprehensive user feedback and aim to create standardization in testing to ensure the rigor of eHealth interventions. The lack of standardization in software testing raises issues concerning consistency in quality assurance, which has the potential to compromise patient safety. Additionally, the lack of clear guidelines for testing can lead to inefficiencies in the allocation of the development team’s time and resources.

Objectives and Methods of Testing

Although few articles used a specific framework for testing, there were some similarities in the general process among the 5 primary research articles[5-9] (Multimedia Appendix 1). For both alpha and beta testing, this involved defining the objectives of testing, selecting testers and methods of evaluation, collecting and analyzing data, and refining the software.

The desired result of testing was the evaluation of different aspects of the eHealth software. Only 2 articles [5,6] clearly stated their objectives for testing. Ahonen et al [5] planned to identify content acceptability, feasibility, and technical issues during alpha testing of their eLearning intervention. For their mHealth intervention, Athilingam et al [6] aimed to evaluate design and functionality during alpha testing, followed by evaluations of helpfulness, usability, and design during beta testing. In addition to these objectives, software testing was used to evaluate safety, reliability, effectiveness, satisfaction, and accessibility, and to determine if the software fulfilled its intended purpose [14]. While the objectives of testing may overlap between alpha and beta testing, alpha testing may have a greater focus on software-specific objectives (eg, safety and bug fixes) and beta testing may focus on user experience–related objectives (eg, design and satisfaction) [4].

Selecting testers was an important testing step mentioned in all articles that described testing; however, the distinction between alpha and beta testing was often obscured at this stage. Several authors [5,6] stated that they were conducting alpha testing, yet the testing sample included members of the end-user population, which is more appropriately aligned with the definition for beta testing. For example, Athilingam et al [6] described alpha testing of their mobile app for patients with heart failure, but the testing sample consisted of the target end users (ie, people with a history of heart failure). Additionally, there was no clear justification for the size of the testing sample, which ranged from 2 to 76 testers [5-9]. In a scoping review, the sample size for software testing was found to vary according to the method of testing, with studies based on qualitative methods having fewer testers than those based on quantitative methods [10]. Most studies opted for a larger number of testers and tested their software only once. Hoffiman et al [9] had only 2 alpha testers who tested their Public Open Space Tool software on 55 different green spaces. The feasibility of this strategy depended on the same tester generating new insights during each round of alpha testing.

The most common methods of testing were questionnaires, “think-aloud” techniques, interviews, and focus groups [10]. The literature suggests using qualitative methods of testing over quantitative methods because qualitative methods generally result in a deeper understanding of user experience and gaps in the software [5,10]. Mixed methods were used in several studies [5,7,8,10], where quantitative methods (eg, questionnaires) were used to gain initial feedback followed by in-depth qualitative data collection (eg, interview or focus group) to ensure that the feedback was valuable and instructive. Using mixed methods allowed development teams to discover latent information and gain a better understanding of their participants’ experiences and needs [7,10].

When selecting a method of testing, development teams should particularly consider their specific testing sample. Methods of testing that may be effective for alpha testers may be unsuccessful when used with beta testers. Factors affecting the accuracy of testing data include the length of testing, question clarity and interpretation, question sequence, and the context in which testing takes place [15]. The general approach to software testing culminated in the collection and analysis of data, which were then used to create an iteration of the eHealth intervention.

Throughout the testing process of eHealth software, it is essential to uphold ethical principles due to the sensitive nature of health data and the potential impact on patient well-being. This includes ensuring patient privacy and confidentiality in compliance with national health care regulations, obtaining informed consent prior to participation, and adopting data protection and security measures to protect sensitive information [16,17].

An Iterative Strategy

The success of eHealth development depends on the ability to adapt to the rapidly evolving nature of the digital world and changing user needs. Development teams interested in building eHealth interventions must consider how to ensure that testing occurs quickly, while still guaranteeing rigor and protecting privacy. Wilson et al [11] proposed an "mHealth Agile and User-Centered Research and Development Lifecycle" that combines an agile approach with traditional clinical trial phases to create high-quality mHealth interventions. Using an agile approach involves continuous iterative cycles that prioritize providing feedback on the software at frequent intervals. Compared to a linear approach to development, continuous evaluation of the developing software enhanced team collaboration, improved the quality of the software, and allowed for ongoing improvement with emphasis on end-user feedback [11]. Wilson et al [11] further suggested that alpha testing can be used to gain first-impression, surface-level insights from the development team, focusing on usability, desire to use, fulfillment of intended purpose, and safety. External testers can then be involved in beta testing, where usefulness, feasibility, and acceptability are evaluated [11]. When developing software for health care settings, several iterative rounds of alpha testing before proceeding to iterative rounds of beta testing may be most effective [11]. To further expand the breadth of feedback and reduce recall bias, iterative rounds of beta testing may be conducted with different samples of the end-user population. Depending on the revisions to the eHealth software after beta testing, a development team may decide to return to alpha testing to begin the process again. This highlights a within-and-between iterative strategy when conducting alpha and beta testing, offering the development team the flexibility to make continuous improvements to their eHealth software.

Conclusion

Currently, there is great variation in how software testing is conducted in health care settings. However, we found that an iterative approach to testing is compatible with the need for an agile development technique for eHealth software. Qualitative methods of testing tend to yield more in-depth user experience feedback during beta testing and researchers benefit when two or more methods are used throughout the beta iteration. Yet, it remains unclear what prompts the transition from alpha to beta testing and when a repeat of testing is required. In the rapidly developing field of eHealth and mHealth interventions, it would be useful to have an agreed upon definition of what constitutes alpha and beta testing. Additionally, with the various frameworks of testing available, the best approach to software testing in health care settings remains unclear. To create clarity in this process, we suggest conducting a systematic review to understand and appraise the full scope of software testing practices within health care settings.

Acknowledgments

OO received funding from the Alberta Children's Hospital Research Institute Summer Studentship Award and KG received funding from the Mitacs Business Strategy Internship to complete this project. We would like to thank Bruce Symbalisty for his feedback on an earlier draft of this article.

Authors' Contributions

KMB conceptualized the study. OO and KG conducted the scan of the literature and wrote the first draft of the manuscript. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

Conflicts of Interest

KMB is the founder and CEO of Liminality Innovations. KG is an employee of Liminality Innovations. OO has no conflicts of interest to report.

Multimedia Appendix 1
Characteristics of included studies.
[DOCX File , 25 KB - nursing_v7i1e56585_app1.docx]

References

1. Benzies KM, Aziz K, Shah V, Faris P, Isaranuwatchai W, Scotland J, Alberta FICare Level II NICU Study Team. Effectiveness of Alberta Family Integrated Care on infant length of stay in level II neonatal intensive care units: a cluster randomized controlled trial. BMC Pediatr 2020 Nov 28;20(1):535 [FREE Full text] [doi: 10.1186/s12887-020-02438-6] [Medline: 33246430]
2. Meier CA, Fitzgerald MC, Smith JM. eHealth: extending, enhancing, and evolving health care. Annu Rev Biomed Eng 2013;15:359-382. [doi: 10.1146/annurev-bioeng-071812-152350] [Medline: 23683088]
3. Bourque P, Fairley RE. Guide to the Software Engineering Body of Knowledge (SWEBOK). IEEE Computer Society. 2014. URL: https://www.computer.org/education/bodies-of-knowledge/software-engineering [accessed 2024-07-11]
4. Hai-Jew S. Alpha testing, beta testing, and customized testing. In: Designing Instruction For Open Sharing. Cham: Springer International Publishing; 2019:381-428.
5. Ahonen EQ, Watson DP, Adams EL, McGuire A. Alpha test results for a Housing First eLearning strategy: the value of multiple qualitative methods for intervention design. Pilot Feasibility Stud 2017 Oct 31;3(1):46 [FREE Full text] [doi: 10.1186/s40814-017-0187-y] [Medline: 29093826]
6. Athilingam P, Osorio RE, Kaplan H, Oliver D, O'neachtain T, Rogal PJ. Embedding patient education in mobile platform for patients with heart failure: theory-based development and beta testing. Comput Inform Nurs 2016 Feb;34(2):92-98. [doi: 10.1097/CIN.0000000000000216] [Medline: 26765655]
7. Cho H, Yen P, Dowding D, Merrill JA, Schnall R. A multi-level usability evaluation of mobile health applications: a case study. J Biomed Inform 2018 Oct;86:79-89 [FREE Full text] [doi: 10.1016/j.jbi.2018.08.012] [Medline: 30145317]
8. Fishbein JN, Nisotel LE, MacDonald JJ, Amoyal Pensak N, Jacobs JM, Flanagan C, et al. Mobile application to promote adherence to oral chemotherapy and symptom management: a protocol for design and development. JMIR Res Protoc 2017 Apr 20;6(4):e62 [FREE Full text] [doi: 10.2196/resprot.6198] [Medline: 28428158]
9. Hoffimann E, Campelo D, Hooper P, Barros H, Ribeiro AI. Development of a smartphone app to evaluate the quality of public open space for physical activity. An instrument for health researchers and urban planners. Landsc Urban Plan 2018 Sep;177:191-195. [doi: 10.1016/j.landurbplan.2018.05.005]
10. Maramba I, Chatterjee A, Newman C. Methods of usability testing in the development of eHealth applications: a scoping review. Int J Med Inform 2019 Jun;126:95-104. [doi: 10.1016/j.ijmedinf.2019.03.018] [Medline: 31029270]
11. Wilson K, Bell C, Wilson L, Witteman H. Agile research to complement agile development: a proposal for an mHealth research lifecycle. NPJ Digit Med 2018 Sep 13;1(1):46. [doi: 10.1038/s41746-018-0053-1] [Medline: 31304326]
12. Darlow S, Wen K. Development testing of mobile health interventions for cancer patient self-management: a review. Health Informatics J 2016 Sep;22(3):633-650 [FREE Full text] [doi: 10.1177/1460458215577994] [Medline: 25916831]
13. Yen P, Bakken S. Review of health information technology usability study methodologies. J Am Med Inform Assoc 2012;19(3):413-422 [FREE Full text] [doi: 10.1136/amiajnl-2010-000020] [Medline: 21828224]
14. Shamsujjoha M, Grundy J, Khalajzadeh H, Lu Q, Li L. Developer and end-user perspectives on addressing human aspects in mobile eHealth apps. Inf Softw Technol 2024 Feb;166:107353. [doi: 10.1016/j.infsof.2023.107353]
15. Kelly B, Margolis M, McCormack L, LeBaron PA, Chowdhury D. What affects people’s willingness to participate in qualitative research? An experimental comparison of five incentives. Field Methods 2017 Jun 05;29(4):333-350. [doi: 10.1177/1525822x17698958]
16. Jokinen A, Stolt M, Suhonen R. Ethical issues related to eHealth: an integrative review. Nurs Ethics 2021 Mar;28(2):253-271 [FREE Full text] [doi: 10.1177/0969733020945765] [Medline: 32930041]
17. Skär L, Söderberg S. The importance of ethical aspects when implementing eHealth services in healthcare: a discussion paper. J Adv Nurs 2018 May 29;74(5):1043-1050. [doi: 10.1111/jan.13493] [Medline: 29105151]

Abbreviations

mHealth: mobile health
NICU: neonatal intensive care unit

Edited by E Borycki; submitted 20.01.24; peer-reviewed by S Gago, A Hassan, S Ashraf; comments to author 17.03.24; revised version received 09.05.24; accepted 11.06.24; published 19.07.24.

Please cite as:
Obigbesan O, Graham K, Benzies KM
Software Testing of eHealth Interventions: Existing Practices and the Future of an Iterative Strategy
JMIR Nursing 2024;7:e56585
URL: https://nursing.jmir.org/2024/1/e56585
doi:10.2196/56585
PMID:39028552

Review

Technology-Supported Guidance Models to Stimulate Nursing Students’ Self-Efficacy in Clinical Practice: Scoping Review

Paula Bresolin[1*], MSc; Simen A Steindal[2,3], PhD; Hanne Maria Bingen[3], PhD; Jaroslav Zlamal[3], MSc; Jussara Gue Martini[1], PhD; Eline Kaupang Petersen[3], MSc; Andréa Aparecida Gonçalves Nes[3,4*], PhD

[1]Federal University of Santa Catarina, Santa Catarina, Brazil
[2]VID Specialized University, Oslo, Norway
[3]Lovisenberg Diacinal University College, Oslo, Norway
[4]Ethics of Care, Faculty of Health Sciences, University of Stavanger, Stavanger, Norway
[*]these authors contributed equally

Corresponding Author:
Andréa Aparecida Gonçalves Nes, PhD
Ethics of Care
Faculty of Health Sciences
University of Stavanger
Kjell Arholms gate 41
Stavanger, 4021
Norway
Phone: 47 51831000
Email: andrea.nes@uis.no

Abstract

Background: In nursing education, bridging the gap between theoretical knowledge and practical skills is crucial for developing competence in clinical practice. Nursing students encounter challenges in acquiring these essential skills, making self-efficacy a critical component in their professional development. Self-efficacy pertains to individual’s belief in their ability to perform tasks and overcome challenges, with significant implications for clinical skills acquisition and academic success. Previous research has underscored the strong link between nursing students’ self-efficacy and their clinical competence. Technology has emerged as a promising tool to enhance self-efficacy by enabling personalized learning experiences and in-depth discussions. However, there is a need for a comprehensive literature review to assess the existing body of knowledge and identify research gaps.

Objective: The aim of this study is to systematically map and identify gaps in published studies on the use of technology-supported guidance models to stimulate nursing students’ self-efficacy in clinical practice.

Methods: This scoping review followed the framework of Arksey and O’Malley and was reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Scoping Reviews (PRISMA-ScR). A systematic, comprehensive literature search was conducted in ERIC, CINAHL, MEDLINE, Embase, PsycINFO, and Web of Science for studies published between January 2011 and April 2023. The reference lists of the included papers were manually searched to identify additional studies. Pairs of authors screened the papers, assessed eligibility, and extracted the data. The data were thematically organized.

Results: A total of 8 studies were included and four thematic groups were identified: (1) technological solutions for learning support, (2) learning focus in clinical practice, (3) teaching strategies and theoretical approaches for self-efficacy, and (4) assessment of self-efficacy and complementary outcomes.

Conclusions: Various technological solutions were adopted in the guidance models to stimulate the self-efficacy of nursing students in clinical practice, leading to positive findings. A total of 7 out of 8 studies presented results that were not statistically significant, highlighting the need for further refinement of the applied interventions. Nurse educators play a pivotal role in applying learning strategies and theoretical approaches to enhance nursing students’ self-efficacy, but the contributions of nurse preceptors and peers should not be overlooked. Future studies should consider involving users in the intervention process and using validated instruments tailored to the studies’ intervention objectives, ensuring relevance and enabling comparisons across studies.

(JMIR Nursing 2024;7:e54443) doi:10.2196/54443

KEYWORDS

clinical practice; guidance model; nursing education; review; self-efficacy; technology; mobile phone; nurse; nurses; nursing; education; allied health; synthesis; review methods; review methodology; search; searches; searching; scoping; MEDLINE; CINAHL; technology enhanced; Technology Enhanced Learning; digital health; guidance; model; models; practical; student; students

Introduction

Nursing students need to acquire both theoretical knowledge and practical skills during their education. Clinical practice is essential for their achievement of competence in communication, teaching, examinations, treatments, management, cooperation, professional approach, and the nursing process [1], yet nursing students experience several challenges in acquiring such competence and skills in clinical practice [2].

Self-efficacy theory has drawn great attention in the health care setting of nursing education and clinical practice. The concept of self-efficacy refers to people's belief in their capability to perform a task or handle a challenging situation [3] and has been used to bridge the theory-practice gap and promote clinical skills acquisition, critical thinking, and general academic success [4-6], so it is important to find ways to foster self-efficacy among nursing students during their clinical education. Effective clinical training of nursing students can enhance self-efficacy, which is a key component of acting independently and competently in the nursing profession [7,8]. Furthermore, nursing students' clinical performance, course completion, and motivation for achievement are closely linked to their perceived self-efficacy [8,9].

Previous research has consistently demonstrated a strong association between nursing students' clinical competence and their overall self-efficacy levels [10,11]. Nursing students with a high degree of self-efficacy tend to exhibit advanced problem-solving skills [12] and demonstrate a strong capacity for self-regulated learning [13], which are critical attributes in their professional training and development. However, nursing students' learning performance and self-efficacy can be significantly impacted by a lack of adequate support to master the complex knowledge and skills required in nursing [14]. Robb [4] found that nursing students with low self-efficacy required emotional and academic support and suggests that nurse educators should be attentive to the strategies millennial students use to acquire information and should provide constructive feedback on student performance. This strategic approach is equally pertinent for Generation Z students, recognized as digital natives, currently undergoing higher education. As they present specific challenges for nurse educators, adapting teaching-learning design strategies and approaches also becomes imperative [15].

The advancement of technology has opened new possibilities for supporting nursing students' knowledge, competence, and skills acquisition in clinical practice [16]. Technology has great potential to improve nursing education by enabling personalized interaction and in-depth discussions of learning topics [16] and by enhancing self-efficacy [17]. The use of customized technological tools in nursing education remains somewhat limited [18]. Earlier systematic reviews have demonstrated opposing results regarding the effectiveness of technology-supported interventions in nursing education [19,20]. The review by Lee et al [19] found that smartphone-based apps could promote nursing students' learning motivation and satisfaction but not their clinical skills and knowledge. In contrast, the review by Kim and Park [20] demonstrated that mobile-based learning could effectively support nursing students' acquisition of knowledge and skills both in and outside of clinical practice settings [20]. Traditionally, clinical practice has played a crucial role in nursing education, organized by guidance models. These models consist of procedures, meetings, and collaboration, aiming to facilitate the development of nursing students' competencies in clinical practice through cooperation between health care and educational institutions [21]. The concept of a technology-supported guidance model in nursing education entails integrating tools, theories, and technological resources to improve guidance and support throughout students' educational journey. The implementation of these technological models, including online platforms, virtual simulations, and digital resources, seeks to enhance the effectiveness and interactivity of nursing education, tailoring it to the users' individual needs [22]. Technology-supported guidance models represent an evolution in teaching methods, incorporating technological elements to improve learning quality and meet the demands of the current educational landscape, aligned with clinical practice expectations. Such models are designed to integrate technological tools into guidance systems, thereby enhancing knowledge and improving students' attitudes and learning outcomes [22].

Given the crucial role of self-efficacy in nursing students' learning process in clinical practice and the potential of technology to optimize the stimulation of self-efficacy, a broad literature review is needed to provide an overview of the published studies on this phenomenon and identify possible research gaps. Our initial literature searches identified only 2 reviews: a systematic mixed studies review synthesized existing evidence on technology-supported guidance models in nursing education, focusing on the development of critical thinking in nursing students in clinical practice [23], and an integrative review evaluated studies on the collaborative use of mobile devices by nursing students and nurse educators during clinical practice but did not investigate the impact on self-efficacy [24]. We were not able to identify previous scoping reviews addressing self-efficacy in the context of technology-supported guidance models in clinical practice in nursing education. Therefore, this scoping review aimed to systematically map and identify gaps in published studies on the use of technology-supported guidance models to stimulate nursing students' self-efficacy in clinical practice.

Methods

Overview

This scoping review used Arksey and O'Malley [25] five-stage framework: (1) identification of the research question; (2) identification of relevant studies; (3) selection of studies; (4) mapping the data; and (5) gathering, summarizing, and reporting the results. The reporting of the review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Scoping Reviews (PRISMA-ScR) [26]. The review's protocol was not registered or published.

Research Question

What is known about the use of technology-supported guidance models to stimulate nursing students' self-efficacy in clinical practice?

Identification of Relevant Literature

A systematic search was conducted on December 13, 2021, and was updated on April 21, 2023, in the following databases: MEDLINE All (Ovid), PsycINFO (Ovid), Embase (Ovid), ERIC (EBSCOhost), CINAHL (EBSCOhost), and Web of Science Core Collection. The search strategy consisted of three main topics: (1) self-efficacy, (2) technology, and (3) nursing students. Based on these 3 topics, we chose search terms using Medical Subject Headings terms and text words. The search strategy was built in MEDLINE by a research librarian, peer reviewed by a second research librarian, and then adapted to the other databases (Multimedia Appendix 1). Moreover, we hand-searched the reference lists of the included papers to assess whether any of the studies mentioned in those references were pertinent to our review. Furthermore, we conducted forward citation searching using the Google Scholar platform to identify relevant studies that had cited the included papers.

Selection of the Studies

The research librarian exported the identified citations to EndNote (Clarivate) to remove duplicates [27]. Subsequently, the citations were exported to Rayyan (Rayyan Systems Inc) [28] for storage, organization, and blinding of the study selection process. Based on the eligibility criteria (Textbox 1) [29], PB and AAGN independently conducted a pilot test of 10% (380/3804) of the citations to screen titles and abstracts, and the eligibility criteria were not modified. Pairs of authors independently screened titles and abstracts to evaluate whether full-text studies met the eligibility criteria (PB+AAGN, Fernando Riegel+JGM, and SAS+JZ in the first search round and PB+JGM and SAS+HMB in the update search round). When doubt arose about a full-text study's inclusion, a third author independently evaluated the full-text study. The decision was based on a negotiated consensus, and the reasons for excluding full-text studies were recorded.

Textbox 1. Eligibility criteria according to the Sample, Phenomenon of Interest, Design, Evaluation, and Research type (SPIDER) framework.

Inclusion criteria

- Sample (S): studies including undergraduate nursing students.
- Phenomenon of interest (PI): use of technology to support guidance in clinical practice to stimulate self-efficacy or similar concepts in an educational institutional context.
- Design (D): studies with qualitative, quantitative, or mixed methods published in peer-reviewed journals from January 2011 to April 21, 2023 (based on our preliminary research, we concluded that the field of Technology-Supported Guidance Models in clinical practice in nursing education is a relatively new research area, and the likelihood of finding studies published in this area before 2011 was low).
- Evaluation (E): undergraduate nursing students' self-efficacy in using technology for stimulating self-efficacy or similar concepts.
- Research type (R): studies of any research type published in English, Portuguese, Spanish, Norwegian, Danish, or Swedish published in peer-reviewed journals.

Exclusion criteria

- Sample (S): studies including health care students other than undergraduate nursing students.
- Phenomenon of interest (PI): educational guidance supported by technology to stimulate self-efficacy unrelated to clinical practice or an educational institution context.
- Design (D): studies published before January 2011 or after April 21, 2023.
- Evaluation (E): the self-efficacy of other health care students' or professionals or nurse educators when it comes to using technology to stimulate self-efficacy.
- Research type (R): non–peer-reviewed studies, any type of review, case study, case report, clinical guideline, master's or PhD thesis, conference proceedings, abstracts, letters, comments, discussion editorials, books, or book chapters.

Mapping the Data

The same pairs of authors that selected the studies extracted data from the included studies. One extracted the data, maintaining the wording and terminology of the studies, and the other checked data accuracy against the studies using a standardized data charting form that included the following information as recommended by the Joanna Briggs Institute [30]: authors, year, country, study objective, population and sample size, research focus or technological models, design, outcomes measures (related to self-efficacy), and findings.

Critical Appraisal

In line with the framework by Arksey and O'Malley [25], a critical appraisal of the methodological quality or risk of bias of the included studies was not performed.

Grouping, Summarizing, and Reporting the Results

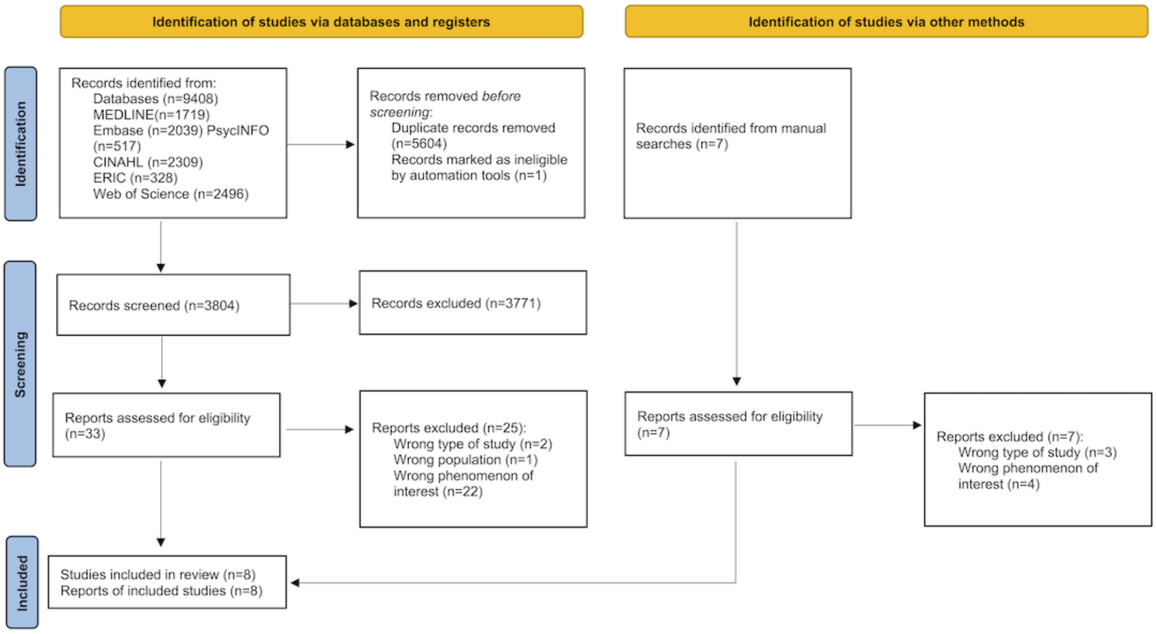
PB and AAGN used an inductive approach to analyze and thematically organize the data from the included studies [25]. The data were extracted from the studies' findings sections and were read several times to identify patterns of similarities and differences across the studies related to our research question. These patterns were organized into thematic groups using a low level of abstraction. Next, the preliminary thematic groups were discussed with the rest of the research team and a consensus was achieved [31-33].

Results

Overview

The database search identified 9408 records, of which 5604 were duplicates, so we screened the titles and abstracts of 3804 records. A total of 33 studies were evaluated for eligibility and 8 studies described in 8 publications were included. We did not find any relevant additional studies through hand searches of the reference lists or forward citations of the included studies. Figure 1 provides an overview of the study selection process and the reasons for the exclusion of full-text reports.

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



Study Characteristics

The included studies were conducted in Taiwan (n=2) [34,35], South Korea (n=2) [36,37], China (n=2) [36,38], Norway (n=1) [39], and Finland (n=1) [40]. In all, 5 studies used a quantitative method and had an experimental design [37-41], and 3 studies used multiple methods [34-36].

The sample size of the studies ranged from 36 to 171 participants, the majority age range (721/770, 93.6%) across the studies was 20-30 years, and most of the participants were female (508/564, 90%). A total of 3 studies did not report the sex of the participants [34,35,37]. In most of the studies (7/8, 88%), the clinical practice was performed in a hospital [34,36-41], whereas 1 study's clinical practice was performed in home care [35]. Table 1 provides a detailed overview of the studies' characteristics and Multimedia Appendix 2 [34-41] provides a description of interventions, duration, and frequency for each study included.

Table 1. Characteristics of the included studies.

Author, year, and country	Study objectives	Population and sample size	Research focus or technological models	Design	Outcomes related to self-efficacy	Findings
Chang et al, 2022 [34], Taiwan	To enable students to learn and think deeply by interacting with a chatbot in the context of handling obstetric vaccine cases	• N=36 • EG[a]: n=18 • CG[b]: n=18 • Age: mean=21 years • Sex: NR[c]	Nursing procedures or chatbot applying natural language processing	Nonrandomized controlled trial with quantitative and qualitative approach	Self-efficacy questionnaire based on Pintrich et al [42]. Individual interviews to investigate students' perceived self-efficacy	Qualitative and quantitative data indicate that applying the mobile chatbot as a learning strategy enhanced nursing students' self-efficacy
Egilsdottir et al, 2023 [39], Norway	To explore changes in nursing competence, factors associated with changes after clinical rotations, and whether an SMLT[d] supports changes in the confident use of B-PAS[e]	• N=171 • Age: The median is between 21-25 years • Sex: n=154 female	B-PAS or SMLT	Quantitative cohort study	Study-specific questionnaire to investigate students' confidence in performing physical assessments	After the clinical rotation, both student groups reported changes in the confidence in performing B-PAS, with statistically significant moderate or large changes in all areas. Confidence in performing B-PAS, the usefulness of the SMLT, and a higher nursing competence at the start of clinical rotation were positively associated with overall nursing competence

Kim and Suh, 2018 [41], South Korea	To evaluate the effect on nursing students of an ICNS[f] mobile app	• N=66
		• EG: n=34
		  • Age: mean=22.6 years
		  • Sex: n=31 female
		• CG: n=32
		  • Age: mean=22.9 years
		  • Sex: n=29 female
			Simulation of nursing procedures or ICNS app	Randomized controlled trial	SECP[g] instrument	The ICNS app enhanced students' knowledge, self-efficacy, and nursing skills performance. The EG showed significantly more improved self-efficacy from before to after the intervention than the CG

Lee and Park, 2018 [37], South Korea	To examine the effect of flipped learning compared to traditional learning in a surgical nursing practicum	• N=102
		• EG: n=51
		  • Age: mean=22.5 years
		  • Sex: NR
		• CG: n=51
		  • Age: mean=22.5 years
		  • Sex: NR
			Clinical practice in surgical nursing or flipped learning with e-learning content with smart learning tool	Two-arm, parallel, stratified group randomized trial	SECP instrument	Both groups showed improvement on all subscales of the SECP in the posttest, but no statistically significant differences were found between the group

Author, year, and country	Study objectives	Population and sample size	Research focus or technological models	Design	Outcomes related to self-efficacy	Findings

Strandell-Laine et al, 2018 [40], Finland	To evaluate the effectiveness of a mobile cooperation intervention in improving students' competence and self-efficacy and the quality of the CLE[h]	• N=102
		• EG: n=52
		  • Age: mean=22.9 years
		  • Sex: n=49 female
		• CG: n=50
		  • Age: mean=23 years
		  • Sex: n=45 female
			Clinical practice or mobile app	Randomized controlled trial	SECP instrument	The results of overall competence, self-efficacy, and overall satisfaction with the CLE showed no significant differences between the groups

Wang et al, 2022 [38], China	To examine the effects of a mobile phone–based psychological intervention program on stress, anxiety, and self-efficacy among undergraduate nursing students during clinical practice	• N=114
		• EG: n=57
		  • Age: mean=22.9 years
		  • Sex: n=50 female
		• CG: n=57
		  • Age: mean=22.2 years
		  • Sex: n=47 female
			Psychological intervention or mobile phone–based	Randomized controlled trial	General Self-Efficacy Scale	More significant improvements in stress, anxiety, and self-efficacy as well as more significant improvement in group-interaction time were observed in the EG than in the CG

Wang et al, 2023 [36], China	To develop and evaluate the effectiveness of an online 5-week professional identity program among nursing students in clinical internship practice during COVID-19 restrictions	• N=111
		• EG: 56
		  • Age: mean=21.3 years
		  • Sex: n=53 female
		• CG: 55
		  • Age: mean=21.3 years
		  • Sex: n=50 female
			Professional identity or online program	Two-armed randomized controlled trial with quantitative and qualitative approach	Professional self-efficacy questionnaire for nursing students	For professional self-efficacy, the group effect, time effect, and group-by-time effect were not significant except for 1 factor related to the capacity for information collection and planning. Students stated that the program enhanced their professional belief, and they felt less stressed in adapting to the stressful atmosphere. The facilitator supported the participants' experiences of internal self-motivation that led to active participation in the program. Building mutual trust and familiarity was essential for the group dynamic

Wu and Sung, 2014 [35], Taiwan	To assess the advantages of mobile devices and cloud learning in a public health practice course using Google+ as the learning platform and integrating various application tools	• N=68
		• EG: n=32
		  • Age: NR
		  • Sex: NR
		• CG: n=36
		  • Age: NR
		  • Sex: NR
			Clinical practice in public health or Google+ as a learning management system	Nonrandomized pilot study with quantitative and qualitative approach	Computer self-efficacy instrument designed by Compeau and Higgins [43]	Most students had past computer experience and often searched for information on the internet. They were confident in computer use and displayed high self-efficacy. The analysis of learning effectiveness showed that students using Google+ had greater learning effectiveness than did those adopting traditional learning

[a] EG: experimental group.
[b] CG: control group.
[c] NR: not reported.
[d] SMLT: suite of mobile learning tools.
[e] B-PAS: basic physical assessment skills.
[f] ICNS: interactive clinical nursing skills.
[g] SECP: Self-Efficacy in Clinical Performance.
[h] CLE: clinical learning environment.

Thematic Groups

To answer the research question, the results were organized into four thematic groups: (1) technological solutions for learning support, (2) learning focus in clinical practice, (3) teaching strategies and theoretical approaches for self-efficacy, and (4) assessment of self-efficacy and complementary outcomes. Textbox 2 provides an overview of the content covered within the thematic groups.

Textbox 2. Content covered within the thematic groups.

Technological solutions for learning support

- Chatbot with artificial intelligence [34]
- Digital platform [35,37]
- Mobile app with simulation [39,41] and without simulation [40]
- Mobile phone [38]
- Online chat [36]

Learning focus in clinical practice

- Nursing procedures: vaccine [34], vital signs, intravenous injection, gastric lavage, endotracheal suction [41], and physical assessment skills [39]
- Specialized nursing area: surgical nursing [37], home care [35], and management and communication [40]
- Students' professional identity [36]
- Students' mental health [38]

Teaching strategies and theoretical approaches for self-efficacy

- Attention, relevance, confidence, and satisfaction theory [41]
- Flipped classroom [37]
- Fundamentals of Care framework [39]
- Nurse educators' feedback on nurse students' learning activities [35,38,40]
- Tajfel's social identity theory and career self-efficacy theory [36]

Assessment of self-efficacy and complementary outcomes

- Computer self-efficacy, experience, anxiety, and system satisfaction and interview [35]
- Confidence in performing basic physical assessment skills and nurse professional competence [39]
- General self-efficacy, learning situation, and interview [34]
- General self-efficacy, stress, and anxiety [38]
- Professional self-efficacy, professional identity, depression, anxiety, stress, and interview [36]
- Self-efficacy in clinical performance (SECP), nursing skills performance, and knowledge [41]
- SECP, quality of the clinical learning environment, and nurse competence [40]
- SECP, self-leadership, and social problems [37]

Technological Solutions for Learning Support

Various technological solutions to support the development of self-efficacy were identified across the included studies, such as a chatbot with artificial intelligence [34], online chat [36], a mobile app with simulation [39,41] and without it [40], a mobile phone [38], and a digital platform [35,37]. The technological tools required internet access to function for the intended purpose. In 7 studies [34-36,38-41], the participants had access to the technological solution on their smartphones anywhere and at any time. The participants used the technical solutions to perform learning activities [34,35,37,39-41] to interact with colleagues [34-36] and to communicate with nurse educators [35,38,40]. In 1 study, the technological solution (with e-learning content) was used as a preparatory learning activity before clinical practice [37].

Learning Focus in Clinical Practice

The included studies focused on specific learning situations in clinical practice, such as nursing procedures [34,39,41] and nursing areas [35,37,40]. Regarding nursing procedures, 1 study provided educational knowledge about infectious diseases and vaccine administration [34], while the other studies included learning situations about vital signs, intravenous injection, gastric lavage, endotracheal suction [41], and physical assessment skills [39]. Regarding nursing areas, the research focus was surgical nursing [37], management and communication [40], and home care [35]. One study investigated students' mental health [38] and another investigated students' professional identity [36].

Teaching Strategies and Theoretical Approaches for Self-Efficacy

Nurse educators were the main facilitators of the technology-supported guidance models. A total of 4 studies applied various teaching strategies, such as educators' feedback on nursing students' learning activities [35,36,38,40] and a flipped classroom [37]. Three of the studies used different theoretical approaches, such as attention, relevance, confidence, satisfaction (ARCS) theory [41], Tajfel's social identity theory (SIT) and career self-efficacy theory (CSET) [36], and the Fundamentals of Care (FoC) framework [39]. One study did not apply teaching strategies or theoretical approaches [34].

Strandell-Laine et al [40] and Wu and Sung [35] designed an app to support clinical learning by stimulating communication between nursing students and nurse educators. In the intervention by Strandell-Laine et al [40], the learning content included the schedule of clinical practice, learning objectives, a learning diary, and midterm and final evaluations. In the study by Wu and Sung [35], students accessed information, uploaded data, posed questions, and discussed the learning situations with nurse educators. In both studies, the intervention content and nursing students' clinical practice experience were the basis of feedback elaboration delivered by the educators. Nursing students also received feedback from nurse educators in Wang et al [38] study, but the focus was on psychological support. The intervention was delivered in three modules: (1) support (the participants were asked to write a paragraph describing their "happy experiences" during their clinical practice sessions); (2) education (2 clinical educators provided weekly lectures on topics to improve clinical and communication skills, find happiness in daily life, build confidence when caring for patients, manage stress and pressure, perform self-care while caring for others, and build social support); and (3) reflection (participants were encouraged to describe stressful situations during their clinical practice to their clinical educators, and the educators helped the participants analyze the situations and provided tailored advice for handling similar situations in the future). In the study by Lee and Park [37], the flipped classroom was used as a teaching strategy, including instructor guidance before clinical training, on-site instruction during clinical practice, and a case conference after the end of clinical practice.

The study by Chang et al [34] used an artificial intelligence–based app developed with natural language processing to encourage nursing students to ask questions or use a pop-up menu to search for needed information in addition to discussing medical issues with their peers and with the chatbot. Kim and Suh [41] used an app flowchart based on the ARCS theory with four phases: (1) the attention phase stimulated the participants' motivation to learn; (2) the relevance phase helped the participants to think about which items they should prepare for each nursing skill and devise a care plan for the patients and themselves; (3) confidence phase; and (4) satisfaction phase, the participants learned interactively by answering messages and quizzes that popped up on their mobile screen. Egilsdottir et al [39] used the FoC framework divided into three main areas: (1) the nurse-patient relationship, (2) integration of care, and (3) contextual factors The study used the basic physical assessment skills (B-PAS) to measure students' performance and used the FoC framework to assess the student (nurse)–patient relationship. Wang et al [36] based their training program on the combined SIT and CSET. The program was designed on the basis of SIT's 3 phases of how social identity is built and modified, including social categorization, social comparison, and positive distinctiveness; the intervention elements embedded in the 3 phases were derived from the CSET, comprising direct experience, substituted experience, physio-psychological condition, and social persuasion.

Assessment of Self-Efficacy and Complementary Outcomes

Three studies [37,40,41] measured self-efficacy using the self-efficacy in clinical performance (SECP) instrument [44], which comprises 37 self-assessed items on an 11-point Likert scale in five domains: (1) assessment, (2) diagnosis, (3) planning, (4) implementation, and (5) evaluation.

Two studies [34,38] measured general self-efficacy with 2 different instruments. Chang et al [34] used a self-efficacy instrument constructed by Pintrich et al [42] that includes 8 self-assessed items with 5-point Likert scales. Wang et al [38] used a self-efficacy scale developed by Jerusalem and Schwarzer [45] with 10 items on a 4-point Likert scale in four domains: (1) strategic, (2) contingency, (3) motivational, and (4) executive effectiveness.

Wang et al [36] measured nursing students' professional self-efficacy with a 27-item questionnaire on a 5-point Likert scale including six factors: (1) professional attitude and belief, (2) problem-solving ability, (3) professional information collection and professional planning capacity, (4) professional cognition, (5) professional value, and (6) professional choice.

Egilsdottir et al [39] created a questionnaire with 13 items using a 7-point Likert scale to map nursing students' perceived confidence related to the examination techniques in B-PAS, which are inspection, palpation, percussion, and auscultation.

The questionnaire items were formulated in line with Bandura's [46] description of self-efficacy.

Wu and Sung [35] revised and applied a computer self-efficacy questionnaire designed by Compeau and Higgins [43] with 24 items on a 5-point Likert scale in three dimensions: (1) computer use experience, (2) computer self-efficacy, and (3) computer anxiety.

In all these self-efficacy instruments, higher scores indicate greater self-efficacy. All the studies measured self-efficacy along with other outcomes, such as basic knowledge [34,41], nursing skills performance [39,41], self-leadership and social problems [37], and professional competence [39,40]. Three studies measured anxiety [35,36,38], 2 measured stress [36,38], 1 measured professional identity [36], and another measured system satisfaction [35]. Furthermore, 3 studies [34-36] conducted interviews to gather qualitative data, exploring participants' perceptions of their feelings, experiences, influencing factors, their understanding of technology's impact on learning experiences in nursing education, and suggestions for improving the intervention.

In all the studies, the self-efficacy scales and other instruments showed improvement in the posttest within the groups. However, 1 showed statistically significant differences between the experimental groups and the control groups [34].

Discussion

Principal Findings

This scoping review aimed to systematically map and identify gaps in published studies on the use of technology-supported guidance models to stimulate nursing students' self-efficacy in clinical practice. The database search identified 3804 citations, but only 33 studies were assessed for eligibility, of which 8 were eligible for inclusion, which may indicate a research gap on the phenomenon of interest. Although the number of studies was small, the technological solutions were diverse, which was not surprising, as it aligns with the findings of a systematic mixed studies review that investigated technology-supported guidance models to stimulate critical thinking [23]. The use of technology to support clinical practice appears to be a relatively new research field, characterized by frequent experimentation. Technological advancement in nursing education has greatly increased, especially during the COVID-19 pandemic [47].

Our findings suggest that technological solutions were organized as technology-supported guidance models with a predefined set of nursing procedures or nursing areas. Nurse educators provided guidance with the support of technological solutions, stimulating nursing students' active learning. This pedagogical approach diverges from traditional education and seeks to transcend teaching based on the unilateral transfer of content so as to stimulate creative, critical, and transformative practices [48]. Active learning is student centered and interactive and offers feedback that meets the student's learning needs [49]. Although only 1 of the included studies [39] provided information on the development of the technological solutions, they seemed to be tailored to meet the individual nursing students' needs for specific knowledge and competence. It would be valuable to ascertain whether the users of the other 7 included studies were actively engaged in the development process due to the potential positive impact of such involvement. Nes et al [50] underscore the significance of incorporating all stakeholders (ie, nursing students, nurse preceptors, and nurse educators) as users during the creation of a technology-supported guidance model. This approach is essential to guarantee that the technological solution aligns with the expected quality standards to meet users' needs and achieve the anticipated educational outcomes in clinical practice.

Half (4/8, 50%) of the included studies applied teaching strategies without a theoretical approach in their technology-supported guidance models, which is in line with the findings of a previous review [23]. The lack of a theoretical approach may make it challenging to explain study findings [51]. Despite positive findings, only 1 of the included studies showed statistically significant effects regarding self-efficacy. Applying a theoretical approach in intervention studies seems to be associated with positive findings and large effect sizes [52]. Therefore, technology-supported guidance models that apply pedagogical theory intended to stimulate self-efficacy may have a better chance of success [53]. A nonsignificant effect in the included studies that used a theoretical approach may result from an insufficient sample size or insufficient duration of intervention. Despite the lack of statistical significance in most studies, the observed effects were consistently positive, aligning with findings in other studies using technological solutions [54-56]. Consequently, interventions integrating technology have the potential to contribute positively to student learning outcomes.

Furthermore, Linnenbrink and Pintrich [57] found evidence for a conceptual framework that demonstrated the connection between motivation, self-regulation, and academic learning and that these connections were not confined solely to the theoretical classroom context but also extended to clinical practice. Motivational factors and cognitive processes may interact in intricate ways to facilitate student learning [57,58].

Aligning with previous research [59,60], our findings underscore the significant role of nurse educators as the primary facilitators of technology-supported guidance models. Nurse educators share responsibility for fostering nursing students' self-beliefs, as these self-beliefs can have positive or negative influences on their performance [61]. Educators and institutions are responsible for helping students develop their competence and confidence as they progress in their studies [62]. However, technological tools should not be incorporated into guidance models in isolation, as such incorporation also requires oversight, support, and mentorship from not only nurse educators but also nurse preceptors and peers optimizing the impact of technology on the educational experience [63].

Only 3 of the included studies used the SECP instrument to assess the self-efficacy of nursing students. Using the same instrument, such as the SECP, facilitates replication and enables comparisons across studies investigating similar outcomes [44,64,65]. By contrast, the use of different instruments to measure the same outcome makes it challenging to compare findings across studies, conduct meta-analyses, and establish standardized thresholds or reference points for specific outcomes [66].

Our findings show that the studies also incorporated other assessment tools. This could be because of the strong correlation between self-efficacy and factors such as motivation [67], satisfaction [63,68], academic achievement [58,69], and student persistence [70]. Furthermore, it is important to acknowledge that other outcomes could be essential in addressing the research questions posed by these studies.

Strengths and Limitations

The strengths of our review are the acknowledged methodological framework for conducting a scoping review, the comprehensive database search, and the systematic process by which pairs of authors independently assessed eligibility and extracted data. Furthermore, the data were analyzed by 2 authors and discussed with the rest of the research team, facilitating credibility, dependability, and intersubjectivity.

We tried to include all possible synonyms of the concept of self-efficacy and similar concepts in our search strategy, but due to the multidimensional nature of self-efficacy, we may have overlooked some synonyms. Our review also had some language restrictions. Consequently, we may have been unable to identify some relevant studies. Another limitation may be that the review protocol was not published. However, the eligibility criteria and search strategy were determined before the study selection process was carried out.

Conclusions

Diverse technological solutions were used in guidance models to stimulate nursing students’ self-efficacy in clinical practice. Even though these interventions showed positive outcomes, they were not statistically significant. This underscores the need for further refinement by tailoring technological tools to meet user needs, making stakeholder involvement essential, and implementing interventions that are developed on the basis of a theoretical approach, as well as applying teaching strategies with a theoretical approach. Although nurse educators are vital for students’ development, the contributions of nurse preceptors and peers should not be underestimated.

Our findings show that a variety of instruments are used to assess self-efficacy and that not all such instruments have been validated. Consequently, future studies should use validated instruments to ensure relevance and enable meaningful comparisons of self-efficacy across studies.

Acknowledgments

The authors thank Kari Mariussen for helping to build the search strategy and for peer reviewing it. They also thank Fernando Riegel in memorium for participating in the first round of the identification and selection of relevant studies. Finally, the authors thank Federal University of Santa Catarina and Lovisenberg Diaconal University College for sponsoring this study. The funding source played no role in this study.

Authors' Contributions

PB was responsible for conceptualization, methodology, formal analysis, writing the original draft, writing and editing the revision, visualization, and project administration. SAS, JZ, HMB, JGM, and EKP were responsible for writing and editing the revision and formal analysis. AAGN was responsible for methodology, formal analysis, writing and editing the revision, visualization, and supervision.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Search strategy used in MEDLINE.
[DOCX File , 30 KB - nursing_v7i1e54443_app1.docx]

Multimedia Appendix 2
The description of interventions for each study included.
[DOCX File , 36 KB - nursing_v7i1e54443_app2.docx]

Multimedia Appendix 3
PRISMA-ScR checklist.
[PDF File (Adobe PDF File), 497 KB - nursing_v7i1e54443_app3.pdf]

References

1. Adam S, UK Bologna Expert. Learning outcomes current developments in Europe: update on the issues and applications of learning outcomes associated with the Bologna process. 2008 Presented at: Bologna Seminar: Learning Outcomes based Higher Education: the Scottish Experience; February 21-22, 2008; Heriot-Watt University, Edinburgh, Scotland.

2. Olaussen C, Aase I, Jelsness-Jørgensen LP, Tvedt CR, Steindal SA. Supplementing clinical practice in nursing homes with simulation training: a qualitative study of nursing students' experiences. SAGE Open Nurs 2020;6:2377960820981786 [FREE Full text] [doi: 10.1177/2377960820981786] [Medline: 35155765]
3. Bandura A. Social cognitive theory in cultural context. Appl Psychol 2002;51(2):269-290. [doi: 10.1111/1464-0597.00092]
4. Robb M. Self-efficacy with application to nursing education: a concept analysis. Nurs Forum 2012;47(3):166-172. [doi: 10.1111/j.1744-6198.2012.00267.x] [Medline: 22861653]
5. Blackman I, Hall M, Darmawan IGN. Undergraduate nurse variables that predict academic achievement and clinical competence in nursing. Int Educ J 2007;8(2):222-236 [FREE Full text]
6. Kuiper R, Pesut D, Kautz D. Promoting the self-regulation of clinical reasoning skills in nursing students. Open Nurs J 2009;3:76-85 [FREE Full text] [doi: 10.2174/1874434600903010076] [Medline: 19888432]
7. Abdal M, Alavi NM, Adib-Hajbaghery M. Clinical self-efficacy in senior nursing students: a mixed- methods study. Nurs Midwifery Stud 2015;4(3):e29143 [FREE Full text] [doi: 10.17795/nmsjournal29143] [Medline: 26576443]
8. Mohamadirizi S, Kohan S, Shafei F, Mohamadirizi S. The relationship between clinical competence and clinical self-efficacy among nursing and midwifery students. Int J Pediatr 2015;3(6-2):1117-1123 [FREE Full text] [doi: 10.22038/ijp.2015.5222]
9. Zhang ZJ, Zhang CL, Zhang XG, Liu XM, Zhang H, Wang J, et al. Relationship between self-efficacy beliefs and achievement motivation in student nurses. Chin Nurs Res 2015;2(2-3):67-70 [FREE Full text] [doi: 10.1016/j.cnre.2015.06.001]
10. Högstedt D, Jansson I, Eriksson E, Engström M. Three paths to a Swedish nursing license: two for internationally educated nurses and one for regular nursing students—a cross-sectional study of self-rated professional competence, self-efficacy, and thriving. Nurse Educ Today 2022;119:105595 [FREE Full text] [doi: 10.1016/j.nedt.2022.105595] [Medline: 36265213]
11. Yu M, Tong H, Li S, Wu XV, Hong J, Wang W. Clinical competence and its association with self-efficacy and clinical learning environments among Chinese undergraduate nursing students. Nurse Educ Pract 2021;53:103055. [doi: 10.1016/j.nepr.2021.103055] [Medline: 33951599]
12. Zhao FF, Lei XL, He W, Gu YH, Li DW. The study of perceived stress, coping strategy and self-efficacy of Chinese undergraduate nursing students in clinical practice. Int J Nurs Pract 2015;21(4):401-409. [doi: 10.1111/ijn.12273] [Medline: 24750234]
13. Chen JH, Björkman A, Zou JH, Engström M. Self-regulated learning ability, metacognitive ability, and general self-efficacy in a sample of nursing students: a cross-sectional and correlational study. Nurse Educ Pract 2019;37:15-21. [doi: 10.1016/j.nepr.2019.04.014] [Medline: 31035075]
14. Zheng Y, Wang J, Doll W, Deng X, Williams M. The impact of organisational support, technical support, and self-efficacy on faculty perceived benefits of using learning management system. Behav Inform Technol 2018;37(4):311-319. [doi: 10.1080/0144929x.2018.1436590]
15. Chicca J, Shellenbarger T. Connecting with Generation Z: approaches in nursing education. Teach Learn Nurs 2018;13(3):180-184. [doi: 10.1016/j.teln.2018.03.008]
16. Solberg MT, Sørensen AL, Clarke S, Nes AAG. Virtual reflection group meetings as a structured active learning method to enhance perceived competence in critical care: focus group interviews with advanced practice nursing students. JMIR Med Educ 2023;9:e42512 [FREE Full text] [doi: 10.2196/42512] [Medline: 36951919]
17. Padilha JM, Machado PP, Ribeiro A, Ramos J, Costa P. Clinical virtual simulation in nursing education: randomized controlled trial. J Med Internet Res 2019;21(3):e11529 [FREE Full text] [doi: 10.2196/11529] [Medline: 30882355]
18. O'Connor S, Andrews T. Using co-design with nursing students to create educational apps for clinical training. Stud Health Technol Inform 2016;225:334-338. [Medline: 27332217]
19. Lee H, Min H, Oh SM, Shim K. Mobile technology in undergraduate nursing education: a systematic review. Healthc Inform Res 2018;24(2):97-108 [FREE Full text] [doi: 10.4258/hir.2018.24.2.97] [Medline: 29770243]
20. Kim JH, Park H. Effects of smartphone-based mobile learning in nursing education: a systematic review and meta-analysis. Asian Nurs Res (Korean Soc Nurs Sci) 2019;13(1):20-29 [FREE Full text] [doi: 10.1016/j.anr.2019.01.005] [Medline: 30659927]
21. Struksnes S, Engelien RI, Bogsti WB, Moen Ö, Nordhagen SS, Solvik E, et al. Nurses' conceptions of how an alternative supervision model influences their competence in assessment of nursing students in clinical practice. Nurse Educ Pract 2012;12(2):83-88. [doi: 10.1016/j.nepr.2011.07.009] [Medline: 21852193]
22. Ahmed V, Opoku A. Technology supported learning and pedagogy in times of crisis: the case of COVID-19 pandemic. Educ Inf Technol (Dordr) 2022;27(1):365-405 [FREE Full text] [doi: 10.1007/s10639-021-10706-w] [Medline: 34462626]
23. Zlamal J, Gjevjon ER, Fossum M, Solberg MT, Steindal SA, Strandell-Laine C, et al. Technology-supported guidance models stimulating the development of critical thinking in clinical practice: mixed methods systematic review. JMIR Nurs 2022;5(1):e37380 [FREE Full text] [doi: 10.2196/37380] [Medline: 35671078]
24. Strandell-Laine C, Stolt M, Leino-Kilpi H, Saarikoski M. Use of mobile devices in nursing student-nurse teacher cooperation during the clinical practicum: an integrative review. Nurse Educ Today 2015;35(3):493-499. [doi: 10.1016/j.nedt.2014.10.007] [Medline: 25456259]
25. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. Int J Soc Res Methodol 2005;8(1):19-32. [doi: 10.1080/1364557032000119616]

26. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Ann Intern Med 2018;169(7):467-473 [FREE Full text] [doi: 10.7326/M18-0850] [Medline: 30178033]
27. Bramer WM, Giustini D, de Jonge GB, Holland L, Bekhuis T. De-duplication of database search results for systematic reviews in EndNote. J Med Libr Assoc 2016;104(3):240-243 [FREE Full text] [doi: 10.3163/1536-5050.104.3.014] [Medline: 27366130]
28. Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A. Rayyan-a web and mobile app for systematic reviews. Syst Rev 2016;5(1):210 [FREE Full text] [doi: 10.1186/s13643-016-0384-4] [Medline: 27919275]
29. Cooke A, Smith D, Booth A. Beyond PICO: the SPIDER tool for qualitative evidence synthesis. Qual Health Res 2012;22(10):1435-1443. [doi: 10.1177/1049732312452938] [Medline: 22829486]
30. Peters MDJ, Godfrey CM, Khalil H, McInerney P, Parker D, Soares CD. Guidance for conducting systematic scoping reviews. Int J Evid Based Healthc 2015;13(3):141-146 [FREE Full text] [doi: 10.1097/XEB.0000000000000050] [Medline: 26134548]
31. Nes AAG, Steindal SA, Larsen MH, Heer HC, Lærum-Onsager E, Gjevjon ER. Technological literacy in nursing education: a scoping review. J Prof Nurs 2021;37(2):320-334 [FREE Full text] [doi: 10.1016/j.profnurs.2021.01.008] [Medline: 33867086]
32. Skedsmo K, Nes AAG, Stenseth HV, Hofsø K, Larsen MH, Hilderson D, et al. Simulation-based learning in palliative care in postgraduate nursing education: a scoping review. BMC Palliat Care 2023;22(1):30 [FREE Full text] [doi: 10.1186/s12904-023-01149-w] [Medline: 36991463]
33. Steindal SA, Nes AAG, Godskesen TE, Dihle A, Lind S, Winger A, et al. Patients' experiences of telehealth in palliative home care: scoping review. J Med Internet Res 2020;22(5):e16218 [FREE Full text] [doi: 10.2196/16218] [Medline: 32369037]
34. Chang CY, Hwang GJ, Gau ML. Promoting students' learning achievement and self-efficacy: a mobile chatbot approach for nursing training. Brit J Educ Tech 2021;53(1):171-188 [FREE Full text] [doi: 10.1111/bjet.13158]
35. Wu TT, Sung TW. Public health practice course using Google Plus. Comput Inform Nurs 2014;32(3):144-152. [doi: 10.1097/CIN.0000000000000040] [Medline: 24445861]
36. Wang A, Wu F, Lin C, Wu M, Jia S, Guo Y, et al. An online 5-week professional identity program for nursing student in clinical rotation practice during the first wave of COVID-19 pandemic: a two-arm randomized trial. Nurse Educ Pract 2023;68:103598 [FREE Full text] [doi: 10.1016/j.nepr.2023.103598] [Medline: 36906948]
37. Lee MK, Park BK. Effects of flipped learning using online materials in a surgical nursing practicum: a pilot stratified group-randomized trial. Healthc Inform Res 2018;24(1):69-78 [FREE Full text] [doi: 10.4258/hir.2018.24.1.69] [Medline: 29503755]
38. Wang L, Guo Y, Liu Y, Yan X, Ding R. The effects of a mobile phone-based psychological intervention program on stress, anxiety and self-efficacy among undergraduate nursing students during clinical practice: a randomized controlled trial. J Prof Nurs 2022;42:219-224. [doi: 10.1016/j.profnurs.2022.07.016] [Medline: 36150864]
39. Egilsdottir H, Heyn LG, Falk RS, Brembo EA, Byermoen KR, Moen A, et al. Factors associated with changes in students' self-reported nursing competence after clinical rotations: a quantitative cohort study. BMC Med Educ 2023;23(1):107 [FREE Full text] [doi: 10.1186/s12909-023-04078-7] [Medline: 36774493]
40. Strandell-Laine C, Saarikoski M, Löyttyniemi E, Meretoja R, Salminen L, Leino-Kilpi H. Effectiveness of mobile cooperation intervention on students' clinical learning outcomes: a randomized controlled trial. J Adv Nurs 2018;74(6):1319-1331 [FREE Full text] [doi: 10.1111/jan.13542] [Medline: 29444335]
41. Kim H, Suh EE. The effects of an interactive nursing skills mobile application on nursing students' knowledge, self-efficacy, and skills performance: a randomized controlled trial. Asian Nurs Res (Korean Soc Nurs Sci) 2018;12(1):17-25 [FREE Full text] [doi: 10.1016/j.anr.2018.01.001] [Medline: 29463484]
42. Pintrich PR, Smith DAF, Garcia T, McKeachie WJ. A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ). Office of Educational Research and Improvement (ED). Washington, DC; 1991. URL: https://eric.ed.gov/?id=ED338122 [accessed 2024-02-22]
43. Compeau DR, Higgins CA. Computer self-efficacy: development of a measure and initial test. MIS Q 1995;19(2):189-211. [doi: 10.2307/249688]
44. Cheraghi F, Hassani P, Yaghmaei F, Alavi-Majed H. Developing a valid and reliable self-efficacy in clinical performance scale. Int Nurs Rev 2009;56(2):214-221. [doi: 10.1111/j.1466-7657.2008.00685.x] [Medline: 19646171]
45. Jerusalem M, Schwarzer R. General self-efficacy scale--revised--English version. American Psychological Association. 1995. URL: https://psycnet.apa.org/doiLanding?doi=10.1037%2Ft18916-000 [accessed 2024-02-22]
46. Bandura A. Self-efficacy: toward a unifying theory of behavioral change. Psychol Rev 1977;84(2):191-215. [doi: 10.1037//0033-295x.84.2.191] [Medline: 847061]
47. Riegel F, Martini JG, Bresolin P, Mohallem AGC, Nes AAG. Developing critical thinking in the teaching of nursing: a challenge in times of Covid-19 pandemic. Esc Anna Nery 2021;25(spe):e20200476 [FREE Full text] [doi: 10.1590/2177-9465-ean-2020-0476]

48. Meschial WC, Sales CCF, Rodrigues BC, Lima MFD, Garanhani ML, Oliveira MLFD. Educational intervention on acute management of burns based on innovative pedagogical methods: nurses' perceptions. Texto Contexto Enferm 2020;29:e20190222 [FREE Full text] [doi: 10.1590/1980-265x-tce-2019-0222]
49. Culha I. Active learning methods used in nursing education. J Pedagogical Res 2019;3(2):74-86 [FREE Full text] [doi: 10.33902/jpr.2019254174]
50. Nes AAG, Zlamal J, Linnerud SCW, Steindal SA, Solberg MT. A technology-supported guidance model to increase the flexibility, quality, and efficiency of nursing education in clinical practice in Norway: development study of the TOPP-N application prototype. JMIR Hum Factors 2023;10:e44101 [FREE Full text] [doi: 10.2196/44101] [Medline: 36735289]
51. Craig P, Dieppe P, Macintyre S, Michie S, Nazareth I, Petticrew M, et al. Developing and evaluating complex interventions: the new Medical Research Council guidance. BMJ 2008;337:a1655 [FREE Full text] [doi: 10.1136/bmj.a1655] [Medline: 18824488]
52. Webb TL, Joseph J, Yardley L, Michie S. Using the internet to promote health behavior change: a systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy. J Med Internet Res 2010;12(1):e4 [FREE Full text] [doi: 10.2196/jmir.1376] [Medline: 20164043]
53. Teo T. Examining the relationship between student teachers' self-efficacy beliefs and their intended uses of technology for teaching: a structural equation modelling approach. Turk Online J Educ Technol 2009;8(4):7-15 [FREE Full text]
54. Chen X, Xie H, Zou D, Hwang GJ. Application and theory gaps during the rise of artificial intelligence in education. Comput Educ 2020;1:100002 [FREE Full text] [doi: 10.1016/j.caeai.2020.100002]
55. Gasparetti F, De Medio C, Limongelli C, Sciarrone F, Temperini M. Prerequisites between learning objects: automatic extraction based on a machine learning approach. Telemat Inform 2018;35(3):595-610. [doi: 10.1016/j.tele.2017.05.007]
56. Hwang GJ, Sung HY, Chang SC, Huang XC. A fuzzy expert system-based adaptive learning approach to improving students' learning performances by considering affective and cognitive factors. Comput Educ 2020;1:100003 [FREE Full text] [doi: 10.1016/j.caeai.2020.100003]
57. Linnenbrink EA, Pintrich PR. The role of self-efficacy beliefs instudent engagement and learning in the classroom. Read Writ Q 2010;19(2):119-137. [doi: 10.1080/10573560308223]
58. Schunk DH. Self-regulated learning: the educational legacy of Paul R. Pintrich. Educ Psychol 2010;40(2):85-94. [doi: 10.1207/s15326985ep4002_3]
59. Skaalvik MW, Henriksen N, Normann HK. The nurse teacher's role in clinical practice—Norwegian nursing students' experiences. A cross-sectional survey. Nordisk sygeplejeforskning 2015;5(4):356-366. [doi: 10.18261/issn1892-2686-2015-04-05]
60. Warne T, Johansson UBJ, Papastavrou E, Tichelaar E, Tomietto M, van den Bossche K, et al. An exploration of the clinical learning experience of nursing students in nine European countries. Nurse Educ Today 2010;30(8):809-815. [doi: 10.1016/j.nedt.2010.03.003] [Medline: 20409620]
61. Hassani P, Cheraghi F, Yaghmaei F. Self-efficacy and self-regulated learning in clinical performance of nursing students: a qualitative research. Iran J Med Educ 2008;8(1):33-42 [FREE Full text]
62. Pajares F. Self-efficacy beliefs, motivation, and achievement in writing: a review of the literature. Read Writ Q 2010;19(2):139-158. [doi: 10.1080/10573560308222]
63. Liaw SS. Investigating students' perceived satisfaction, behavioral intention, and effectiveness of e-learning: a case study of the blackboard system. Comput Educ 2008;51(2):864-873. [doi: 10.1016/j.compedu.2007.09.005]
64. Haririan H, Rahmani A, Porter JE, Heidarzadeh M, Azadi A, Faghani S, et al. Nursing students' attitude and preparedness for nurse prescribing and its relationship with self-efficacy. Nurse Educ Pract 2021;54:103126. [doi: 10.1016/j.nepr.2021.103126] [Medline: 34171575]
65. Moeini M, Sarikhani-Khorrami E, Ghamarani A. The effects of self-compassion education on the self-efficacy of the clinical performance of nursing students. Iran J Nurs Midwifery Res 2019;24(6):469-471 [FREE Full text] [doi: 10.4103/ijnmr.IJNMR_77_18] [Medline: 31772923]
66. Liberati A, Altman DG, Tetzlaff J, Mulrow C, Gøtzsche PC, Ioannidis JPA, et al. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. Ann Intern Med 2009;151(4):W65-W94 [FREE Full text] [doi: 10.7326/0003-4819-151-4-200908180-00136] [Medline: 19622512]
67. Graham S, Weiner B. Theories and principles of motivation. In: Berliner DC, Calfee RC, editors. Handbook of Educational Psychology. London: MacMillan Library Reference; 1996:63-84.
68. Artino AR. Motivational beliefs and perceptions of instructional quality: predicting satisfaction with online training*. Comput Assist Learn 2007;24(3):260-270. [doi: 10.1111/j.1365-2729.2007.00258.x]
69. Schunk DH. Self-efficacy and academic motivation. Educ Psychol 2011;26(3-4):207-231. [doi: 10.1080/00461520.1991.9653133]
70. Martinez M. High attrition rates in e-learning: challenges, predictors, and solutions. eLearn Developers J 2003;2(2):1-9 [FREE Full text]

Abbreviations

ARCS: attention, relevance, confidence, satisfaction
B-PAS: basic physical assessment skills
CSET: career self-efficacy theory
FoC: Fundamentals of Care
PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Scoping Reviews
SECP: self-efficacy in clinical performance
SIT: social identity theory

Edited by E Borycki; submitted 09.11.23; peer-reviewed by SQ Yoong, S Nadolny; comments to author 23.12.23; revised version received 09.02.24; accepted 21.02.24; published 08.03.24.

Please cite as:
Bresolin P, Steindal SA, Bingen HM, Zlamal J, Gue Martini J, Petersen EK, Nes AAG
Technology-Supported Guidance Models to Stimulate Nursing Students' Self-Efficacy in Clinical Practice: Scoping Review
JMIR Nursing 2024;7:e54443
URL: https://nursing.jmir.org/2024/1/e54443
doi:10.2196/54443
PMID:38457802

Review

Privacy Barriers in Health Monitoring: Scoping Review

Luyi Sun[1], MS; Bian Yang[1], PhD; Els Kindt[2], PhD; Jingyi Chu[3], MS

[1]Department of Information Security and Communication Technology, Faculty of Information Technology and Electrical Engineering, Norwegian University of Science and Technology, Gjøvik, Norway

[2]Centre for IT & IP Law, Faculty of Law and Criminology, KU Leuven, Leuven, Belgium

[3]Administrative Law, Faculty of Law, China University of Political Science and Law, Beijing, China

Corresponding Author:
Luyi Sun, MS
Department of Information Security and Communication Technology
Faculty of Information Technology and Electrical Engineering
Norwegian University of Science and Technology
Teknologivegen 22
Gjøvik, 2815
Norway
Phone: 47 96864781
Email: luyi.sun@ntnu.no

Abstract

Background: Health monitoring technologies help patients and older adults live better and stay longer in their own homes. However, there are many factors influencing their adoption of these technologies. Privacy is one of them.

Objective: The aim of this study was to provide an overview of the privacy barriers in health monitoring from current research, analyze the factors that influence patients to adopt assisted living technologies, provide a social psychological explanation, and propose suggestions for mitigating these barriers in future research.

Methods: A scoping review was conducted, and web-based literature databases were searched for published studies to explore the available research on privacy barriers in a health monitoring environment.

Results: In total, 65 articles met the inclusion criteria and were selected and analyzed. Contradictory findings and results were found in some of the included articles. We analyzed the contradictory findings and provided possible explanations for current barriers, such as demographic differences, information asymmetry, researchers' conceptual confusion, inducible experiment design and its psychological impacts on participants, researchers' confirmation bias, and a lack of distinction among different user roles. We found that few exploratory studies have been conducted so far to collect privacy-related legal norms in a health monitoring environment. Four research questions related to privacy barriers were raised, and an attempt was made to provide answers.

Conclusions: This review highlights the problems of some research, summarizes patients' privacy concerns and legal concerns from the studies conducted, and lists the factors that should be considered when gathering and analyzing people's privacy attitudes.

(JMIR Nursing 2024;7:e53592) doi:10.2196/53592

KEYWORDS

privacy attitudes; health monitoring technologies; privacy concerns; privacy barriers; legal concerns; social psychology

Introduction

Background

The proportion of older adults around the world is growing sharply. According to the 2021 aging report published by the European Commission [1], the ratio in the European Union (EU) between people aged ≥65 years and those aged 20 to 64 years (also known as the demographic old-age dependency ratio) will increase greatly in the coming decades, from approximately 34% in 2019 to 59% in 2070. In Norway, the population of older adults (aged ≥65 years) will increase from 17.4% in 2019 to 27.8% in 2070 [1]. Because of this, the term "aging in place" was put forward in social policy, which refers to providing assisted living facilities to enable older adults to remain in their own homes for as long as possible [2]. Various ongoing research projects in ambient assisted living technologies are being, or have been, conducted to help older adults, such as the European AALIANCE2 project; the Ambient Assisted Living Joint

Programme, financed by the European Commission [3]; and the Active and Assisted Living Programme, also financed by the European Commission [4].

In the meantime, patients are also in need of health monitoring systems. The aging population and patients' growing needs for health care support have facilitated the development of different types of health monitoring and assisted living technologies, such as socially assistive robots, wearable trackers, telemedicine, image sensors, and so on. According to the study by Rostad and Stokke [5], these technologies can be categorized into localization technologies (eg, GPS), compensation technologies (eg, remote control of light and heating, robot vacuums, and cognitive or physical aids), safety technologies (eg, social alarm systems and fall detection sensors), technologies for social contact (eg, tablet computers, smartphones, and gaming devices), therapeutic robots, and treatment technologies (eg, medical remote monitoring and automated pill dispensers), all used for different purposes in health monitoring.

The application of the aforementioned intelligent devices is supposed to enhance the quality of patients' lives. Nevertheless, various factors impact patients' acceptance of health monitoring devices [6], including intervention factors (eg, privacy concerns, security concerns, frequency, a lack of awareness, and the observability of outcomes), environmental factors (eg, social influence, social implication, change in technology use by society over time, and group participation), technology factors (eg, complexity, reliability, interface design, compatibility, functionalities, features, aesthetics, and cost), individual factors (eg, level of innovativeness, level of technology learnability, and living alone), psychological factors (eg, attitudinal factors and perception factors), support and training factors (eg, training, quality of training, and facilitating support) in general. Among all these factors, our attention was seized by *privacy concerns*.

There are different types of privacy; therefore, privacy concerns can be analyzed from different perspectives. The way that researchers distinguish privacy has reflected their different concerns arising from their professional backgrounds; for example, Rosenberg [7] distinguished 3 kinds of privacy: territorial privacy, individual privacy, and informational privacy. Clarke [8] outlined 4 types of privacy: privacy of a person, privacy of personal data, privacy of personal behavior, and privacy of personal communication. However, with the development of emerging technologies, different categories arose. Some researchers extended the categories formulated by Rosenberg [7] and added 3 more categories: privacy of thoughts and feelings, privacy of location and space, privacy of association (including group privacy) [9]. More specifically, in different scenarios, users have different privacy concerns, and these concerns can be categorized case by case; for instance, web-based social network users can have 4 dimensions of privacy concerns: virtual territorial privacy, factual privacy, interactional privacy, and psychological privacy [10]. Furthermore, Serenko [11] narrowed the scope in health care and put forward 3 privacy dimensions: informational privacy, physical privacy, and psychological privacy. These 3 privacy dimensions were regarded as determinants of patient behavior in health care.

Although privacy concerns are known to be barriers for patients with regard to adopting health monitoring technologies according to some studies [12], it is not sufficient to analyze factors impacting the adoption of health monitoring technologies individually because these influential factors may impact each other; for example, despite the fact that privacy concerns are included in intervention factors [6], psychological factors, as well as support and training factors with regard to privacy awareness, can also impact patients' privacy concerns. Patients' awareness of privacy-related laws in the health care environment will also influence their privacy concerns and decision-making out of respect for authority [13]. Considering privacy issues in society, privacy attitudes and concerns are always analyzed from the legal perspective. For patients, their privacy attitudes may have a straight impact on the informed consent process, and they are expected to know how to obtain legal aid in case they encounter technology abuse, or their privacy is intruded upon. For technology vendors, industry standards or privacy policies need to be carefully checked and complied with before their product is released. They need to carry out data protection impact assessments to minimize privacy risks [14]. Apart from older patients who are most in need of health monitoring and assisted living technologies, members of the general public are also potential users of these technologies as they age or develop health conditions. Furthermore, with regard to members of the general public, their prevalent uncertainty regarding, and trust issues with, technologies may prompt legislators to adopt a more cautious and conservative approach with regard to such technologies. However, *privacy-friendly* approaches can be seen as a way to motivate technology vendors to be more transparent and, on the one hand, foster *privacy by design*, while, on the other hand, promote social awareness and trust by bridging the information gap. In all, various factors and their relationships need to be always taken into consideration at the same time. Meanwhile, the question persists as to whether privacy concerns are truly barriers because of the rapid changes in society, such as the development of privacy-enhancing technologies. Thus, the rationality of privacy concerns should also be discussed.

In the past few years, researchers have conducted a series of studies to gather different privacy attitudes or privacy concerns regarding health monitoring and assisted living technologies from people with different demographic characteristics. However, the results vary from study to study not only because of the different user groups to which the participants belong (eg, older adults' attitudes compared to those of younger adults and female participants' attitudes compared to those of male participants) but also because of the different experimental approaches used and the different scenarios provided in these studies.

Research Questions

In summary, the implementation of assisted living technologies in the aging population era faces several challenges. First, multiple factors impede patients' adoption of these technologies, and the interrelations among these factors have not been thoroughly explored. Second, the extent to which privacy concerns affect technology adoption needs further investigation. Third, the study design and current results require consolidation for researchers to make meaningful improvements. Addressing these challenges, we pose 4 research questions and conduct a scoping review with the aim of providing an overview of the privacy barriers in health monitoring from current research and elucidating answers to these research questions. The four research questions are listed herein, and the answers to these questions are provided in the Results section.

1. What are the influential factors that lead to different privacy attitudes and concerns?
2. How will the methodologies used in different studies influence participants' privacy awareness with regard to health monitoring technologies from the perspective of social psychology?
3. What are the legal challenges regarding people's privacy attitudes and concerns today?
4. What should be taken into consideration in subsequent studies related to privacy attitudes and concerns in the context of social psychology?

On the basis of the selected articles, we have summarized 5 hypotheses particularly related to the second challenge, which are clarified in the Results section. The contribution of this paper includes observing the inconsistency of these hypotheses, looking into experimental approaches in each article, and seeking answers to the 4 research questions. We have tried to come up with suggestions that should be taken into consideration comprehensively before implementing health monitoring technologies.

Methods

Overview

A scoping review was conducted to explore the privacy attitudes of different groups of participants in the context of legal norms and social psychology in health monitoring technologies by adopting the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement (Multimedia Appendix 1) [15]. Scoping reviews include all quantitative, qualitative, and mixed methods studies that are identified as literature on a particular topic or research area [16,17]. They differ from systematic reviews but can be used to inform systematic reviews because more specific questions are usually addressed in a more precise systematic review [18]. Of note, there are other approaches to evidence synthesis for systematic reviews, such as realist reviews [19], mixed methods reviews [19], concept analyses [20], and so on. In this study, with the aim of identifying and mapping the available studies, examining how research is conducted in a certain field, summarizing findings, and analyzing results, a scoping review is the best choice compared to other approaches.

Eligibility Criteria

We conducted a review for articles published between January 1, 2016, and March 31, 2022. Search parameters were established to identify articles published during this period regarding different participants' privacy attitudes with regard to health monitoring technologies as well as legal norms regarding privacy in health monitoring in Norway, the EU, and the United States. For an in-depth investigation into the research questions, we acknowledge the regional characteristics evident in previous studies, often shaped by factors such as cultural backgrounds and legal norms. To address this, we have selected these regions. Specifically, this decision is motivated by 2 key considerations. First, EU policies extend to Norway, the authors' country of residence, thereby potentially impacting health service delivery and the deployment of assisted living technologies. Second, certain EU countries share a common cultural background, suggesting that individuals in these regions may harbor more similar privacy perspectives than individuals in other locations. Furthermore, studies published in the United States were included because it is one of the most developed countries owning quantities of health monitoring technologies. It is worth mentioning that for the articles we identified, even if the authors did not specify the review region or if the authors' countries of residence were outside the region, we still included these articles because they provided comprehensive views. Other than region specification, studies were included if they (1) reflected the privacy attitudes or privacy concerns of any group of people, (2) reflected any legal concerns or legal frameworks that should be taken into account, (3) were peer-reviewed publications, and (4) were written in English. All study methods (quantitative, qualitative, and multimethod) were eligible for the review.

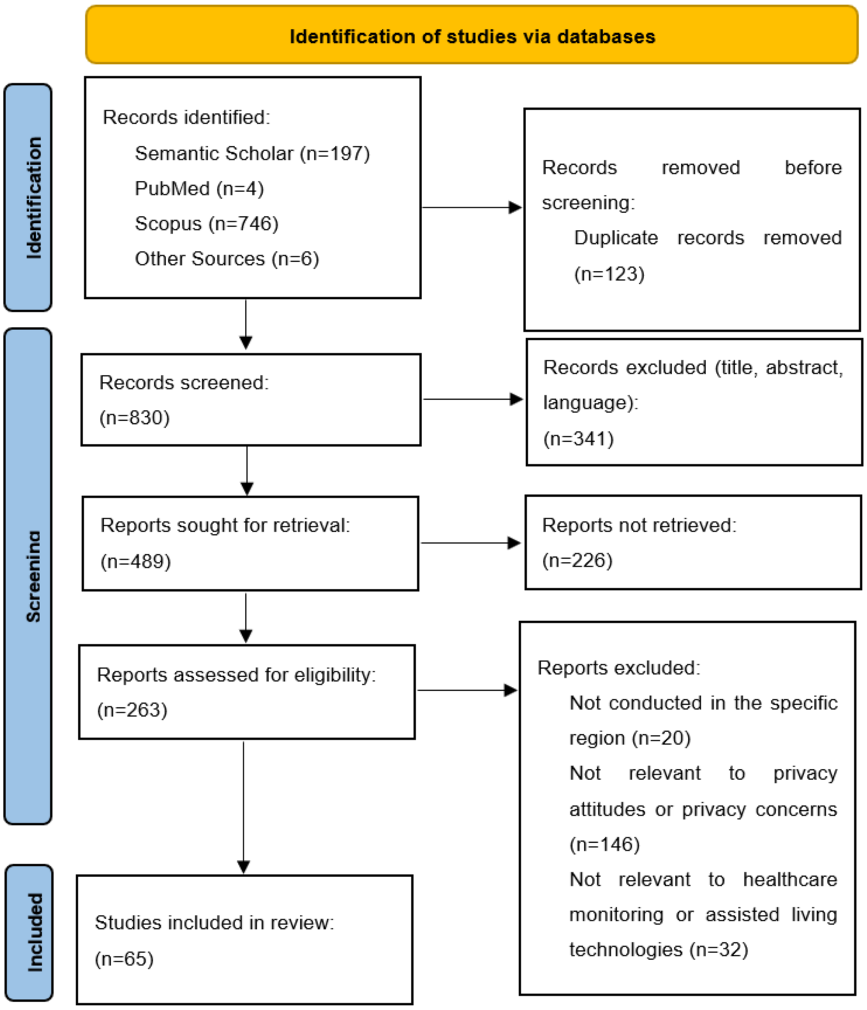
Search Terms, Strategy, and Sources

Instead of searching for privacy barriers directly, we sought studies relevant to people's privacy attitudes or legal norms regarding privacy in the health monitoring environment and tried to summarize the barriers described in these studies. The literature search was conducted by listing the following search terms in the search string: ("privacy attitudes" OR "legal norms") AND (("healthcare monitoring" AND "nursing homes") OR "homecare monitoring") AND ("Norway" OR "EU" OR "the U.S."). The sources of the articles on privacy attitudes and legal norms were mainly 5 databases: Semantic Scholar, PubMed, IEEE Xplore, ScienceDirect, and Scopus. As no relevant articles met the eligibility criteria in IEEE Xplore and ScienceDirect, only articles in the rest of the 3 databases were included. Additional works identified in other databases, such as ACM Digital Library, were categorized into *other sources* because we sorted the articles by relevance and scanned the results directly based on the title and abstract provided at the first attempt instead of following the PRISMA steps strictly, which was the approach we followed for the 5 main databases. Therefore, instead of making an exhaustive selection, we merely added the most relevant and important works.

Study Selection

The PRISMA flow diagram is presented in Figure 1. The search process resulted in the identification of 953 studies. Before the screening, 122 (12.9%) duplicate records were removed from these 953 studies. The first screening was performed on the title, abstract, and language, and 341 (41%) of the 830 articles were identified as not meeting the eligibility criteria. Of the remaining 489 articles, 226 (46.3%) could not be retrieved, leaving 263 (53.7%) reports for assessment. After the second screening, of the 263 articles, we excluded 198 (75.2%) because they (1) were not conducted in the regions specified, (2) were not relevant to privacy attitudes or privacy concerns, and (3) were not relevant to health monitoring or assisted living technologies, leaving 66 (24.8%) articles for the final review, from which we extracted and categorized useful information.

Figure 1. The review steps.



Data Extraction and Categorization

The methods for data extraction and categorization were established through the literature review process. Useful information was extracted and input into a form, including title; authors; year of publication; region; topic; technology; participant inclusion criteria (if any); study design; location of the study; key findings; and laws, rules, regulations, directives, and policies mentioned.

Categories

The categories we formulated are presented in Textbox 1.

Textbox 1. Categorization of the article included for review.

Categories

- Article information: title, authors, year of publication, and region
- Topic: identified and categorized based on the field covered by the articles; instead of setting the topic as “privacy attitudes” or “legal norms” in general, 5 topics were defined (privacy attitudes, privacy concerns, legal concerns, legal frameworks, and privacy barriers); some of the articles have covered several topics at the same time; reasons for classification are clarified in the *Results* section
- Technology: includes health monitoring technologies mentioned in the article; some of the articles have covered a specific device (eg, human behavior modeling [21]), while some provide privacy attitudes or legal norms of a general designation, such as smart home technology
- Participant inclusion criteria: specifically created for studies with participants invited to take part; inclusion criteria include the number of participants, age, nationality, whether they have any diseases, and place of residence
- Key findings: any information related to the 5 topics listed in the Topic category
- Laws, rules, regulations, directives, and policies mentioned: specifically created for studies covering legal frameworks or legal barriers; all legal documents mentioned in the articles were extracted

Results

Overview

In this section, we will provide the results in the form of categories. As mentioned in the Eligibility Criteria subsection, the review was focused on Norway, the EU, and the United States, or reviews worldwide. When it comes to review articles, they are included regardless of region. Among the 65 articles, there were 4 (6%) from France, 2 (3%) from Finland, 1 (2%) from Sweden, 3 (5%) from Germany, 1 (2%) from Ireland, 2 (3%) from Italy, 3 (5%) from the Netherlands, 5 (8%) from Norway, 2 (3%) from Poland, 1 (2%) from Portugal, 1 (2%) from Spain, 1 (2%) conducted jointly in Germany and Denmark, and 30 (46%) from the United States. Of the remaining 9 articles, 1 (11%) discussed telemonitoring at the EU level; 1 (11%) reviewed laws, standards, and recommendations applicable at the EU level; and 7 (78%) were literature reviews whose authors' countries of residence were not part of the specified regions. As the results of the reviews were general in nature, they were not categorized into specific areas.

Privacy Attitudes, Privacy Concerns, and Privacy Barriers

Articles reflecting privacy concerns were classified into 3 subcategories: privacy attitudes, privacy concerns, and privacy barriers. According to Kokolakis [22], although privacy attitudes and privacy concerns have a close relationship, they differ from each other because privacy attitudes are bound to specific contexts such as the appraisal of specific privacy behaviors, while privacy concerns are not, and they can be generic. It is worth mentioning that the articles that either gathered participants' general privacy concerns or participants' privacy attitudes were included in the review. The key findings extracted from the results should be categorized as privacy concerns according to the definition. However, we set the topic as *privacy attitudes* if any privacy attitudes were gathered in these studies. Thus, articles covering either privacy concerns or privacy attitudes were included when we compared the findings.

In contrast to the studies that gathered and analyzed participants' privacy attitudes or concerns, 11 (17%) of the 66 studies [23-33] discussed people's adoption of health monitoring technologies. Although some of these studies, such as the study by Charness et al [26], also recruited participants, gathered their privacy attitudes, and analyzed results from the attitudes (similar to the methods used by Sánchez et al [21] and Caldeira et al [34]), these studies provide a broad view from the perspective of technology adoption and acceptance; for instance, in the study by Biermann et al [25], researchers came up with several barriers to technology adoption, such as financial reasons, restriction of privacy, and a feeling of surveillance. Among all barriers, concern regarding privacy is merely one of the factors that may influence participants' technology adoption. Therefore, even if the findings reflecting privacy concerns are similar to those reflecting privacy attitudes and privacy barriers, articles stating that concern regarding privacy is one of the barriers to the adoption and acceptance of assisted living technologies were classified into a different category: privacy barriers.

Contradictions Among Perceptions of Privacy in Key Findings

All included studies reflect privacy attitudes, privacy concerns, and privacy barriers, which show many contradictions. In general, the results can be classified into five hypotheses according to the extent of participants' privacy concerns: (1) participants do not have privacy concerns (Table 1); (2) participants have privacy concerns, and they are a major barrier (Table 2); (3) participants have privacy concerns, but they do not seem to be a significant barrier (Table 3); (4) participants' privacy concerns vary from person to person, and there is insufficient statistical evidence across a large population to validate whether the concerns will have a significant influence (Textbox 2); and (5) participants have privacy concerns, and their perceptions of privacy are influenced by their background (Table 4). It is worth mentioning that some of the studies satisfied 2 hypotheses at the same time because the fifth hypothesis does not violate the second, third, or fourth hypothesis.

Table 1. Studies that provide evidence for the first hypothesis.

Study	Methodology	Evidence
Sánchez et al [21]	Interview (exploratory qualitative approach)	"It was noteworthy that the majority of participants had no privacy concerns."
Caldeira et al [34]	Interview (qualitative approach)	"Privacy did not seem to be a significant issue for our informants."

Table 2. Studies that provide evidence for the second hypothesis.

Study	Methodology	Evidence
Schomakers et al [35]	Qualitative prestudy+quantitative main study (multimethod approach)	"As an important barrier, privacy requirements should thus be considered for mHealth [mobile health] apps for aftercare."
Vassli and Farshchian [23]	Systematic review	"Many studies found that some or all participants have concerns about privacy. Privacy is regarded as a 'bigger barrier to adoption, more so than usability.'"
Harrington et al [36]	Questionnaire (quantitative study)	"Privacy was among the leading concerns regarding SARs [socially assistive robots] among the current sample of older Americans."
Choi et al [37]	Questionnaire+semistructured interview (multimethod approach)	"The participant feedback suggests that perceived privacy concerns, perceived usefulness, and curiosity to technology were strong factors when considering which device to have installed in their home."
Tural et al [38]	Web-based and in-person surveys+focus group (multimethod approach)	"Privacy and security of personal information seem to be a core issue for willingness to use smart home products as also highlighted by others."
Attié et al [39]	Survey	"Privacy concerns are the main obstacles to the adoption of SCOs [smart connected objects]."
Lederman et al [31]	Review	"Other researchers suggested that risk perception that is influenced by concern over privacy, security and the learning-curve can have a negative impact on the adoption of IoT [Internet of Things] solutions by medical staff...These risks to privacy and security are a major challenge for IoT in healthcare."
Karlsen et al [40]	Review	"The lack of security and privacy was a prominent concern due to the constant recording of data and location tracking that comes with the use of a smartwatch."
Gimpel et al [41]	Survey	"In healthcare digitalization, privacy concerns are one of the major barriers for individuals to accept and use healthcare technologies."
Mujirishvili et al [42]	Scoping review	"With privacy being a major barrier to video-based AAL [active and assisted living] technologies, security and medical safety were identified as the major benefits across the studies."
Wilczewski et al [43]	Questionnaire	"Participants commented on privacy concerns with providing personal information to the chatbot. This category had the majority of negative comments (n=10/15 codes; 66.7%) with some participants finding the chatbot 'a bit intrusive.'"

Table 3. Studies that provide evidence for the third hypothesis.

Study	Methodology	Evidence
Jaschinski et al [44]	Web-based survey (qualitative approach)	“Older adults’ privacy concerns were secondary to the perceived benefits of AAL [Ambient Assisted Living] in terms of health, safety and independence.”
Gettel et al [28]	Scoping review	“One study highlighted that older adults were concerned about privacy, but other studies found that privacy was not a barrier to AAL [Ambient Assisted Living] technology adoption.”
Chung et al [45]	Survey (qualitative approach)	“The proportion for the privacy concern increased slightly, though not statistically significant, indicating that participants were not bothered by the existence of the device at home.”
Fruchter and Liccardi [46]	Web-based review	“While we found that privacy and security related issues are present within our corpus, our results suggest these topics related to home assistants are rarely voiced, or openly reported by consumers in their online reviews. We can conclude that, for the most part, consumers who review home assistants tend to not discuss privacy or security concerns.”
Piau et al [47]	Web-based survey (qualitative approach)	“Less than a third were concerned about privacy breaches when using these technologies.”
Tan et al [48]	Semistructured interviews (qualitative approach)	“When asked about potential privacy or security concerns, our analysis of participant responses surfaced 6 types of reactions that may explain why they expressed little concern with privacy and security.”
Schomakers and Ziefle [49]	Questionnaire (quantitative approach)	“Our data suggests that privacy concerns are outweighed by security-related benefits in the acceptance decisions, as long as certain lines are not crossed—the unacceptable and must-have characteristics.”

Textbox 2. Studies that provide evidence for the fourth hypothesis.

Study and methodology

- Randall et al [50]: focus group or qualitative approach
- Gerłowska et al [51]: literature review
- Soro et al [52]: review
- Wang et al [53]: focus group+survey (multimethod approach)
- Pilozzi and Huang [54]: no methods directly related to the results
- Pekmezaris et al [55]: focus group+interview (multimethod approach)
- Biermann et al [25]: web-based questionnaire (empirical quantitative approach)
- Kodate et al [56]: questionnaire (quantitative approach)
- Berridge et al [57]: survey (qualitative approach)
- Mittelstadt [58]: systematic survey
- Koo and Fallon [59]: interview (qualitative approach)
- Joe et al [60]: focus group+questionnaire (multimethod approach)
- Chan et al [27]: literature review
- Chan et al [29]: literature review
- Sánchez et al [61]: literature review
- Hjelm et al [62]: semistructured interview (qualitative approach)
- Cristiano et al [63]: interview+focus group (qualitative approach)
- Zhang et al [64]: questionnaire (quantitative approach)
- Mallinson and Shafi [32]: review
- Guazzini et al [65]: questionnaire+focus group (multimethod approach)
- Wan et al [66]: literature review+semistructured interviews (multimethod approach)
- Zheng et al [67]: semistructured interviews (qualitative approach)
- Yao et al [68]: focus group+co-design activities (qualitative approach)
- Ahmad et al [69]: semistructured interviews (qualitative approach)
- Kheirinejad et al [70]: questionnaire (quantitative approach)

Table 4. Studies that provide evidence for the fifth hypothesis.

Study	Methodology	Evidence	Influential factors
Schomakers et al [35]	Qualitative prestudy+quantitative main study (multimethod approach)	“Acceptance and privacy depend on the context and type of the technology.”	Context and type of technology
Vassli and Farshchian [23]	Systematic review	“Systems that are considered intrusive or causing infringement on privacy might still be accepted by older adults if their health needs are great enough.”	Age and health needs
Shin et al [24]	Systematic review	“Personal trust and the device’s usability could affect users’ privacy perception of wearable activity trackers.”	Personal trust and the device’s usability
Soro et al [52]	Review	“When it comes to privacy, older adults are very thoughtful and want to be empowered and to retain the sense of the home as a haven with respect for their autonomy.”	Age and autonomy
Wang et al [53]	Focus group+survey (multimethod approach)	“Older adults scored lower in the privacy pragmatic and unconcerned categories and much higher in the privacy fundamentalist category.”	Age
Reeder et al [71]	Semistructured interview (qualitative approach)	“Older women’s privacy concerns related to sensor technology can vary according to their sociocultural context (e.g., Korean American older adults and Korean older adults VS Caucasian older adults).”	Age, gender, and sociocultural context
Pilozzi and Huang [54]	No methods directly related to the results	“Individuals with Parkinson’s disease were almost three times more likely to have data-privacy related concerns than controls.”	Disease (Parkinson disease)
Halvorsrud et al [72]	Interview (qualitative approach)	“This study reveals that older adults’ perspectives on assistive technology (AT) are multifaceted and complex, and can partly be explained by the interacting factors in the HAAT [human activity assistive technology] model: person, technology, environment, and context.”	Person, technology, environment, and context
Langer et al [73]	No methods directly related to the results	“Women tend to be more concerned with privacy and safety than men, often preferring enclosed latrines in or near their homes.”	Gender
Jaschinski and Ben Allouch [74]	Semistructured interview (qualitative approach)	“Informal caregivers had a more positive attitude than care receivers.”	User role
Charness et al [26]	Questionnaire (quantitative approach)	“Older adults, particularly males, showed less concern than younger adults about privacy.”	Age
Chan et al [27]	Literature review	“There is tension between assistance and autonomy, or privacy and independence that characterizes the individual’s judgment in using telehealth technology.”	Assistance, autonomy, and independence
Sánchez et al [61]	Literature review	“Privacy can be compromised for persons in need of support...People with higher risk of harm often require intense surveillance to avoid unsafe situations.”	Support and safety
Łukasik et al [75]	Questionnaire (quantitative approach)	“Medical students were more aware of privacy issues in the statement concerning the possibility of switching off the robot in specific situations.”	User role
Lanne and Leikas [30]	Semistructured interview+literature review (multimethod approach)	“Using AI [artificial intelligence] in social and health care contains many general challenges. Some of the most commonly discussed topics were related to social trust and the experience of autonomy, power structures, privacy concerns, transparency, and biases leading to unfair treatment of individuals and patient groups.”	Autonomy, trust, and transparency
Simpson et al [76]	Review	“Privacy concerns are reported as being the main reason patients may choose not to share data in a clinical context, though these concerns mostly relate to the potential for future sharing with external third parties.”	Potential use of the data
Zhang et al [64]	Questionnaire (quantitative approach)	“Privacy awareness (P=.08) has positive effects on privacy concerns.”	Privacy awareness
Seberger and Patil [77]	Semistructured interviews (qualitative approach)	“In the context of pandemic mitigation technology, including app-based tracking, people perceive a core trade-off between public health and personal privacy.”	Public health

Study	Methodology	Evidence	Influential factors
Kolakowsk et al [33]	Literature review	"Cultural barriers will likely result in unequal diffusion of robot use in elderly assistance over time."	Social context
Chaparro et al [78]	Review	"There is a list of factors that affect the attitude and intention to use technologies supporting independent living. These personal and device-related factors comprise user expectancy, biophysical ageing restrictions, anxiety, the previous required knowledge, intrinsic motivation, personality and privacy concerns."	Emotion, knowledge, and personality
Gimpel et al [41]	Survey	"Several studies have shown that Germans have higher privacy concerns than citizens in most other countries. Most authors attribute this to German's historical legacy."	Region and sociocultural context
Zheng et al [67]	Semistructured interviews (qualitative approach)	"IoT [Internet of Things] device users in different regions may have differing privacy concerns. For example, American users may be generally more accepting of data collection by industry versus the state, in contrast to consumers in Europe...Since interview participants expressed greater privacy concern about devices that record voice and video, we recommend that such visual indicators be used extensively to indicate these activities, especially in devices traditionally without recording capabilities (e.g. doorbells, lightbulbs, etc.)."	Region and data type collected by devices
Yao et al [68]	Focus group+co-design activities or qualitative approach	"In general, bystanders had more privacy concerns in the temporary residence scenario and the playdate scenario than the cohabitant scenario. Bystanders also expressed more concerns regarding the video and audio data collected by devices with microphones and cameras (e.g., voice assistants, security cameras) but barely any concern with other devices (e.g., smart coffee makers)."	User role and residence scenario
Ahmad et al [79]	Semistructured interviews	"Older participants may have different privacy concerns as well as different interpretations of IoT [Internet of Things] designs and indicators. Although one worry may be that younger populations are less concerned about their privacy, we note that Singh et al. [reference citation] found that when it comes to sharing information with smart devices, younger adults are more reluctant than older adults."	Age

Discussion

The aforementioned contradictory hypotheses have led to the formulation of our research questions, which we attempt to answer in this section.

Research Question 1: What Are the Influential Factors That Lead to Different Hypotheses?

To identify the influential factors, we looked into the methodologies used in these studies in detail. To sum up, qualitative, quantitative, and multimethod studies as well as reviews were included in these studies. Except for reviews, the other 3 approaches recruited participants during the study. On the basis of the participant inclusion criteria, we found that the number of participants would influence the results. For those studies that concluded that the majority of participants do not have privacy concerns, the number of participants recruited was small [21,34]. Hence, one could argue that there might have been sampling bias in the qualitative approach applied by the studies conducted. As the number of participants increased, the fact that people had privacy concerns seemed to become a common conclusion.

Nevertheless, it still seemed hard for researchers to come to an agreement on the importance of privacy issues. Some stated that privacy is an important barrier without verification and regarded it as a consensus [35]. However, according to a scoping review of ambient assisted living technology adoption, most studies found that privacy was not a barrier [28]. Because of the uncertainty mentioned above [22], we agree with the fourth and fifth hypotheses. Although some of the studies presented in Textbox 2 have not provided sufficient evidence in support of any conclusions, we regard this fact as indirect evidence for the fourth hypothesis as well. Furthermore, people's privacy concerns, as presented in Table 4, may be influenced by the following factors: (1) context and type of technology; (2) age; (3) health needs; (4) personal trust and the device's usability; (5) trade-off among privacy, autonomy, assistance, safety, or independence; (6) health status; (7) region; (8) gender; (9) user roles; (10) sociocultural context; (11) emotion; (12) previous knowledge; (13) personality; and (14) potential use of personal data.

Research Question 2: How Will the Methodologies Influence Participants' Privacy Awareness With

Regard to Health Monitoring Technologies From the Perspective of Social Psychology?

Even if most of the studies satisfied the fourth and fifth hypotheses, the researchers' confirmation bias could have influenced the results and participants' answers. More specifically, in reviews, such bias exists when researchers search for evidence that can support their own beliefs [80]. For the other 3 approaches (qualitative, quantitative, and multimethod), researchers' confirmation bias could also impact their interaction with participants, such as raising inducible questions or providing insufficient information [81]. It has already been pointed out that most people lack the cognitive ability to calculate privacy risks and to make rational privacy decisions because of incomplete information, bounded rationality, and information asymmetries [49]. Therefore, the information provided to the interviewees might compel them to give answers that match researchers' expectations. For multimethod studies that include several experiments, the design of the experiments will also guide participants to make different privacy decisions; for example, because several studies found that there is a trade-off among privacy, autonomy, assistance, safety, or independence, we believe that a privacy-related question in the first experiment might encourage the participants to be concerned more about privacy rather than autonomy in the experiments that follow.

Furthermore, social influence in groups should also be emphasized because participants' privacy awareness might be influenced not only by the sociocultural context but also by the other participants; for example, a herd mentality can lead participants to converge on a consensus answer and make irrational privacy decisions [82].

On the one hand, researchers found that the wisdom of small groups of people tends to outstrip that of both individuals and a large group of people. According to one of the findings, when there are 4 groups, and the number of participants in a focus group is 5, although opinions within a group might converge, there are still diversities among the different groups, and researchers will be able to gather different views from these groups [82]. On the basis of these findings, we analyzed the experiment design of focus groups in the selected studies and found that most experiments lacked diversity in terms of participants' backgrounds [35,50,55,63].

On the other hand, even if the diversity in terms of participants' backgrounds is enhanced, the results of a group cannot always represent personal privacy attitudes because of group polarization [83], that is, it remains questionable whether the decisions made by these groups can represent the views of individuals in the group accurately. In all, we cannot ignore the need and significance with regard to clarifying the ultimate goal of gathering and analyzing privacy attitudes.

Legal Concerns and Legal Frameworks

Legal norms, overall, refer to social norms that are enforced by a relatively strong degree of coercion [84]. However, few of the articles we identified can be categorized into the topic of legal norms straightforwardly. Therefore, instead of categorizing them into legal norms, we classified the articles describing legal issues into 2 subcategories: legal concerns and legal frameworks. More precisely, the articles reflecting legal concerns were not describing participants' concerns about the existing legal frameworks; rather, they were describing participants' attitudes toward technology adoption in light of their awareness of legal obligations; for example, Sánchez et al [21] presented the fact that even if participants were aware of municipalities' legal obligations to provide health care services for older people, they preferred to buy anything they could afford or adopt welfare technologies. The study by Sánchez et al [61] also did not present any legal concerns directly gathered from participants, but it highlighted the importance of legal liability for different user roles (physicians, nurses, or relatives of the patients) during a visit to patients and regarded it as legal concern. As a matter of fact, among the studies we selected, there were only a few conducted for gathering people's legal concerns regarding privacy with respect to health monitoring and assisted living technologies. However, people's legal concerns regarding privacy and the problems in current legal frameworks might be considered one of the influential factors when it comes to adopting health monitoring technologies, which constitute one of the privacy barriers.

Regarding legal frameworks, we extracted regulations, laws, policies, directives, and rules from the findings (Textbox 3). These documents are not limited to assisted living technologies; rather, they cover legal aspects in health care in general; for instance, the legal challenges in the home care or health care environment include data privacy, data management, stakeholders' interests, and informed consent [85].

It is worth mentioning that not all legal documents concerning health monitoring or assisted living technologies are exhaustively listed in Textbox 3 because different countries have different laws or rules regulating aspects of health care. Some of the articles pointed out the shortcomings in the existing frameworks. Among these articles, Ryu [91] revealed the fact of the absence of legal guidelines in the mobile health domain regarding privacy and confidentiality in more than half of the EU countries and the United States and suggested that mobile health should be included within the framework in different countries; Ambrosino et al [92] provided the conclusion that a full legal framework for telemedicine was still lacking in European countries; and Sánchez et al [61] stated that the standardization, research, and assessment of the legal aspects should be addressed in an international perspective. However, in this paper, we only focus on the impact of legal norms on privacy concerns.

Textbox 3. Legal frameworks.

Study and the laws, rules, regulations, directives, and policies mentioned

- Sánchez et al [21]: Norwegian Municipal Health and Care Services Act of 2011 (ACT 24/06/2011 no. 30; act relating to municipal health and care services, and so on)
- Gerłowska et al [51]: European Parliament resolution of February 16, 2017, with recommendations to the European Commission on Civil Law Rules on Robotics (European Parliament, 2017)
- Garg et al [86]: Health Information Technology for Economic and Clinical Health Act, United States (2009); Health Insurance Portability and Accountability Act, United States (1996)
- Costa et al [87]: Article 8 of the Charter of Fundamental Rights of the European Union (2010); Article 16 of the Treaty on the Functioning of the European Union (consolidated version of the Treaty on the Functioning of the European Union, 2012); Portuguese data protection law; General Data Protection Regulation
- Jin et al [88]: Health Insurance Portability and Accountability Act, United States (1996)
- Garzo and Garay-Vitoria [89]: Regulation 2016/679 (also known as General Data Protection Regulation); Regulation 2017/745 on medical devices (2017); Regulation 536/2014 relating to clinical tests with medication for human use (2014); harmonized standard ISO 14155 related to good clinical practice (International Organization for Standardization, 2020)
- Ross et al [90]: General Data Protection Regulation; Health Insurance Portability and Accountability Act, United States (1996)

Research Question 3: What Are the Legal Challenges Regarding People's Privacy Attitudes and Concerns Today?

The articles included in the review show the absence of research on legal norms regarding privacy or people's legal concerns with regard to assisted living technologies in the health monitoring environment; for example, informed consent for various scenarios in health care, different user roles (eg, device owners, bystanders [68], and technology developers), and different types of health monitoring technologies require researchers to pay more attention to the legal frameworks rather than merely point out that they are inadequate.

To this end, a few of the included studies have investigated patients' informed consent requirements in a health monitoring environment. As stated by Demiris and Hensel [93], when patients or older adults approach the end of their lives, they have opportunities to become familiar with smart home applications and perhaps change their minds and consent to use them in light of their value. Patients with cognitive impairment [68] who are gradually losing their cognitive ability to make decisions might prefer to disclose more information in exchange for better medical help when giving informed consent. Thus, informed consent requirements need to be updated.

This also applies to privacy decision-making in health care; for instance, informed consent could be obtained through a shared decision-making framework [93]. Generally, informed consent includes data processing, such as storage, transmission, collection, erasure, and sharing. However, when it is applied to a specific field, more concrete explanations of the risks and benefits need to be provided. In shared decision-making, which requires the involvement of patients and clinicians, informed consent serves as a legal process used to promote patient autonomy and self-determination as well as legal rights [94]. While shared decision-making includes treatment decision-making, it can also include, for example, privacy decision-making because it allows people to discuss how confidential information can be used and shared [95,96]. As shared decision-making is a collaborative process and aims to help patients better understand problems and make rational decisions with support from clinicians, both patients' and clinicians' opinions need to be taken into consideration. To be compliant with patients' privacy needs and the cognitive changes they may be experiencing, we believe that informed consent requirements need to be updated continually as well [97].

The aforementioned cases only serve as examples of applications of legal concerns. More scenarios and elements remain to be clarified, such as identifying direct and indirect stakeholders and their responsibilities and distinguishing the need for informed consent when there are more user roles to be considered (formal caregivers as well as informal caregivers such as friends or relatives) in the health monitoring environment. Some scholars have pointed out that informed consent is not always necessary if the disclosure of information is consistent with respect for underlying human dignity or individual autonomy, which is referred to as "reasonable expectations of privacy" [98,99]. They argue there are circumstances in which confidential information can be better protected, precluding the need to rely on implied consent. By shifting from implied consent to "reasonable expectations of privacy," the pressure to classify cases as *implied consent* could be eased [100].

As researchers are currently focusing more on reasonable expectations of privacy with regard to the sharing of confidential health information, reasonable expectations of privacy for adopting health monitoring and assisted living technologies or privacy decision-making concerning these technologies can possibly be taken into account in data protection legislation as well. Although we agree that reasonable expectations of privacy can help reduce participants' burden when giving consent, the scope of reasonable expectations of privacy still relies on social psychological factors, such as the quality of the physician-patient relationship [99]; for example, trust between physicians and patients will increase the level of reasonable expectations of privacy when patients are making decisions, such as whether to allow the health monitoring system to send alerts to the clinician staff under some circumstances.

Research Question 4: What Should Be Taken Into Consideration in Subsequent Studies Related to Privacy Attitudes and Concerns in the Context of Social Psychology?

Vassli and Farshchian [23] state that one of the most cited reasons that the authors found that might influence participants' adoption of assisted living technologies was that monitoring devices made them feel observed. This has inspired us to suggest experiments (refer to the following paragraphs) that should be conducted in future studies.

First, as far as we could find, the selected studies had not looked into the problem of the Hawthorne effect [101], which refers to a phenomenon in which people alter their behavior in response to being watched or monitored, that is, they might make an instantaneous modification in their behavior once they become aware that they are being observed. People behave differently even when looking into a mirror (rather than being watched by someone else) [102]. In this sense, installing monitoring devices might affect people's behavior even if they have consented to the use of these technologies.

Holden [103] suggested in 2001 that the possible presence of a Hawthorne effect could lead to participants drawing conclusions subconsciously. Therefore, we cannot predict the influences wrought by the Hawthorne effect, while this remains of key importance because it will consequently impact user experience and influence their decision-making in real life. Although some participants in the studies by Vassli and Farshchian [23] and Biermann et al [25] tended to ignore the feeling of being observed, the Hawthorne effect can cause positive impacts as well; for example, in the study by Cristiano et al [63], even if participants had negative feelings of privacy intrusion when being monitored, this was not always the case because older adults stated that they felt secure when being monitored. This also reflected the trade-off between privacy concerns and security concerns. The researchers claimed in their paper that negative feelings of privacy intrusion could be overcome by providing older adults with appropriate information. In another study of clinical trials in dementia, researchers who were aware of the Hawthorne effect found that more intensive follow-ups would cause better cognitive functioning outcomes [104]. Another observation from the Norwegian University of Science and Technology Nord-Trøndelag Health Study [103] showed that participants surveyed by the project regularly over many years exhibited statistically better health states than those not surveyed, which might be attributed to the Hawthorne effect as well. In this way, the feeling of being observed can turn out to be a good thing, although some technology researchers try to hide the monitoring devices to reduce patients' feeling of being observed.

In all, the Hawthorne effect is a complex phenomenon that can lead to unknown bias. There should be more experiments to compare patients' or older adults' behaviors when they are aware of being observed and their behaviors with hidden observation during such research.

Second, in the follow-up experiment design of observing participants' privacy behaviors, researchers should keep an eye not only on the privacy paradox phenomenon but also on the stress of cognitive dissonance caused by the phenomenon. The privacy paradox reveals the fact that there are discrepancies between users' self-declared privacy attitudes and their privacy behavior [105,106]. These discrepancies will cause cognitive dissonance, which appears when people hold conflicting beliefs, or their behaviors contradict their beliefs [107,108].

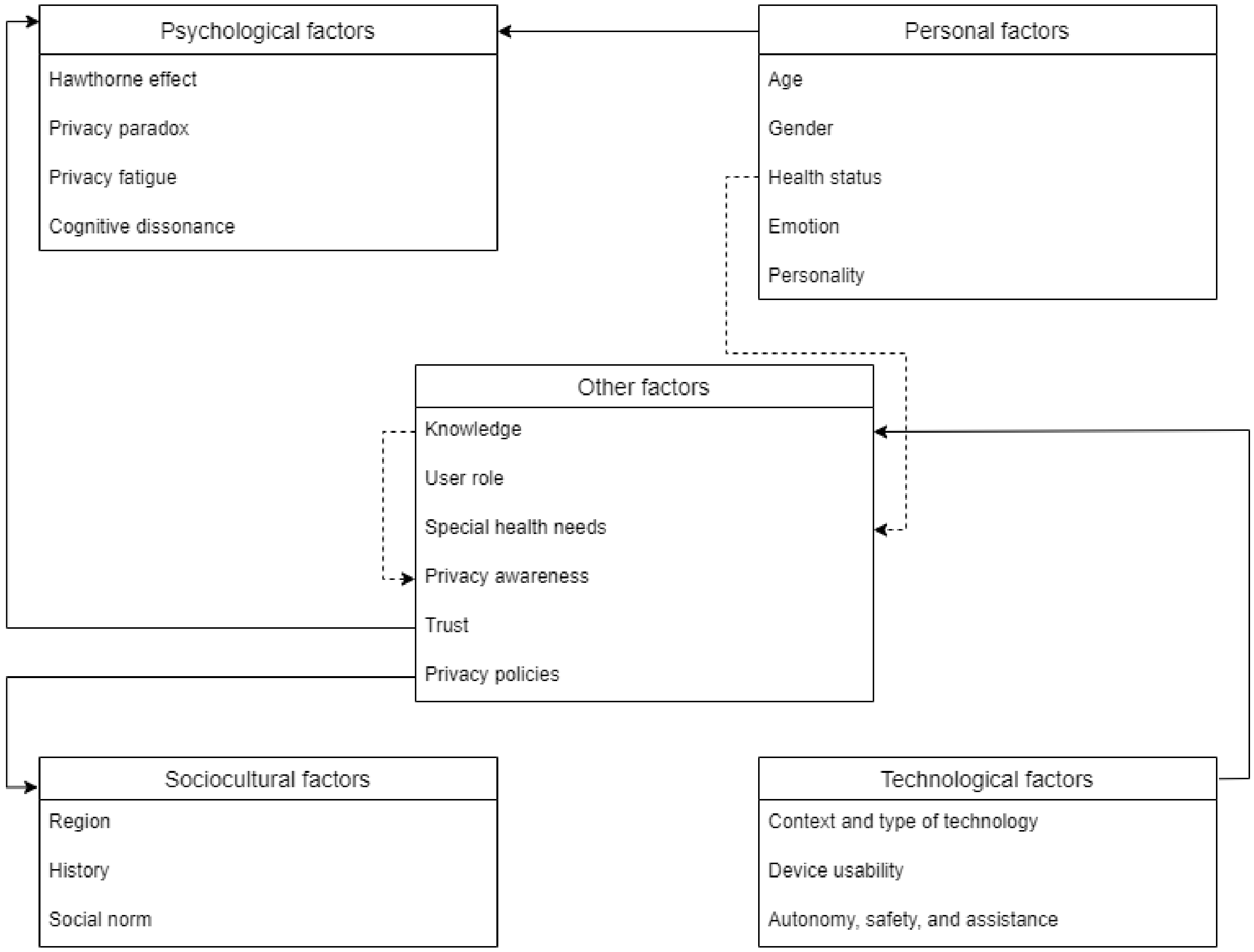
It is mentally stressful to cope with contradictory experiences or beliefs, and cognitive dissonance will make conditions for patients or older adults in health care settings even more stressful [109]. But there can also be positive effects if researchers use a patient's or an older adult's motivation to mitigate the dissonance to change their behaviors [105]. A few researchers also found that the contrast between privacy concerns and privacy-protecting behaviors is caused by privacy fatigue [106], referring to the reduced intention of privacy protection when faced with the increasing complexity of privacy settings or regulations. Because of this, some participants even became confused about the laws or regulations and lacked the ability to make appropriate decisions or give consent [107].

Third, there is a lack of longitudinal studies on privacy attitudes with regard to assisted living technologies. Even if some studies had adopted multimethod approaches, and participants had been invited to take part in several experiments, it is hard for us to identify their cognitive changes over time. Because of the problem we have outlined in research question 1, current experiments might even induce participants to give the answers we want. Thus, we need long-term studies to test patients' cognitive changes over the technologies.

Overview

From the findings we extracted, we aimed to provide a comprehensive understanding of privacy barriers in health monitoring. We have explained the interaction of different factors, especially people's privacy concerns and legal concerns, and pointed out the impact of social psychological factors on these factors. We suggest that to ensure people's autonomy while protecting their privacy, the rules applied to them need to meet their demographic characteristics, health conditions, and health needs. Among the listed hypotheses and research questions, we tend to support the fourth hypothesis: people's privacy concerns vary from person to person, and there is insufficient evidence to validate the importance of privacy barriers currently. As information asymmetries will also lead people to make different privacy decisions, we suppose that the more accurate and useful the information they provide, the more precise the decisions they will make. To intuitively present the influential factors we found in research question 1, we highlight the elements that should be considered and analyzed to measure a person's privacy concerns (Figure 2). The categorization of the elements is flexible; for instance, both social trust and technical trust can affect privacy concerns (refer to the inner relations among the elements [solid lines] and subelements [dashed lines] plotted in Figure 2).

Figure 2. Influential factors of privacy concerns.



On the basis of these factors, we have determined that there are few studies investigating the privacy attitudes of other user roles with regard to these technologies. We found that, of the 66 included articles, only 1 (2%) [74] has conducted interviews with caregivers, while 2 (3%) [68,69] discuss the privacy concerns of bystanders. In addition, there are only a few studies that were not conducted within the specified geographic regions that collected technology researchers' perceptions of ethical issues (privacy is one of the ethical issues interviewed) with regard to smart home technologies [108]. Although bystanders will not be the majority of the users of assisted living technologies, we insist that privacy concerns should be gathered from them too. In addition, clinicians' and technical researchers' views need to be explored because they can provide more information based on their professional background. Therefore, more studies are required to be conducted from the perspective of different user roles, enabling shared privacy decision-making among them.

This review also reveals the problems in current research, such as an insufficient number of participants recruited, a lack of diversity regarding focus groups, the confirmation bias of researchers during study design, and the fuzzy definitions of different concepts, and provides suggestions for some of the barriers especially from the perspective of social psychology, such as improving cognitive functioning by applying the Hawthorne effect or reducing cognitive inconsistency by using cognitive dissonance.

To help participants make more accurate and stable decisions, we suggest that more empirical studies should be conducted that observe participants' behaviors and measure the distances between behaviors and attitudes. In combination with the self-perception theory [110], the participants are expected to observe themselves, notice the inconsistencies, and interpret their attitudes from their behaviors. In subsequent steps, researchers can also guide the participants appropriately based on the social learning theory [109], notify participants about the inconsistencies, and ask them to adjust their attitudes or behaviors to reduce the distances. On the basis of the newly gathered attitudes, participants' preferences and behaviors in real life are expected to be predicted more precisely on the machine level, by using appropriate predicting algorithms.

Study Limitations

Despite all the interesting findings, we acknowledge the limitations of the review. First, the scope of findings deviated somewhat from the search terms we set at the beginning. Because of the limited number of articles identified regarding legal concerns and legal frameworks, the legal frameworks and documents that we have listed are not exhaustive; therefore, we have not ventured in depth in this direction. Although we have classified the findings into subcategories of our creation, we cannot deny the fact that few studies are directly related to legal norms regarding privacy in health monitoring. Second, although some search terms were updated continually based on the new ideas we generated, to be compliant with the inclusion criteria (eg, the region specification), some important studies might have been excluded, although their findings may not be applicable and adaptable to the authors' country of residence. However, we encourage future works to be carried out in other regions to obtain a more comprehensive overview of the problem. Last but not least, although we have tried to interpret the findings from the perspective of social psychology, the evidence we have presented is inconclusive, and they remain to be investigated in long-term studies.

Conclusions

This scoping review has synthesized existing published research on privacy barriers with regard to the adoption of assisted living technologies. On the basis of the findings and main topics, the studies were classified into five categories: (1) privacy attitudes, (2) privacy concerns, (3) legal concerns, (4) legal frameworks, and (5) privacy barriers. Subsequently, we investigated the methodology and participant inclusion criteria. We have listed the factors that influence people's privacy concerns and analyzed the social psychological influence of the experiments on people's privacy awareness. Example legal challenges regarding privacy attitudes have been put forward, and the interaction between privacy factors and legal factors has been discussed. Future research might involve longitudinal studies on the privacy attitudes of different user roles and the informed consent obtained, with more psychological impacts such as the Hawthorne effect and confirmation bias carefully considered.

Acknowledgments

This work has been cofunded by the Initiative for ICT and digital innovation program of the Research Council of Norway under the scope of and as part of the outcome from the research project Reinforcing the Health Data Infrastructure in Mobility and Assurance through Data Democratization (Health Democratization, 2019–2024, project number 288856).

Conflicts of Interest

None declared.

Multimedia Appendix 1
PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.
[PDF File (Adobe PDF File), 549 KB - nursing_v7i1e53592_app1.pdf]

References

1. The 2021 ageing report: underlying assumptions and projection methodologies. The European Commission. URL: https://economy-finance.ec.europa.eu/publications/2021-ageing-report-underlying-assumptions-and-projection-methodologies_en [accessed 2024-04-04]
2. Lewis C, Buffel T. Aging in place and the places of aging: a longitudinal study. J Aging Stud 2020 Sep;54:100870 [FREE Full text] [doi: 10.1016/j.jaging.2020.100870] [Medline: 32972616]
3. The Ambient Assisted Living joint programme. ERA LEARN. URL: https://www.era-learn.eu/network-information/networks/aal-jp [accessed 2023-10-09]
4. Active and Assisted Living 2. ERA LEARN. URL: https://www.era-learn.eu/network-information/networks/aal-2 [accessed 2023-10-09]
5. Rostad HM, Stokke R. Integrating welfare technology in long-term care services: nationwide cross-sectional survey study. J Med Internet Res 2021 Aug 16;23(8):e22316 [FREE Full text] [doi: 10.2196/22316] [Medline: 34398791]
6. Vichitvanichphong S, Talaei-Khoei A, Kerr D, Ghapanchi AH. Assistive technologies for aged care: comparative literature survey on the effectiveness of theories for supportive and empowering technologies. Inf Technol People 2018;31(2):405-427. [doi: 10.1108/ITP-03-2017-0090]
7. Rosenberg RS. The Social Impact of Computers. Amsterdam, The Netherlands: Elsevier; Feb 1992.
8. Roger Clarke's privacy introduction and definitions. Xamax Consultancy. URL: http://www.rogerclarke.com/DV/Intro.html [accessed 2023-10-10]
9. Gutwirth S, Leenes R, de Hert P, Poullet Y. European Data Protection: Coming of Age. Dordrecht, The Netherlands: Springer; 2013.
10. Wang A, Zhang AN, Xu Y. Privacy in online social networks. In: Proceedings of the 11th International Conference on Computer and Information Science. 2012 Presented at: ICIS 2012; May 30-June 1, 2012; Shanghai, China. [doi: 10.12681/eadd/42507]
11. Serenko N. Informational, physical, and psychological privacy as determinants of patient behaviour in health care. In: Patient Safety and Quality Care through Health Informatics. Hershey, PA: IGI Global; 2014.
12. Ferguson C, Hickman LD, Turkmani S, Breen P, Gargiulo G, Inglis SC. "Wearables only work on patients that wear them": barriers and facilitators to the adoption of wearable cardiac monitoring technologies. Cardiovasc Digit Health J 2021 Apr 06;2(2):137-147 [FREE Full text] [doi: 10.1016/j.cvdhj.2021.02.001] [Medline: 35265900]

13. Tyler TR, Lind EA. A relational model of authority in groups. Exp Soc Psychol 1992;25:115-191 [FREE Full text] [doi: 10.1016/S0065-2601(08)60283-X]
14. Data protection impact assessment (DPIA). General Data Protection Regulation. URL: https://gdpr.eu/data-protection-impact-assessment-template/ [accessed 2023-10-09]
15. Liberati A, Altman DG, Tetzlaff J, Mulrow C, Gøtzsche PC, Ioannidis JP, et al. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. PLoS Med 2009 Jul 21;6(7):e1000100 [FREE Full text] [doi: 10.1371/journal.pmed.1000100] [Medline: 19621070]
16. Pham MT, Rajić A, Greig JD, Sargeant JM, Papadopoulos A, McEwen SA. A scoping review of scoping reviews: advancing the approach and enhancing the consistency. Res Synth Methods 2014 Dec;5(4):371-385 [FREE Full text] [doi: 10.1002/jrsm.1123] [Medline: 26052958]
17. Price ML, Surr CA, Gough B, Ashley L. Experiences and support needs of informal caregivers of people with multimorbidity: a scoping literature review. Psychol Health 2020 Jan;35(1):36-69. [doi: 10.1080/08870446.2019.1626125] [Medline: 31321995]
18. Armstrong R, Hall BJ, Doyle J, Waters E. Cochrane update. 'Scoping the scope' of a Cochrane review. J Public Health (Oxf) 2011 Mar;33(1):147-150. [doi: 10.1093/pubmed/fdr015] [Medline: 21345890]
19. Pawson R, Greenhalgh T, Harvey G, Walshe K. Realist review--a new method of systematic review designed for complex policy interventions. J Health Serv Res Policy 2005 Jul;10 Suppl 1:21-34. [doi: 10.1258/1355819054308530] [Medline: 16053581]
20. Matarese M, Lommi M, De Marinis MG, Riegel B. A systematic review and integration of concept analyses of self-care and related concepts. J Nurs Scholarsh 2018 May;50(3):296-305. [doi: 10.1111/jnu.12385] [Medline: 29645402]
21. Sánchez VG, Anker-Hansen C, Taylor I, Eilertsen G. Older people's attitudes and perspectives of welfare technology in Norway. J Multidiscip Healthc 2019 Oct 16;12:841-853 [FREE Full text] [doi: 10.2147/JMDH.S219458] [Medline: 31802884]
22. Kokolakis S. Privacy attitudes and privacy behaviour: a review of current research on the privacy paradox phenomenon. Comput Secur 2017 Jan;64:122-134 [FREE Full text] [doi: 10.1016/j.cose.2015.07.002]
23. Vassli LT, Farshchian BA. Acceptance of health-related ICT among elderly people living in the community: a systematic review of qualitative evidence. Int J Hum Comput Interact 2018;34(2):99-116. [doi: 10.1080/10447318.2017.1328024]
24. Shin G, Jarrahi MH, Fei Y, Karami A, Gafinowitz N, Byun A, et al. Wearable activity trackers, accuracy, adoption, acceptance and health impact: a systematic literature review. J Biomed Inform 2019 May;93:103153 [FREE Full text] [doi: 10.1016/j.jbi.2019.103153] [Medline: 30910623]
25. Biermann H, Offermann-van Heek J, Ziefle M. Older users’ benefit and barrier perception of using ultrasonic whistles in home care. In: Proceedings of the Human Aspects of IT for the Aged Population. Design for the Elderly and Technology Acceptance. 2019 Presented at: HCII 2019; July 26-31, 2019; Orlando, FL. [doi: 10.1007/978-3-030-22012-9_10]
26. Charness N, Best R, Evans J. Supportive home health care technology for older adults: attitudes and implementation. Gerontechnology 2016 Feb 23;15(4):233-242 [FREE Full text] [doi: 10.4017/gt.2016.15.4.006.00] [Medline: 29033700]
27. Chan M, Estève D, Fourniols JY, Escriba C, Campo E. Smart wearable systems: current status and future challenges. Artif Intell Med 2012 Nov;56(3):137-156 [FREE Full text] [doi: 10.1016/j.artmed.2012.09.003] [Medline: 23122689]
28. Gettel CJ, Chen K, Goldberg EM. Dementia care, fall detection, and ambient-assisted living technologies help older adults age in place: a scoping review. J Appl Gerontol 2021 Dec;40(12):1893-1902 [FREE Full text] [doi: 10.1177/07334648211005868] [Medline: 33853428]
29. Chan M, Campo E, Estève D, Fourniols JY. Smart homes - current features and future perspectives. Maturitas 2009 Oct 20;64(2):90-97 [FREE Full text] [doi: 10.1016/j.maturitas.2009.07.014] [Medline: 19729255]
30. Lanne M, Leikas J. Ethical AI in the re-ablement of older people: opportunities and challenges. Gerontechnology 2021;20(2):1-13. [doi: 10.4017/gt.2021.20.2.26-473.11]
31. Lederman R, Ben-Assuli O, Vo TH. The role of the internet of things in healthcare in supporting clinicians and patients: a narrative review. Health Policy Technol 2021 Sep;10(3):100552 [FREE Full text] [doi: 10.1016/j.hlpt.2021.100552]
32. Mallinson DJ, Shafi S. Smart home technology: challenges and opportunities for collaborative governance and policy research. Rev Policy Res 2022 Feb 20;39(3):330-352. [doi: 10.1111/ropr.12470]
33. Kolakowski H, Shepley MM, Valenzuela-Mendoza E, Ziebarth NR. How the COVID-19 pandemic will change workplaces, healthcare markets and healthy living: an overview and assessment. Sustainability 2021 Sep 09;13(18):10096 [FREE Full text] [doi: 10.3390/su131810096]
34. Caldeira C, Bietz M, Vidauri M, Chen Y. Senior care for aging in place: balancing assistance and independence. In: Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing. 2017 Presented at: CSCW '17; February 25-March 1, 2017; Portland, OR. [doi: 10.1145/2998181.2998206]
35. Schomakers EM, Vervier L, Ziefle M. The impact of user diversity on the acceptance of mHealth for aftercare - identifying the user types ‘assistance seekers’ and ‘privacy supporters’. In: Proceedings of the Human Aspects of IT for the Aged Population. 2020 Presented at: HCII 2020; July 19-24, 2020; Copenhagen, Denmark. [doi: 10.1007/978-3-030-50249-2_28]
36. Harrington EE, Bishop AJ, Do HM, Sheng W. Perceptions of socially assistive robots: a pilot study exploring older adults’ concerns. Curr Psychol 2021 Mar 18;42:2145-2156. [doi: 10.1007/s12144-021-01627-5]

37. Choi YK, Thompson HJ, Demiris G. Use of an internet-of-things smart home system for healthy aging in older adults in residential settings: pilot feasibility study. JMIR Aging 2020 Nov 10;3(2):e21964 [FREE Full text] [doi: 10.2196/21964] [Medline: 33170128]
38. Tural E, Lu D, Austin Cole D. Safely and actively aging in place: older adults' attitudes and intentions toward smart home technologies. Gerontol Geriatr Med 2021 May 22;7:23337214211017340 [FREE Full text] [doi: 10.1177/23337214211017340] [Medline: 34095352]
39. Attié E, Meyer-Waarden L. The acceptance and usage of smart connected objects according to adoption stages: an enhanced technology acceptance model integrating the diffusion of innovation, uses and gratification and privacy calculus theories. Technol Forecast Soc Change 2022 Mar;176:121485 [FREE Full text] [doi: 10.1016/j.techfore.2022.121485]
40. Karlsen IC, Colomo-Palacios R, Holone H. The medical use of smartwatches: a tertiary study comparing northern and southern European nursing homes. In: Proceedings of the Ninth International Conference on Technological Ecosystems for Enhancing Multiculturality. 2021 Presented at: TEEM'21; October 26-29, 2021; Barcelona, Spain. [doi: 10.1145/3486011.3486470]
41. Gimpel H, Manner-Romberg T, Schmied F, Winkler TJ. Understanding the evaluation of mHealth app features based on a cross-country Kano analysis. Electron Mark 2021;31(4):765-794 [FREE Full text] [doi: 10.1007/s12525-020-00455-y] [Medline: 35602116]
42. Mujirishvili T, Maidhof C, Florez-Revuelta F, Ziefle M, Richart-Martinez M, Cabrero-García J. Acceptance and privacy perceptions toward video-based active and assisted living technologies: scoping review. J Med Internet Res 2023 May 01;25:e45297 [FREE Full text] [doi: 10.2196/45297] [Medline: 37126390]
43. Wilczewski H, Soni H, Ivanova J, Ong T, Barrera JF, Bunnell BE, et al. Older adults' experience with virtual conversational agents for health data collection. Front Digit Health 2023 Mar 15;5:1125926 [FREE Full text] [doi: 10.3389/fdgth.2023.1125926] [Medline: 37006821]
44. Jaschinski C, Allouch SB, Peters O, van Dijk J. The influence of privacy on the acceptance of technologies for assisted living. In: Proceedings of the 6th International Conference on Human Aspects of IT for the Aged Population. 2020 Presented at: ITAP 2020; July 19-24, 2020; Copenhagen, Denmark. [doi: 10.1007/978-3-030-50249-2_33]
45. Chung J, Bleich M, Wheeler DC, Winship JM, McDowell B, Baker D, et al. Attitudes and perceptions toward voice-operated smart speakers among low-income senior housing residents: comparison of pre- and post-installation surveys. Gerontol Geriatr Med 2021 Mar 26;7:23337214211005869 [FREE Full text] [doi: 10.1177/23337214211005869] [Medline: 35047655]
46. Fruchter N, Liccardi I. Consumer attitudes towards privacy and security in home assistants. In: Proceedings of the Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems. 2018 Presented at: CHI EA '18; April 21-26, 2018; Montreal, QC. [doi: 10.1145/3170427.3188448]
47. Piau A, Steinmeyer Z, Mattek N, Lindauer A, Sharma N, Bouranis N, et al. Caregiving in older adults; experiences and attitudes toward smart technologies. J Clin Med 2023 Feb 23;12(5):1789 [FREE Full text] [doi: 10.3390/jcm12051789] [Medline: 36902576]
48. Tan NH, Wong RY, Desjardins A, Munson SA, Pierce J. Monitoring pets, deterring intruders, and casually spying on neighbors: everyday uses of smart home cameras. In: Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems. 2022 Presented at: CHI '22; April 29-May 5, 2022; New Orleans, LA. [doi: 10.1145/3491102.3517617]
49. Schomakers EM, Ziefle M. Privacy vs. security: trade-offs in the acceptance of smart technologies for aging-in-place. Int J Hum Comput Interact 2022 Jun 12;39(5):1043-1058. [doi: 10.1080/10447318.2022.2078463]
50. Randall N, Bennett CC, Šabanović S, Nagata S, Eldridge L, Collins S, et al. More than just friends: in-home use and design recommendations for sensing socially assistive robots (SARs) by older adults with depression. Paladyn J Behav Robot 2019;10:237-255. [doi: 10.1515/pjbr-2019-0020]
51. Gerłowska J, Furtak-Niczyporuk M, Rejdak K. Robotic assistance for people with dementia: a viable option for the future? Expert Rev Med Devices 2020 Jun;17(6):507-518. [doi: 10.1080/17434440.2020.1770592] [Medline: 32511027]
52. Soro A, Ambe AH, Brereton M. Minding the gap: reconciling human and technical perspectives on the IoT for healthy ageing. Wirel Commun Mob Comput 2017;2017:1-15. [doi: 10.1155/2017/7439361]
53. Wang S, Bolling K, Mao W, Reichstadt J, Jeste D, Kim HC, et al. Technology to support aging in place: older adults' perspectives. Healthcare (Basel) 2019 Apr 10;7(2):60 [FREE Full text] [doi: 10.3390/healthcare7020060] [Medline: 30974780]
54. Pilozzi A, Huang X. Overcoming Alzheimer's disease stigma by leveraging artificial intelligence and blockchain technologies. Brain Sci 2020 Mar 23;10(3):183 [FREE Full text] [doi: 10.3390/brainsci10030183] [Medline: 32210011]
55. Pekmezaris R, Williams MS, Pascarelli B, Finuf KD, Harris YT, Myers AK, et al. Adapting a home telemonitoring intervention for underserved Hispanic/Latino patients with type 2 diabetes: an acceptability and feasibility study. BMC Med Inform Decis Mak 2020 Dec 07;20(1):324 [FREE Full text] [doi: 10.1186/s12911-020-01346-0] [Medline: 33287815]
56. Kodate N, Donnelly S, Suwa S, Tsujimura M, Kitinoja H, Hallila J, et al. Home-care robots - attitudes and perceptions among older people, carers and care professionals in Ireland: a questionnaire study. Health Soc Care Community 2022 May;30(3):1086-1096 [FREE Full text] [doi: 10.1111/hsc.13327] [Medline: 33970511]
57. Berridge C, Halpern J, Levy K. Cameras on beds: the ethics of surveillance in nursing home rooms. AJOB Empir Bioeth 2019;10(1):55-62. [doi: 10.1080/23294515.2019.1568320] [Medline: 30794112]

58. Mittelstadt B. Ethics of the health-related internet of things: a narrative review. Ethics Inf Technol 2017 Jul 4;19:157-175 [FREE Full text] [doi: 10.1007/s10676-017-9426-4]
59. Koo SH, Fallon K. Explorations of wearable technology for tracking self and others. Fash Text 2018 Mar 28;5:8. [doi: 10.1186/s40691-017-0123-z]
60. Joe J, Chaudhuri S, Chung J, Thompson H, Demiris G. Older adults' attitudes and preferences regarding a multifunctional wellness tool: a pilot study. Inform Health Soc Care 2016;41(2):143-158. [doi: 10.3109/17538157.2014.965305] [Medline: 25325513]
61. Sánchez VG, Taylor I, Bing-Jonsson PC. Ethics of smart house welfare technology for older adults: a systematic literature review. Int J Technol Assess Health Care 2017 Nov 20;33(6):691-699. [doi: 10.1017/s0266462317000964]
62. Hjelm K, Hedlund L. Internet-of-things (IoT) in healthcare and social services - experiences of a sensor system for notifications of deviant behaviours in the home from the users' perspective. Health Informatics J 2022;28(1):14604582221075562 [FREE Full text] [doi: 10.1177/14604582221075562] [Medline: 35225069]
63. Cristiano A, Musteata S, De Silvestri S, Bellandi V, Ceravolo P, Cesari M, et al. Older adults' and clinicians' perspectives on a smart health platform for the aging population: design and evaluation study. JMIR Aging 2022 Feb 28;5(1):e29623 [FREE Full text] [doi: 10.2196/29623] [Medline: 35225818]
64. Zhang D, Lim J, Zhou L, Dahl AA. Breaking the data value-privacy paradox in mobile mental health systems through user-centered privacy protection: a web-based survey study. JMIR Ment Health 2021 Dec 24;8(12):e31633 [FREE Full text] [doi: 10.2196/31633] [Medline: 34951604]
65. Guazzini A, Fiorenza M, Panerai G, Duradoni M. What went wrong? Predictors of contact tracing adoption in Italy during COVID-19 pandemic. Future Internet 2021 Nov 15;13(11):286 [FREE Full text] [doi: 10.3390/fi13110286]
66. Wan L, Müller C, Randall D, Wulf V. Design of a GPS monitoring system for dementia care and its challenges in academia-industry project. ACM Trans Comput Hum Interact 2016 Oct 10;23(5):1-36. [doi: 10.1145/2963095]
67. Zheng S, Apthorpe N, Chetty M, Feamster N. User perceptions of smart home IoT privacy. Proc ACM Hum Comput Interact 2018 Nov 01;2(CSCW):1-20. [doi: 10.1145/3274469]
68. Yao Y, Basdeo JR, Mcdonough OR, Wang Y. Privacy perceptions and designs of bystanders in smart homes. Proc ACM Hum Comput Interact 2019 Nov 07;3(CSCW):1-24. [doi: 10.1145/3359161]
69. Ahmad I, Farzan R, Kapadia A, Lee AJ. Tangible privacy: towards user-centric sensor designs for bystander privacy. Proc ACM Hum Comput Interact 2020 Oct 15;4(CSCW2):1-28. [doi: 10.1145/3415187]
70. Kheirinejad S, Alorwu A, Visuri A, Hosio S. Contrasting the expectations and experiences related to mobile health use for chronic pain: questionnaire study. JMIR Hum Factors 2022 Sep 06;9(3):e38265 [FREE Full text] [doi: 10.2196/38265] [Medline: 36066960]
71. Reeder B, Chung J, Lyden K, Winters J, Jankowski CM. Older women's perceptions of wearable and smart home activity sensors. Inform Health Soc Care 2020 Jan;45(1):96-109. [doi: 10.1080/17538157.2019.1582054] [Medline: 30919711]
72. Halvorsrud L, Holthe T, Karterud D, Thorstensen E, Lund A. Perspectives on assistive technology among older Norwegian adults receiving community health services. Disabil Rehabil Assist Technol 2023 Jul;18(5):685-692. [doi: 10.1080/17483107.2021.1906962] [Medline: 33861681]
73. Langer A, Meleis A, Knaul FM, Atun R, Aran M, Arreola-Ornelas H, et al. Women and health: the key for sustainable development. Lancet 2015 Sep 19;386(9999):1165-1210. [doi: 10.1016/S0140-6736(15)60497-4] [Medline: 26051370]
74. Jaschinski C, Ben Allouch S. Listening to the ones who care: exploring the perceptions of informal caregivers towards ambient assisted living applications. J Ambient Intell Humaniz Comput 2018 May 25;10:761-778. [doi: 10.1007/s12652-018-0856-6]
75. Łukasik S, Tobis S, Kropińska S, Suwalska A. Role of assistive robots in the care of older people: survey study among medical and nursing students. J Med Internet Res 2020 Aug 12;22(8):e18003 [FREE Full text] [doi: 10.2196/18003] [Medline: 32784187]
76. Simpson E, Brown R, Sillence E, Coventry L, Lloyd K, Gibbs J, et al. Understanding the barriers and facilitators to sharing patient-generated health data using digital technology for people living with long-term health conditions: a narrative review. Front Public Health 2021 Nov 23;9:641424 [FREE Full text] [doi: 10.3389/fpubh.2021.641424] [Medline: 34888271]
77. Seberger JS, Patil S. Post-COVID public health surveillance and privacy expectations in the United States: scenario-based interview study. JMIR Mhealth Uhealth 2021 Oct 05;9(10):e30871 [FREE Full text] [doi: 10.2196/30871] [Medline: 34519667]
78. Chaparro JD, Ruiz JF, Romero MJ, Peño CB, Irurtia LU, Perea MG, et al. The SHAPES smart mirror approach for independent living, healthy and active ageing. Sensors (Basel) 2021 Nov 28;21(23):7938 [FREE Full text] [doi: 10.3390/s21237938] [Medline: 34883942]
79. Felber NA, Tian YJ, Pageau F, Elger BS, Wangmo T. Mapping ethical issues in the use of smart home health technologies to care for older persons: a systematic review. BMC Med Ethics 2023 Mar 29;24(1):24 [FREE Full text] [doi: 10.1186/s12910-023-00898-w] [Medline: 36991423]
80. Sun L, Yang B. Your privacy preference matters: a qualitative study envisioned for homecare. In: Proceedings of the IEEE Symposium on Computers and Communications (ISCC). 2021 Presented at: ISCC 2021; September 5-8, 2021; Athens, Greece. [doi: 10.1109/iscc53001.2021.9631403]

81. Elridge S. Cognitive bias. Britannica. URL: https://www.britannica.com/science/cognitive-bias [accessed 2023-10-09]
82. Nickerson RS. Confirmation bias: a ubiquitous phenomenon in many guises. Rev Gen Psychol 1998 Jun 01;2(2):175-220. [doi: 10.1037/1089-2680.2.2.175]
83. Groupthink vs the wisdom of crowds. The Learning NGO. URL: https://thelearningngo.wordpress.com/2010/05/15/groupthink-vs-the-wisdom-of-crowds/ [accessed 2024-04-04]
84. Vicsek L. A scheme for analyzing the results of focus groups. Int J Qual Method 2016 Nov 30;6(4):20-34. [doi: 10.1177/160940690700600402]
85. Daci J. Legal principles, legal values and legal norms: are they the same or different? Academicus Int Sci J 2010 Jul(2). [doi: 10.7336/academicus.2010.02.11]
86. Garg SK, Lyles CR, Ackerman S, Handley MA, Schillinger D, Gourley G, et al. Qualitative analysis of programmatic initiatives to text patients with mobile devices in resource-limited health systems. BMC Med Inform Decis Mak 2016 Feb 06;16:16 [FREE Full text] [doi: 10.1186/s12911-016-0258-7] [Medline: 26851941]
87. Costa A, Yelshyna A, Moreira TC, Andrade FC, Julián V, Novais P. A legal framework for an elderly healthcare platform: a privacy and data protection overview. Comput Law Secur Rev 2017 Oct;33(5):647-658 [FREE Full text] [doi: 10.1016/j.clsr.2017.03.021]
88. Jin MX, Kim SY, Miller LJ, Behari G, Correa R. Telemedicine: current impact on the future. Cureus 2020 Aug 20;12(8):e9891 [FREE Full text] [doi: 10.7759/cureus.9891] [Medline: 32968557]
89. Garzo A, Garay-Vitoria N. Ethical and legal implications for technological devices in clinical research in Europe: flowchart design for ethical and legal decisions in clinical research. In: Proceedings of the XXI International Conference on Human Computer Interaction. 2021 Presented at: Interacción '21; September 22-24, 2021; Málaga, Spain. [doi: 10.1145/3471391.3471403]
90. Ross G, Zhao Y, Bosman A, Geballa-Koukoula A, Zhou H, Elliott C, et al. Best practices and current implementation of emerging smartphone-based (bio)sensors – part 1: data handling and ethics. TrAC Trend Anal Chem 2023 Jan;158:116863 [FREE Full text] [doi: 10.1016/j.trac.2022.116863]
91. Ryu S. Book Review: mHealth: new horizons for health through mobile technologies: based on the findings of the second global survey on eHealth (Global Observatory for eHealth Series, Volume 3). Healthc Inform Res 2012;18(3):231-233 [FREE Full text] [doi: 10.4258/hir.2012.18.3.231]
92. Ambrosino N, Vitacca M, Dreher M, Isetta V, Montserrat JM, Tonia T, et al. Tele-monitoring of ventilator-dependent patients: a European Respiratory Society statement. Eur Respir J 2016 Sep;48(3):648-663 [FREE Full text] [doi: 10.1183/13993003.01721-2015] [Medline: 27390283]
93. Demiris G, Hensel B. “Smart homes” for patients at the end of life. J Housing Elder 2009 Feb 20;23(1-2):106-115. [doi: 10.1080/02763890802665049]
94. Cognitive impairment: a call for action, now!. Centers for Disease Control and Prevention. URL: http://www.cdc.gov/aging/pdf/cognitive_impairment/cogimp_poilicy_final.pdf [accessed 2024-03-19]
95. Sample informed consent language library: describing technologies used in research. Harvard Catalyst. URL: https://catalyst.harvard.edu/publications-documents/sample-informed-consent-language-library-describing-technologies-used-in-research/ [accessed 2023-10-10]
96. Whitney SN, McGuire AL, McCullough LB. A typology of shared decision making, informed consent, and simple consent. Ann Intern Med 2004 Jan 06;140(1):54-59. [doi: 10.7326/0003-4819-140-1-200401060-00012] [Medline: 14706973]
97. Sanchez VG, Pfeiffer CF. Legal aspects on smart house welfare technology for older people in Norway. In: Novais P, Konomi S, editors. Intelligent Environments. Amsterdam, The Netherlands: IOS Press; 2016:125-134.
98. Mosca F, Such JM, McBurney P. Value-driven collaborative privacy decision making. King's College London. 2019. URL: https://nms.kcl.ac.uk/hasp/pubs/Value_driven_Collaborative_Decision_Making__Privacy_Application__PAL2019_.pdf [accessed 2024-03-19]
99. Taylor MJ, Wilson J. Reasonable expectations of privacy and disclosure of health data. Med Law Rev 2019 Aug 01;27(3):432-460 [FREE Full text] [doi: 10.1093/medlaw/fwz009] [Medline: 31220873]
100. Shared decision making. National Institute for Health and Care Excellence. 2021 Jun 17. URL: https://www.nice.org.uk/guidance/ng197 [accessed 2023-10-10]
101. Wilkins RG. Defining the "reasonable expectation of privacy": an emerging tripartite analysis. Vanderbilt Law Rev 1987;40(5):1077. [doi: 10.4135/9781452234243.n643]
102. Kent G. Shared understandings for informed consent: the relevance of psychological research on the provision of information. Soc Sci Med 1996 Nov;43(10):1517-1523 [FREE Full text] [doi: 10.1016/0277-9536(96)00173-6] [Medline: 8923623]
103. Holden JD. Hawthorne effects and research into professional practice. J Eval Clin Pract 2001 Feb 07;7(1):65-70. [doi: 10.1046/j.1365-2753.2001.00280.x] [Medline: 11240840]
104. Martin DU, Perry C, Kaufman J. Effects of a mirror on young children's transgression in a gift-delay task. Br J Dev Psychol 2020 Jun 27;38(2):205-218. [doi: 10.1111/bjdp.12312] [Medline: 31774193]
105. Barth S, de Jong MD. The privacy paradox – Investigating discrepancies between expressed privacy concerns and actual online behavior – A systematic literature review. Telemat Inform 2017 Nov;34(7):1038-1058. [doi: 10.1016/j.tele.2017.04.013]

106. Norberg PA, Horne DR, Horne DA. The privacy paradox: personal information disclosure intentions versus behaviors. J Consum Affairs 2007 Mar 06;41(1):100-126. [doi: 10.1111/j.1745-6606.2006.00070.x]
107. Balakrishnan J, Dwivedi YK. Role of cognitive absorption in building user trust and experience. Psychol Mark 2021 Feb 24;38(4):643-668. [doi: 10.1002/mar.21462]
108. Ghosh I, Singh V. Using cognitive dissonance theory to understand privacy behavior. Proc Assoc Inf Sci Technol 2017 Oct 24;54(1):679-681. [doi: 10.1002/pra2.2017.14505401114]
109. Krokstad S, Langhammer A, Hveem K, Holmen TL, Midthjell K, Stene TR, et al. Cohort Profile: the HUNT Study, Norway. Int J Epidemiol 2013 Aug;42(4):968-977. [doi: 10.1093/ije/dys095] [Medline: 22879362]
110. McCarney R, Warner J, Iliffe S, van Haselen R, Griffin M, Fisher P. The Hawthorne Effect: a randomised, controlled trial. BMC Med Res Methodol 2007 Jul 03;7:30 [FREE Full text] [doi: 10.1186/1471-2288-7-30] [Medline: 17608932]

Abbreviations

EU: European Union
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Edited by E Borycki; submitted 11.10.23; peer-reviewed by Y Zhuang, I Mircheva; comments to author 03.11.23; revised version received 20.12.23; accepted 13.03.24; published 09.05.24.

Please cite as:
Sun L, Yang B, Kindt E, Chu J
Privacy Barriers in Health Monitoring: Scoping Review
JMIR Nursing 2024;7:e53592
URL: https://nursing.jmir.org/2024/1/e53592
doi:10.2196/53592
PMID:38723253

Review

Remote Patient Monitoring at Home in Patients With COVID-19: Narrative Review

Justien Cornelis[1], BSc, MSc, PhD; Wendy Christiaens[1], BSc, MSc, PhD; Christophe de Meester[1], BSc, MSc, PhD; Patriek Mistiaen[1], BSc, MSc, PhD

Belgian Health Care Knowledge Centre, Brussels, Belgium

Corresponding Author:
Justien Cornelis, BSc, MSc, PhD
Belgian Health Care Knowledge Centre
Kruidtuinlaan 55
Brussels, 1000
Belgium
Phone: 32 475834741
Email: justien.cornelis@kce.fgov.be

Abstract

Background: During the pandemic, health care providers implemented remote patient monitoring (RPM) for patients experiencing COVID-19. RPM is an interaction between health care professionals and patients who are in different locations, in which certain patient functioning parameters are assessed and followed up for a certain duration of time. The implementation of RPM in these patients aimed to reduce the strain on hospitals and primary care.

Objective: With this literature review, we aim to describe the characteristics of RPM interventions, report on patients with COVID-19 receiving RPM, and provide an overview of outcome variables such as length of stay (LOS), hospital readmission, and mortality.

Methods: A combination of different searches in several database types (traditional databases, trial registers, daily [Google] searches, and daily PubMed alerts) was run daily from March 2020 to December 2021. A search update for randomized controlled trials (RCTs) was performed in April 2022.

Results: The initial search yielded more than 4448 articles (not including daily searches). After deduplication and assessment for eligibility, 241 articles were retained describing 164 telemonitoring studies from 160 centers. None of the 164 studies covering 248,431 patients reported on the presence of a randomized control group. Studies described a “prehosp” group (96 studies) with patients who had a suspected or confirmed COVID-19 diagnosis and who were not hospitalized but closely monitored at home or a “posthosp” group (32 studies) with patients who were monitored at home after hospitalization for COVID-19. Moreover, 34 studies described both groups, and in 2 studies, the description was unclear. In the prehosp and posthosp groups, there were large variations in the number of emergency department (ED) visits (0%-36% and 0%-16%, respectively) and no convincing evidence that RPM leads to less or more ED visits or hospital readmissions (0%-30% and 0%-22%, respectively). Mortality was generally low, and there was weak to no evidence that RPM is associated with lower mortality. Moreover, there was no evidence that RPM shortens previous LOS. A literature update identified 3 small-scale RCTs, which could not demonstrate statistically significant differences in these outcomes. Most papers claimed savings; however, the scientific base for these claims was doubtful. The overall patient experiences with RPM were positive, as patients felt more reassured, although many patients declined RPM for several reasons (eg, technological embarrassment, digital literacy).

Conclusions: Based on these results, there is no convincing evidence that RPM in COVID-19 patients avoids ED visits or hospital readmissions and shortens LOS or reduces mortality. On the other hand, there is no evidence that RPM has adverse outcomes. Further research should focus on developing, implementing, and evaluating an RPM framework.

(JMIR Nursing 2024;7:e44580) doi:10.2196/44580

KEYWORDS

COVID-19; coronavirus disease; telemonitoring; remote patient monitoring; review; pandemic; at-home monitoring; implementation; health care; patient care

Introduction

The COVID-19 pandemic caused health care services around the globe to rapidly respond to the needs of people diagnosed with SARS-CoV-2 infection [1]. However, health care services in most countries were underprepared for this large-scale biological event and were stretched [2]. At the beginning of the pandemic, it was especially difficult to increase hospital capacity and upscale staffing levels. During the summer of 2020 with the possibility of a second wave in mind, health care providers started to adjust their preparedness and response protocols in order to be better prepared. During the subsequent waves of the pandemic, characterized by increased infection rates, the development and expansion of new health care services were boosted.

On the one hand, there was a need for community management of people who were infected and were presenting with symptoms, especially to reduce the strain on hospital resources (intensive care bed capacity, staffing, ventilators, etc) and health care worker exposure (personal protective equipment, etc). On the other hand, there was a need to increase responsiveness as primary care was overwhelmed and emergency departments (EDs) noticed that patients were receiving the care they needed too late. Remote patient monitoring (RPM) involves an interaction between health care professionals and patients who are at different locations, during which certain patient parameters are assessed and followed up for a certain duration of time. The idea arose to remotely monitor patients at home as much as possible in order to prevent these patients from going to the general practitioner (GP) and avoid hospitalization. GPs initiated their own RPM by means of telephone calls and remote assessments of parameters (eg, heart rate, blood pressure, oxygen saturation, weight, symptoms) measured by patients or their relatives at home or by ambulatory care nurses (data were transferred via electronic devices [Bluetooth, digital modes, broadband, wireless, etc]). Moreover, hospitals with prior experience in RPM for chronic pathologies, in which RPM was effective [3-5], started to develop care paths to spare hospital beds. This remote interaction involves several elements, such as patients, RPM staff, interaction content, and equipment. These elements and therefore the characteristics of RPM might differ owing to the simultaneous development of RPM across health care settings and health care providers around the globe, the quick initiation endorsed by the crisis situation, and the varying available resources and experiences.

COVID-19 was an unfamiliar pathology characterized by a rapidly changing nature and context. Owing to the novelty of the pathology and the variations in clinical presentations across infection waves and in formats of remote care, health care professionals indicated that valid risk stratification scales and assessment tools were lacking. Patients with COVID-19 (suspected) infection who had deteriorating symptoms, which usually occurred within 14 days after illness onset, needed to be identified in time [6]. A decision-aid report published on June 1, 2021 [7] mentioned intensified home care involving telemonitoring performed at least 2 to 3 times a day, with assessment of clinical parameters measured by patients, caregivers, or health care professionals. Based on the information obtained, advice could be given and therapy could be initiated (thromboprophylaxis, oxygen therapy, corticosteroids, other drugs [paracetamol and antibiotics], etc). Moreover, short-term oxygen therapy could be initiated at home. Patients eligible for remote monitoring could be sent home with RPM and oxygen therapy instead of being hospitalized. However, in this specific pathology, there was limited evidence on the most successful health care model for community management of COVID-19 patients and RPM.

Telemonitoring can be used to recognize and treat changes in the patient's health status as a stand-alone approach (eg, early detection) or as part of a telerehabilitation intervention. Moreover, the adoption of new care models is often challenged by unfamiliarity with program eligibility, services, and logistics, leading most providers to select the care option with which they are familiar (ie, traditional hospitalization and ED or GP visits). Patients can be reluctant to try out new approaches of care. For COVID-19, patients raised many questions, were very anxious, and requested admission for specialized care.

Health care organizations and professionals mainly initiated RPM in 2 specific groups of patients with COVID-19: (1) "prehosp" group with patients who had a suspected or confirmed COVID-19 diagnosis and were admitted to the GP's practice or ED but were not hospitalized and instead closely monitored at home, and (2) "posthosp" group with patients who were monitored at home after hospitalization for COVID-19. This study will focus on both groups and differentiate between the groups regarding outcome measures.

The purpose of this study is to find out if noninvasive RPM has been applied for COVID-19 patients to avoid hospital admission (prehosp) and to discharge patients earlier from the hospital (posthosp) (ie, number of hospital readmissions). Moreover, in the prehosp and posthosp groups, the study aims to investigate whether RPM in patients with COVID-19 is feasible or has an effect on the following outcomes: length of stay (LOS), number of ED visits, mortality, costs, savings, and patient experiences.

Methods

Several types of databases and sources were consulted as many COVID-19 studies were not yet published in traditional databases (Table 1). A combination of different searches in several database types (traditional databases, trial registers, daily Google searches, and daily PubMed alerts) was performed from March 2020 to December 2021. The searches were updated on April 16, 2022, but selection for relevant articles was limited to randomized controlled trials (RCTs).

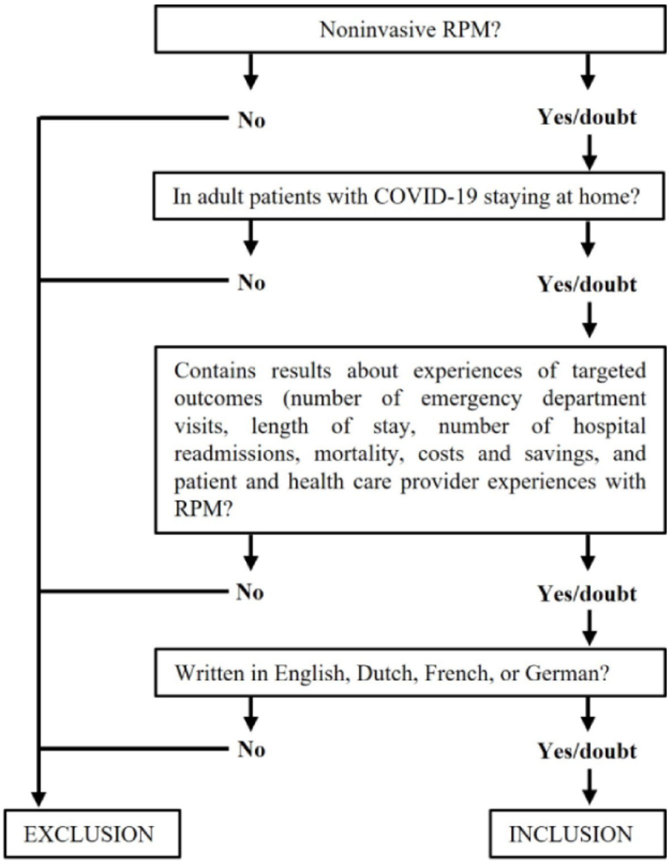
Table 1. Database type and source.

Database type	Source	Retrieved articles, n
Traditional database	PubMed, CINAHL, EMBASE, LISSA, and Cochrane Library	2520
Specifically developed for COVID-19 literature	NBCI [8], BVSalud [9], Cochrane Library [10], EBSCO Medical [11], COVID-19 Reviews [12], CEBM [13], and CADTH [14]	1910
Preprint server	bioRxiv [15], arXiv [16], Archives Ouvertes France [17], JMIR Preprints [18], and medRxiv [19]	0
Clinical Trials register	ClinicalTrials.gov [20], Clinical Trials Register Europe [21], WHO Clinical Trials Registry Platform [22], and Clinical Trials Database Belgium [19]	18
Worldwide web	Google Advanced and Google Scholar by means of the Publish or Perish interface	—[a]

[a] Not applicable as daily and monthly searches were performed continuously throughout the analysis of the retrieved articles in order not to miss newly published studies.

The adapted PICO(T) search was used. The search strategy aimed to include patients with COVID-19 residing at home (P), who were receiving noninvasive RPM (I), to follow their clinical status. Keywords were combined to describe the patient population ((Covid-19 OR Covid* OR corona OR Sars-Cov2) AND (home OR discharge OR post-hospital)) and intervention ((Telemonitor OR “remote monitor” OR “remote patient monitoring” OR “remote home monitoring” OR “hospital at home” OR “virtual visit” OR “virtual round” OR “virtual hospital” OR telehealth OR telemedicine OR smartphone OR wearable OR “mobile health” OR mhealth)). In some databases, specially developed search filters for COVID-19 were used. No specific keywords were added to the search, but selection criteria were set a priori. Articles were selected based on main outcomes (O) if the citations reported on the experiences of patients, ED visits, hospital readmission, LOS, or mortality, or if the costs or savings of telemonitoring were reported. In the initial search, all study types were included (T) irrespective of the comparator (C). The updated search was limited to RCTs. Articles were excluded if they concerned invasive RPM, involved patients residing at locations other than home, were not describing one of the main outcomes, or were published in a language other than English, French, Dutch, or German (Figure 1). Reference lists were checked for any topic-related studies. Expert opinions and recommendations on ongoing unpublished studies or other relevant data were gathered. The corresponding authors of studies were contacted to obtain any missing information or data. If means or SDs were not mentioned, these values were obtained by recalculation.

Figure 1. Inclusion and exclusion process. RPM: remote patient monitoring.



The references were retrieved and imported into EndNote for deduplication. Initially, 1 researcher (PM) screened the results from the electronic searches to select relevant citations based on titles and abstracts. Full-text articles were retrieved and evaluated based on the set selection criteria (Figure 1). In case of uncertainty, a second investigator (JC) evaluated the citation and consensus was sought during a meeting.

Owing to the crisis situation, we adopted an “ongoing” search (over more than 1 year) in order to detect articles published across the COVID-19 waves of infections. Therefore, we could not provide an overall estimation of hits. In addition, this approach of continuously searching may have provided us with more articles at a faster pace compared with systematic searching methods in traditional databases.

The data from the studies were extracted by 1 researcher (PM). The primary data extracted were related to the main outcomes (ie, number of ED visits, number of hospital readmissions, LOS, mortality, costs and savings, and patient experiences). The secondary data extracted were related to the general characteristics of the studies (ie, authors, publication year, study design, origin/country, and specific team/center), the characteristics of the patient population (eg, prehosp or posthosp, number of patients included, confirmed presence of COVID-19 infection, stage of COVID-19, place of residence, severity of symptoms, presence of comorbidities, risk profile, selection), and the characteristics of the intervention (eg, intervention elements, platform used, health care practitioners involved in monitoring, parameters monitored, duration of monitoring, number of clinical interventions, number of alerts). Data on costs, savings, and patient experiences were retrieved. In case the outcomes for a combined group of prehosp and posthosp were reported, the articles were left out from the main outcome analysis, except for the patient satisfaction outcome.

Results

Overview

The initial search yielded more than 4448 articles (Table 1). In addition, periodical searches in traditional databases and daily searches were performed. As these did not provide the total hits per search, they have not been included in this number. After deduplication and assessment for eligibility, 241 articles were retained, which described 164 telemonitoring studies from 160 centers [1,6,23-261].

General Characteristics of the Studies

Studies were conducted across the globe in over 28 countries. Most studies were from the United States (n=64), United Kingdom (n=15), Australia (n=11), Spain (n=11), and Italy (n=10). Studies were also conducted in Argentina, Belgium, Bolivia, Brazil, Canada, China, Czech Republic, Egypt, France, Gambia, Germany, India, Iran, Ireland, Israel, Japan, Malaysia, Peru, Portugal, Saudi Arabia, South Korea, Switzerland, and The Netherlands.

All the included articles concerned observational studies, with some of them including a kind of comparison arm (eg, patients who received telemonitoring in certain areas versus patients from another area who presumably had not received telemonitoring, patients with symptoms versus asymptomatic patients, patients with RPM at home versus patients with RPM in a quarantine hotel, patients receiving low-intensity RPM versus patients receiving high-intensity RPM, or prehosp RPM versus posthosp RPM). Seven studies [67,81,118,133,165,211,253] applied a matched control study design in which RPM was compared to no RPM and patient characteristics (such as comorbidities and risk profiles) were taken into account in a weighted way. Among these matched control studies, 6 [67,118,134,203,211,253] concerned prehosp patients, while 3 [81,118,165] described posthosp patients. With a search update, 3 small RCTs were included. Since limited RCTs were retrieved, no methodological assessment was performed.

General Characteristics of the Patient Population

The research population size varied from 10 to 43,103. Fifty studies were small-scale studies with less than 100 patients, but there were also 6 studies [47,123,124,147,167,253] with more than 10,000 patients. Overall, the included 164 studies covered 248,431 patients.

The patients included in the retrieved studies had proven or suspected COVID-19 infection and were residing at home. The moment of RPM initiation varied among patients and included the day of being suspected with COVID-19, the day of the first symptoms, the day of a positive test, the day of an ED visit, the day of worsening of symptoms, and the day of hospital discharge.

Among the studies, 96 concerned only prehosp patients and 32 concerned only posthosp patients. Moreover, 34 studies described both groups, and in 2 studies, it was unclear if prehosp or posthosp patients were considered.

The patients were in a certain stage of the COVID-19 disease (asymptomatic, immediately after suspicion of COVID-19 infection, mild symptomatic, or severe disease presentation) and had comorbidities or risk factors (which were not always described in the studies). Some of the studies (eg, [39,100,136,163]) included only high-risk patients (eg, aged ≥65 years and 1 comorbidity), while others (eg, [28,79,146,160]) included only low-risk patients or did not select the population based on risk stratification. The way in which and the criteria on which the risk was assessed differed or was not described. In some cases, deterioration risk assessment was used to select patients, while in others, it was used to adapt the intervention to the risk profile (increasing frequency of measuring parameters, additional parameters to follow, adapted alert settings, etc). Some studies focused on special populations with COVID-19, such as oncological patients [59,62,63,70,84,109,122,133-135,137,140,153,179,225], children [64,218,238], liver transplant patients [239], and pregnant or postpartum women [170,180,223,240,245].

General Characteristics of the Intervention

Across the studies, a variety of health care professionals, such as nurses, nurse practitioners, physician assistants, physiotherapists, respiratory specialists, psychologists, social workers, dieticians, medical and nursing students, GPs, and medical specialists, remotely monitored patients with

COVID-19. Sometimes a stepped approach was applied (eg, nurses performed the monitoring, but in case of deterioration, the monitoring was transferred to a medical specialist).

In many studies, existing RPM staff and infrastructure for managing telemonitoring in patients with other diseases were used and extended. RPM studies were mainly hospital initiated, but in some cases [1,26,68,79,131,138,162,176,203,219,252], primary care professionals also applied a form of RPM. The sizes of the telemonitoring teams described in the studies varied from a single professional to a larger multidisciplinary telemonitoring team. Sometimes a specialized telemonitoring team, external of a hospital, was used (eg, [102,174]). The articles rarely mentioned full-time equivalents. Many studies used volunteers, and retired and redeployed health care professionals (eg, [26,47,49,57,68,80,82,126,128,166,206,212,232]). In addition, administrative and technical staff members were added. The staff members assigned to conduct RPM differed across studies and settings and were not always clearly described.

Patients needed a smartphone, computer, or tablet for information exchange and a number of measuring devices (eg, thermometer, saturation meter, blood pressure meter, pulse meter), either as a separate device for each parameter or a single device for a combination of parameters (eg, smartwatch and in-ear device). Some measuring devices took measurements automatically, sometimes in a continuous way, and were sometimes connected via the internet or Bluetooth to the patient's electronic device. In addition to objective registration of physiologic measurable parameters, studies also used daily surveys monitoring subjective variables such as dyspnea, fatigue, and pain. All parameter data were sent to and processed on an information and communication system to provide health care professionals with numerical and graphical insights into patient functioning. This information and communication system could either be stand-alone or integrated into the electronic patient record of a hospital or a GP. The devices and digital infrastructure used to conduct RPM differed across studies and settings and were not always clearly described.

The interaction mode between the patient and the RPM team could involve 1-way communication (patient to RPM team) or 2-way communication. Different combinations of telephone audio calls, video calls, text messages, and specially created software platforms were used. At the time of initiating the telemonitoring, a combination was sometimes made with a home visit (by one or more health care professionals; eg, [102,233,262]) for instructions or technology set-up. The interaction mode for conducting RPM differed across studies and settings and was not always clearly described.

Owing to the lack of controlled studies, a large variation was found in patient functioning variables that were monitored across the different studies (eg, general well-being, fatigue, coughing, diarrhea, smell, mobility, temperature, heart rate, respiratory rate, shortness of breath, oxygen saturation). The parameter that was most often monitored was oxygen saturation, followed by subjective dyspnea. The ways in which these variables were assessed varied (patient self-assessment, assessment by a health care professional [at site or remotely], or assessment by means of a connected device). Moreover, alerting cutoffs for each parameter varied. In some cases, the numbers of monitored variables (and devices) were scaled up or down depending on patients' conditions. The assessment frequency varied widely from once per 2 days and 5 times per day to 24×7 continuously (eg, [48,53,72,89,90,92,121,131,142,154,163,164,172,188,196,201,209,210,250]) for some parameters, and the frequency could vary during the course depending on the presenting symptoms [174]. In both the prehosp and posthosp groups, telemonitoring was sometimes accompanied (eg, [102,134,152,177,178,185,197,203,205,208,211,221,233,238,256,260]) by other interventions, such as oxygen therapy, antibiotics, antipyretics, anticoagulants, corticosteroids, hydroxychloroquine, and lopinavir or ritonavir. However, details about dose, frequency, and duration were mostly lacking. Many articles did not mention whether there were co-interventions. From the articles, it was not clear to what extent these co-interventions influenced the measured functioning variables and outcomes.

Based on the data received (the interaction content), reactions from the RPM team were provided. These reactions varied and included (1) no reaction as long as parameters were within the set limits ("no news is good news" strategy), (2) a reassuring reaction toward the patient each time parameters were uploaded to tell them they were received and normal, (3) an automatically generated signal or a call to patients to reassess a parameter when this was suspicious, (4) a call to a GP or registered nurse that a parameter was suspicious and further investigation or a home visit could be useful, (5) a call to the patient to visit the GP or ED for further check-up, and (6) a call to the patient to immediately present to the hospital for admission. Sometimes deviating parameters were first discussed within the RPM team and with specialist consultants before a reaction. It was unclear what types of interventions were deployed on what types of alerts for which parameters and if all these reactions were systematically registered in the systems by the RPM team. The interaction content and reactions of the telemonitoring team differed across studies and settings and were not always clearly described.

Overall, a high heterogeneity in the technology used and the characteristics of the interventions (ie, amount of staffing, devices and digital infrastructure, details on the health care settings, details on the health care system, interaction mode, interaction content, and reactions of the telemonitoring team) was observed among studies. Moreover, the lack of RCTs limited the control of monitored variables and the risk stratification of patients. The described results were not provided by all studies as the information was not always available. Therefore, it was not possible to compare RPM between different COVID-19 interventions and between studies.

Results for the Main Outcomes

There were large variations in outcomes that were measured and reported. Studies discussed process outcomes (number of patients who refused RPM, eg, [40,81,119,147,153,171,177,191,199,251]; number of alerts, eg, [23,29,50,58,59,62,66,81,92,98,111,117,124,127,135,142,154,155,165,166,174-176,181,185,204,210,250];

number of interactions and reactions of the RPM team, eg, [70,72,81,86,90,117,152,154,174,179,203,212,225,238,240,245,252,254,256]; number of technical problems, eg, [50,91,105,175,244]; and duration of RPM), clinical outcomes (number of ED visits, number of hospital readmissions, and mortality), economical outcomes (cost of RPM, hospital days avoided, and cost savings, eg, [6,28,35,43,61,75,76,85,96,114,126,130,139,144,158,159,172,173,176,178,185,187,202-204,241,251,256,261]), and experiences of health care professionals (eg, [28,37,38,49,51,53,70,75,87,92,110,131,139,149,160,170,172,173,181,187,189,200,230,236]) and patients (eg, [25,28-30,34,36-38,47,48,53,54,57,62,63,65,68,70,72,75,83,86,87,91,92,96,99,100,107,109,114,116,119-121,124,126,130,131,135,139,144,149,151,153,158,163,165,168,169,172-174,178,181,187,189,199,207,208,213,214,220,222,224,226,235,236,243,247,248,254]). The periods wherein the outcome measurements were performed and registered were rarely clear. The lack of RCTs limited controlling for these outcomes.

Some studies (eg, [150,174]) presented separate analyses for low- and high-risk patients with substantive differences between them. In these studies, low-risk patients received lower intensity interventions. The outcomes presented in studies that did not make this risk differentiation should be read cautiously.

As noted in the description of the outcomes, there was a large variation in reported outcomes. Moreover, the lack of RCTs limited controlling for these outcomes. Furthermore, among studies that reported on similar outcomes, the measurement procedure or time of measurement (eg, in which period was ED admission or mortality measured, when was it decided to stop measuring) mostly differed from study to study, making the pooling of results very difficult. However, we extracted these data from the studies as much as possible and succeeded in pooling the results. With regard to clinical outcomes, for both groups, we retrieved the duration of RPM, the number of ED visits, hospital readmission, and mortality. For the hospitalized patients in the posthosp group, LOS was retrieved. As seen in Table 2, more studies reported on these outcome measures in the prehosp group. The duration of RPM varied from a single day to several weeks. The median duration of RPM was 10 and 13.6 days for the prehosp and posthosp groups, respectively. ED visits were more frequent in the prehosp group (11.2%) than in the posthosp group (6%). Similar percentages of hospital admissions (6.4%) in the prehosp group and readmissions (5.4%) in the posthosp group were noted. In both the prehosp and posthosp groups, low mortality rates (0.15% and 0%, respectively) were reported. The median LOS for hospitalized (posthosp) patients was 6 days (with a large variation between 1.7 and 38 days). It was not possible to correlate these outcomes to certain variables, such as the RPM duration to certain patient population risk profiles, comorbidities, or end points, for the reasons mentioned earlier. Concerning specific patient populations, RPM appears to be feasible in these patients. More detailed information can be found in another publication [263].

Table 2. Description (pooling results) of studies reporting on the targeted clinical outcomes.

Outcome variable	Prehosp group			Posthosp group		
	Studies, n	Median (range)	Percentile (P25-P75)	Studies, n	Median (range)	Percentile (P25-P75)
Duration of RPM[a] (days)	33	10.0 (3.5-21.8)	8.0-13.1	16	13.6 (3.1-90.0)	11.8-20.5
Emergency department visits (%)	54	11.2 (0.0-36.0)	5.7-19.9	13	6.0 (0.0-15.8)	2.8-10.3
Hospital readmissions (%)	81	6.4 (0.0-30.4)	3.1-11.4	23	5.4 (0.0-22.2)	2.0-10.5
Mortality (%)	55	0.15 (0.0-8.8)	0.0-1.1	14	0.0 (0.0-4.2)	0.0-1.4
Length of stay (days)	—[b]	—	—	11	6.0 (1.7-38.0)	4.0-10.0

[a] RPM: remote patient monitoring.

[b] Not applicable.

We described the clinical outcomes reported in the studies applying a matched control design separately. An overview of the prehosp group is provided in Table 3, and an overview of the posthosp group is provided in Table 4.

Table 3. Clinical outcomes in the prehosp group in matched control studies.

Study	Participants, n		ED[a] visits at 30 days			ED visits at 90 days			30-day hospital admission			Mortality at 30 days			Mortality at 60 days		
	I[b]	C[c]	I, n (%)	C, n (%)	Adj OR[d] (95% CI)	I, n (%)	C, n (%)	Adj OR (95% CI)	I, n (%)	C, n (%)	Adj OR (95% CI)	I, n (%)	C, n (%)	Adj OR (95% CI)	I, n (%)	C, n (%)	Adj OR (95% CI)
Beaney et al [253]	639	14,982	192 (30.1)	3568[e] (23.8)	1.37 (1.16-1.63)	—[f]	—	—	152 (23.8)	3180[e] (21.2)	1.59 (1.32-1.91)	9 (1.4)	430[e] (2.9)	0.48 (0.25-0.93)	—	—	—
Delgado et al [211]	3488	4377	489 (14.0)	252 (5.7)	0.06 (0.04-0.07)	—	—	—	211 (6.1)	141 (3.2)	1.93 (1.56-2.41)	3 (0.1)	12 (0.3)	0.32 (0.12-0.72)	5 (0.1)	16 (0.4)	0.34 (0.16-0.67)
Dirikgil et al [67]	55	110	—	—	—	—	—	—	5 (9.1)	30 (27.0)	0.27 (0.10-0.73)	—	—	—	—	—	—
Misra-Hebert et al[g] [118]	2672	1950	273 (10.2)	193 (9.9)	1.03 (0.76-1.39)	382 (14.3)	275 (14.1)	1.01 (0.78-1.31)	302 (11.3)	242 (12.4)	0.90 (0.68-1.20)	—	—	—	—	—	—
Pritchett et al[h] [134]	71	116	7 (9.9)	18 (15.5)	0.59 (0.24-1.51)	—	—	—	3 (4.2)	15 (12.9)	0.33 (0.09-1.17)	0 (0.0)	4 (3.4)	0.17 (0.01-3.30)	—	—	—

[a] ED: emergency department.

[b] I: intervention group, group receiving remote patient monitoring.

[c] C: control group.

[d] Adj OR: adjusted odds ratio.

[e] Recalculated from OR.

[f] Not applicable.

[g] Based on the number mentioned for outpatients who did not present first to the ED.

[h] Concerning cancer patients with COVID-19.

Table 4. Clinical outcomes in the posthosp group in matched control studies.

Study	Participants, n		ED[a] visits at 30 days			30-day hospital admission			Mortality at 14 days			Length of stay (days)		
	I[b]	C[c]	I, n (%)	C, n (%)	Adj OR[d] (95% CI)	I, n (%)	C, n (%)	Adj OR (95% CI)	I, n (%)	C, n (%)	Adj OR (95% CI)	I[e]	C[e]	Adj OR (95% CI)
Gordon et al [81]	225	1061	11 (4.9)	46 (4.3)	NS[f]	3 (1.3)	60 (5.7)	0.22 (0.07-0.71)	—[g]	—	—	5 (3-8)	5 (3-8)	NS
Ye et al [165]	217	192	18 (8.3)	27 (14.1)	NS	15 (6.9)	16 (8.3)	NS	3 (1.4)	4 (2.1)	0.66 (0.15-2.99)	5 (3.9)	4.2 (3.2)	NS

[a] ED: emergency department.

[b] I: intervention group, group receiving remote patient monitoring.

[c] C: control group.

[d] Adj OR: adjusted odds ratio.

[e] Data are presented as mean (range) or mean (SD).

[f] Not significant.

[g] Not applicable.

Regarding the clinical outcomes in the prehosp group, 4 studies [118,134,211,253] reported on the number of ED visits. Two of them [211,253] found a significantly higher number of ED visits within 30 days for RPM, while the other 2 did not find a difference. Five studies [67,118,134,211,253] reported on the 30-day hospitalization rate. Two studies [211,253] found a significantly higher number of hospital admissions in the RPM group, 2 [118,134] found no significant difference, and 1 [67] found a significantly lower number of hospital admissions in the RPM group. However, the latter study was a small-scale study, and the 30 patients who were “admitted” in the control group consisted of 25 patients who stayed for less than 24 hours. It could be questioned if this should be regarded as a real hospital admission. When these were taken out of the analysis, there was no longer a significant difference. Three studies [134,211,253] reported on the 30-day mortality rate. Two studies [211,253] found significantly less mortality in the RPM group, and 1 study found the same effect at day 60. The third study [134] was a small-scale study in cancer patients with COVID-19, and there was no significant difference.

One study [118] only included patients who presented first in primary care and excluded patients who presented first to the ED. Moreover, another study [134] concerned patients with cancer and COVID-19. Regarding the effect found in 1 article [253], 2 other publications on the same project used another research design investigating a period without the availability of RPM versus a period with the availability of RPM [257] and investigating regions with higher uptake of RPM versus regions with lower uptake of RPM [258]. The pre-post analysis [257] also found a slightly higher ED attendance in the RPM period, but the regional analysis [258] did not show an effect on ED visits and hospital admissions.

Regarding the clinical outcomes in the posthosp group, 2 studies [81,165] from the United States performed a matched control comparison and found no significant difference in ED visits (with more ED visits in the control group). One study [81] found significantly less hospital readmissions with RPM in multivariate analysis. The control group consisted of patients who did not receive RPM (for unclear reasons). Another study [165] found less hospital readmissions with RPM, but the difference was nonsignificant. A nonsignificant difference in the percentage of patients who died within 14 days was found between those referred to RPM and those not referred to RPM [165]. No significant differences were found for LOS.

In summary, there was a large variety in the number of ED visits across prehosp studies and there was no convincing evidence that prehosp or posthosp RPM leads to less or more ED visits. Moreover, there was no convincing evidence that prehosp or posthosp RPM is associated with less or more hospital readmissions. Mortality with prehosp or posthosp RPM was generally low based on the studies presented in Tables 3 and 4, and there was weak to no evidence showing that RPM is associated with lower mortality than non-RPM. Although some of the presented studies reported a lower mortality for patients with RPM, this finding was not significant. No studies reporting on mortality provided statistics on the general mortality rate per country or health care setting, and the studies had a matched control design (no RCTs). There was no evidence that RPM shortens previous hospital LOS.

The initial search (until December 15, 2021) did not identify RCTs. However, searches showed that there are ongoing studies [264-290], of which 9 [264,265,268,276,277,281,286-288] are RCTs in which at-home patients with COVID-19 will be randomized (yes or no RPM). With the database search update (until April 16, 2022) limited to RCTs, 475 hits were screened, and 3 RCTs were retrieved and discussed [276,291,292].

Two small-scale RCTs with 62 [292] and 150 [291] posthosp patients were identified. van Goor et al [292] concluded that remote hospital care for recovering COVID-19 patients is feasible, but there was no increase in hospital-free days in the 30 days following randomization. They found that the mean difference in hospital-free days was 1.7 (26.7 days in the control group vs 28.4 days in the intervention group, 95% CI of difference −0.5 to 4.2; P=.11). In the intervention group, the index hospital LOS was 1.6 days shorter (95% CI −2.4 to −0.8; P<.001), but the total duration of care under hospital responsibility was 4.1 days longer (95% CI 0.5-7.7; P=.03). A per-protocol analysis [291] indicated that patients in the control group were significantly more likely to return to the ED for COVID-19–related reasons than those in the experimental group (7.9% vs 0%; P=.03). However, no differences were observed in the intention-to-treat analysis. Satisfaction with outpatient monitoring was rated more highly by the experimental group in both the per-protocol and intention-to-treat analyses. There were no statistically significant differences reported in the health status questionnaire or anxiety scale by the end of follow-up. Thus, both posthosp trials could not demonstrate statistically significant differences in outcomes between the experimental and control groups.

One RCT [276] compared patients without wearable monitoring technology undergoing routine standard of care at the hospital (n=150) to patients diagnosed with COVID-19 undergoing self-quarantine while being closely monitored using a wearable device (n=130) in the prehosp group. Based on the preliminary results, no significant differences in outcomes between the experimental and control groups were seen. The study has not been published yet, and this conclusion is based on the preliminary data available in the clinical trial register.

In summary, no statistically significant differences were observed in the studies, except [292], which showed that the index hospital LOS was shorter for posthosp patients (suggesting an earlier discharge when patients could be followed up at home with RPM after discharge), but the total duration of care under hospital responsibility was significantly longer. The results of the RCTs are in line with the results of the matched control studies.

Results on Costs and Savings

Several articles [6,28,29,35,36,43,45,48,55,61,67,75,76,81,83,85,96,97,114-116,118,126,130,134,139,141,144,150,157-159,165,172,173,176,178,185,187,202-204,214,241,251,256,261] included information on the costs of the intervention or made claims on savings with RPM in terms of avoided ED visits, avoided hospital admissions, and reductions in LOS (sometimes expressed in monetary values). The details on the costs and claims on savings were assessed. All these claims were in favor of RPM. However, it needs to be considered that none of these claims and conclusions are based on RCTs. Only a few studies used some kind of comparison group, and the findings are mainly based on expert opinion. In most articles claiming savings, a clear methodology was lacking. Therefore, the scientific base for these claims is doubtful.

Results on Patient Experiences

Overall, 73 articles [25,28-30,34,36-38,47,48,53,54,57,62,63,65,68,70,72,75,83,86,87,91,92,96,99,100,107,109,114,116,119-121,124,126,130,131,135,139,144,149,151,153,158,163,165,168,169,172-174,178,181,187-189,199,207,208,213,214,220,222,224,226,235,236,243,247,248,254] mentioned an indicator of patient experience. In general, patient reports were very positive about RPM. Patients mainly experienced a feeling of reassurance.

However, this overall positive picture might be skewed, because several studies only included patients who already had some digital proficiency and were familiar with smartphone use [167]. Moreover, in most studies, patient satisfaction questionnaires were only answered by some patients who received RPM, increasing the chance for self-selection bias. Some studies (eg, [40,81,119,147,153,171,177,191,199,251]) reported that RPM was offered but patients declined it for several reasons (eg, feeling good enough and too much technological embarrassment expected).

Discussion

Principal Findings

The objective of this study was to find out if noninvasive RPM has been used among COVID-19 patients to avoid hospital admissions (prehosp) and to discharge patients earlier from the hospital (posthosp) (ie, number of hospital readmissions). Moreover, in the prehosp and posthosp groups, it aimed to investigate whether RPM is feasible and has an effect on the following outcomes in patients with COVID-19: LOS, number of ED visits, mortality, costs and savings, and patient experiences.

None of the 160 original studies (241 articles) covering 248,431 patients reported on the presence of a randomized control group. Among the studies, 96 described a “prehosp” group with patients who had a suspected or confirmed COVID-19 diagnosis and who were not hospitalized but closely monitored at home, 32 described a “posthosp” group with patients who were monitored at home after hospitalization for COVID-19, and 34 described both groups. In 2 studies, the descriptions were unclear.

All studies aimed to lower the pressure on hospital resources or capacity by avoiding ED visits and hospital readmissions and shortening hospital LOS. In the prehosp and posthosp groups, there was a large variation in the number of ED visits (0%-36% and 0%-16%, respectively) and no convincing evidence that RPM leads to less or more ED visits or hospital readmissions (0%-30% and 0%-22%, respectively). Moreover, there was no evidence that RPM shortens LOS. The studies focused on the timely upscaling of health care interventions in case of possible deterioration of the patient, avoiding deterioration and mortality, plausible cost savings, and reassuring patients. Mortality was generally low. Most papers claimed that savings and overall patient experiences with RPM were positive.

Considerations

With regard to the characteristics of patients with COVID-19, in the prehosp group, some studies focused on high-risk patients, while others focused on low-risk patients (or somewhere in between). Some studies did not provide this information. Focusing on low-risk patients implies that a higher number of patients should be monitored and consequently more devices are needed. Therefore, there is a higher workload for the RPM team. On the other hand, it provides more certainty that patients showing deterioration are detected, which is certainly an advantage in a pandemic involving a disease course that is largely unknown, and that patients with silent hypoxia can be better detected (contributing more to the goal of early detection before escalation). Focusing on high-risk patients limits the number of patients who need RPM and may ensure that patients with the highest risk are monitored and deterioration is detected in a timely manner. The best choice in the case of an unknown disease is probably to follow-up all patients and consider end points to define prognostic variables. However, there was limited time or resources to do this. In the future, RPM could target both groups but with a differentiated approach (such as number of parameters to be followed, frequency of monitoring, type of devices, and stepped RPM team). Regarding posthosp RPM studies, it was remarked [293,294] that most studies did not use clear criteria to decide which patients could be discharged earlier and followed by RPM. Objective discharge criteria were generally lacking or were not reported (such as afebrile, oxygen independency, and no medication needed). With less criteria applied, more patients could leave the hospital and free up beds (some studies reported on a LOS of 1 day). However, when patients had a longer LOS, they also required a higher complexity of needed postdischarge care and probably had a higher chance of deterioration (some studies reported on patients who were admitted during weeks at the intensive care unit). There is limited clarity regarding when posthosp RPM is useful, which are the end points of RPM, and when the change toward teleconsultation [295] or telerehabilitation [296] can best be made.

Moreover, valid risk stratification scales and assessment tools for patients with COVID-19 were lacking. As stated previously, throughout the pandemic, attempts were made to construct valid risk stratification scales. Formulating clear criteria for safe discharge and establishing end points for RPM follow-up after hospital discharge could be useful. Gavin et al [255] showed that the simplified HOSPITAL score is an applicable instrument to triage patients with COVID-19 for hospitalization according to their risk for potentially avoidable readmissions. Moreover, other studies [262,297-300] have provided useful information on the relationship between patient characteristics and risk for readmission after hospital discharge. However, the number of studies examining risk factors for hospital readmission and postdischarge mortality is small, and sometimes their quality is low owing to various reasons [301].

Regarding the effects of RPM on LOS, several articles stated that LOS was shortened because of the implementation of posthosp RPM. However, it was seen that the rate of readmission in posthosp patients differed greatly and that the timeframe (7, 15, 30, and 60 days after discharge) was not always mentioned.

A shorter LOS does not mean much if these patients need to be rehospitalized soon after discharge, and there are indeed indications that a shorter LOS is related to higher rates of readmission (ie, "Short-stay hospitalization had significantly increased odds of rehospitalization within 7 days" [262]; "However, patients who were readmitted had significantly shorter initial LOS (median 7 days (range: 2-54) versus 8 days (range: 2-107), $P<.001$)" [300]; "During the COVID-19 pandemic and its outbreaks, the lack of hospital beds, medical facilities, and human resources caused patients to be discharged too early, leading to increased hospital readmissions and possible post-discharge deaths" [301]).

The results show that it is difficult to interpret if an ED visit is regarded as "good" or "wrong." On one hand, RPM aims to timely detect deterioration in order to stop further deterioration. On the other hand, RPM aims to avoid ED visits and hospital readmission. These aims are somewhat contradictory. On detecting deterioration, it could be appropriate to further assess the patient in the ED or admit the patient to the hospital. In this way, a large percentage of ED visits and hospital admissions could be interpreted as not only "success" but also "failure." On sensitive detection of deterioration, RPM could lead to more ED visits and hospital admissions compared to the absence of RPM, but this would lead to more pressure on hospitals, which is contrary to the aim of RPM.

Regarding mortality, no statistically significant differences were noted [118,165,211,253]. Therefore, the intervention seems to be feasible as there are no indications for reverse unexpected outcomes. In the absence of RCTs, it was impossible to correctly estimate mortality. The overall mortality statistics during a period within a country were not provided. RPM was also applied in special patient populations experiencing COVID-19 and was shown to be feasible. Moreover, when patient experiences were mentioned in articles, they were in general positive as patients felt more reassured. However, many patients declined RPM for several reasons (eg, technological embarrassment, digital literacy), questioning the accessibility of RPM. Most studies only registered these patient experiences descriptively, and qualitative methods could be applied in future studies to indicate the strengths and limitations of RPM for users.

Most RPM studies aimed at reducing the strain on hospital resources and capacity by trying to avoid ED visits and hospital readmissions, and shortening LOS. As explained, we did not find convincing statistically significant evidence on this. Moreover, augmenting RPM interventions could also increase the strain on hospital resources. Since most RPM studies were hospital led, hospital personnel are needed to staff the RPM teams. It was seen that "successful" studies (ie, including many patients), such as those from France (COVIDOM [57,66,166,167,190,200]), Brazil (UNIMED [123]), United States (Kaiser Permanente Virtual Home Care Program [124,147]), and Spain (Telea [50,111,136]), staffed their RPM teams with volunteers, students, and retired personnel. Moreover, many other RPM studies partially staffed their RPM teams with these profiles. This might have led to a reduction in strain on hospital personnel but is of course only a temporary solution and not an option in the long run. Thus, RPM may save a hospital bed but not necessarily hospital personnel. It could be the case if RPM teams would be staffed by primary care personnel, but this scenario would inevitably lead to increased workload for primary care, which was confronted with already high workload during the COVID-19 pandemic and which was considered in the aims of several studies (ie, to reduce workload on primary care professionals).

The authors of the described economic studies themselves acknowledged that their results were still preliminary and should be used with caution. Because of the low quality of these studies, no concrete conclusions can be drawn, except that if RPM really allows to avoid hospitalization and if the cost of RPM is inferior to hospital costs, savings could be made, at least initially. However, it is necessary to further investigate whether there are more complications in RPM patients than in hospitalized patients, which could lead to higher costs in the long run. More studies are therefore needed and RPM in COVID-19 must, based on our results, currently be considered as an alternative if hospitals are overcrowded rather than a cost-effective strategy.

Future Directions

Although RPM appears feasible to apply, there are many questions remaining concerning the characteristics of the RPM interventions. Characteristics, such as the amount of staffing, the digital infrastructure, details on the health care settings, details on the health care system, the interaction mode, the interaction content, the reactions of the telemonitoring teams, the characteristics of the patients included, and the technologies used to obtain those aims, were very heterogeneously implemented across studies and health care settings. Standardized data should be collected, and the following elements should be clarified.

First, regarding the use of technology, diverse devices were applied across studies ranging from very basic and cheap thermometers to advanced, expensive, connected, multiparameter measuring devices. It will be essential in the future to investigate which parameters are essential to follow and what range of precision or accuracy is needed for the measuring devices. Several studies did not always use measuring devices but relied on a survey, asking for subjective parameters such as rate of fatigue and dyspnea. Some questionnaires were very exhaustive. For that, the need and utility of subjective measurements should also be investigated further.

Second, it was questioned which parameter cutoffs are "safe" (eg, oxygen saturation of 92%) or should the cutoffs be adjusted for each patient individually (depending on comorbidities or risk profile). Consequently, it was questioned when the RPM team should react and which action is appropriate for which parameter cutoff. Moreover, the optimal frequency of parameter measurement is unclear (ie, Is continuous and automated transfer of parameters needed or are previously agreed time points sufficient?). These elements may have consequences for the workforce needed for RPM (and consequently staffing and resources for a team). Many unnecessary alerts require more workforce to react and can lead to alarm tiredness, while too few alerts require less workforce but may cause adverse patient events.

Third, variations in the type and amount of personnel in RPM teams were observed. It remains unclear which health care professionals are the most appropriate and what levels of qualifications are required. Although most studies were hospital led, it remains unclear if this setup environment is superior to primary care–led RPM. Perhaps an RPM team can be replaced or greatly assisted by a kind of virtual care assistant as researched by García Bermúdez et al [302], and the question remains who needs to take up the medical responsibility in this care model.

Finally, what is the role of governments in RPM policy design, upscaling, solving barriers, reimbursement, technology requirements, and setting up research programs and evaluation frameworks for patients with COVID-19 and those with other conditions? There already exist some inspiring articles [303-307] that could be used as starting points.

Limitations

There were some limitations. First, at the time of our searches (ie, in the heat of the COVID-19 pandemic), studies were published as soon as possible to quickly inform the rest of the world, often at the detriment of quality. We did not perform a quality assessment, but often information was not reported and studies did not include a control group. The lack of RCTs illustrates the difficulty to build up evidence during a health crisis. The absence of RCTs limited controlling for variables to assess the effectiveness of RPM on outcomes. We encountered large heterogeneity across studies in patient populations, monitored variables, monitoring modes, involved health care professionals, and intervention doses and modes, prohibiting combining studies and making overall conclusions on the effects or effectivity of telemonitoring in patients with COVID-19. Moreover, a large part of this information was not described in the retrieved studies. Furthermore, countries had different health care systems and health care organizations, which had different levels of crisis preparedness. COVID-19 had an impact in terms of speed and volume of the population affected, and the consequences on surge capacity differed. The stages in which the studies were conducted differed, leading to high heterogeneity in the described characteristics and outcomes. We aimed to group the studies in several ways, such as country of origin and patient inclusion criteria (risk profiling). However, there were no validated risk-profiling scales for COVID-19 patients.

Second, although we aimed to describe the effectiveness of RPM, we encountered many limitations owing to a lack of randomization and controlling for confounding factors as explained earlier. To provide input on effectiveness, we conducted daily updates and performed an update of the search strategy to detect published RCTs. Only 3 small RCTs were detected, illustrating the difficulty to conduct solid research during a crisis. To assess the cost-effectiveness of RPM in patients with COVID-19, larger RCTs should be prospectively conducted. We came across several publications in which only the intervention was presented without any outcome data. It might be expected that at a later stage, follow-up publications will arrive from these studies with outcome data.

Third, it is important to understand that COVID-19 presented in infection waves and with different clinical presentations. Depending on the wave, patients appeared well during the first few days of infection and deteriorated later. The included articles did not report on vaccination status, but across the period of the pandemic, the hospital capacity changed because of mass vaccination. It is unclear if vaccination had an effect on the clinical status in patients who received RPM across the study period. It was difficult to carry out RCTs because of this continuously changing situation and because of the lower influx of patients due to mass vaccination later.

Fourth, we only searched for publications in English, Dutch, German, or French. There might have been publications in other languages from other countries as COVID-19 spread across the world. We coincidentally came across relevant publications in other languages, which we did not include. Moreover, we encountered English written publications from non-English speaking countries. It may be assumed that these are only the tip of the iceberg of what was ongoing in those countries.

Finally, although this review included results from over 160 research studies covering about 250,000 patients, it provides only a partial view of the evidence, and no in-depth analysis of the outcome data could be performed. Therefore, our conclusions need to be regarded as partial, preliminary, and mainly descriptive. Updates of this review should be performed to have a more conclusive view of the effectiveness of RPM in patients with COVID-19 in the future.

Conclusions

Telemonitoring in patients with COVID-19 has been used frequently and across the world. As RPM in COVID-19 was developed as a reaction to the pandemic and not as an anticipation, these studies are characterized by high degrees of heterogeneity in the patient population, intervention content, process characteristics, and outcomes. Moreover, there was a lack of RCTs. There is no statistically significant evidence that RPM in patients with COVID-19 is effective in avoiding ED visits and hospital readmissions, and shortening LOS or reducing mortality, but there is also no indication that RPM has reverse unexpected outcomes. The lack of clear evidence does not mean that COVID-19 RPM was not cost-effective, but instead means that no research was set up in such a way that this could be shown. This review led to a list of questions that need to be answered before the best combination of elements and the most cost-effective combination can be defined. It is essential that solid scientific evidence is gathered to standardize COVID-19 RPM and to create a framework to effectively implement and rapidly scale virtual strategies for providing hospital-like care at home. While more convincing evidence on COVID-19 RPM is required, there is enough expert-based and other disease-related evidence to continue with the current RPM practice. We learned from COVID-19 that there is no way back for telehealth, telemedicine, and RPM. However, RPM should be developed and standardized. In this development process, attention should be given to the accessibility and feasibility of RPM.

Acknowledgments

This study was funded by the Belgian Healthcare Knowledge Centre (KCE). The KCE is a federal institution that is financed by the National Institute for Health and Disability Insurance (NIHDI, RIZIV – INAMI); the Federal Public Service of health, food chain safety, and environment; and the Federal Public Service of social security. The development of health services research studies is part of the legal mission of the KCE. Although the development of the studies is funded by the KCE budget, the sole mission of the KCE is to provide scientifically valid information.

Authors' Contributions

JC contributed to conceptualization, methodology, investigation, writing of the original draft, visualization, and project administration. WC contributed to conceptualization, methodology, investigation, and reviewing and editing. CDM contributed to conceptualization, methodology, visualization, and reviewing editing. PM contributed to conceptualization, methodology, investigation, visualization, supervision, reviewing and editing, and project administration.

Conflicts of Interest

None declared.

References

1. Clarke AC, Hull S, Semciw AI, Jessup RL, Campbell D, Fabri AM, et al. Descriptive analysis of a telephone based community monitoring service for COVID-19. J Community Health 2021 Dec;46(6):1124-1131 [FREE Full text] [doi: 10.1007/s10900-021-00996-z] [Medline: 33977436]
2. Assessing the management of hospital surge capacity in the first wave of the COVID-19 pandemic in Belgium. KCE. 2020. URL: https://kce.fgov.be/en/publications/an-eq-5d-5l-value-set-for-belgium-how-to-value-health-related-quality-of-life/assessing-the-management-of-hospital-surge-capacity-in-the-first-wave-of-the-covid-19-pandemic-in [accessed 2024-09-26]
3. Buekers J, De Boever P, Vaes AW, Aerts J, Wouters EFM, Spruit MA, et al. Oxygen saturation measurements in telemonitoring of patients with COPD: a systematic review. Expert Rev Respir Med 2018 Feb;12(2):113-123. [doi: 10.1080/17476348.2018.1417842] [Medline: 29241369]
4. Barbosa MT, Sousa CS, Morais-Almeida M, Simões M, Mendes P. Telemedicine in COPD: An Overview by Topics. COPD 2020 Oct;17(5):601-617. [doi: 10.1080/15412555.2020.1815182] [Medline: 32892650]
5. Farnia T, Jaulent M, Steichen O. Evaluation criteria of noninvasive telemonitoring for patients with heart failure: systematic review. J Med Internet Res 2018 Jan 16;20(1):e16 [FREE Full text] [doi: 10.2196/jmir.7873] [Medline: 29339348]
6. Llorens P, Moreno-Pérez O, Espinosa B, García T, Payá A, Sola S, et al. An integrated emergency department/hospital at home model in mild COVID-19 pneumonia: feasibility and outcomes after discharge from the emergency department. Intern Emerg Med 2021 Sep 24;16(6):1673-1682 [FREE Full text] [doi: 10.1007/s11739-021-02661-8] [Medline: 33625661]
7. Jonckheer P, Belche J, Castanares-Zapatero D, Henrard G, Jespers V, De Laet C, et al. Intensified home-management for worrisome COVID-19 adult patients. KCE. 2021. URL: https://kce.fgov.be/sites/default/files/2021-12/COVID-19_KCE%20Contribution_Ambulatory_care.pdf [accessed 2024-09-26]
8. LitCovid. National Center for Biotechnology Information. URL: https://www.ncbi.nlm.nih.gov/research/coronavirus/ [accessed 2024-09-26]
9. Global research on coronavirus disease (COVID-19). WHO. URL: https://search.bvsalud.org/global-literature-on-novel-coronavirus-2019-ncov/ [accessed 2024-09-26]
10. Cochrane library collections full. Cochrane Library. URL: https://www.cochranelibrary.com/collections/doi/SC000043/full [accessed 2024-09-26]
11. COVID-19. EBSCO Medical. URL: https://covid-19.ebscomedical.com/ [accessed 2024-09-26]
12. Covid-19 Reviews. URL: https://www.covid19reviews.org/index.cfm?cat=3 [accessed 2024-09-26]
13. Oxford COVID-19 Evidence Service. The Centre for Evidence-Based Medicine. URL: https://www.cebm.net/oxford-covid-19-evidence-service/ [accessed 2024-09-26]
14. COVID-19 Evidence Portal. Canada’s Drug Agency. URL: https://covid.cadth.ca/ [accessed 2024-09-26]
15. bioRxiv. URL: https://www.biorxiv.org/ [accessed 2024-09-26]
16. arXiv. URL: https://arxiv.org/ [accessed 2024-09-26]
17. Archives ouvertes France. HAL. URL: https://hal.archives-ouvertes.fr/ [accessed 2024-09-26]
18. JMIR preprints. JMIR. URL: https://preprints.jmir.org/ [accessed 2024-09-26]
19. Clinical trials database. URL: https://clinicaltrialsdatabase.be/ [accessed 2024-09-26]
20. ClinicalTrials.gov. URL: https://clinicaltrials.gov/ [accessed 2024-09-26]
21. EU Clinical Trials Register. URL: https://www.clinicaltrialsregister.eu/ [accessed 2024-09-26]
22. Clinical Trials Registry Platform. WHO. URL: https://www.who.int/clinical-trials-registry-platform [accessed 2024-09-26]
23. Aalam AA, Hood C, Donelan C, Rutenberg A, Kane EM, Sikka N. Remote patient monitoring for ED discharges in the COVID-19 pandemic. Emerg Med J 2021 Mar 20;38(3):229-231. [doi: 10.1136/emermed-2020-210022] [Medline: 33472870]

24. Abellas SM, Lozano GC, Garcia SC, Franco DE, Hernandez MA, Moreno PJ, et al. Monitoring of QTc interval in patients with COVID-19. First experience with a portable EKG-recording device. Europace 2021;23(Supplement_3):iii566-iii567 [FREE Full text] [doi: 10.1093/europace/euab116.516]
25. Adly AS, Adly MS, Adly AS. Telemanagement of Home-Isolated COVID-19 Patients Using Oxygen Therapy With Noninvasive Positive Pressure Ventilation and Physical Therapy Techniques: Randomized Clinical Trial. J Med Internet Res 2021 Apr 28;23(4):e23446 [FREE Full text] [doi: 10.2196/23446] [Medline: 33819166]
26. Agarwal P, Mukerji G, Laur C, Chandra S, Pimlott N, Heisey R, et al. Adoption, feasibility and safety of a family medicine-led remote monitoring program for patients with COVID-19: a descriptive study. CMAJ Open 2021 Apr 01;9(2):E324-E330 [FREE Full text] [doi: 10.9778/cmajo.20200174] [Medline: 33795222]
27. Agarwal P, Mukerji G, Laur C, Chandra S, Pimlott N, Heisey R, et al. COVIDCare@Home: Lessons from a Family Medicine Led Remote Monitoring Program. medRxiv. 2020. URL: https://www.medrxiv.org/content/10.1101/2020.07.20.20158386v1 [accessed 2024-09-26]
28. Al-Tawfiq J, Kheir H, Al-Dakheel T, Al-Qahtani S, AlKhadra H, Sarhan A, et al. COVID-19 home monitoring program: healthcare innovation in developing, maintaining, and impacting the outcome of SARS-CoV-2 infected patients. Travel Med Infect Dis 2021;43:102089 [FREE Full text] [doi: 10.1016/j.tmaid.2021.102089] [Medline: 34087448]
29. Annis T, Pleasants S, Hultman G, Lindemann E, Thompson JA, Billecke S, et al. Rapid implementation of a COVID-19 remote patient monitoring program. J Am Med Inform Assoc 2020 Aug 01;27(8):1326-1330 [FREE Full text] [doi: 10.1093/jamia/ocaa097] [Medline: 32392280]
30. Thuismonitoring verkort ligduur Covid-19 patiënten. ICTHealth. 2020. URL: https://www.icthealth.nl/nieuws/thuismonitoring-verkort-ligduur-covid-19-patienten/ [accessed 2024-09-26]
31. Telemonitoring beperkt druk op zorgcapaciteit door corona. ICTHealth. 2020. URL: https://www.icthealth.nl/nieuws/telemonitoring-beperkt-druk-op-zorgcapaciteit-door-corona/ [accessed 2024-09-26]
32. Op de digitale corona-afdeling van het UZA zijn patiënten hun eigen verpleegkundige. “Er liggen nu precies evenveel coronapatiënten in ons ziekenhuis als thuis”. HLN. 2021. URL: https://tinyurl.com/4h9vp93y [accessed 2024-09-26]
33. 58% minder ligdagen bij thuismonitoring covid-19 patiënten. ICTHealth. 2021. URL: https://icthealth.nl/nieuws/58-minder-ligdagen-bij-thuismonitoring-covid-19-patienten [accessed 2024-09-26]
34. Thuisbehandeling COVID-19 patiënten St. Jansdal. ICTHealth. 2021. URL: https://www.icthealth.nl/nieuws/thuisbehandeling-covid-19-patienten-st-jansdal/ [accessed 2024-09-26]
35. Thuismonitoring levert minder ligdagen per coronapatiënt op. ICTHealth. 2021. URL: https://www.icthealth.nl/nieuws/thuismonitoring-levert-minder-ligdagen-per-coronapatient-op/ [accessed 2024-09-26]
36. Anonymous. Coronapatiënten sneller naar huis dankzij thuismonitoring. Vietamine 2021;12(2):7.
37. Bae YS, Kim KH, Choi SW, Ko T, Jeong CW, Cho B, et al. Information Technology-Based Management of Clinically Healthy COVID-19 Patients: Lessons From a Living and Treatment Support Center Operated by Seoul National University Hospital. J Med Internet Res 2020 Jun 12;22(6):e19938 [FREE Full text] [doi: 10.2196/19938] [Medline: 32490843]
38. Bae YS, Kim KH, Choi SW, Ko T, Lim JS, Piao M. Satisfaction and Usability of an Information and Communications Technology-Based System by Clinically Healthy Patients With COVID-19 and Medical Professionals: Cross-sectional Survey and Focus Group Interview Study. JMIR Form Res 2021 Aug 26;5(8):e26227 [FREE Full text] [doi: 10.2196/26227] [Medline: 34254946]
39. Bell LC, Norris-Grey C, Luintel A, Bidwell G, Lanham D, Marks M, University College London Hospitals COVID response team. Implementation and evaluation of a COVID-19 rapid follow-up service for patients discharged from the emergency department. Clin Med (Lond) 2021 Jan;21(1):e57-e62 [FREE Full text] [doi: 10.7861/clinmed.2020-0816] [Medline: 33355255]
40. Blair P, Brown D, Jang M, Antar A, Keruly J, Bachu V, Ambulatory COVID Study Team. The Clinical Course of COVID-19 in the Outpatient Setting: A Prospective Cohort Study. Open Forum Infect Dis 2021 Feb;8(2):ofab007 [FREE Full text] [doi: 10.1093/ofid/ofab007] [Medline: 33614816]
41. Blazey-Martin D, Barnhart E, Gillis J, Vazquez GA. Primary Care Population Management for COVID-19 Patients. J Gen Intern Med 2020 Oct 27;35(10):3077-3080 [FREE Full text] [doi: 10.1007/s11606-020-05981-1] [Medline: 32720239]
42. Bokolo AJ. Exploring the adoption of telemedicine and virtual software for care of outpatients during and after COVID-19 pandemic. Ir J Med Sci 2021 Feb;190(1):1-10 [FREE Full text] [doi: 10.1007/s11845-020-02299-z] [Medline: 32642981]
43. Boniface M, Burns D, Duckworth C, Ahmed M, Duruiheoma F, Armitage H, et al. COVID-19 Oximetry @home: evaluation of patient outcomes. BMJ Open Qual 2022 Mar;11(1):7899 [FREE Full text] [doi: 10.1136/bmjoq-2021-001584] [Medline: 35347065]
44. Boniface M, Zlatev Z, Guerrero-Luduena R, Armitage H. An evidence-based approach to quality improvement for COVIDoximetry@Home. University of Southampton Institutional Repository. 2020. URL: https://eprints.soton.ac.uk/445388/ [accessed 2024-09-26]
45. Borgen I, Romney MC, Redwood N, Delgado B, Alea P, George BH, et al. From Hospital to Home: An Intensive Transitional Care Management Intervention for Patients with COVID-19. Popul Health Manag 2021 Feb 01;24(1):27-34. [doi: 10.1089/pop.2020.0178] [Medline: 33054603]

46. Bruni T, Lalvani A, Richeldi L. Reply to Fenton et al: An Expanded COVID-19 Telemedicine Intermediate Care Model Using Repurposed Hotel Rooms. Am J Respir Crit Care Med 2020 Oct 15;202(8):1192-1193 [FREE Full text] [doi: 10.1164/rccm.202008-3063LE] [Medline: 32790518]
47. Buck C, Kobb R, Sandreth R, Alexander L, Olliff S, Anderson C, et al. Maximizing VA Remote Patient Monitoring During the COVID-19 Response. TMT 2021 Jul 30;6(3):281. [doi: 10.30953/tmt.v6.281]
48. CovidCare@Home Demonstrates Benefits of Remote Patient Monitoring. Byteflies. 2021. URL: http://impact.dimesociety.org/wp-content/uploads/2021/06/V1C-vignette-Byteflies-_-CC@H-DiMe-Server.pdf [accessed 2024-09-26]
49. Casale PN, Vyavahare M, Coyne S, Kronish I, Greenwald P, Ye S, et al. The Promise of Remote Patient Monitoring: Lessons Learned During the COVID-19 Surge in New York City. Am J Med Qual 2021;36(3):139-144 [FREE Full text] [doi: 10.1097/01.JMQ.0000741968.61211.2b] [Medline: 33941721]
50. Casariego-Vales E, Blanco-López R, Rosón-Calvo B, Suárez-Gil R, Santos-Guerra F, Dobao-Feijoo M, et al. Efficacy of Telemedicine and Telemonitoring in At-Home Monitoring of Patients with COVID-19. J Clin Med 2021 Jun 29;10(13):2893 [FREE Full text] [doi: 10.3390/jcm10132893] [Medline: 34209725]
51. Castelnuovo G, Pietrabissa G, Manzoni G, Sicurello F, Zoppis I, Molinari E. Fighting the COVID-19 pandemic using the technology-based second-line in Italy and Lombardy: The urgent need of home-based remote monitoring systems to avoid the collapse of the hospital-centred first line. J Glob Health 2020 Dec;10(2):010371-010374 [FREE Full text] [doi: 10.7189/jogh.10.020371] [Medline: 33214881]
52. Cellai M, O'Keefe J. Characterization of prolonged COVID-19 symptoms in an outpatient telemedicine clinic. Open Forum Infect Dis 2020 Oct;7(10):ofaa420 [FREE Full text] [doi: 10.1093/ofid/ofaa420] [Medline: 33117851]
53. Chau NVV, Hai HB, Greeff H, Phan Nguyen Quoc K, Trieu HT, Khoa LDV, et al. Wearable remote monitoring for patients with COVID-19 in low-resource settings: case study. BMJ Innov 2021 Mar 31;7(Suppl 1):s12-s15. [doi: 10.1136/bmjinnov-2021-000706]
54. Cheng C, Manji K, Appel L, Smith C. Abstracts from the 10th International Conference for Healthcare and Medical Students (ICHAMS) : Virtual. 12-13 February 2021. BMC Proc 2021 Apr 02;15(Suppl 3):6 [FREE Full text] [doi: 10.1186/s12919-021-00209-4] [Medline: 33794894]
55. Chou S, McWilliams A, Murphy S, Sitammagari K, Liu T, Hole C, et al. Factors associated with risk for care escalation among patients with COVID-19 receiving home-based hospital care. Ann Intern Med 2021 Aug;174(8):1188-1191 [FREE Full text] [doi: 10.7326/M21-0409] [Medline: 33971099]
56. Clarke J, Flott K, Fernandez Crespo R, Ashrafian H, Fontana G, Benger J, et al. Assessing the Safety of Home Oximetry for COVID-19: a multi-site retrospective observational study. medRxiv Preprint posted online on December 16, 2020 [FREE Full text] [doi: 10.1101/2020.12.16.20248302]
57. AP–HP/universités/Inserm Covid-19 Collaboration. Retour d’expérience sur Covidom : une solution de télésurveillance pour les patients porteurs ou suspectés Covid-19. Ann Fr Med Urgence 2020 Oct 16;10(4-5):314-320. [doi: 10.3166/afmu-2020-0267]
58. Copeland D, Eisenberg E, Edwards C, Shah N, Powell C. Post COVID-19 Remote Patient Monitoring Following Discharge from NYC Hospital. American Journal of Respiratory and Critical Care Medicine 2021;203:A1727 [FREE Full text] [doi: 10.1164/ajrccm-conference.2021.203.1_MeetingAbstracts.A1727]
59. Cotner C, Manz C, Balachandran M, Ferrell W, Khan N, Kopinsky M, et al. Cancer COVID Watch: a feasibility study of intensive remote symptom monitoring via automated text messages with integrated nurse practitioner triage for patients with cancer and suspected or confirmed COVID-19. J Clin Oncol 2021 May 20;39(15_suppl):e13580-e13580. [doi: 10.1200/jco.2021.39.15_suppl.e13580]
60. Crane SJ, Ganesh R, Post JA, Jacobson NA. Telemedicine consultations and follow-up of patients with COVID-19. Mayo Clin Proc 2020 Sep;95(9S):S33-S34 [FREE Full text] [doi: 10.1016/j.mayocp.2020.06.051] [Medline: 32948258]
61. TechFlash: at-home remote monitoring of COVID-19 patients. Vizient. 2020. URL: https://newsroom.vizientinc.com/en-US/releases/innovative-technology-for-remote-monitoring-and-ventilator-weaning-available-during-covid-crisis [accessed 2024-09-26]
62. D’Onofrio K. One Center’s experience with remote patient monitoring of COVID-19 patients. Urban Health Today. URL: https://urbanhealthtoday.com/post/one-centers-experience-with-remote-patient-monitoring-of-covid-19-positive-patients [accessed 2024-09-26]
63. Daly RM, Lauria T, Holland JC, Garcia J, Majeed J, Walters C, et al. Oncology patients’ perspectives on remote patient monitoring for COVID-19. J Clin Oncol 2021 May 20;39(15_suppl):1504-1504. [doi: 10.1200/jco.2021.39.15_suppl.1504]
64. de Oliveira TA, Ribeiro AC, Lora FM, de Oliveira FI, Afonso RC. Telemonitoring of children with COVID-19: experience report of the first 100 cases. Telemed Rep 2021;2(1):39-45 [FREE Full text] [doi: 10.1089/tmr.2020.0006] [Medline: 35720739]
65. Changes to telehealth policy, delivery, and outcomes in response to COVID-19. Patient-Centered Outcomes Research Institute (PCORI). URL: https://www.pcori.org/resources/changes-telehealth-policy-delivery-and-outcomes-response-covid-19-landscape-review [accessed 2024-09-26]

66. Dinh A, Bleibtreu A, Deconinck L, Katlama C, Debuc E, Villie P, et al. COVIDOM : une expérience de télémédecine unique pour la gestion du COVID-19. Médecine Maladies Infectieuses 2020 Sep;50(6):S19. [doi: 10.1016/j.medmal.2020.06.044]
67. Dirikgil E, Roos R, Groeneveld GH, Heringhaus C, Silven AV, Petrus AHJ, et al. Home monitoring reduced short stay admissions in suspected COVID-19 patients: COVID-box project. Eur Respir J 2021 Aug;58(2):2100636 [FREE Full text] [doi: 10.1183/13993003.00636-2021] [Medline: 33795321]
68. Driver J, Strymish J, Clement S, Hayes B, Craig K, Cervera A, et al. Front-Line innovation: rapid implementation of a nurse-driven protocol for care of outpatients with COVID-19. J Clin Nurs 2021 Jun;30(11-12):1564-1572 [FREE Full text] [doi: 10.1111/jocn.15704] [Medline: 33555618]
69. Edwards C, Costello E, Curley M, Smyth L, O'Seaghdha C, Costello R, et al. Patient-reported symptom severity and pulse oximetry in the Covid-19 Remote Monitoring Programme in Ireland. Am J Respiratory Crit Care Med 2021;203:A1728 [FREE Full text] [doi: 10.1164/ajrccm-conference.2021.203.1_meetingabstracts.a1728]
70. Ferrua M, Mathivon D, Duflot-Boukobza A, Abbas M, Charles C, Barrais A, et al. Nurse navigators' telemonitoring for cancer patients with COVID-19: a French case study. Support Care Cancer 2021 Aug 18;29(8):4485-4492 [FREE Full text] [doi: 10.1007/s00520-020-05968-y] [Medline: 33462724]
71. Ferry OR, Moloney EC, Spratt OT, Whiting GFM, Bennett CJ. A Virtual Ward Model of Care for Patients With COVID-19: Retrospective Single-Center Clinical Study. J Med Internet Res 2021 Feb 10;23(2):e25518 [FREE Full text] [doi: 10.2196/25518] [Medline: 33529157]
72. Ford D, Harvey JB, McElligott J, King K, Simpson KN, Valenta S, et al. Leveraging health system telehealth and informatics infrastructure to create a continuum of services for COVID-19 screening, testing, and treatment. J Am Med Inform Assoc 2020 Dec 09;27(12):1871-1877 [FREE Full text] [doi: 10.1093/jamia/ocaa157] [Medline: 32602884]
73. Francis NA, Stuart B, Knight M, Vancheeswaran R, Oliver C, Willcox M, et al. Predictors of adverse outcome in patients with suspected COVID-19 managed in a ‘virtual hospital’ setting: a cohort study. medRxiv. 2020. URL: https://www.medrxiv.org/content/10.1101/2020.11.09.20228189v2.full [accessed 2024-09-26]
74. Francis NA, Stuart B, Knight M, Vancheeswaran R, Oliver C, Willcox M, et al. Predictors of clinical deterioration in patients with suspected COVID-19 managed in a 'virtual hospital' setting: a cohort study. BMJ Open 2021 Mar 23;11(3):e045356 [FREE Full text] [doi: 10.1136/bmjopen-2020-045356] [Medline: 33757955]
75. Fulop N, Vindrola C, Sidhu M, Sherlaw-Johnson C, Georghiou T, Tomini S, et al. Rapid evaluation of remote home monitoring models during COVID-19 pandemic in England. Nuffield Trust. URL: https://www.nuffieldtrust.org.uk/sites/default/files/vw-evaluation-final-slideset-for-dissemination-12th-oct-2020.pdf [accessed 2024-09-26]
76. Gaeta T, Chiricolo G, Mendoza C, Vaccari N, Melville L, Melniker L, et al. 124 Impact of a Novel Telehealth Follow-Up Protocol for At-Risk Emergency Department Patients Discharged With Presumptive or Confirmed COVID-19. Annals of Emergency Medicine 2020 Oct;76(4):S49. [doi: 10.1016/j.annemergmed.2020.09.135]
77. Ganesh R, Salonen BR, Bhuiyan MN, Bierle DM, Moehnke D, Haddad TC, et al. Managing Patients in the COVID-19 Pandemic: A Virtual Multidisciplinary Approach. Mayo Clin Proc Innov Qual Outcomes 2021 Feb;5(1):118-126 [FREE Full text] [doi: 10.1016/j.mayocpiqo.2020.12.003] [Medline: 33521583]
78. Gingras LF, Pelzman FN, Marquez A, Arias D, Tung J. The Cough Cold and Fever Clinic: A Model for the Safe Management of Ambulatory Patients With Suspected COVID-19. Qual Manag Health Care 2022;31(1):38-42 [FREE Full text] [doi: 10.1097/QMH.0000000000000334] [Medline: 34310547]
79. Gios L, Crema Falceri G, Micocci S, Patil L, Testa S, Sforzin S, et al. Use of eHealth platforms and apps to support monitoring and management of home-quarantined patients with COVID-19 in the Province of Trento, Italy: app development and implementation. JMIR Form Res 2021 May 31;5(5):e25713 [FREE Full text] [doi: 10.2196/25713] [Medline: 33909586]
80. Gootenberg DB, Kurtzman N, O'Mara T, Ge JY, Chiu D, Shapiro NI, et al. Developing a pulse oximetry home monitoring protocol for patients suspected with COVID-19 after emergency department discharge. BMJ Health Care Inform 2021 Jul 23;28(1):e100330 [FREE Full text] [doi: 10.1136/bmjhci-2021-100330] [Medline: 34301725]
81. Gordon WJ, Henderson D, DeSharone A, Fisher HN, Judge J, Levine DM, et al. Remote Patient Monitoring Program for Hospital Discharged COVID-19 Patients. Appl Clin Inform 2020 Oct;11(5):792-801 [FREE Full text] [doi: 10.1055/s-0040-1721039] [Medline: 33241547]
82. Graça T, Santos AL, Yamamoto G, de Souza RW, Srougé M, Pacheco RL, et al. Telemonitoring programme on COVID-19 for a low-income community in Brazil: case study. BMJ Innov 2021 Apr 17;7(2):342-346. [doi: 10.1136/bmjinnov-2020-000619] [Medline: 34192021]
83. Grutters LA, Majoor KI, Mattern ESK, Hardeman JA, van Swol CFP, Vorselaars ADM. Home telemonitoring makes early hospital discharge of COVID-19 patients possible. J Am Med Inform Assoc 2020 Nov 01;27(11):1825-1827 [FREE Full text] [doi: 10.1093/jamia/ocaa168] [Medline: 32667985]
84. Haddad TC, Blegen RN, Prigge JE, Cox DL, Anthony GS, Leak MA, et al. A Scalable Framework for Telehealth: The Mayo Clinic Center for Connected Care Response to the COVID-19 Pandemic. Telemed Rep 2021 Feb 01;2(1):78-87 [FREE Full text] [doi: 10.1089/tmr.2020.0032] [Medline: 35720756]

85. Heller D, Ornstein K, DeCherrie L, Saenger P, Ko F, Rousseau C, et al. Adapting a hospital-at-home care model to respond to New York City's COVID-19 crisis. J Am Geriatr Soc 2020 Sep;68(9):1915-1916 [FREE Full text] [doi: 10.1111/jgs.16725] [Medline: 32638355]
86. Heo H, Lee K, Jung E, Lee H. Developing the first telenursing service for COVID-19 patients: the experience of South Korea. Int J Environ Res Public Health 2021 Jun 26;18(13):6885 [FREE Full text] [doi: 10.3390/ijerph18136885] [Medline: 34206977]
87. Heo J, Park JA, Han D, Kim H, Ahn D, Ha B, et al. COVID-19 outcome prediction and monitoring solution for military hospitals in South Korea: development and evaluation of an application. J Med Internet Res 2020 Nov 04;22(11):e22131 [FREE Full text] [doi: 10.2196/22131] [Medline: 33048824]
88. Houlding E, Mate KKV, Engler K, Ortiz-Paredes D, Pomey M, Cox J, et al. Barriers to use of remote monitoring technologies used to support patients with COVID-19: rapid review. JMIR Mhealth Uhealth 2021 Apr 20;9(4):e24743 [FREE Full text] [doi: 10.2196/24743] [Medline: 33769943]
89. Hutchings O, Dearing C, Jagers D, Shaw M, Raffan F, Jones A, et al. Virtual health care for community management of patients with COVID-19. medRxiv Preprint posted online on May 15, 2020 [FREE Full text] [doi: 10.1101/2020.05.11.20082396]
90. Hutchings OR, Dearing C, Jagers D, Shaw MJ, Raffan F, Jones A, et al. Virtual health care for community management of patients with COVID-19 in Australia: observational cohort study. J Med Internet Res 2021 Mar 09;23(3):e21064 [FREE Full text] [doi: 10.2196/21064] [Medline: 33687341]
91. Indraratna P, Biswas U, Yu J, Schreier G, Ooi S, Lovell NH, et al. Trials and tribulations: mHealth clinical trials in the COVID-19 pandemic. Yearb Med Inform 2021 Aug;30(1):272-279 [FREE Full text] [doi: 10.1055/s-0041-1726487] [Medline: 33882601]
92. Iqbal FM, Joshi M, Davies G, Khan S, Ashrafian H, Darzi A. The pilot, proof of concept REMOTE-COVID trial: remote monitoring use in suspected cases of COVID-19 (SARS-CoV 2). BMC Public Health 2021 Apr 01;21(1):638 [FREE Full text] [doi: 10.1186/s12889-021-10660-9] [Medline: 33794832]
93. Jethwa T, Ton A, Paredes Molina CS, Speicher L, Walsh K, Knight D, et al. Establishing Mayo Clinic's Coronavirus Disease 2019 Virtual Clinic: A Preliminary Communication. Telemed J E Health 2020 Nov;26(11):1419-1423. [doi: 10.1089/tmj.2020.0145] [Medline: 32516070]
94. Khoshrounejad F, Hamednia M, Mehrjerd A, Pichaghsaz S, Jamalirad H, Sargolzaei M, et al. Telehealth-based services during the COVID-19 pandemic: a systematic review of features and challenges. Front Public Health 2021;9:711762 [FREE Full text] [doi: 10.3389/fpubh.2021.711762] [Medline: 34350154]
95. Kim JH, Choi WS, Song JY, Yoon YK, Kim MJ, Sohn JW. The role of smart monitoring digital health care system based on smartphone application and personal health record platform for patients diagnosed with coronavirus disease 2019. BMC Infect Dis 2021 Feb 27;21(1):229 [FREE Full text] [doi: 10.1186/s12879-021-05898-y] [Medline: 33639861]
96. Monitoring en zuurstof thuis na covid-opname: veilig en prettig. Nursing. 2021. URL: https://www.nursing.nl/praktijk/e-health/monitoring-en-zuurstof-thuis-na-covid-opname-veilig-en-prettig/ [accessed 2024-09-26]
97. Knight M, Evans D, Vancheeswaran R, Van der Watt M, Smith AN, Oliver C, et al. A virtual hospital model can help tackle the COVID-19 pandemic. Health Service Journal. URL: https://www.hsj.co.uk/technology-and-innovation/a-virtual-hospital-model-can-help-tackle-the-covid-19-pandemic/7027340.article [accessed 2024-09-26]
98. Ko SQ, Hooi BMY, Koo C, Chor DWP, Ling ZJ, Chee Y, et al. Remote monitoring of marginalised populations affected by COVID-19: a retrospective review. BMJ Open 2020 Dec 31;10(12):e042647 [FREE Full text] [doi: 10.1136/bmjopen-2020-042647] [Medline: 33384398]
99. Kodama R, Arora S, Anand S, Choudhary A, Weingarten J, Francesco N, et al. Reengineering the Discharge Transition Process of COVID-19 Patients Using Telemedicine, Remote Patient Monitoring, and Around-the-Clock Remote Patient Monitoring from the Emergency Department and Inpatient Units. Telemed J E Health 2021 Oct;27(10):1188-1193. [doi: 10.1089/tmj.2020.0459] [Medline: 33320031]
100. Kricke G, Roemer P, Barnard C, Peipert J, Henschen B, Bierman J, et al. Rapid implementation of an outpatient COVID-19 monitoring program. NEJM Catalyst Innovations Care Deliv 2020:214. [doi: 10.1056/CAT.20.0214]
101. Kyriakides J, Khani A, Kelly C, Coleman R. 161 Analysis of an ambulatory care pathway for patients with COVID-19 utilising remote pulse oximetry. Emerg Med J 2020 Nov 23;37(12):843.2-84843. [doi: 10.1136/emj-2020-rcemabstracts.37]
102. Giuzio F, Bonomo M, Armenante G, Barra G, Casolaro G, Di Ludovico C, et al. The monitoring model for COVID-19 patients in the context of territorial medicine: The experience of the COVID special unit (USCO) of Potenza. PharmacologyOnLine 2021;1:214-223 [FREE Full text]
103. Lam PW, Sehgal P, Andany N, Mubareka S, Simor AE, Ozaldin O, et al. A virtual care program for outpatients diagnosed with COVID-19: a feasibility study. CMAJ Open 2020;8(2):E407-E413 [FREE Full text] [doi: 10.9778/cmajo.20200069] [Medline: 32447283]
104. Laur CV, Agarwal P, Mukerji G, Goulbourne E, Baranek H, Pus L, et al. Building Health Services in a Rapidly Changing Landscape: Lessons in Adaptive Leadership and Pivots in a COVID-19 Remote Monitoring Program. J Med Internet Res 2021 Jan 13;23(1):e25507 [FREE Full text] [doi: 10.2196/25507] [Medline: 33417588]

105. Lim HM, Teo CH, Ng CJ, Chiew TK, Ng WL, Abdullah A, et al. An Automated Patient Self-Monitoring System to Reduce Health Care System Burden During the COVID-19 Pandemic in Malaysia: Development and Implementation Study. JMIR Med Inform 2021 Feb 26;9(2):e23427 [FREE Full text] [doi: 10.2196/23427] [Medline: 33600345]
106. Louie T, Kwan B, Susanto C, Ng A. Respiratory failure, clinical course and community management of COVID-19 patients in a large Australian cohort. Intern Med J 2021 Mar;51(3):334-340 [FREE Full text] [doi: 10.1111/imj.15206] [Medline: 33629801]
107. Lwin N, Burgess J, Johnston C, Johnson N, Chung S. Hospital-in-the-Home experience of first 23 COVID-19 patients at a regional NSW hospital. Intern Med J 2020 Oct 18;50(10):1271-1273 [FREE Full text] [doi: 10.1111/imj.15016] [Medline: 32945610]
108. Maghrabi F, Bazaz R, Wilson E, O'Reilly S, Calisti G, Richardson R. S57 The development and implementation of a virtual discharge ward for patients with COVID-19 pneumonia: data on the first 300 patients. Thorax 2021;76(Suppl 1):A35. [doi: 10.1136/thorax-2020-BTSabstracts.62]
109. Majeed J, Garcia J, Holland J, Daly B, Robson M, Reidy-Lagunes D. When a Cancer Patient Tests Positive for Covid-19. Harvard Business Review. 2020. URL: https://hbr.org/2020/07/when-a-cancer-patient-tests-positive-for-covid-19 [accessed 2024-09-26]
110. Marinello R, Brunetti E, Luppi C, Bianca D, Tibaldi V, Isaia G, et al. Telemedicine-assisted care of an older patient with COVID-19 and dementia: bridging the gap between hospital and home. Aging Clin Exp Res 2021 Jun;33(6):1753-1756 [FREE Full text] [doi: 10.1007/s40520-021-01875-2] [Medline: 34003476]
111. Martínez-García M, Bal-Alvarado M, Santos GF, Ares-Rico R, Suárez-Gil R, Rodríguez-Álvarez A. Monitoring of COVID-19 patients via telemedicine with telemonitoring. Revista Clínica Española (English Edition) 2020:472-479 [FREE Full text] [doi: 10.1016/j.rceng.2020.07.001]
112. Maurizi N, Fumagalli C, Cecchi F, Olivotto I. Use of Smartphone-operated ECG for home ECG surveillance in COVID-19 patients. Eur Heart J Digit Health 2021 Mar;2(1):175-178 [FREE Full text] [doi: 10.1093/ehjdh/ztab009] [Medline: 37155659]
113. Early prediction of aggressive COVID-19 progression and hospitalization. Mayo Clinic. URL: https://www.mayo.edu/research/remote-monitoring-covid19-symptoms/people-with-covid19 [accessed 2024-09-26]
114. Mead A. Remote Patient Monitoring Helps Rural Patients Recover at Home. Rural Health Info. 2021. URL: https://www.ruralhealthinfo.org/rural-monitor/remote-patient-monitoring [accessed 2024-09-26]
115. Medina M, Babiuch C, Card M, Gavrilescu R, Zafirau W, Boose E, et al. Home monitoring for COVID-19. Cleve Clin J Med 2020 Jun 11:ccc028 [FREE Full text] [doi: 10.3949/ccjm.87a.ccc028] [Medline: 32409432]
116. Thuismonitoring van corona-patiënten door het Albert Schweitzer ziekenhuis is succesvol. Westfalen Medical. URL: https://tinyurl.com/yejkhf6s [accessed 2024-09-26]
117. Micallef M, Hurley S, Brell N, Cook R, Post J, Overton K. Telehealth outpatient coronavirus disease 2019 case management at a tertiary hospital in Sydney. J Telemed Telecare 2021 Jun 21:1357633X211024097. [doi: 10.1177/1357633X211024097] [Medline: 34152869]
118. Misra-Hebert AD, Ji X, Jehi L, Milinovich A, Pfoh ER, Kattan MW, et al. COVID-19 Home Monitoring After Diagnosis and Health Care Utilization in an Integrated Health System. JAMA Health Forum 2021 May 06;2(5):e210333 [FREE Full text] [doi: 10.1001/jamahealthforum.2021.0333] [Medline: 35977306]
119. Morgan A, Balachandran M, Do D, Lam D, Parambath A, Chaiyachati K, et al. Remote Monitoring of Patients with Covid-19: Design, implementation, and outcomes of the first 3,000 patients in COVID Watch. NEJM Catalyst Innovations in Care Delivery 2020:342. [doi: 10.1056/CAT.20.0342]
120. Motta LP, Silva PPFD, Borguezan BM, Amaral JLMD, Milagres LG, Bóia M, et al. An emergency system for monitoring pulse oximetry, peak expiratory flow and body temperature of patients with COVID-19 at home: Development and preliminary application. medRxiv. 2020. URL: https://www.medrxiv.org/content/10.1101/2020.12.11.20247650v1 [accessed 2024-09-26]
121. Motta LP, Silva PPFD, Borguezan BM, Amaral JLMD, Milagres LG, Bóia M, et al. An emergency system for monitoring pulse oximetry, peak expiratory flow, and body temperature of patients with COVID-19 at home: Development and preliminary application. PLoS One 2021 Mar 26;16(3):e0247635 [FREE Full text] [doi: 10.1371/journal.pone.0247635] [Medline: 33770093]
122. Chang P, Engle J. Telemedicine and Virtual Interventions in Cancer Rehabilitation: Practical Application, Complications and Future Potentials. Current Oncology Reports 2024 Nov 06. [doi: 10.1007/s11912-024-01612-8] [Medline: 39503989]
123. Nascimento B, Brant L, Castro A, Froes L, Ribeiro A, Cruz L, et al. Impact of a large-scale telemedicine network on emergency visits and hospital admissions during the coronavirus disease 2019 pandemic in Brazil: Data from the UNIMED-BH system. J Telemed Telecare 2020 Oct 25;29(2):103-110. [doi: 10.1177/1357633x20969529]
124. Huynh DN, Millan A, Quijada E, John D, Khan S, Funahashi T. Description and Early Results of the Kaiser Permanente Southern California COVID-19 Home Monitoring Program. TPJ 2021 Sep;25(3):1-7. [doi: 10.7812/tpp/20.281]
125. Nogués X, Sánchez-Martinez F, Castells X, Díez-Pérez A, Sabaté R, Petit I, et al. Hospital-at-Home Expands Hospital Capacity During COVID-19 Pandemic. J Am Med Dir Assoc 2021 May;22(5):939-942 [FREE Full text] [doi: 10.1016/j.jamda.2021.01.077] [Medline: 33639115]

126. Nunan J, Clarke D, Malakouti A, Tannetta D, Calthrop A, Xu XH, et al. Triage Into the Community for COVID-19 (TICC-19) Patients Pathway - Service evaluation of the virtual monitoring of patients with COVID pneumonia. Acute Med 2020;19(4):183-191. [Medline: 33215171]
127. O'Carroll O, MacCann R, O'Reilly A, Dunican EM, Feeney ER, Ryan S, et al. Remote monitoring of oxygen saturation in individuals with COVID-19 pneumonia. Eur Respir J 2020 Aug 02;56(2):2001492 [FREE Full text] [doi: 10.1183/13993003.01492-2020] [Medline: 32616588]
128. O'Keefe JB, Tong EJ, O'Keefe GD, Tong DC. Description of symptom course in a telemedicine monitoring clinic for acute symptomatic COVID-19: a retrospective cohort study. BMJ Open 2021 Mar 05;11(3):e044154 [FREE Full text] [doi: 10.1136/bmjopen-2020-044154] [Medline: 33674374]
129. O'Keefe JB, Tong EJ, Taylor T, O'Keefe G, Tong DC. Use of a Telemedicine Risk Assessment Tool to Predict the Risk of Hospitalization of 496 Outpatients With COVID-19: Retrospective Analysis. JMIR Public Health Surveill 2021 Apr 30;7(4):e25075 [FREE Full text] [doi: 10.2196/25075] [Medline: 33667174]
130. Owens L. Remote monitoring helps COVID patients at home, where they heal best. HealthTech Magazine. 2021. URL: https://www.healthtechmagazines.com/remote-monitoring-helps-covid-patients-at-home-where-they-heal-best/ [accessed 2024-09-26]
131. Panicacci S, Donati M, Lubrano A, Vianello A, Ruiu A, Melani L, et al. Telemonitoring in the Covid-19 Era: The Tuscany Region Experience. Healthcare (Basel) 2021 Apr 29;9(5):516 [FREE Full text] [doi: 10.3390/healthcare9050516] [Medline: 33946633]
132. Pericàs J, Cucchiari D, Torrallardona-Murphy O, Calvo J, Serralabós J, Alvés E, Hospital Clínic 4H Team (Hospital at Home-Health Hotel). Hospital at home for the management of COVID-19: preliminary experience with 63 patients. Infection 2021 Apr 29;49(2):327-332 [FREE Full text] [doi: 10.1007/s15010-020-01527-z] [Medline: 32995970]
133. Pritchett J, Desai A, Borah BJ, Xie Z, Saliba AN, Leventakos K, et al. Association of use of remote patient monitoring (RPM) with reduced hospitalizations in cancer patients with COVID-19. JCO 2021 May 20;39(15_suppl):1503-1503. [doi: 10.1200/jco.2021.39.15_suppl.1503]
134. Pritchett JC, Borah BJ, Desai AP, Xie Z, Saliba AN, Leventakos K, et al. Association of a Remote Patient Monitoring (RPM) Program With Reduced Hospitalizations in Cancer Patients With COVID-19. JCO Oncology Practice 2021 Sep;17(9):e1293-e1302. [doi: 10.1200/op.21.00307]
135. Pugliese L, Garcia J, Holland JC, Majeed J, Silverman M, Moy M, et al. Use of remote patient monitoring in the care of COVID-positive patients in oncology. JCO 2021 May 20;39(15_suppl):1554-1554. [doi: 10.1200/jco.2021.39.15_suppl.1554]
136. Rabuñal R, Suarez-Gil R, Golpe R, Martínez-García M, Gómez-Méndez R, Romay-Lema E, et al. Usefulness of a telemedicine tool TELEA in the management of the COVID-19 pandemic. Telemed J E Health 2020 Nov;26(11):1332-1335. [doi: 10.1089/tmj.2020.0144] [Medline: 32501747]
137. Ragon BK, Sumrall AL, Blackley K, Osunkwo I, Moyo TK, Kabrich L, et al. Patient navigation plus hospital at home to improve COVID-19 outcomes for cancer patients. J Clin Oncol 2021 May 20;39(15_suppl):1524-1524. [doi: 10.1200/jco.2021.39.15_suppl.1524]
138. Ryan P, Hawkins K, Altman S, Granatowski L, Shy B, Long J, et al. A novel virtual hospital at home model during the coronavirus disease 2019 (COVID-19) pandemic. Infect Control Hosp Epidemiol 2021 Sep;42(9):1140-1142 [FREE Full text] [doi: 10.1017/ice.2020.435] [Medline: 32829735]
139. Schultz K, Vickery H, Campbell K, Wheeldon M, Barrett-Beck L, Rushbrook E. Implementation of a virtual ward as a response to the COVID-19 pandemic. Aust Health Rev 2021 Aug;45(4):433-441. [doi: 10.1071/AH20240] [Medline: 33840420]
140. Scotté F, Minvielle E, Mir O, André F, Barlesi F, Soria J. A patient reported outcome platform, a useful tool to improve monitoring and effective management of Covid-19-positive patients with cancer. Eur J Cancer 2020 Jun;132:1-4 [FREE Full text] [doi: 10.1016/j.ejca.2020.03.020] [Medline: 32294611]
141. Selleslagh P. Telemonitoring beperkt druk op Aalsterse ziekenhuizen (proefproject). Numerikare. 2021. URL: https://www.numerikare.be/nl/nieuws/beroepsnieuws/telemonitoring-beperkt-druk-op-aalsterse-ziekenhuizen-proefproject.html [accessed 2024-09-26]
142. Serra CM, Serra CM, Marzal Martín D, Moro JV, Tomás Martínez JF. Remote Monitoring of Patients with COVID-19 after Hospital Discharge with Connected Health Platform: Outcomes and Quality of Life. JICOA 2020 Sep 21:1-5. [doi: 10.31487/j.jicoa.2020.05.05]
143. Shah S, Majmudar K, Stein A, Gupta N, Suppes S, Karamanis M, et al. Novel use of home pulse oximetry monitoring in COVID-19 patients discharged from the emergency department identifies need for hospitalization. Acad Emerg Med 2020 Aug;27(8):681-692 [FREE Full text] [doi: 10.1111/acem.14053] [Medline: 32779828]
144. Shah SS, Gvozdanovic A, Knight M, Gagnon J. Mobile app-based remote patient monitoring in acute medical conditions: prospective feasibility study exploring digital health solutions on clinical workload during the COVID crisis. JMIR Form Res 2021 Jan 15;5(1):e23190 [FREE Full text] [doi: 10.2196/23190] [Medline: 33400675]
145. Shahabi S, Maharlouei N, Jalali M, Bagheri Lankarani K. Virtual hospitals during COVID-19 pandemic: pros and cons. Shiraz E-Med J 2021 May 31;22(6):e112781. [doi: 10.5812/semj.112781]

146. Shapiro Ben David S, Cohen D, Karplus R, Irony A, Ofer-Bialer G, Potasman I, et al. COVID-19 community care in Israel-a nationwide cohort study from a large health maintenance organization. J Public Health (Oxf) 2021 Dec 10;43(4):723-730 [FREE Full text] [doi: 10.1093/pubmed/fdab055] [Medline: 33690854]
147. Shaw JG, Sankineni S, Olaleye CA, Johnson KL, Locke JL, Patino J, et al. A Novel Large Scale Integrated Telemonitoring Program for COVID-19. Telemed J E Health 2021 Nov;27(11):1317-1321. [doi: 10.1089/tmj.2020.0384] [Medline: 33544043]
148. Shiel E, Miyakis S, Tennant E, Fernando S, Kizny-Gordon A, Koh B, et al. Clinical characteristics and outcomes of COVID-19 in a low-prevalence, well resourced setting, Sydney, Australia. Intern Med J 2021 Oct;51(10):1605-1613 [FREE Full text] [doi: 10.1111/imj.15445] [Medline: 34228387]
149. Silven AV, Petrus AHJ, Villalobos-Quesada M, Dirikgil E, Oerlemans CR, Landstra CP, et al. Telemonitoring for Patients With COVID-19: Recommendations for Design and Implementation. J Med Internet Res 2020 Sep 02;22(9):e20953 [FREE Full text] [doi: 10.2196/20953] [Medline: 32833660]
150. Sitammagari K, Murphy S, Kowalkowski M, Chou S, Sullivan M, Taylor S, et al. Insights From Rapid Deployment of a “Virtual Hospital” as Standard Care During the COVID-19 Pandemic. Ann Intern Med 2021 Feb;174(2):192-199. [doi: 10.7326/m20-4076]
151. Siwicki B. Metro Health's telehealth and RPM program is helping patients avoid hospital stays. Healthcare IT News. 2021. URL: https://www.healthcareitnews.com/news/metro-healths-telehealth-and-rpm-program-helping-patients-avoid-hospital-stays [accessed 2024-09-26]
152. Steel PAD, Siegal J, Zhang Y, Cato K, Greenwald P, Melville LD, et al. Telehealth follow up in emergency department patients discharged with COVID-like illness and exertional hypoxia. Am J Emerg Med 2021 Nov;49:426-430 [FREE Full text] [doi: 10.1016/j.ajem.2021.02.052] [Medline: 33722432]
153. Steimer M, Leabo J, Wang H, Heyer D, Addison N, Bowles N, et al. Remote Home Monitoring of Patients With Cancer During the COVID Pandemic: A Pilot Study. JCO Oncol Pract 2021 Sep;17(9):e1286-e1292 [FREE Full text] [doi: 10.1200/OP.20.00995] [Medline: 33793345]
154. Tabacof L, Kellner C, Breyman E, Dewil S, Braren S, Nasr L, et al. Remote Patient Monitoring for Home Management of Coronavirus Disease 2019 in New York: A Cross-Sectional Observational Study. Telemed J E Health 2021 Jun;27(6):641-648. [doi: 10.1089/tmj.2020.0339] [Medline: 33232204]
155. Tabacof L, Wood J, Mohammadi N, Link KE, Tosto-Mancuso J, Dewil S, et al. Remote patient monitoring identifies the need for triage in patients with acute COVID-19 infection. Telemed J E Health 2022 Apr;28(4):495-500. [doi: 10.1089/tmj.2021.0101] [Medline: 34292768]
156. Terry K. ‘Hospital at home’ increases COVID-19 care capacity. Chest Physician. 2020. URL: https://www.chestnet.org/-/media/chesnetorg/publications/documents/chest-physician/vol-15-2020/122020.ashx [accessed 2024-09-26]
157. Thornton J. The "virtual wards" supporting patients with covid-19 in the community. BMJ 2020 Jun 04;369:m2119. [doi: 10.1136/bmj.m2119] [Medline: 32499317]
158. van Herwerden M, van Steenkiste J, el Moussaoui R, den Hollander J, Helfrich G, Verberk I. Thuisbehandeling van covid-19-patiënten met zuurstof en telemonitoring: Veiligheid, patiënttevredenheid en kosteneffectiviteit. NTvG. 2021. URL: https://www.ntvg.nl/artikelen/thuisbehandeling-van-covid-19-patienten-met-zuurstof-en-telemonitoring [accessed 2024-09-26]
159. Vandendriessche B. CovidCare@Home – Telemedicine for COVID-19 Patients: Rapid roll-out demonstrates healthcare providers are ready to adopt digital medicine technologies on a larger scale. Medium. 2021. URL: https://medium.com/byteflies/covidcare-home-telemedicine-for-covid-19-patients-96d1e7ad46ea [accessed 2024-09-26]
160. Wariri O, Okomo U, Cerami C, Okoh E, Oko F, Jah H, et al. Establishing and operating a 'virtual ward' system to provide care for patients with COVID-19 at home: experience from The Gambia. BMJ Glob Health 2021 Jun 17;6(6):e005883 [FREE Full text] [doi: 10.1136/bmjgh-2021-005883] [Medline: 34140303]
161. Weinbergerova B, Mayer J, Hrabovsky S, Novakova Z, Pospisil Z, Martykanova L, et al. COVID-19's natural course among ambulatory monitored outpatients. Sci Rep 2021 May 12;11(1):10124. [doi: 10.1038/s41598-021-89545-1] [Medline: 33980931]
162. Wilcock J, Grafton-Clarke C, Coulson T. What is the value of community oximetry monitoring in people with SARS-Cov-2? – a prospective, open-label clinical study. Arch Clin Biomed Res 2021;05(05):689-701. [doi: 10.26502/acbr.50170194]
163. Wurzer D, Spielhagen P, Siegmann A, Gercekcioglu A, Gorgass J, Henze S, et al. The telecovid study: remote monitoring of COVID-19 positive high-risk patients in domestic isolation. SSRN J 2021:1 [FREE Full text] [doi: 10.2139/ssrn.3845981]
164. Xu H, Huang S, Qiu C, Liu S, Deng J, Jiao B, et al. Monitoring and management of home-quarantined patients with COVID-19 using a WeChat-based telemedicine system: retrospective cohort study. J Med Internet Res 2020 Jul 02;22(7):e19514 [FREE Full text] [doi: 10.2196/19514] [Medline: 32568727]
165. Ye S, Hiura G, Fleck E, Garcia A, Geleris J, Lee P, et al. Hospital readmissions after implementation of a discharge care program for patients with COVID-19 illness. J Gen Intern Med 2021 Mar;36(3):722-729 [FREE Full text] [doi: 10.1007/s11606-020-06340-w] [Medline: 33443699]

166. Yordanov Y, Dechartres A, Lescure X, Apra C, Villie P, Marchand-Arvier J, et al. Covidom, a telesurveillance solution for home monitoring patients with COVID-19. J Med Internet Res 2020 Oct 22;22(10):e20748 [FREE Full text] [doi: 10.2196/20748] [Medline: 33006938]
167. Yordanov Y, Dinh A, Bleibtreu A, Mensch A, Lescure F, Debuc E, et al. Clinical characteristics and factors associated with hospital admission or death in 43 103 adult outpatients with coronavirus disease 2019 managed with the Covidom telesurveillance solution: a prospective cohort study. Clin Microbiol Infect 2021 Aug;27(8):1158-1166 [FREE Full text] [doi: 10.1016/j.cmi.2021.04.010] [Medline: 33915287]
168. Zuccotti GV, Bertoli S, Foppiani A, Verduci E, Battezzati A. COD19 and COD20: an italian experience of active home surveillance in COVID-19 patients. Int J Environ Res Public Health 2020 Sep 14;17(18):6699 [FREE Full text] [doi: 10.3390/ijerph17186699] [Medline: 32938009]
169. Bernocchi P, Bonometti F, Serlini M, Assoni G, Zanardini M, Pasotti E, et al. Telehealth and telecare: a real-life integrated experience in the COVID-19 pandemic. Telemed J E Health 2022 May;28(5):720-727. [doi: 10.1089/tmj.2021.0181] [Medline: 34402684]
170. Krenitsky N, Spiegelman J, Sutton D, Syeda S, Moroz L. Primed for a pandemic: implementation of telehealth outpatient monitoring for women with mild COVID-19. Semin Perinatol 2020 Nov;44(7):151285 [FREE Full text] [doi: 10.1016/j.semperi.2020.151285] [Medline: 32854962]
171. Lenze EJ, Mattar C, Zorumski CF, Stevens A, Schweiger J, Nicol GE, et al. Fluvoxamine vs placebo and clinical deterioration in outpatients with symptomatic COVID-19: a randomized clinical trial. JAMA 2020 Dec 08;324(22):2292-2300 [FREE Full text] [doi: 10.1001/jama.2020.22760] [Medline: 33180097]
172. Smith T. Remote monitoring allows patients with COVID-19, including a pregnant mom, to recover safely at home. UCHealth Today. 2020. URL: https://www.uchealth.org/today/remote-patient-monitoring-allows-covid-19-patients-including-pregnant-mom-to-recover-safely-at-home/ [accessed 2024-09-26]
173. Smith T. Remote patient monitoring of COVID-19 brings peace of mind. UCHealth Today. 2021. URL: https://www.uchealth.org/today/remote-patient-monitoring-of-covid-19-brings-peace-of-mind/ [accessed 2024-09-26]
174. Coffey JD, Christopherson LA, Glasgow AE, Pearson KK, Brown JK, Gathje SR, et al. Implementation of a multisite, interdisciplinary remote patient monitoring program for ambulatory management of patients with COVID-19. NPJ Digit Med 2021 Aug 13;4(1):123. [doi: 10.1038/s41746-021-00490-9] [Medline: 34389787]
175. Connolly S, Katolo H, Cronin C, Creed M, Lambert J, Cotter A. Home SPO2 monitoring of patients with COVID-19: the mater cvc project. Top Antiviral Med 2021;29(1):289-290.
176. John J, Zallman L, Blau J. Our hospital’s community management strategy for Covid-19 works. Yours can, too. STAT News. 2020. URL: https://www.statnews.com/2020/04/23/community-management-strategy-for-covid-19-works/ [accessed 2024-09-26]
177. Kasiri H, Mahjub C, Mazaeri M, Naderi-Behdani F, Bazi A, Ghazaeian M, et al. A Clinical Monitoring Program of COVID-19 Outpatients: A Prospective Cohort Study. Can J Infect Dis Med Microbiol 2021;2021:6644570 [FREE Full text] [doi: 10.1155/2021/6644570] [Medline: 34336065]
178. Kesavadev J, Basanth A, Krishnan G, Vitale R, Parameswaran H, Shijin S, et al. A new interventional home care model for COVID management: Virtual Covid IP. Diabetes Metab Syndr 2021;15(5):102228 [FREE Full text] [doi: 10.1016/j.dsx.2021.102228] [Medline: 34330071]
179. Mathivon D, Abbas M, Barrais A, Duflot-Boukobza A, Ferrua M, Legendre J, et al. CN27 Value of nurse navigators (NNs) telemonitoring for cancer patients (pts) tested positive for COVID-19. Annals of Oncology 2020 Sep;31:S1137 [FREE Full text] [doi: 10.1016/j.annonc.2020.08.2135]
180. McCabe M, Gerson KD, Hirshberg A. 892 Remote monitoring of pregnant and postpartum women with COVID-19. American Journal of Obstetrics and Gynecology 2021 Feb;224(2):S553-S554 [FREE Full text] [doi: 10.1016/j.ajog.2020.12.915]
181. McKinstry B, Alexander H, Maxwell G, Blaikie L, Patel S, Guthrie B, Technology Enabled Care TeleCOVID Group. The Use of Telemonitoring in Managing the COVID-19 Pandemic: Pilot Implementation Study. JMIR Form Res 2021 Sep 27;5(9):e20131 [FREE Full text] [doi: 10.2196/20131] [Medline: 34449404]
182. O'Horo J, Cerhan J, Cahn E, Bauer P, Temesgen Z, Ebbert J, et al. Outcomes of COVID-19 with the Mayo Clinic Model of Care and Research. Mayo Clin Proc 2021 Mar;96(3):601-618 [FREE Full text] [doi: 10.1016/j.mayocp.2020.12.006] [Medline: 33673913]
183. Vinton D, Thomson N. 51 interactive home monitoring of ED patients with suspected or confirmed COVID-19. Ann Emerg Med 2020 Oct;76(4):S21. [doi: 10.1016/j.annemergmed.2020.09.061]
184. Over 120 people admitted to 4-star ‘Virtual Covid Ward’ at Leicester’s Hospitals. NHS University Hospitals of Leicester. 2021. URL: https://www.leicestershospitals.nhs.uk/aboutus/our-news/press-release-centre/2021/over-120-people-admitted-to-4-star-virtual-covid-ward-at-leicesters-hospitals/ [accessed 2024-09-26]
185. Swift J, Harris Z, Woodward A, O?Kelly N, Barker C, Ghosh S. The implementation of a virtual ward using digital solutions informing community clinicians in early supported discharge of patients with SARS-Cov2 respiratory symptoms from an

acute hospital setting. medRxiv. URL: https://www.medrxiv.org/content/10.1101/2021.03.29.21254548v2 [accessed 2024-09-26]
186. Bailey V. Mayo Clinic RPM model improves outcomes for acute COVID-19 treatment. TechTarget. 2021. URL: https://mhealthintelligence.com/news/mayo-clinic-rpm-model-improves-outcomes-for-acute-covid-19-treatment [accessed 2024-09-26]
187. Huma: Medopad, evaluation of the remote digital care platform. NHS England. URL: https://transform.england.nhs.uk/covid-19-response/technology-nhs/huma-medopad-evaluation-remote-digital-care-platform/ [accessed 2024-09-26]
188. Raffan F, Anderson T, Sinclair T, Shaw M, Amanatidis S, Thapa R, et al. The Virtual Care Experience of Patients Diagnosed With COVID-19. J Patient Exp 2021;8:23743735211008310 [FREE Full text] [doi: 10.1177/23743735211008310] [Medline: 34179437]
189. Lim H, Abdullah A, Ng C, Teo C, Valliyappan I, Abdul Hadi H, et al. Utility and usability of an automated COVID-19 symptom monitoring system (CoSMoS) in primary care during COVID-19 pandemic: A qualitative feasibility study. Int J Med Inform 2021 Nov;155:104567 [FREE Full text] [doi: 10.1016/j.ijmedinf.2021.104567] [Medline: 34536808]
190. Dinh A, Jaulmes L, Dechartres A, Duran C, Mascitti H, Lescure X, AP-HP/Universities/INSERM COVID-19 Research Collaboration, Data-Sciences Committee, Scientific Committee, Covidom Regional Centre Steering Commitee. Time to resolution of respiratory and systemic coronavirus disease 2019 symptoms in community setting. Clin Microbiol Infect 2021 Dec;27(12):1862.e1-1862.e4 [FREE Full text] [doi: 10.1016/j.cmi.2021.08.021] [Medline: 34481989]
191. Steinberg R, Anderson B, Hu Z, Johnson TM, O'Keefe JB, Plantinga LC, et al. Associations between remote patient monitoring programme responsiveness and clinical outcomes for patients with COVID-19. BMJ Open Qual 2021 Sep;10(3):e001496 [FREE Full text] [doi: 10.1136/bmjoq-2021-001496] [Medline: 34518302]
192. Clarke J, Flott K, Fernandez Crespo R, Ashrafian H, Fontana G, Benger J, et al. Assessing the safety of home oximetry for COVID-19: a multisite retrospective observational study. BMJ Open 2021 Sep 14;11(9):e049235 [FREE Full text] [doi: 10.1136/bmjopen-2021-049235] [Medline: 34521666]
193. Loubet P, Czeschan C, Sintes M, Sotto A, Laureillard D. Use of short message service in at-home COVID-19 patient management. BMC Med 2020 Dec 16;18(1):391 [FREE Full text] [doi: 10.1186/s12916-020-01863-9] [Medline: 33323098]
194. Mapelli M, Vignati C, Gugliandolo P, Fumagalli D, Agostoni P. Feasibility of remote home monitoring with a T-shirt wearable device in post-recovery COVID-19 patients. J Cardiovasc Med (Hagerstown) 2021 Nov 01;22(11):860-863. [doi: 10.2459/JCM.0000000000001165] [Medline: 34534155]
195. Pimlott N, Agarwal P, McCarthy LM, Luke MJ, Hum S, Gill S, et al. Clinical learnings from a virtual primary care program monitoring mild to moderate COVID-19 patients at home. Fam Pract 2021 Sep 25;38(5):549-555 [FREE Full text] [doi: 10.1093/fampra/cmaa130] [Medline: 33340398]
196. Wurzer D, Spielhagen P, Siegmann A, Gercekcioglu A, Gorgass J, Henze S, et al. Remote monitoring of COVID-19 positive high-risk patients in domestic isolation: a feasibility study. PLoS One 2021;16(9):e0257095 [FREE Full text] [doi: 10.1371/journal.pone.0257095] [Medline: 34559832]
197. Cavanna L, Cremona G, Citterio C, Nunzio CD, Muroni M, Andena AM, et al. COVID-19 outbreak in Italy: report on the first 124 consecutive patients treated at home. Tohoku J Exp Med 2021 Sep;255(1):61-69. [doi: 10.1620/tjem.255.61] [Medline: 34588347]
198. Pedretti A, Marquez Fosser S, Pasquinelli R, Vallone M, Plazzotta F, Luna D, et al. Risk of readmission to the emergency department in mild COVID-19 outpatients with telehealth follow-up. Rev Fac Cien Med Univ Nac Cordoba 2021 Aug 23;78(3):249-256 [FREE Full text] [doi: 10.31053/1853.0605.v78.n3.32414] [Medline: 34617705]
199. Kerr C, O' Regan S, Creagh D, Hughes G, Geary U, Colgan M, et al. Acceptability of and symptom findings from an online symptom check-in tool for COVID-19 outpatient follow-up among a predominantly healthcare worker population. BMJ Open 2021 Sep 28;11(9):e050444 [FREE Full text] [doi: 10.1136/bmjopen-2021-050444] [Medline: 34588254]
200. Jourdain P, Artigou J, Hryschyschyn N, Berthelot E, Bailly M, Dinh A, et al. [Telemedicine from experimentation (ETAPES) to COVIDOM… a new era ?]. Ann Cardiol Angeiol (Paris) 2021 Nov;70(5):317-321. [doi: 10.1016/j.ancard.2021.09.016] [Medline: 34627623]
201. Müller A, Haneke H, Kirchberger V, Mastella G, Dommasch M, Merle U, et al. Integration of mobile sensors in a telemedicine hospital system: remote-monitoring in COVID-19 patients. Z Gesundh Wiss 2022;30(1):93-97 [FREE Full text] [doi: 10.1007/s10389-021-01655-2] [Medline: 34667714]
202. Padula W, Miano M, Kelley M, Crawford S, Choy B, Hughes R, et al. A Cost-Utility Analysis of Remote Pulse-Oximetry Monitoring of Patients With COVID-19. Value Health 2022 Jun;25(6):890-896 [FREE Full text] [doi: 10.1016/j.jval.2021.09.008] [Medline: 35667779]
203. Khalid I, Imran M, Imran M, Khan S, Akhtar MA, Amanullah K, et al. Telemedicine monitoring of high-risk coronavirus disease 2019 (COVID-19) patients by family medicine service after discharge from the emergency department. J Family Community Med 2021;28(3):210-216 [FREE Full text] [doi: 10.4103/jfcm.jfcm_184_21] [Medline: 34703382]
204. Dinh A, Mercier J, Jaulmes L, Artigou J, Juillière Y, Yordanov Y, AP-HP/Universities/INSERM COVID-19 Research Collaboration. Safe Discharge Home With Telemedicine of Patients Requiring Nasal Oxygen Therapy After COVID-19. Front Med (Lausanne) 2021 Nov 3;8:703017 [FREE Full text] [doi: 10.3389/fmed.2021.703017] [Medline: 34805196]

205. Banerjee J, Canamar CP, Voyageur C, Tangpraphaphorn S, Lemus A, Coffey C, et al. Mortality and Readmission Rates Among Patients With COVID-19 After Discharge From Acute Care Setting With Supplemental Oxygen. JAMA Netw Open 2021 Apr 01;4(4):e213990 [FREE Full text] [doi: 10.1001/jamanetworkopen.2021.3990] [Medline: 33792728]
206. Artandi M, Barman L, Srinivasan M, Thomas S, Singh J, Asch SM, et al. A specialized acute COVID-19 outpatient clinic at an academic medical center. Am J Med Qual 2022;37(3):221-226 [FREE Full text] [doi: 10.1097/JMQ.0000000000000006] [Medline: 34310381]
207. Bouabida K, Malas K, Talbot A, Desrosiers M, Lavoie F, Lebouché B, et al. Remote patient monitoring program for COVID-19 patients following hospital discharge: a cross-sectional study. Front Digit Health 2021;3:721044 [FREE Full text] [doi: 10.3389/fdgth.2021.721044] [Medline: 34859244]
208. Chechter M, Dutra da Silva G, E Costa R, Miklos T, Antonio da Silva N, Lorber G, et al. Evaluation of patients treated by telemedicine in the beginning of the COVID-19 pandemic in São Paulo, Brazil: A non-randomized clinical trial preliminary study. Heliyon 2023 Apr;9(4):e15337 [FREE Full text] [doi: 10.1016/j.heliyon.2023.e15337] [Medline: 37073324]
209. Larimer K, Wegerich S, Splan J, Chestek D, Prendergast H, Vanden Hoek T. Personalized Analytics and a Wearable Biosensor Platform for Early Detection of COVID-19 Decompensation (DeCODe): Protocol for the Development of the COVID-19 Decompensation Index. JMIR Res Protoc 2021 May 26;10(5):e27271 [FREE Full text] [doi: 10.2196/27271] [Medline: 33949966]
210. Richards DM, Tweardy MJ, Steinhubl SR, Chestek DW, Hoek TLV, Larimer KA, et al. Wearable sensor derived decompensation index for continuous remote monitoring of COVID-19 diagnosed patients. NPJ Digit Med 2021 Nov 08;4(1):155. [doi: 10.1038/s41746-021-00527-z] [Medline: 34750499]
211. Delgado MK, Morgan AU, Asch DA, Xiong R, Kilaru AS, Lee KC, et al. Comparative effectiveness of an automated text messaging service for monitoring COVID-19 at home. Ann Intern Med 2022 Feb;175(2):179-190. [doi: 10.7326/m21-2019]
212. Akama-Garren EH, Shah SA, Zinzuwadia AN, Bartuska A, Hashimoto M, Chu JT, et al. Outcomes of a student-led telemedicine clinic in response to COVID-19. J Ambul Care Manage 2021;44(3):197-206 [FREE Full text] [doi: 10.1097/JAC.0000000000000380] [Medline: 34016847]
213. Bajracharya A, Foster B, Robinson C, Keane N, Broach J, McManus D. Home-sat: A multimodal post-discharge virtual follow up program for covid-19 patients. J Gen Intern Med 2021;36:S375 [FREE Full text] [doi: 10.1007/s11606-021-06830-5]
214. Brennan KA, Kang H, Kraus S, Kang J, Malkawi D. Harnessing remote patient monitoring technology to improve transitions of care. J American Geriatrics Society 2021;69(S1):S63. [doi: 10.1111/jgs.17115]
215. Brown H, Alexander AB, Strachan C, Pang P, Rininger A, Bernhardt R. A novel approach to outpatient follow-up for coronavirus disease patients discharged from the emergency department. Acad Emerg Med 2021;28 Suppl 1(S1):S290 [FREE Full text] [doi: 10.1111/acem.14249] [Medline: 33945187]
216. Cabral C, Campos MJ, Soares MM, Pinheiro N, Rosário V, Salgueiro M. The role of hospital-at-home service in surveillance of COVID-19 elderly patients. Eur Geriatr Med 2020;11(Suppl 1):S82 [FREE Full text] [doi: 10.1007/s41999-020-00428-6] [Medline: 33346896]
217. Cheney C. Virtual hospital expands inpatient capacity during coronavirus pandemic. Accreditation & Quality Compliance Center. 2020. URL: https://www.accreditationqualitycenter.com/articles/virtual-hospital-expands-inpatient-capacity-during-coronavirus-pandemic [accessed 2024-09-26]
218. Clemente V, Tripiciano C, Moras P, Deriu D, Di Giuseppe M, Piscitelli A, et al. Post-discharge telephonic follow-up of pediatric patients affected by SARS-CoV2 infection in a single Italianpediatric COVID center: a safe and feasible way to monitor children after hospitalization. Ital J Pediatr 2021 Jun 02;47(1):119 [FREE Full text] [doi: 10.1186/s13052-021-01065-w] [Medline: 34078420]
219. Coronado-Vázquez V, Ramírez-Durán M, Gómez-Salgado J, Dorado-Rabaneda MS, Benito-Alonso E, Holgado-Juan M, et al. Evolution of a Cohort of COVID-19 Infection Suspects Followed-Up from Primary Health Care. J Pers Med 2021 May 24;11(6):459 [FREE Full text] [doi: 10.3390/jpm11060459] [Medline: 34073666]
220. Dallabrida S, Linke H, Shah P, Culbreth-Notaro M. PNS105 Patient Preferences and Feedback Regarding Daily Reporting of COVID-19 Symptoms Using Personal Smartphones for the Obvio-19 Study. Value in Health 2021 Jun;24:S192. [doi: 10.1016/j.jval.2021.04.959]
221. D'Amato G, Acanfora L, Delli Paoli L, D'Amato M. Preventive home therapy for symptomatic patients affected by COVID-19 and followed by teleconsultations. Multidiscip Respir Med 2021 Jan 15;16(1):748 [FREE Full text] [doi: 10.4081/mrm.2021.748] [Medline: 33532070]
222. Fadaizadeh L, Jamaati H, Varahram M, Taheri MJ, Sanaat M. Follow-Up of Coronavirus Infected Patients Using Telemedicine in a Referral Pulmonary Center. Tanaffos 2020 Dec;19(4):356-363 [FREE Full text] [Medline: 33959173]
223. Gutiérrez M, Durán-Vila A, Ruiz-Labarta J, Payá-Martínez P, Pintado Recarte P, Bujan J, et al. A New Multiplatform Model for Outpatient Prenatal and Postpartum Care in a Cohort of COVID-19-Affected Obstetric Patients. Int J Environ Res Public Health 2021 May 12;18(10):5144 [FREE Full text] [doi: 10.3390/ijerph18105144] [Medline: 34066255]
224. Horton L, Jenks J, Bharti A, Ritter M, Bordeaux K. Using telemedicine to provide virtual care for COVID-19 patients at home. Open Forum Infectious Diseases 2020;7(Suppl 1):S303 [FREE Full text] [doi: 10.1093/ofid/ofaa439.667]

225. Jankovic J, Da Silva Lopes A, Morez A, Darnac C, Demicheli R, Dalla-Vale M, et al. Suivi téléphonique des patients testés positifs au SARS-CoV-2 au Département d'oncologie du CHUV. Revue Médicale Suisse 2021;17(733):703-707. [doi: 10.53738/REVMED.2021.17.733.0703]
226. Kagiyama N, Hiki M, Matsue Y, Dohi T, Matsuzawa W, Daida H, et al. Validation of telemedicine-based self-assessment of vital signs for patients with COVID-19: A pilot study. J Telemed Telecare 2023 Sep 09;29(8):600-606 [FREE Full text] [doi: 10.1177/1357633X211011825] [Medline: 33966523]
227. Khidir H, DeLuca M, Macias-Konstantopoulos WL, Samuels-Kalow M, Jasrasaria R, Risley K, et al. The Health and Social Needs of Patients Discharged From the Emergency Department With Suspected COVID-19. Public Health Rep 2021 May;136(3):309-314 [FREE Full text] [doi: 10.1177/0033354920982579] [Medline: 33593138]
228. Kohlbrenner D, Kuhn M, Stüssi-Helbling M, Spielmanns M, Nordmann Y, Clarenbach C. Recovery in patients with SARS-CoV-2 associated respiratory failure. Euro Respir J 2021;58:PA302. [doi: 10.1183/13993003.congress-2021.PA302]
229. Kyriakides J, Khani A, Kelly C, Coleman R. Analysis of an ambulatory care pathway for patients with COVID-19 utilising remote pulse oximetry. Clin Med (Lond) 2021 Mar 02;21(Suppl 2):48-49 [FREE Full text] [doi: 10.7861/clinmed.21-2-s48] [Medline: 34078698]
230. Lam R, Becerra R, Wigglesworth K, Buliga-Stoian M, McGing M, Davis D, et al. 106 Learning from the Long Term Experiences of Patients Recovering from COVID-19: Utilizing a Novel Approach to a Transition of Care Curriculum to Benefit Students and Patients. Annals of Emergency Medicine 2021 Aug;78(2):S48. [doi: 10.1016/j.annemergmed.2021.07.108]
231. Lee Y, Han JO, Lee H, Lim S. The development and operation of a home management system during the COVID-19 pandemic: experience of the local government Gyeonggi-do in Korea. J Korean Med Sci 2021 May 17;36(19):e134 [FREE Full text] [doi: 10.3346/jkms.2021.36.e134] [Medline: 34002552]
232. Lejeune J, Morquin D, Attal J, Makinson A, Atoui N, Favier C, et al. Gestion multidisciplinaire des patients infectés par le SARS-Cov-2 maintenus à domicile : rôle d'un dispositif de télé-suivi sur smartphone en situation de crise sanitaire. Médecine Maladies Infectieuses 2020 Sep;50(6):S99. [doi: 10.1016/j.medmal.2020.06.201]
233. Lisker G, Narasimhan M, Greenberg H, Ramdeo R, McGinn T. "Ambulatory Management of Moderate to High Risk COVID-19 Patients: The Coronavirus Related Outpatient Work Navigators (CROWN) Protocol". Home Health Care Manage Pract 2020 Oct 15;33(1):49-53. [doi: 10.1177/1084822320964196]
234. Margolius D, Hennekes M, Yao J, Einstadter D, Gunzler D, Chehade N, et al. On the front (phone) lines: results of a COVID-19 hotline. J Am Board Fam Med 2021 Feb 23;34(Supplement):S95-S102. [doi: 10.3122/jabfm.2021.s1.200237]
235. A hospital at home program and the role of the care management team. Hospital Case Management. 2021. URL: https://www.reliasmedia.com/articles/148503-a-hospital-at-home-program-and-the-role-of-the-care-management-team [accessed 2024-09-26]
236. Silva CBD, Trindade LDL, Kolhs M, Barimacker SV, Schacht L, Bordignon M. Implementation of COVID-19 telemonitoring: repercussions in nursing academic training. Rev Gaucha Enferm 2021;42(spe):e20200395 [FREE Full text] [doi: 10.1590/1983-1447.2021.20200395] [Medline: 34524361]
237. Nina-Mollinedo JM, Quesada-Cubo V, Rivera-Zabala L, Miranda-Rojas SH, Olmos-Machicado JR, Arce-Alarcon N, et al. Hundred days of teleconsultations and their usefulness in the management of COVID-19: experience of the COVID-19 National Call Center in Bolivia. Telemed J E Health 2022 May;28(5):654-665. [doi: 10.1089/tmj.2021.0250] [Medline: 34382821]
238. Nogueira López J, Grasa Lozano C, Ots Ruiz C, Alonso García L, Falces-Romero I, Calvo C, Grupo de Trabajo de SARS-CoV-2 del Servicio de Pediatría del Hospital Universitario La Paz. [Telemedicine follow-ups for COVID-19: Experience in a tertiary hospital]. An Pediatr (Engl Ed) 2020 Nov 02;95(5):336-344 [FREE Full text] [doi: 10.1016/j.anpedi.2020.10.017] [Medline: 33328150]
239. Padilla-Machaca PM, Cardenas B, Cerron C, Escajadillo N, Bacilio W, Mantilla O. MD. Hepatology 2020;72(S1):291A-292A. [doi: 10.1002/hep.31579]
240. Reforma LG, Duffy C, Collier AY, Wylie BJ, Shainker SA, Golen TH, et al. A multidisciplinary telemedicine model for management of coronavirus disease 2019 (COVID-19) in obstetrical patients. Am J Obstet Gynecol MFM 2020 Nov;2(4):100180 [FREE Full text] [doi: 10.1016/j.ajogmf.2020.100180] [Medline: 32838271]
241. Shah S, Gvozdanovic A, Knight M, Gagnon J. PMD35 Remote Patient Monitoring in ACUTE Medical Conditions; CAN Digital Health Solutions Reduce Clinician Workload and Ease the Pressure on Healthcare Providers during the COVID Crisis? Value in Health 2020 Dec;23:S582. [doi: 10.1016/j.jval.2020.08.1068]
242. Siegal J, Steel P, Zhang Y, Cato K, Park JC, Melville LD. Exertional hypoxia and virtual follow-up in emergency department patients discharged with COVID-19-like illness. Acad Emerg Med 2021;28 Suppl 1(S1):S243 [FREE Full text] [doi: 10.1111/acem.14249] [Medline: 33945187]
243. Timmers T, Janssen L, Stohr J, Murk JL, Berrevoets MAH. Using eHealth to Support COVID-19 Education, Self-Assessment, and Symptom Monitoring in the Netherlands: Observational Study. JMIR Mhealth Uhealth 2020 Jun 23;8(6):e19822 [FREE Full text] [doi: 10.2196/19822] [Medline: 32516750]

244. Smith SW, Tiu J, Caspers CG, Lakdawala VS, Koziatek CA, Swartz JL, et al. Virtual Urgent Care Quality and Safety in the Time of Coronavirus. Jt Comm J Qual Patient Saf 2021 Feb;47(2):86-98 [FREE Full text] [doi: 10.1016/j.jcjq.2020.10.001] [Medline: 33358323]
245. Trostle ME, Silverstein JS, Tubridy E, Limaye MA, Rose J, Brubaker SG, et al. COVID-19 in pregnancy: creating an outpatient surveillance model in a public hospital system. J Perinat Med 2020 Nov 26;48(9):959-964 [FREE Full text] [doi: 10.1515/jpm-2020-0309] [Medline: 32809968]
246. Tu J, Gang M, Ramdin C, Natale-Pereira A. Outpatient follow-up of discharged COVID-19 patients with intermediate oxygen saturations during a pandemic surge. Acad Emerg Med 2021;28 Suppl 1(S1):S156 [FREE Full text] [doi: 10.1111/acem.14249] [Medline: 33945187]
247. Vella D, Thomas M, Pak J, Aarons K, Devanathan R, Scott B. Nurse-led remote HITH program provides safe and effective care for patients with COVID-19. Australian Nursing & Midwifery Journal 2021;27(3):36-38 [FREE Full text]
248. Walsh M, O'Grady M, Sweeney A, Martin L, Kennedy M, Plant B, et al. Supported discharge for COVID-19. Ir Med J 2021;114(4):336 [FREE Full text]
249. Vignati C, Mapelli M, Gugliandolo P, Fumagalli D, Mattavelli I, Salvioni E. Feasibility of remote home monitoring with a t-shirt wearable device in post-recovery COVID-19 patients. Giornale Italiano Cardiologia 2020;21(12 SUPPL 2):e86-e87.
250. Yamagami K, Nomura A, Kometani M, Shimojima M, Sakata K, Usui S, et al. Early detection of symptom exacerbation in patients with SARS-CoV-2 infection using the Fitbit Charge 3 (DEXTERITY): pilot evaluation. JMIR Form Res 2021 Sep 16;5(9):e30819 [FREE Full text] [doi: 10.2196/30819] [Medline: 34516390]
251. Kilaru A, Porges S, Grossman L, Delgado M, Morgan A, Chaiyachati K, et al. An accelerated hospital observation pathway to reduce length of stay for patients with COVID-19. Am J Manag Care 2022 Jun 17;28(6):262-268 [FREE Full text] [doi: 10.37765/ajmc.2022.88789] [Medline: 35738222]
252. Baena-Díez J, Gonzalez-Casafont I, Cordeiro-Coelho S, Fernández-González S, Rodríguez-Jorge M, Pérez-Torres C, et al. Effectiveness of Telephone Monitoring in Primary Care to Detect Pneumonia and Associated Risk Factors in Patients with SARS-CoV-2. Healthcare (Basel) 2021 Nov 13;9(11):1548 [FREE Full text] [doi: 10.3390/healthcare9111548] [Medline: 34828594]
253. Beaney T, Clarke J, Alboksmaty A, Flott K, Fowler A, Benger J, et al. Evaluating the impact of a pulse oximetry remote monitoring programme on mortality and healthcare utilisation in patients with COVID-19 assessed in emergency departments in England: a retrospective matched cohort study. Emerg Med J 2023 Jun 28;40(6):460-465 [FREE Full text] [doi: 10.1136/emermed-2022-212377] [Medline: 36854617]
254. Ford D, Warr E, Hamill C, He W, Pekar E, Harvey J, et al. Not Home Alone: Leveraging Telehealth and Informatics to Create a Lean Model for COVID-19 Patient Home Care. Telemed Rep 2021;2(1):239-246 [FREE Full text] [doi: 10.1089/tmr.2021.0020] [Medline: 34841422]
255. Gavin W, Rager J, Russ J, Subramoney K, Kara A. Accuracy of the Simplified HOSPITAL Score in Predicting COVID-19 Readmissions-Exploring Outcomes from a Hospital-at-Home Program. J Healthc Manag 2021 Nov 23;67(1):54-62. [doi: 10.1097/JHM-D-21-00092] [Medline: 34816806]
256. Grutters LA, Majoor KI, Pol-Mattern ESK, Hardeman JA, van Swol CFP, Vorselaars ADM. Home-monitoring reduces hospital stay for COVID-19 patients. Eur Respir J 2021 Nov;58(5):2101871 [FREE Full text] [doi: 10.1183/13993003.01871-2021] [Medline: 34561294]
257. Beaney T, Clarke J, Alboksmaty A, Flott K, Fowler A, Benger J, et al. Population-level impact of a pulse oximetry remote monitoring programme on mortality and healthcare utilisation in the people with COVID-19 in England: a national analysis using a stepped wedge design. Emerg Med J 2022 Aug;39(8):575-582 [FREE Full text] [doi: 10.1136/emermed-2022-212378] [Medline: 35418406]
258. Sherlaw-Johnson C, Georghiou T, Morris S, Crellin NE, Litchfield I, Massou E, et al. The impact of remote home monitoring of people with COVID-19 using pulse oximetry: A national population and observational study. EClinicalMedicine 2022 Mar;45:101318 [FREE Full text] [doi: 10.1016/j.eclinm.2022.101318] [Medline: 35252824]
259. Dorner S, Carlson L, DeSharone A, Thompson R, Pu C, Mark E, et al. 131 a novel mobile integrated health program for COVID-19 response. Ann Emerg Med 2020 Oct;76(4):S52. [doi: 10.1016/j.annemergmed.2020.09.142]
260. Nicolás D, Camós-Carreras A, Spencer F, Arenas A, Butori E, Maymó P, et al. A prospective cohort of SARS-CoV-2-infected health care workers: clinical characteristics, outcomes, and follow-up strategy. Open Forum Infect Dis 2021 Jan;8(1):ofaa592 [FREE Full text] [doi: 10.1093/ofid/ofaa592] [Medline: 33537362]
261. Faro JM, Cutrona SL. Extending a lifeline to nonhospitalized patients with COVID-19 through automated text messaging. Ann Intern Med 2022 Feb;175(2):291-292. [doi: 10.7326/m21-4273]
262. Kilaru AS, Lee K, Grossman L, Mankoff Z, Snider CK, Bressman E, et al. Short-stay hospitalizations for patients with COVID-19: a retrospective cohort study. J Clin Med 2021 May 03;10(9):1966 [FREE Full text] [doi: 10.3390/jcm10091966] [Medline: 34063729]
263. Cornelis J, Van Grootven B, Alvarez Irusta L, de Meester C, Christiaens W, Van Durme T, et al. Remote monitoring of patients with COVID-19. KCE. 2022. URL: https://www.kce.fgov.be/en/remote-monitoring-of-patients-with-covid-19 [accessed 2024-09-26]

264. Aalaei S, Khoshrounejad F, Saleh LA, Amini M. Design of a Mobile Application and Evaluation of Its Effects on Psychological Parameters of Covid-19 Inpatients: A Protocol for a Randomized Controlled Trial. Front Psychiatry 2021;12:612384 [FREE Full text] [doi: 10.3389/fpsyt.2021.612384] [Medline: 34108892]
265. Brakenhoff TB, Franks B, Goodale BM, van de Wijgert J, Montes S, Veen D, et al. A prospective, randomized, single-blinded, crossover trial to investigate the effect of a wearable device in addition to a daily symptom diary for the remote early detection of SARS-CoV-2 infections (COVID-RED): a structured summary of a study protocol for a randomized controlled trial. Trials 2021 Jun 22;22(1):412 [FREE Full text] [doi: 10.1186/s13063-021-05241-5] [Medline: 34158099]
266. Ciccone EJ, Zivich PN, Lodge EK, Zhu D, Law E, Miller E, et al. SARS-CoV-2 infection in health care personnel and their household contacts at a tertiary academic medical center: protocol for a longitudinal cohort study. JMIR Res Protoc 2021 Apr 30;10(4):e25410 [FREE Full text] [doi: 10.2196/25410] [Medline: 33769944]
267. Douwes A, Loeff F. Innovatief klinisch onderzoek COVID-RED: Een COVID-infectie opsporen terwijl je slaapt. COVID-RED. 2021. URL: https://www.covid-red.eu/wp-content/uploads/2021/08/COVID-RED-VAPvisieAnalyse-4-2021_edit.pdf [accessed 2024-09-26]
268. Remote Patient Monitoring (RPM) for patients with COVID-19 and other infection. German Clinical Trials Register. URL: https://drks.de/search/en/trial/DRKS00023553 [accessed 2024-09-26]
269. Early transfer of hospitalized patients incl. COVID-19 to a virtual hospital at home model - a clinical feasibility study (Influenz-er). ClinicalTrials.gov. URL: https://clinicaltrials.gov/study/NCT05087082 [accessed 2024-09-26]
270. Fox R, Mulcahy Symmons S, De Brún A, Joyce D, Muldoon EG, McGinty T, et al. Mixed methods protocol to examine the acceptability and clinical characteristics of a remote monitoring programme for delivery of COVID-19 care, among healthcare staff and patients. BMJ Open 2021 Sep 29;11(9):e051408 [FREE Full text] [doi: 10.1136/bmjopen-2021-051408] [Medline: 34588258]
271. Support for COVID19 Patients at Home (Mirato). ClinicalTrials.gov. URL: https://clinicaltrials.gov/study/NCT04898179 [accessed 2024-09-26]
272. Gonzalez-Gerez JJ, Bernal-Utrera C, Anarte-Lazo E, Garcia-Vidal JA, Botella-Rico JM, Rodriguez-Blanco C. Therapeutic pulmonary telerehabilitation protocol for patients affected by COVID-19, confined to their homes: study protocol for a randomized controlled trial. Trials 2020 Jun 29;21(1):588 [FREE Full text] [doi: 10.1186/s13063-020-04494-w] [Medline: 32600378]
273. Haran JP, Pinero JC, Zheng Y, Palma NA, Wingertzahn M. Virtualized clinical studies to assess the natural history and impact of gut microbiome modulation in non-hospitalized patients with mild to moderate COVID-19 a randomized, open-label, prospective study with a parallel group study evaluating the physiologic effects of KB109 on gut microbiota structure and function: a structured summary of a study protocol for a randomized controlled study. Trials 2021 Apr 02;22(1):245 [FREE Full text] [doi: 10.1186/s13063-021-05157-0] [Medline: 33810796]
274. Iqbal FM, Joshi M, Davies G, Khan S, Ashrafian H, Darzi A. Design of the pilot, proof of concept REMOTE-COVID trial: remote monitoring use in suspected cases of COVID-19 (SARS-CoV-2). Pilot Feasibility Stud 2021 Mar 05;7(1):62 [FREE Full text] [doi: 10.1186/s40814-021-00804-4] [Medline: 33673868]
275. Jalilian Khave L, Vahidi M, Shirini D, Sanadgol G, Ashrafi F, Arab-Ahmadi M, et al. Clinical and epidemiological characteristics of postdischarge patients with COVID-19 in Tehran, Iran: protocol for a prospective cohort study (Tele-COVID-19 Study). JMIR Res Protoc 2021 Feb 02;10(2):e23316 [FREE Full text] [doi: 10.2196/23316] [Medline: 33471777]
276. Use of remote monitoring for COVID-19 patient (RPM). ClinicalTrials.gov. URL: https://clinicaltrials.gov/study/NCT04425720 [accessed 2024-09-26]
277. Comparative Effectiveness of Readmission Reduction Interventions for Individuals With Sepsis or Pneumonia (ACCOMPLISH). ClinicalTrials.gov. URL: https://clinicaltrials.gov/study/NCT04829188 [accessed 2024-09-26]
278. Prospective study analyzing course of disease and outcome in patients with acute COVID-19 with remote Patient monitoring. World Health Organization Trial Search. URL: https://trialsearch.who.int/Trial2.aspx?TrialID=DRKS00025091 [accessed 2024-09-26]
279. Performance of a remote monitoring program for patients diagnosed with COVID-19 (RPM). ClinicalTrials.gov. URL: https://clinicaltrials.gov/study/NCT05063812 [accessed 2024-09-26]
280. Nanni O, Viale P, Vertogen B, Lilli C, Zingaretti C, Donati C, et al. PROTECT Trial: a cluster-randomized study with hydroxychloroquine versus observational support for prevention or early-phase treatment of coronavirus disease (covid-19): a structured summary of a study protocol for a randomized controlled trial. Trials 2020 Jul 31;21(1):689 [FREE Full text] [doi: 10.1186/s13063-020-04527-4] [Medline: 32736597]
281. Using Biovitals® Sentinel to monitor disease progression in subjects quarantined for suspected COVID-19. ClinicalTrials.gov. URL: https://clinicaltrials.gov/study/NCT04343794 [accessed 2024-09-26]
282. Prospective study analyzing course of disease and outcome in patients with acute COVID-19 with remote Patient monitoring. German Clinical Trials Register. URL: https://drks.de/search/en/trial/DRKS00025091 [accessed 2024-09-26]
283. Home monitoring of respiration in Covid-19 patients using smartphone technology. University College Dublin. URL: https://www.ucd.ie/research/covid19response/news/homemonitoringofrespiration/ [accessed 2024-09-26]

284. At home monitoring for patients with Covid19. Reagan-Udall Foundation. URL: https://reaganudall.org/clinical-trial/home-monitoring-patients-covid19 [accessed 2024-09-26]
285. Regionaal georganiseerde COVID-19 thuismonitoring ondersteunt huisartsen in Drenthe. Analyse Nederland. 2021. URL: https://nos.nl/artikel/2369357-coronapatienten-in-drenthe-gaan-hun-eigen-zuurstofgehalte-meten [accessed 2024-09-26]
286. Early@home: Telemedicine for recovering COVID-19 patients. Trial Register. URL: https://onderzoekmetmensen.nl/en/trial/49189 [accessed 2024-09-26]
287. Sensor based vital signs monitoring of Covid 19 patients during home isolation (HSC19). ClinicalTrials.gov. URL: https://clinicaltrials.gov/study/NCT04335097 [accessed 2024-09-26]
288. Wong CK, Ho DTY, Tam AR, Zhou M, Lau YM, Tang MOY, et al. Artificial intelligence mobile health platform for early detection of COVID-19 in quarantine subjects using a wearable biosensor: protocol for a randomised controlled trial. BMJ Open 2020 Jul 22;10(7):e038555 [FREE Full text] [doi: 10.1136/bmjopen-2020-038555] [Medline: 32699167]
289. At Home Monitoring for Patients With Covid19. ClinicalTrials.gov. URL: https://clinicaltrials.gov/study/NCT04453774 [accessed 2024-09-26]
290. Remote patient monitoring (RPM) for patients with COVID-19 and other infection. Outbreak.info. URL: https://outbreak.info/resources/DRKS00023553 [accessed 2024-09-26]
291. Marquez-Algaba E, Sanchez M, Baladas M, España C, Dallo HS, Requena M, et al. COVID-19 Follow-App. Mobile app-based monitoring of COVID-19 patients after hospital discharge: a single-center, open-label, randomized clinical trial. J Pers Med 2022 Jan 01;12(1):24 [FREE Full text] [doi: 10.3390/jpm12010024] [Medline: 35055339]
292. van Goor HMR, Breteler MJM, van Loon K, de Hond TAP, Reitsma JB, Zwart DLM, et al. Remote hospital care for recovering COVID-19 patients using telemedicine: a randomised controlled trial. J Clin Med 2021 Dec 17;10(24):5940 [FREE Full text] [doi: 10.3390/jcm10245940] [Medline: 34945234]
293. Brunk D. Survey offers a snapshot of nationwide COVID-19 discharge practices. The Hospitalist. 2021. URL: https://www.the-hospitalist.org/hospitalist/article/239467/transitions-care/survey-offers-snapshot-nationwide-covid-19-discharge [accessed 2024-09-26]
294. Greysen SR, Auerbach AD, Mitchell MD, Goldstein JN, Weiss R, Esmaili A, HOMERuN collaborative working group. Discharge Practices for COVID-19 Patients: Rapid Review of Published Guidance and Synthesis of Documents and Practices at 22 US Academic Medical Centers. J Gen Intern Med 2021 Jun;36(6):1715-1721 [FREE Full text] [doi: 10.1007/s11606-021-06711-x] [Medline: 33835314]
295. Raesi R, Shaye ZA, Saghari S, Sheikh Beig Goharrizi MA, Raei M, Hushmandi K. The impact of education through nurse-led telephone follow-up (telenursing) on the quality of life of COVID-19 patients. J Egypt Public Health Assoc 2021 Nov 08;96(1):30. [doi: 10.1186/s42506-021-00093-y] [Medline: 34748085]
296. Leite V, Rampim D, Jorge V, de Lima M, Cezarino L, da Rocha C, et al. Persistent symptoms and disability after COVID-19 hospitalization: data from a comprehensive telerehabilitation program. Arch Phys Med Rehabil 2021 Jul;102(7):1308-1316 [FREE Full text] [doi: 10.1016/j.apmr.2021.03.001] [Medline: 33711279]
297. Günster C, Busse R, Spoden M, Rombey T, Schillinger G, Hoffmann W, et al. 6-month mortality and readmissions of hospitalized COVID-19 patients: a nationwide cohort study of 8,679 patients in Germany. PLoS One 2021;16(8):e0255427 [FREE Full text] [doi: 10.1371/journal.pone.0255427] [Medline: 34351975]
298. Lavery AM, Preston LE, Ko JY, Chevinsky JR, DeSisto CL, Pennington AF, et al. Characteristics of hospitalized COVID-19 patients discharged and experiencing same-hospital readmission - United States, March-August 2020. MMWR Morb Mortal Wkly Rep 2020 Nov 13;69(45):1695-1699. [doi: 10.15585/mmwr.mm6945e2] [Medline: 33180754]
299. Ramos-Martínez A, Parra-Ramírez LM, Morrás I, Carnevali M, Jiménez-Ibañez L, Rubio-Rivas M, et al. Frequency, risk factors, and outcomes of hospital readmissions of COVID-19 patients. Sci Rep 2021 Jul 02;11(1):13733. [doi: 10.1038/s41598-021-93076-0] [Medline: 34215803]
300. Verna E, Landis C, Brown J, Mospan A, Crawford J, Hildebrand J, et al. Factors associated with readmission in the united states following hospitalization with coronavirus disease 2019. Clin Infect Dis 2022 May 30;74(10):1713-1721 [FREE Full text] [doi: 10.1093/cid/ciab464] [Medline: 34015106]
301. Ramzi Z. Hospital readmissions and post-discharge all-cause mortality in COVID-19 recovered patients; a systematic review and meta-analysis. Am J Emerg Med 2022 Jan;51:267-279 [FREE Full text] [doi: 10.1016/j.ajem.2021.10.059] [Medline: 34781153]
302. García Bermúdez I, González Manso M, Sánchez Sánchez E, Rodríguez Hita A, Rubio Rubio M, Suárez Fernández C. Usefulness and acceptance of telephone monitoring by a virtual assistant for patients with COVID-19 following discharge. Rev Clin Esp (Barc) 2021 Oct;221(8):464-467 [FREE Full text] [doi: 10.1016/j.rceng.2021.01.007] [Medline: 34172430]
303. Irving G, Neves AL. What next for COVID Oximetry and virtual ward? Br J Gen Pract 2021 Aug 26;71(710):425-426. [doi: 10.3399/bjgp21x717041]
304. Neves AL, Li E, Gupta PP, Fontana G, Darzi A. Virtual primary care in high-income countries during the COVID-19 pandemic: policy responses and lessons for the future. Eur J Gen Pract 2021 Dec;27(1):241-247 [FREE Full text] [doi: 10.1080/13814788.2021.1965120] [Medline: 34431426]
305. Azevedo S, Rodrigues TC, Londral AR. Domains and methods used to assess home telemonitoring scalability: systematic review. JMIR Mhealth Uhealth 2021 Aug 19;9(8):e29381 [FREE Full text] [doi: 10.2196/29381] [Medline: 34420917]

306. Toetsingskader IGJ ‘Telemonitoring volwassenen thuis’ geldig per 11 oktober 2021. Inspectie Gezondheidszorg en Jeugd. 2021. URL: https://www.igj.nl/binaries/igj/documenten/toetsingskaders/2021/11/16/toetsingskader-telemonitoring-volwassenen-thuis/Toetsingskadertelemonitoringvolwassenenthuis.pdf [accessed 2024-09-26]
307. Salvatore FP, Fanelli S. The Healthcare Organization in COVID-19 Age: An Evaluation Framework for the Performance of a Telemonitoring Model. Sustainability 2021 Nov 18;13(22):12765. [doi: 10.3390/su132212765]

Abbreviations

ED: emergency department
GP: general practitioner
LOS: length of stay
RCT: randomized controlled trial
RPM: remote patient monitoring

Edited by E Borycki; submitted 30.11.22; peer-reviewed by M Moz, H Veldandi, S Ye; comments to author 12.01.23; revised version received 01.05.23; accepted 13.09.24; published 19.11.24.

Please cite as:
Cornelis J, Christiaens W, de Meester C, Mistiaen P
Remote Patient Monitoring at Home in Patients With COVID-19: Narrative Review
JMIR Nursing 2024;7:e44580
URL: https://nursing.jmir.org/2024/1/e44580
doi:10.2196/44580
PMID:39287362

Calculating Optimal Patient to Nursing Capacity: Comparative Analysis of Traditional and New Methods

Anna Ware, MPH, MS; Terri Blumke, BSc; Peter Hoover, MS; David Arreola, BS

National Center for Collaborative Healthcare Innovation, Veterans Affairs Palo Alto Health Care System, Palo Alto, CA, United States

Corresponding Author:
Anna Ware, MPH, MS
National Center for Collaborative Healthcare Innovation, Veterans Affairs Palo Alto Health Care System, , Palo Alto, CA, , United States

Abstract

Background: Optimal nurse staffing levels have been shown to impact patients' prognoses and safety, as well as staff burnout. The predominant method for calculating staffing levels has been patient-to-nurse (P/N) ratios and nursing hours per patient day. However, both methods fall short of addressing the dynamic nature of staffing needs that often fluctuate throughout the day as patients' clinical status changes and new patients are admitted or discharged from the unit.

Objective: In this evaluation, the Veterans Affairs Palo Alto Health Care System (VAPAHCS) piloted a new dynamic bed count calculation in an effort to target optimal staffing levels every hour to provide greater temporal resolution on nurse staffing levels within the Veterans Health Administration.

Methods: The dynamic bed count uses elements from both the nursing hours per patient day and P/N ratio to calculate current and target staffing levels, every hour, while balancing across nurse types (registered nurses to nurse assistants) to provide improved temporal insight into staff allocation. The dynamic bed count was compared with traditional P/N ratio methods of calculating patient capacity at the VAPAHCS, to assess optimal patient capacity within their acute care ward from January 1, 2023, through May 25, 2023. Descriptive statistics summarized patient capacity variables across the intensive care unit (ICU), medical-surgical ICU, and 3 acute care units. Student *t* tests (2-tailed) were used to analyze differences between patient capacity measures.

Results: Hourly analysis of patient capacity information displayed how the dynamic bed count provided improved temporal resolution on patient capacity. Comparing the dynamic bed count to the P/N ratio, we found the patient capacity, as determined by the P/N ratio, was, on average, higher than that of the dynamic bed count across VAPAHCS acute care units and the medical-surgical ICU ($P<.001$). For example, in acute care unit 3C, the average dynamic bed count was 21.6 (SD 4.2) compared with a P/N ratio of 28.6 (SD 3.2). This suggests that calculating patient capacity using P/N ratios alone could lead to units taking on more patients than what the dynamic bed count suggests the unit can optimally handle.

Conclusions: As a new patient capacity calculation, the dynamic bed count provided additional details and timely information about clinical staffing levels, patient acuity, and patient turnover. Implementing this calculation into the management process has the potential to empower departments to further optimize staffing and patient care.

(JMIR Nursing 2024;7:e59619) doi:10.2196/59619

KEYWORDS

nurse scheduling; nurse; patient ratio; nursing hours per patient day; NHPPD; nursing administration; workload; comparative analysis; nursing; staffing; nurse staffing; registered nurses; nurse assistants; staff allocation; patient capacity

Introduction

Nurse staffing levels can impact patients' prognoses and safety, as well as staff burnout, job satisfaction, workplace injury, and illness [1-4]. A common method for assessing and managing nurse staffing levels is the patient-to-nurse (P/N) ratio, or the total number of patients that are assigned to one nurse during their shift [5-7]. Target ratios are typically based on the type of clinical environment; however, when the unit's nursing team determines a patient has greater needs, the P/N ratio may be adjusted. The P/N ratio is intended as an efficient tool to assess staffing needs [5], but it primarily focuses on the direct care provided by registered nurses (RNs) and does not inherently account for the full range of nursing and support staff, including licensed practical nurses (LPNs), licensed vocational nurses (LVNs) and nurse assistants (NAs) [8,9].

An alternative to the P/N ratio is the nursing hours per patient day (NHPPD), which account for all nursing types and support staff on the floor, as well as patient complexity, patient turnover, and the presence of higher acuity patients [9-12]. NHPPD provide a comprehensive measure by including the total hours of care provided by each type of nursing staff per patient per day, adjusting for patient acuity, and considering the distribution of nursing care across different shifts and skill levels. Research has shown that using NHPPD significantly decreases mortality and length of stay, and improves patient outcomes [12-14]. While both measures aim to represent the ratio between staffing resources and patient demands, patient needs (and therefore staffing needs) are dynamic throughout the day, and standard intermittent tracking of staffing workloads can lead to inappropriate or incomplete staffing adjustments.

The Veterans Affairs Palo Alto Health Care System (VAPAHCS) is one of the largest medical centers in the Veterans Health Administration (VHA), and operates over 800 patient beds, including 3 acute care units and 6 critical care units [15]. Traditionally, the VAPAHCS used P/N ratios alone to establish patient capacity and staffing levels on the floor in real time for their clinical units. To address the limitations of the P/N ratio and optimize nurse staffing, the VAPAHCS implemented a new staffing solution that integrates the strengths of both the NHPPD and P/N ratio while providing greater temporal resolution, the dynamic bed count. This innovative approach was developed within the Issio Health Care Workforce Optimization Platform [16] through ongoing collaborations with the VAPAHCS charge nurses, nurse managers, and nursing supervisors. The dynamic bed count calculates optimal staffing levels every hour, allowing for more precise and timely adjustments based on real-time patient acuity and turnover.

The need for such a dynamic approach is supported by evidence that traditional staffing metrics often fail to account for the fluctuating nature of patient care demands. For instance, a study found that real-time staffing adjustments based on current patient needs can significantly improve patient outcomes and reduce staff burnout compared with static models [17]. In this pilot assessment, we compare the dynamic bed count to the P/N ratio to describe patient capacity and staffing allocation within the acute ward of the VAPAHCS. The aim of this paper is to evaluate whether the dynamic bed count provides a more accurate and responsive method for determining optimal nurse staffing levels compared with the traditional P/N ratio.

Methods

Setting

We analyzed patient capacity data for 3 VAPAHCS acute care units, 1 intensive care unit (ICU), and 1 medical-surgical (Med-Surg) ICU from January 1, 2023, to May 25, 2023. This time frame was selected, as it represents the pilot period for implementing the dynamic bed count solution prior to rolling it out to other VHA hospitals. The selected units were chosen for this pilot due to the fluctuating care requirements for these patients. Being treated for acute conditions (eg, infections, heart conditions, and postoperative care), the care and assistance these patients require vary greatly throughout the day. As such, nursing staff would greatly benefit from a new staffing measurement that accounts for these dynamic and fluctuating patient requirements along with considering various nursing types and specialties. The new measurement was calculated in tandem with legacy methods to ensure that all VA policies and compliance standards were upheld throughout the analysis.

Patient Capacity Data

Two main data sources were used for this assessment and for the dynamic bed count calculation as follows: (1) the VHA's national electronic health record database, the Corporate Data Warehouse (CDW [18]) and (2) manually tracked data from nursing staff in real time.

The CDW was queried to provide the dynamic bed count solution information regarding each unit's patient census. The patient census information is captured through admission and discharge data in the CDW. Specifically, the patient census is a precalculated column in the CDW using admission and discharge information and was collected using SQL queries. The maximum number of beds the unit can support when fully staffed is referred to as the unit's "authorized capacity" and was also obtained through querying the CDW. The authorized capacity is a relatively stable metric and would only change based on factors that reduce the overall number of physical beds a unit could successfully support such as construction, or long-term staffing constraints. Per the legacy processes, the P/N ratio was established by the units' nursing supervisors at the beginning of every shift, dictated by California P/N ratio laws [3,19], and was captured by charge nurses entering this information into the Dynamic Bed Count solution. These metrics (patient census, authorized capacity, and P/N ratio) were captured hourly for each unit within the assessment period.

Dynamic Bed Count

The dynamic bed count calculation within the Issio Health Care Workforce Optimization Platform is designed to represent the number of available staffed beds based on the type of care each nurse is qualified to provide to support their patients. For example, an RN is qualified to perform more tasks when caring for a patient (eg, medication administration, patient triage, and patient education) than an LPN/LVN or NA.

The dynamic bed count uses both target and current staffing levels in its calculation, along with other key staffing variables such as nurse type, shift assignment, patient acuity, and unit regulations. Target staffing levels are the total required minutes of care provided to all patients in the unit within the given hour, considering the average need of a patient as determined by the unit's NHPPD requirements. NHPPD account for the overall care hours per day that a patient must receive, broken down by shift mix (percentage basis across shifts: night, day, and evening) and skill mix (percentage basis across nursing and support staff skills: RN, LPN/LVN, and NA). Current staffing levels represent the aggregate of the current staff providing direct patient care and their shift assignments. Nursing staff can have their shift assignments (direct or indirect care) dynamically changed throughout the shift, which is entered into the dynamic bed count solution every hour for data accuracy.

The dynamic bed count also considers the average patient's direct care requirements and allows for granular refinement based on patient acuity adjustments. Patient acuity, as determined by the unit's charge nurse, uses P/N ratios to adjust care levels based on the required level of care and monitoring. For example, high-acuity patients have a P/N ratio of 1:1, medium-acuity patients have a P/N ratio of 2:1 or 3:1, and low-acuity patients have a P/N ratio of 4:1 or 5:1. Additionally, the calculation includes minutes of care required for admissions and discharges, ensuring that the dynamic bed count reflects the unit's actual workload every hour. A more detailed description and example of the dynamic bed count calculation is available in Multimedia Appendix 1. The output of the dynamic bed count calculation is displayed on a "Patient Capacity Whiteboard" in Issio's Command Center or accessible to charge nurses via a web link to inform nursing staff when a unit is under, over, or adequately staffed every hour so they can make the necessary staffing adjustments across adjacent units (Multimedia Appendix 2). By providing a detailed and responsive method for calculating optimal nurse staffing levels, the dynamic bed count enables more accurate and timely adjustments to staff allocation, improving overall patient care and resource management.

Statistical Analysis

Analyses were performed using Python (version 3.8.5; Python Software Foundation) in a Jupyter Notebook Environment. Descriptive statistics summarized patient capacity variables (patient census, authorized capacity, P/N ratio, and the dynamic bed count). The paired Student *t* test (2-tailed) determined any significant differences between the P/N ratio and dynamic bed count. The unit of analysis for the *t* test was the hourly rates of patient capacity as calculated by both methods. We then plotted the average patient capacity variables for each unit during the assessment period to visually assess differences between the dynamic bed count and the P/N ratio.

To further compare P/N ratios and the dynamic bed count, we analyzed all data points from each unit during the assessment period and calculated the δ between the dynamic bed count and the P/N ratio for each unit. We additionally randomly selected 10 dates and times from the unit with the most variance (ie, SD) in their dynamic bed count calculation hour-by-hour during the assessment period to provide a snapshot of the data points. This was done using Python's "random" library to generate random numbers corresponding to the indices of dates in our dataset, thereby ensuring unbiased data representation and mitigating any selection bias. This was then plotted to visualize the hourly differences within the selected unit between methods during the assessment period. All graphical representations were accomplished using Python packages such as "matplotlib" for plotting and "pandas" for data manipulation and analysis.

Ethical Considerations

This quality improvement and assessment project received a Determination of Non-Research from the Stanford Institutional Review Board (IRB; Stanford University, Stanford, California; #73003). The Stanford IRB serves as the affiliated IRB for the VAPAHCS, ensuring ethical oversight and compliance with federal regulations. Informed consent was not required for this project, as it was determined to be a nonresearch quality improvement initiative. All procedures adhered to institutional and federal guidelines to protect participant rights and confidentiality.

Results

Patient Capacity Data

Over the assessment period, the number of patients that the different units supported varied (Table 1). For example, the acute care unit 3C had an average of 23.2 (SD 4.5) patients occupying their unit compared with an average of 9.5 (SD 2.0) patients in the ICU. Compared with the P/N ratio, the average dynamic bed count was significantly lower in all acute care unit locations, with the exception of the ICU, (Table 1; *P*<.001). This is further represented in Figure 1, where we can see that the P/N ratio was consistently higher across most units during the assessment period.

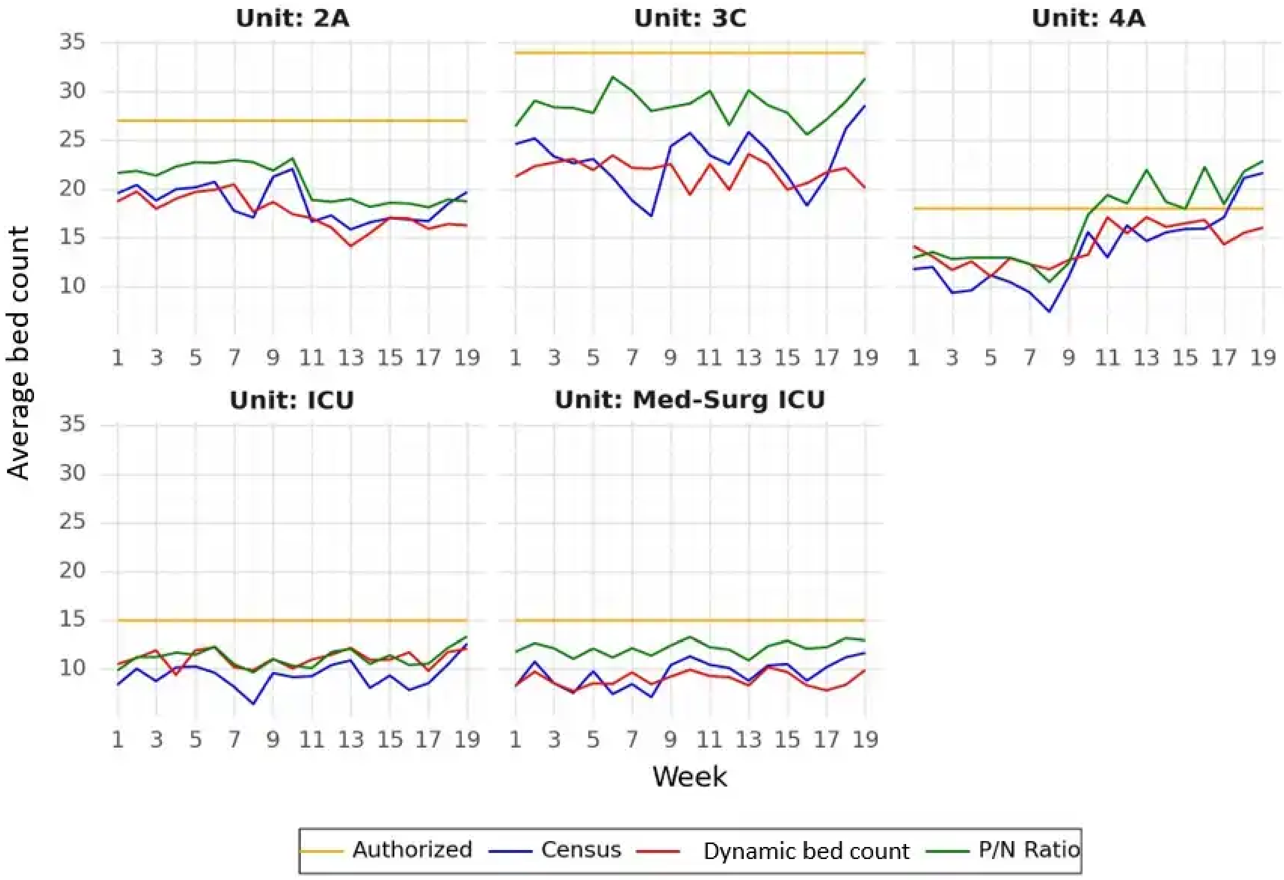
Table . Average patient capacity and occupancy characteristics by Palo Alto Veterans Affairs Health Care System's acute care units.

Acute care unit locations	Patient census, mean (SD)	Authorized capacity[a], mean (SD)	Patient capacity calculations		
			Dynamic bed count, mean (SD)	Patient-to-nurse ratio, mean (SD)	*P* value
2A	18.6 (3.8)	27.0 (0.0)	17.5 (2.9)	20.5 (2.1)	<.001
3C	23.2 (4.5)	34.0 (0.0)	21.6 (4.2)	28.6 (3.2)	<.001
4A	14.1 (4.4)	18.0 (0.0)	14.3 (3.5)	16.7 (4.2)	<.001
Intensive care unit	9.5 (2.0)	15.0 (0.0)	11.2 (1.8)	11.2 (1.5)	.40
Med-Surg[b] intensive care unit	9.7 (2.1)	15.0 (0.0)	9.0 (2.1)	12.3 (1.5)	<.001
All units	15.0 (6.4)	21.8 (0.0)	14.7 (5.4)	17.8 (6.9)	<.001

[a] Authorized capacity is the maximum number of beds the unit can support when fully staffed.

[b] Med-Surg: medical-surgical.

Figure 1. Average patient capacity across Palo Alto Veterans Affairs Health Care System’s acute units, January 1, 2023, through May 25, 2023. In this graph, the yellow lines depict the authorized bed count, which is the maximum number of physical beds a unit could successfully support. The blue lines represent the average patient census for each unit location. The red lines depict the average dynamic bed count calculation for patient capacity while the green lines represent the average patient-to-nurse (P/N) ratio across the assessment period for each acute care unit. Med-Surg ICU: medical-surgical intensive care unit.



Dynamic Bed Count

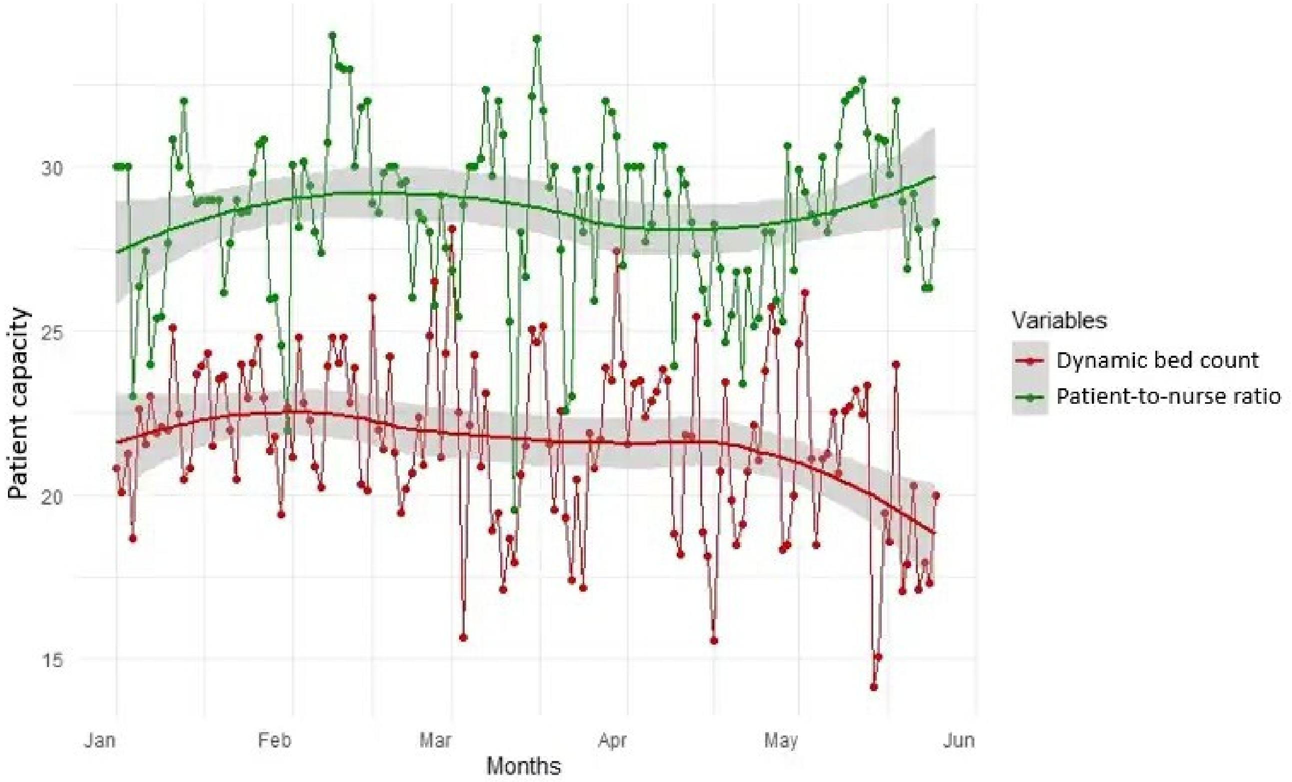
To provide a snapshot of the comparison of P/N ratios and the dynamic bed count, we evaluated the unit with the most variance within the dynamic bed count calculation (displayed in Table 1) across the assessment period. This resulted in a random sample of 10 dates and times within the acute care unit 3C (Table 2). The full dataset is provided in Multimedia Appendix 3. The “Difference” column compares the P/N ratio and the dynamic bed count, where a negative value indicates that the unit should have less patient capacity while a positive value indicates the unit could have taken on additional patients. The amplitude of the value defines how many fewer (negative value) or more (positive value) patients the unit could have handled during any given hour. These data points demonstrate the swing between the quick math “in the moment” patient capacity calculation (P/N ratios) and the standardized, repeatable computation in real time (the dynamic bed count).

Additionally, we graphically represented unit 3C to further display the difference between the P/N ratio and the dynamic bed count calculation throughout the assessment period (Figure 2). In this graph, we can see the difference (δ) between the 2 methods where resource allocation could be improved.

Table . Random sampling of hours within the acute care unit 3C showing the differences between calculated patient capacity as determined by the patient-to-nurse (P/N) ratio and the dynamic bed count calculation.

Acute care unit location	Date	Time	Patient census, n	Patient capacity calculations		Difference (dynamic bed count vs P/N ratio)
				P/N ratio	Dynamic bed count	
3C	January 1, 2023	7 AM	21	30.0	18.7	−11.3
3C	January 9, 2023	10 PM	29	25.0	20.5	−4.5
3C	February 12, 2023	4 PM	15	30.0	32.2	2.2
3FC	February 19, 2023	6 PM	15	30.0	25.8	−4.2
3C	March 2, 2023	4 PM	29	25.0	25.8	0.8
3C	March 5, 2023	3 PM	22	30.0	26.4	−3.6
3C	April 8, 2023	10 PM	21	25.0	17.6	−7.4
3AC	April 13, 2023	6 AM	20	26.0	29.3	3.3
3C	May 3, 2023	8 AM	26	28.0	17.8	−10.2
3C	May 24, 2023	1 PM	24	29.0	20.3	−8.7

Figure 2. Average patient-to-nurse (P/N) ratio and dynamic bed count calculations across Veterans Affairs Palo Alto Health Care System's acute unit 3C Location, January 1, 2023, through May 25, 2023. The analysis of patient capacity metrics over the evaluation period revealed an upward trend in the P/N ratio, indicated by the green line, suggesting an increase in the number of patients assigned to each nurse on average. In contrast, the dynamic bed count, shown in red, demonstrates a slight downward trend. Notably, the shaded regions around the trend lines, which represent the SE, suggest greater variability in the dynamic bed count than in the P/N ratio. The divergence in trends between the 2 metrics underscores the complexity of health care resource management and the need for strategies that optimize staffing levels.



Discussion

In efforts to improve nurse scheduling and optimize workload across acute care and critical care units of the VAPAHCS, we implemented the dynamic bed count to calculate the optimal workload of each unit every hour. The main findings of this assessment revealed that the dynamic bed count can provide a more accurate and responsive method for determining optimal nurse staffing levels compared with the traditional P/N ratios. Through comparison of the P/N ratio and the dynamic bed count, we found that the P/N ratios implemented by the nursing staff, with the exception of the ICU, resulted in significantly higher calculated patient capacity levels on average than what the unit can adequately accommodate. Inadequate staffing levels could result in an increased risk of burnout and workplace injury among our nursing staff and have been shown to worsen patient outcomes [7,20,21]. Furthermore, when looking at VAPAHCS units hour-by-hour, we found times when the units could support a higher patient capacity than what was calculated by the nursing staff. By accounting for dynamic changes within units with the dynamic bed count, nursing supervisors can allocate staff appropriately across units without necessarily having to hire additional staff.

As seen in previous research, the P/N ratio falls short of fully grasping a true picture of optimal workload. In one study, researchers found that the P/N ratio cannot properly capture admissions and discharges of patients, or where nurses work as a team [22]. For example, the P/N ratio implies that each nurse has responsibility for a set group of patients. However, that is often not the case. A nurse's patient load changes as patients are admitted and discharged during a shift. For example, this can result in a nurse starting their shift with 5 patients who are eventually replaced by 5 other patients later in the shift as they are admitted/discharged. Additionally, although P/N ratios can be adjusted [17], they inherently only account for RN staffing types and no other support staff on the floor. This can be an important aspect of the team dynamic that is often present in health care units, such as those seen in the VAPAHCS acute care ward.

As an alternative to P/N ratios, the NHPPD have been endorsed by the National Quality Forum to measure appropriate nurse staffing levels [11] and are known to reliably increase the quality of care for patients [10-12]. The NHPPD staffing measure classifies units into 1 of 7 categories as determined by patient complexity, intervention levels, presence of high-dependency beds, and patient turnover [10-12]. It has been implemented in the long-term care clinics within VHA, where researchers found that higher NHPPD levels were inversely associated with falls resulting in major injury [21]. While the NHPPD can be seen as a marked improvement to the P/N ratio, it is important to acknowledge that both methods are based on similar input variables, and both serve to represent the ratio between staffing resources and patient demands. However, the key distinction lies in the level of aggregation and the time frame over which these metrics are applied. P/N ratios provide a snapshot based on the number of patients per nurse, which can be adjusted as needed but typically lacks granularity in real-time adjustments [17]. NHPPD, on the other hand, offer a comprehensive approach by accounting for the total hours of care from all types of nursing staff per patient per day, incorporating patient acuity and turnover [12]. Despite these strengths, NHPPD may fall short of addressing the dynamic nature of staffing needs that can fluctuate throughout the day.

The dynamic bed count addresses these limitations by providing hourly updates on staffing levels and patient acuity, allowing for more precise and timely adjustments. This method separates the assessment of demand (patients, admissions, discharges, and patient acuity) and supply (nurses, skill, and shift assignment), identifying opportunities to move staff or manage patient flow more effectively. Given the capacity use of the units, such as the range of around 19 - 28 patients in unit 3C, the potential for optimizing staffing and improving patient outcomes is substantial. By integrating elements from both the P/N ratios and NHPPD, the dynamic bed count offers a balanced and dynamic solution that reflects real-time conditions within the units, thereby enhancing the overall efficiency and effectiveness of nurse staffing.

Tools such as the dynamic bed count solution can be powerful in helping charge nurses better understand the rationale behind the load balancing of staff. By including staffing types and patient acuity, the dynamic bed count can help charge nurses determine the most effective combination of staff to deliver high-quality and cost-effective patient care. This can be especially important in the face of rising demand for health services and shortages of nurses and other health care workers both within the VHA and other US health care sectors [22-24]. Additionally, the diversity of staffing models in our health care system is essential to determine which staff members should be included in the staffing calculations to reflect personnel who deliver direct care relevant to patient outcomes [22].

Implementing the dynamic bed count solution does present certain challenges and limitations. One potential concern is the additional workload on nursing staff to maintain accurate data entry. However, in this pilot implementation, charge nurses only entered data into the dynamic bed count solution at the start of every shift, when their staff was changed from direct to indirect (or vice versa) shift assignments, and when there were changes in patient acuity, which aligns with their existing workflow and did not add extra burden to the nursing staff. The dynamic bed count solution then uses this information to display and communicate optimal patient capacity and suggestions for resource allocation in real time, effectively lessening the burden on charge nurses by providing them with actional insights and reducing the need for manual calculations and adjustments.

Another challenge is the potential cultural adjustment required for staff to embrace new technology and processes. Although all units are part of the same health care system, reallocating personnel from a well-staffed ward to an understaffed ward can be undesirable to the unit losing personnel, and can be a stressful experience for the transferred nurse due to unfamiliarity with the adjacent unit [25]. This challenge can be mitigated through cross-training, or implementing a "buddy system" across units, which in turn can increase job satisfaction [25]. Increasing "float pools" is another strategy to mitigate this issue and has been shown to significantly reduce turnover and overall staffing costs [26,27].

The dynamic bed count's strength lies in its development, which stemmed from continuous collaborations with VAPAHCS nursing leadership. These collaborations ensured a comprehensive understanding of crucial data points for accurate capacity assessment and validation of the calculation's precision. Each variable can change at a moment's notice and can have a major impact on a unit's capacity. This information, as soon as it is changed, must be presented to "need to know" parties, like nursing supervisors and patient flow coordinators, so quick and accurate decisions can be made about floating staff to areas where they are needed. With the overall complexity differences between P/N ratios and dynamic bed count, it is easy to understand why P/N ratios take place on the floor “in the moment,” but with technology that can account for the additional complexities easily, accurately, and quickly, we can see improved accuracy in the staffing decision-making processes.

This assessment has some limitations. First, these findings are only relevant for the VAPAHCS acute care ward during the assessment period. Our findings could vary for other time frames and in other units. Future assessments will be needed to test the implementation of the dynamic bed count on any improved patient outcomes.

In conclusion, we believe that a new calculation such as the dynamic bed count, as presented here, could be a marked improvement from the P/N ratio for the VAPAHCS acute care ward. Implementing this calculation into a web-based report that supervisors could use to allocate nursing staff could significantly improve the workflow of our health care system.

Acknowledgments

We would like to thank the Issio Solutions team for their assistance in developing the calculation behind the dynamic bed count that is used in their Healthcare Workforce Optimization Platform.

Disclaimer

The findings and conclusions in this report are those of the authors and do not necessarily represent the views of the US Department of Veterans Affairs or the US government.

Data Availability

The datasets generated or analyzed during this evaluation are not publicly available due to US Department of Veterans Affairs (VA) regulations and ethics agreements, but are available from the corresponding author on reasonable request.

Authors' Contributions

AW, TB, ZV, and TO were responsible for conceptualization and methodology. TB and DA handled data curation. AW and ZV conducted the formal analysis. AW and ZV wrote the original draft, while ZV, AW, TB, DA, PH, JF, and TO contributed to reviewing and editing the draft.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Description of the dynamic bed count calculation.
[DOCX File, 25 KB - nursing_v7i1e59619_app1.docx]

Multimedia Appendix 2
Depiction of “Patient Capacity Whiteboard.”
[DOCX File, 484 KB - nursing_v7i1e59619_app2.docx]

Multimedia Appendix 3
Sampling of hours within the acute care unit 3C displaying the differences between calculated patient capacity as determined by the patient-to-nurse ratio and the dynamic bed count calculation.
[PDF File, 4318 KB - nursing_v7i1e59619_app3.pdf]

References

1. Kim Y, Kim J, Shin SA. Relationship between the legal nurse staffing standard and patient survival after perioperative cardiac arrest:a cross-sectional analysis of Korean administrative data. Int J Nurs Stud 2019 Jan;89:104-111. [doi: 10.1016/j.ijnurstu.2018.09.012] [Medline: 30359876]
2. Chen YC, Guo YLL, Chin WS, Cheng NY, Ho JJ, Shiao JSC. Patient-nurse ratio is related to nurses’ intention to leave their job through mediating factors of burnout and job dissatisfaction. Int J Environ Res Public Health 2019 Nov 29;16(23):4801. [doi: 10.3390/ijerph16234801] [Medline: 31795420]
3. Leigh JP, Markis CA, Iosif AM, Romano PS. California’s nurse-to-patient ratio law and occupational injury. Int Arch Occup Environ Health 2015 May;88(4):477-484. [doi: 10.1007/s00420-014-0977-y]
4. Bae SH. Intensive care nurse staffing and nurse outcomes: a systematic review. Nurs Crit Care 2021 Nov;26(6):457-466. [doi: 10.1111/nicc.12588]
5. Phillips J, Malliaris A, Bakerjian D. Nursing and patient safety. Patient Safety Network. 2021. URL: https://psnet.ahrq.gov/primer/nursing-and-patient-safety [accessed 2023-08-31]

6. Choi J, Staggs VS. Comparability of nurse staffing measures in examining the relationship between RN staffing and unit-acquired pressure ulcers: a unit-level descriptive, correlational study. Int J Nurs Stud 2014 Oct;51(10):1344-1352. [doi: 10.1016/j.ijnurstu.2014.02.011]
7. Wynendaele H, Willems R, Trybou J. Systematic review: association between the patient–nurse ratio and nurse outcomes in acute care hospitals. J Nurs Manag 2019 Jul;27(5):896-917. [doi: 10.1111/jonm.12764]
8. Lasater KB, Sloane DM, McHugh MD, et al. Evaluation of hospital nurse-to-patient staffing ratios and sepsis bundles on patient outcomes. Am J Infect Control 2021 Jul;49(7):868-873. [doi: 10.1016/j.ajic.2020.12.002] [Medline: 33309843]
9. Ernst KM, McComb SA, Ley C. Nurse ‐ to ‐ nurse shift handoffs on medical–surgical units: a process within the flow of nursing care. J Clin Nurs 2018 Mar;27(5-6). [doi: 10.1111/jocn.14254]
10. Min A, Scott LD. Evaluating nursing hours per patient day as a nurse staffing measure. J Nurs Manag 2016 May;24(4):439-448. [doi: 10.1111/jonm.12347] [Medline: 26576931]
11. Twigg D, Duffield C. A review of workload measures: a context for a new staffing methodology in Western Australia. Int J Nurs Stud 2009 Jan;46(1):131-139. [doi: 10.1016/j.ijnurstu.2008.08.005] [Medline: 18789439]
12. Twigg D, Duffield C, Bremner A, Rapley P, Finn J. The impact of the nursing hours per patient day (NHPPD) staffing method on patient outcomes: a retrospective analysis of patient and staffing data. Int J Nurs Stud 2011 May;48(5):540-548. [doi: 10.1016/j.ijnurstu.2010.07.013] [Medline: 20696429]
13. Drennan J, Duffield C, Scott AP, et al. A protocol to measure the impact of intentional changes to nurse staffing and skill-mix in medical and surgical wards. J Adv Nurs 2018 Dec;74(12):2912-2921. [doi: 10.1111/jan.13796] [Medline: 30019346]
14. Milstein R, Schreyoegg J. The relationship between nurse staffing levels and nursing-sensitive outcomes in hospitals: assessing heterogeneity among unit and outcome types. Health Policy 2020 Oct;124(10):1056-1063. [doi: 10.1016/j.healthpol.2020.07.013] [Medline: 32839013]
15. About us. Veterans Affairs. 2023. URL: https://www.va.gov/palo-alto-health-care/about-us/ [accessed 2023-08-02]
16. Issio healthcare workforce optimization platform. Issio Solutions, Inc. URL: https://www.issio.com/solutions/workforce-optimization-platform/ [accessed 2024-07-02]
17. Dall'Ora C, Saville C, Rubbo B, Turner L, Jones J, Griffiths P. Nurse staffing levels and patient outcomes: a systematic review of longitudinal studies. Int J Nurs Stud 2022 Oct;134:104311. [doi: 10.1016/j.ijnurstu.2022.104311] [Medline: 35780608]
18. Corporate Data Warehouse (CDW). U.S. Department of Veterans Affairs. URL: https://www.hsrd.research.va.gov/for_researchers/cdw.cfm [accessed 2023-08-02]
19. Coffman JM, Seago JA, Spetz J. Minimum nurse-to-patient ratios in acute care hospitals in California. Health Aff (Millwood) 2002;21(5):53-64. [doi: 10.1377/hlthaff.21.5.53] [Medline: 12224909]
20. White EM, Aiken LH, Sloane DM, McHugh MD. Nursing home work environment, care quality, registered nurse burnout and job dissatisfaction. Geriatr Nurs 2020;41(2):158-164. [doi: 10.1016/j.gerinurse.2019.12.007]
21. Brown LM, Gauss CH, Billings P, et al. Nurse staffing and veteran outcomes in the Veterans Health Administration's Community Living Centers. J Nurs Care Qual 2023;38(4):297-303. [doi: 10.1097/NCQ.0000000000000700] [Medline: 36827702]
22. Schlak AE, Poghosyan L, Liu J, et al. The association between health professional shortage area (HPSA) status, work environment, and nurse practitioner burnout and job dissatisfaction. J Health Care Poor Underserved 2022;33(2):998-1016. [doi: 10.1353/hpu.2022.0067]
23. Doyle JM, Streeter RA. Veterans' location in health professional shortage areas: implications for access to care and workforce supply. Health Serv Res 2017 Feb;52 Suppl 1(Suppl 1):459-480. [doi: 10.1111/1475-6773.12633] [Medline: 27957733]
24. Juraschek SP, Zhang X, Ranganathan V, Lin VW. United States registered nurse workforce report card and shortage forecast. Am J Med Qual 2019;34(5):473-481. [doi: 10.1177/1062860619873217] [Medline: 31479295]
25. Walden AM, Moyse T, Meyer JR, Whitaker B, Briskin I, Albert NM. Enhancing the caregiver float experience. Nurs Manag (Harrow) 2020;51(7):14-20. [doi: 10.1097/01.NUMA.0000669108.28985.67]
26. Wright PD, Bretthauer KM. Strategies for addressing the nursing shortage: coordinated decision making and workforce flexibility. Dec Sci 2010 May;41(2):373-401. [doi: 10.1111/j.1540-5915.2010.00269.x]
27. Straw CN. Engagement and retention in float pools: keeping the team above water. Nurs Manage (Springhouse) 2018;49(10):30-36. [doi: 10.1097/01.NUMA.0000546201.01962.0d]

Abbreviations

CDW: Corporate Data Warehouse
ICU: intensive care unit
IRB: Institutional Review Board
LPN: licensed practical nurse
LVN: licensed vocational nurse
Med-Surg: medical-surgical
NA: nurse assistant

NHPPD: nursing hours per patient day
P/N: patient-to-nurse
RN: registered nurse
VAPAHCS: Veterans Affairs Palo Alto Health Care System
VHA: Veterans Health Administration

Edited by E Borycki; submitted 17.04.24; peer-reviewed by J Choi, M Simon; revised version received 10.09.24; accepted 13.09.24; published 22.11.24.

Please cite as:
Ware A, Blumke T, Hoover P, Arreola D
Calculating Optimal Patient to Nursing Capacity: Comparative Analysis of Traditional and New Methods
JMIR Nursing 2024;7:e59619
URL: https://nursing.jmir.org/2024/1/e59619
doi:10.2196/59619

Original Paper

Sentiment Analysis of Patient- and Family-Related Sepsis Events: Exploratory Study

Mabel Ntiamoah[1*], MBA-MHA; Teenu Xavier[1*], PhD, RN; Joshua Lambert[1*], PhD

University of Cincinnati, Cincinnati, OH, United States

*all authors contributed equally

Corresponding Author:
Joshua Lambert, PhD
University of Cincinnati
3110 Vine St
Cincinnati, OH, 45221
United States
Phone: 1 (513) 558 5500
Email: joshua.lambert@uc.edu

Abstract

Background: Despite the life-threatening nature of sepsis, little is known about the emotional experiences of patients and their families during sepsis events. We conducted a sentiment analysis pertaining to sepsis incidents involving patients and families, leveraging textual data retrieved from a publicly available blog post disseminated by the Centers for Disease Control and Prevention (CDC).

Objective: This investigation involved a sentiment analysis of patient- and family-related sepsis events, leveraging text responses sourced from a publicly accessible blog post disseminated by the CDC. Driven by the imperative to elucidate the emotional dynamics encountered by patients and their families throughout sepsis incidents, the overarching aims centered on elucidating the emotional ramifications of sepsis on both patients and their families and discerning potential avenues for enhancing the quality of sepsis care.

Methods: The research used a cross-sectional data mining methodology to investigate the sentiments and emotional aspects linked to sepsis, using a data set sourced from the CDC, which encompasses 170 responses from both patients and caregivers, spanning the period between September 2014 and September 2020. This investigation used the National Research Council Canada Emotion Lexicon for sentiment analysis, coupled with a combination of manual and automated techniques to extract salient features from textual responses. The study used negative binomial least absolute shrinkage and selection operator regressions to ascertain significant textual features that correlated with specific emotional states. Moreover, the visualization of Plutchik's Wheel of Emotions facilitated the discernment of prevailing emotions within the data set.

Results: The results showed that patients and their families experienced a range of emotions during sepsis events, including fear, anxiety, sadness, and gratitude. Our analyses revealed an estimated incidence rate ratio (IRR) of 1.35 for fear-related words and a 1.51 IRR for sadness-related words when mentioning "hospital" in sepsis-related experiences. Similarly, mentions of "intensive care unit" were associated with an average occurrence of 12.3 fear-related words and 10.8 sadness-related words. Surviving patients' experiences had an estimated 1.15 IRR for joy-related words, contrasting with discussions around organ failure, which were associated with multiple negative emotions including disgust, anger, fear, and sadness. Furthermore, mentions of "death" were linked to more fear and anger words but fewer joy-related words. Conversely, longer timelines in sepsis events were associated with more joy-related words and fewer fear-related words, potentially indicating improved emotional adaptation over time.

Conclusions: The study's outcomes underscore the imperative for health care providers to integrate emotional support alongside medical interventions for patients and families affected by sepsis, emphasizing the emotional toll incurred and highlighting the necessity of acknowledgment and resolution, advocating for the use of sentiment analysis as a means to tailor personalized emotional aid, and thereby potentially augmenting both patient and family welfare and overall outcomes.

(JMIR Nursing 2024;7:e51720) doi:10.2196/51720

KEYWORDS

families; patients; sentiment analysis; sepsis

Introduction

Sepsis is a life-threatening medical emergency that affects millions of people worldwide each year. It is estimated that sepsis affects over 30 million people worldwide annually, resulting in over 6 million deaths each year [1], with a substantial economic burden and long-term morbidity among survivors [2]. It is characterized by a dysregulated immune response to an infection, leading to organ dysfunction and, in severe cases, mortality. Despite advances in sepsis care, the high mortality rate underscores the need for a comprehensive understanding of the patient's experience.

The concept of patient-centered care has gained recognition in health care, highlighting the importance of incorporating patient perspectives, needs, and preferences into the care delivery process [3]. Within the context of sepsis, understanding the emotional experiences of patients and their families during sepsis events is crucial for providing holistic and patient-centered care. Although there is a lack of extensive research on the emotional experiences of patients and their families, specifically during sepsis events, studies conducted in related fields highlight the crucial role of emotional support and its impact on patient outcomes [4]. For instance, in critical care settings, emotional distress and psychological well-being have been shown to significantly influence patient recovery and quality of life [5,6]. Similarly, in chronic illness contexts, emotional support has been linked to improved patient coping, treatment adherence, and overall well-being [7].

In sepsis care, it is important to recognize and address the emotional needs of both patients and their families [8]. This approach contributes to a more comprehensive and patient-centered method of care [9]. Numerous studies indicate that providing emotional support during critical illness can alleviate anxiety, reduce psychological distress, and improve overall satisfaction with care for patients and their families [10,11].

To gain a deeper understanding of the emotional experiences of patients and their families, researchers have turned to sentiment analysis as a valuable technique [12]. Sentiment analysis has gained prominence in recent years as a powerful tool for comprehending patients and health care workers' experiences, opinions, and attitudes toward health care [13,14]. Sentiment analysis is a computational approach that analyzes the emotional tone or sentiment expressed in text data [15]. By applying sentiment analysis to patient and family feedback related to sepsis events, health care providers can better understand the emotional impact of sepsis on patients and their families and identify areas for improvement in sepsis care. Furthermore, analyzing patient and family feedback can aid health care providers in comprehending the patient's sepsis experience and developing strategies to enhance sepsis care [16].

This study aims to perform a sentiment analysis on the experiences of patients and their families during sepsis events gathered from 174 narratives, with the goal of comprehending the emotional toll of sepsis and pinpointing opportunities for enhancing sepsis care. Through the examination of feedback from patients and their families, the study seeks to enrich the existing literature on sepsis care. The insights gained from this study are poised to equip health care providers with insights that could lead to better management of patient and family emotional needs.

Methods

Overview

Sepsis-related patient and caregiver text responses were obtained from a public data set provided by the Centers for Disease Control and Prevention (CDC), originating from their Division of Healthcare Quality Promotion Public Inquiries Team. The CDC data set, collected between September 16, 2014, and September 19, 2020, comprised 174 comments. In a 2014 blog post titled *A Family's Perspective - "The Brutality of Sepsis will Haunt Us for the Rest of Our Lives"* [16], author Franchot Karl describes his 84-year-old grandmother's death from sepsis and offers advice for those yet to be affected by the disease. The comments were reader descriptions of their personal experiences related to sepsis and a direct response to the 2014 blog post.

These reader comments were subsequently downloaded and exported to Excel (Microsoft Corporation) and analyzed using JMP Pro (version 16; SAS Institute), R (version 4; R Core Team), and Python (version 3.9; Python Software Foundation).

A total of 4 responses were removed due to missing information or spam-related comments. The remaining 170 responses submitted by patients and caregivers were analyzed using the National Research Council Canada (NRC) Emotion Lexicon, which produced 8 distinct emotional sentiment scores [17]. The lexicon emphasizes unigrams, with each word assigned ratings based on its positive or negative sentiment and potential association with emotions, including anger, fear, anticipation, trust, surprise, sadness, joy, and disgust. The scoring method involved tabulating the number of words in each response that received at least 1 of the 8 sentiment scores and categorizing the number of words in each response that expressed each emotion. This generated 8 count variables, which served as the study's outcome variables.

The research team implemented a rigorous, multistep manual and automated process to extract diverse features from the text responses. This entailed a comprehensive analysis of each response to identify recurring or predetermined features, such as patient age, respondent relationship to the patient, inferred sex of the patient and caregiver, patient survival, and sepsis-related conditions like severe sepsis and septic shock. Additionally, indicator variables (1 or 0) were developed for frequently occurring words, such as "sepsis," "hospital," and "doctor." The team compiled a list of recurrent sepsis-related terms by examining the responses, which were then used to create indicator variables—assigned a value of "1" if present in the text and "0" if not present in the text. In instances of coding discrepancies, the team reviewed the responses and deliberated to reach a consensus. These indicators played a crucial role in tackling elements of our research questions, particularly in identifying dominant themes or subjects within the sepsis events involving patients and their families. Temporal references, such as hours, months, days, and years, were classified as timelines, which were further categorized into short and long timelines. Short timelines could only include terms such as “suddenly,” “days,” “hours,” “immediately,” “quickly,” “seconds,” and “currently,” whereas all other timelines were deemed long timelines. Due to concerns regarding reliability and substantial missing data, textual information such as age and the sex of the caregiver and patient was excluded from the analysis. However, a separate bivariate analysis was conducted to explore the potential influence of these variables on the 8 NRC emotions.

A total of 8 negative binomial least absolute shrinkage and selection operator (LASSO) regressions [18] were used to identify patient and caregiver text response features associated with the count of anger, anticipation, disgust, fear, joy, sadness, surprise, and trust sentiments in the responses. A negative binomial was chosen a priori over Poisson regression as it was believed the outcomes would likely be over dispersed. Upon inspection, the data were not zero-inflated, so zero-inflated models were not considered. Model selection was performed by selecting the model that had the smallest Akaike information criterion corrected [19].

To visualize Plutchik’s [20] Wheel of Emotions, we used the *PyPlutchik* (Alfonso Semeraro) Python package [21]. This package offers functionality to generate visual representations of the Wheel of Emotions proposed by Plutchik [20]. To determine the dominant emotion within the wheel, we selected the emotion with the highest frequency and assigned it a score of 1. We then calculated the scores for the remaining emotions based on their ratio to the dominant emotion. As a result, emotions within the wheel are scored on a scale from 0 to 1, with 1 being the emotion that occurred most frequently.

Ethical Considerations

This study was conducted in accordance with ethical standards regarding research involving nonhuman subjects. The ethics committee of the University of Cincinnati granted approval on May 5, 2023, for the study (2023-0396). The privacy of participants' personal information was rigorously protected, securely stored, and only accessible by the study team.

Results

Variables with reliability issues, missing values, or chosen to not be included in the analysis were first checked bivariately with the outcome variables. None of these variables were related bivariately to the 8 outcomes and were therefore not included in any further analysis.

Table 1 presents a numerical summary of the average values for the 8 NRC emotions, as categorized by extracted text features. The estimates are obtained column-wise, with larger numbers signifying an increase in the number of words associated with a particular emotion, while a smaller number denotes a decrease in the number of words related to that emotion. For instance, responses containing “medical” terminology (medical professionals, medical issues, medical field, medical records, and medical history) exhibited an average of 7.7 anticipation words. An increase in anticipation words could be considered unfavorable in this context. Conversely, joy and trust have inverse scales, as a greater presence of joy or trust emotions signifies improvement compared to fewer instances of joy or trust. When responses included “medical” terminology, an average of 12.4 trust words were observed. From these 2 results, we can see that, consequently, the “medical” terminology indicator is associated with both heightened anticipation and increased trust. Owing to the extensive results presented in Table 1, further insights are elaborated upon in the discussion section and are also available for the reader to examine independently. Due to the large number of results in Table 1, the discussion section has an overview of the results that the authors found interesting or notable. The readers are encouraged to review Table 1, as it may present other, undiscussed findings.

Table 1. Average of the 8 National Research Council Canada emotions by gathered text features.

Columns by categories	Number, n	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust
Alive	55	3.8	4.9	3.4	11.6	3.4	9.9	2.0	6.8
Sepsis indicator	125	4.0	4.8	3.6	11.5	2.9	10.5	2.3	7.0
Hospital indicator	111	4.4	5.3	4.3	12.8	3.1	11.8	2.6	8.4
Doctor indicator	67	5.3	6.5	5.2	14.5	3.8	13.5	3.2	10.0
Pain indicator	46	5.3	6.0	4.5	15.4	3.7	14.2	2.5	8.5
Surgery indicator	40	6.2	6.1	5.8	16.6	3.3	15.4	3.1	8.9
Infection indicator	48	5.2	5.4	4.7	15.0	3.3	12.3	2.9	8.4
Heart indicator	42	6.3	7.1	6.3	16.1	4.1	14.4	3.3	10.4
Septic indicator	49	5.7	4.8	5.7	12.8	2.7	11.3	3.2	7.0
Shock indicator	53	5.1	4.3	4.6	11.0	2.5	9.6	3.1	6.2
ED[a] indicator	31	5.5	6.8	6.2	15.9	3.7	14.2	3.5	10.3
Medical indicator	34	6.5	7.7	5.7	17.3	3.7	15.1	3.3	12.4
Antibiotics indicator	36	5.1	6.8	5.3	16.7	3.6	14.3	3.3	10.6
ICU[b] indicator	32	4.5	5.0	4.9	12.3	3.3	10.8	2.9	7.3
Symptoms indicator	29	5.3	5.6	4.3	14.8	3.6	14.0	2.7	9.3
Fever indicator	21	4.3	4.9	4.2	15.5	2.9	12.9	2.3	8.6
Failure indicator	20	6.7	7.5	8.7	16.8	3.9	15.7	3.9	10.9
Death indicator	72	4.3	4.4	4.0	11.0	2.6	10.1	2.6	7.0
Long timeline	116	4.2	5.1	4.3	11.8	3.2	11.0	2.6	7.8
Short timeline	34	3.4	2.9	2.5	8.3	1.5	6.8	1.4	4.2
Responder									
Child	88	3.7	4.1	3.4	9.9	2.5	9.3	1.7	6.2
Patient	27	5.6	6.1	4.6	14.9	4.2	12.7	2.9	8.6
Spouse	26	2.7	3.8	2.8	7.8	2.0	7.4	2.3	6.0
Parent	7	2.6	3.3	4.3	7.7	2.6	7.1	2.4	5.0
Other	22	3.1	3.5	3.2	9.9	2.3	8.9	2.5	6.3

[a] ED: emergency department.

[b] ICU: intensive care unit.

Table 2 presents a numerical summary of the 8 NRC emotions negative binomial LASSO regression model estimates. The contents of these 8 multivariable models are presented in Table 2 column-wise, where variables that were included in the model have presented a numerical estimated regression coefficient, while variables that were not chosen by the LASSO procedure have a "–" in their cell. The estimates are obtained column-wise, with larger numbers signifying an increase in the estimated rate of words associated with a particular emotion, while smaller numbers signify a decrease in the estimated rate of words related to that emotion. For example, the model for NRC anger suggested that respondents who used the word "medical" were estimated to have 1.75 times the number of anger-related words than those respondents who did not use the word "medical." As with Table 1, there are many results in Table 2, and we discuss these further in context within the discussion section. The readers are encouraged to review Table 2, as it may present other, undiscussed findings.

Table 2. Negative binomial least absolute shrinkage and selection operator regression parameter estimates.

Columns by categories	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust
Alive	—[a]	1.09	—	—	1.15	—	—	—
Sepsis indicator	1.19	1.19	1.14	1.39	1.07	1.33	1.24	—
Hospital indicator	1.01	1.25	—	1.35	1.12	1.51	1.08	1.77
Doctor indicator	1.30	1.39	1.58	1.29	1.34	1.29	1.61	1.42
Pain indicator	1.32	1.36	1.22	1.44	1.31	1.50	—	1.25
Surgery indicator	1.13	—	1.13	1.20	—	1.26	1.03	—
Infection indicator	—	—	—	1.14	—	—	1.10	—
Heart indicator	1.32	1.49	1.09	1.26	1.42	1.23	1.02	1.40
Septic indicator	1.33	—	1.74	1.12	—	1.11	1.14	—
Shock indicator	1.25	—	—	1.03	—	—	1.82	—
ED[b] indicator	1.12	1.14	1.32	1.11	1.07	1.14	1.22	1.11
Medical indicator	1.75	1.55	1.55	1.47	1.11	1.39	1.28	1.64
Antibiotics indicator	—	1.03	—	1.12	—	1.02	1.13	1.06
ICU[c] indicator	—	—	—	—	—	—	—	—
Symptoms indicator	—	—	0.77	—	—	—	—	1.08
Fever indicator	—	—	—	1.26	—	1.16	—	1.11
Failure indicator	1.49	1.26	2.02	1.29	—	1.28	1.49	1.14
Death indicator	1.09	—	—	1.03	0.90	—	—	—
Any timeline	1.30	—	1.47	1.22	—	1.03	1.17	—
Long timeline	1.05	1.32	1.56	1.03	1.62	1.20	1.65	1.25
Short timeline	—	—	—	—	—	—	—	—
Responder								
Child	—	—	—	—	—	—	0.68	—
Patient	1.57	1.15	1.30	1.23	1.17	1.12	1.05	1.12
Spouse	—	—	0.98	—	0.96	—	—	—
Parent	0.89	—	1.12	—	—	—	0.89	—
Other	0.95	0.91	—	—	—	—	—	—

[a] Not available.

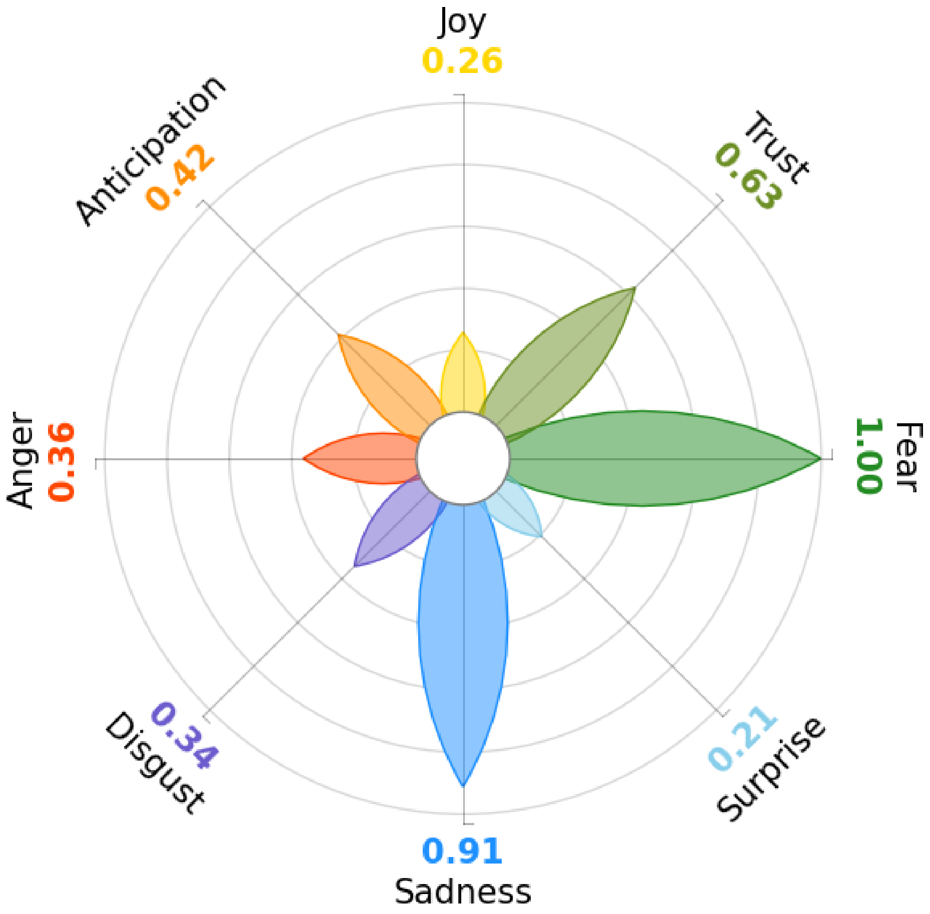
[b] ED: emergency department.

[c] ICU: intensive care unit.

Table S1 in Multimedia Appendix 1 presents various model fit details (number of parameters, Bayesian information criterion, corrected Akaike information criterion, and dispersion) for the 8 negative binomial LASSO regression models. These fit details are provided for transparency and reproducibility. Table S2 in Multimedia Appendix 1 presents a correlation matrix of the 8 NRC emotion outcome. Sadness and fear (*r*=0.9405) had the strongest correlation, while anger and joy (*r*=0.5755) had the weakest correlation of all possible emotional pairs.

Figure 1 display the Wheel of Emotions [13] for the sample overall.

Figure 1. Plutchik Wheel of Emotions of all sepsis-related responses.



Discussion

Overview

This study examined the emotional responses of patients and caregivers to sepsis-related events using sentiment analysis. The analyzed text responses from 170 patients, caregivers, children, spouses, and others showed that there were numerous text features that indicated elevated emotional patterns and trends. These patterns and trends are discussed in the following subsections.

Medical, Hospital, Intensive Care Unit, Sepsis, and Emergency Department Indicators

Our analysis revealed that there was a higher occurrence of fear- and sadness-related words when hospital, sepsis, or emergency department (ED) were mentioned in sepsis-related experiences (Table 2). For example, when the word "hospital" is mentioned, there is a 1.35 times higher frequency of fear-related words and a 1.51 times higher frequency of sadness-related words. These findings underscore the profound emotional impact of sepsis, which is characterized by its critical nature and the uncertainty surrounding its prognosis, leading to heightened emotional distress. Moreover, the traumatic aspects of sepsis, including its sudden onset, severe symptoms, near-death experience, and the urgent need for immediate medical intervention and life support, can cause psychological trauma and further contribute to intensified feelings of fear and sadness [22-24]. The admission of a patient to the hospital or ED can be particularly shocking for patients, families, and friends, especially when the illness was unexpected. The constant highs and lows can be emotionally draining when the future is uncertain, with worries about losing loved ones or coping with disabilities from sepsis [24]. Our findings are consistent with the findings of Apitzsch et al [22] and Gallop et al [24] who qualitatively explored the mental impact of surviving sepsis and discovered that survivors often harbor a great sense of fear of experiencing sepsis again and becoming critically ill again.

The "medical" indicator was associated with heightened anticipation and anger as well as increased trust. Patient experiences may trigger heightened anticipation or concern due to the seriousness of the medical matters discussed. This association is reflected in the increased usage of words associated with anticipation within these contexts. Simultaneously, the concurrent rise in expressions of trust when "medical" terms are used implies that, despite heightened anticipation or worry, respondents also demonstrate a level of trust or reliance on medical professionals or care within these conversations. Moreover, the discovery that individuals using the term "medical" tend to express more words associated with anger suggests potential frustration or discontent during discussions involving medical elements. Recognizing these connections holds significance for health care professionals, indicating the necessity for improved communication strategies to address patient and family apprehensions. This emphasizes the importance of conveying medical terminologies in a manner that minimizes negative emotional reactions, ultimately enhancing patient and family experiences in navigating such discussions.

The results of our analysis indicated an increase in the average occurrence of words related to fear and sadness when the term "ICU" was mentioned. Specifically, fear-related words had an average occurrence of 12.3, while sadness-related words had an average occurrence of 10.8 (Table 1). These findings align with a study conducted by Kang et al [25], who performed sentiment analysis on responses from intensive care unit (ICU) survivors and reported the highest scores for sadness and fear. This consistency in findings suggests that the mention of the ICU in sepsis-related experiences elicits heightened emotional expressions of fear and sadness, reflecting the emotional impact of the ICU environment and the experiences associated with a critical illness. However, interestingly, ICU was not included in the 8 regression models, suggesting that other factors, possibly related to ICU exposure, better explain the variation noted by the word "ICU."

Life, Failure, Death, and Shock

Our findings suggest that if the outcome of the patients were alive, the responses had 1.15 times more joy-related words. Surviving patients and relatives often experience relief and joy after recovering from a serious illness such as sepsis. The recovery of a patient can lead to an overall increase in the positive language used when discussing the patient's outcomes or experiences. This was also noted by Papathanassoglou and Patiraki [26], who investigated the long-term effects of critical illness on survivors and found that participants frequently highlighted emotions of personal transformation, joy, and a newfound appreciation for the wonders of life.

Sepsis is a complication of infection that often leads to organ failure, including the heart, kidneys, respiratory organs, and liver [27]. The results of this study reveal a noteworthy trend: when respondents discuss failure in relation to organ failures, such as kidney failure, liver failure, or heart failure, their responses tend to contain a higher frequency of words associated with disgust, anger, fear, sadness, and surprise. This observation can be attributed to the fact that organ failure is a severe and potentially life-threatening condition that profoundly affects both patients and their families. They experience psychological burdens due to feelings of indefinite care over time, and constant uncertainty, and worry about deteriorating health and death [28].

Given the significant emotional impact of organ failure, it is crucial for health care providers to recognize this and offer appropriate emotional support and resources. By acknowledging and addressing the emotional challenges faced by patients and their families in addition to the physical ones, health care professionals can enhance the overall well-being and coping mechanisms of those affected by organ failure [28]. It is imperative to shift the perspective and no longer view the family as merely a resource for patient care but instead integrate them into the health care process, valuing their input and involving them in decision-making.

Our findings suggest that the mention of the word "death" was associated with more fear- and anger-related words and fewer joy-related words. The mention of death or the patient's death due to sepsis in responses can signal a significant and often tragic event that has occurred, which can contribute to the overall emotional tone of the language used. The mention of death can be associated with feelings of loss, helplessness, and regret, which can diminish the experience of joy. The finding that responses containing the word "death" had more fear-related words suggests that the concept of death can evoke fear in individuals. The relatives of the patients might be terrified because of the unexpected death of patients due to sepsis and its sudden onset, which might provoke feelings of anger as they navigate through the grieving process [29]. The unexpected death of a loved one is widely recognized as one of the most profoundly traumatic experiences in an individual's life [30]. In the context of sepsis, the fear experienced by relatives following the death of a patient can stem from various factors. These may include the fear of losing someone dear to them, the fear of not understanding the exact cause of death, and the fear of the unknown. The emotional impact of such circumstances can be immense, underscoring the importance of providing support to bereaved relatives during the grieving process.

The results indicate that if the word "shock" is mentioned in a response, there is an increased occurrence of words associated with surprise. Shock developed due to sepsis can be a serious and potentially life-threatening condition and is often the most common cause of death [31] that can lead to a range of physical and emotional responses. The experience of shock may be unexpected and sudden, leading to a heightened emotional response that includes surprise. Additionally, shock can be categorized as a word that depicts surprise, and it is possible that the sentiment analysis might have considered shock as a factor of surprise rather than its specific context related to sepsis. It is also possible that when counting the number of NRC surprise words, "shock" was counted as a surprise word, as another definition of "shock" is a sudden upsetting or surprising event or experience. This additional count could have led to increases in this count variable, and thus showing an increase in our tables.

Timelines

Long timelines, as compared to a short or quick timeline, related to sepsis and sepsis-related events had more joy-related words and fewer fear-related words. Patients who make progress toward recovery and achieve improvements in their health may experience joy and satisfaction as they reach milestones and see improvements in their quality of life. Long timelines may allow individuals to gain a broader perspective and distance themselves from the initial stress and fear of the illness, enabling them to concentrate on more optimistic aspects such as recovery and healing. That may be the reason for the reduction in the frequency of fear-related words in their responses. Additionally, as time passes, individuals and family members may have had more opportunities to process their experiences and emotions related to sepsis, potentially leading to a greater sense of acceptance, peace, and gratitude. These findings are consistent with a review conducted by Paul and Rattray [32], which examined the short- and long-term impact of critical illness on relatives. The review reported that emotional distress among relatives tends to diminish over time, influenced by factors such as their coping mechanisms and the support they receive from their social networks [32]. The exclusion of short timelines of sepsis-related events from the model may be because respondents did not have enough time to fully process their emotions and experiences related to these events.

Relationship With the Patient

The findings suggest that the relationship between the responder and the patient can have a significant impact on their emotional experience and expression of emotions related to sepsis.

The finding that responses from spouses were associated with fewer joy-related words suggests that caring for a partner with sepsis can be a challenging and stressful experience. Spouses may feel overwhelmed by the responsibilities of caregiving and the uncertainty of their partner's health, which could contribute to a more negative emotional response overall. Additionally, spouses may also be dealing with their own emotions about losing their partner or the potential loss of their partner, further reducing the frequency of joy-related words in their responses. Studies have found that severe sepsis, in particular, can impose a significant burden on spouses, who are susceptible to the detrimental effects of psychological stress that can impair their health-related quality of life [33,34].

If the respondent was a patient who had sepsis, they were estimated to have 5.6 times more anger words as compared to responders who themselves were not patients. This could be indicative of the intense emotional experience that patients with sepsis undergo. Sepsis is a life-threatening condition that can cause physical and emotional distress. Patients who have experienced sepsis may have gone through a traumatic experience that can leave a lasting impact [23,25]. The anger expressed by the patient in their responses may be a result of their frustration with the experience of sepsis and its aftermath. They might feel angry about the loss of their independence, perceiving themselves as a burden to their loved ones who have assumed caregiving responsibilities, as well as the pain, discomfort, and disruption to their lives caused by sepsis [25]. Research has shown that sepsis survivors may experience a sense of depersonalization, feeling like they have become a different person in certain situations. This alteration in their identity can have a negative impact on their family and social relationships [23]. On the other hand, responders who were not patients may have had a more detached perspective on the situation, which could explain why they had fewer anger words in their responses. Without experiencing sepsis firsthand, they may not fully understand the emotional toll it can take on a patient.

Our findings reveal that responses provided by parents of patients with sepsis contained fewer anger- and surprise-related words. Parents may feel a sense of responsibility and obligation to remain calm and composed for the sake of their child, which could contribute to a lower frequency of anger-related words in their responses. A study conducted by Vermunt et al [35] supports this notion, as parents of children who survived septic shock reported learning to cope with the event, gaining strength from it, and developing a heightened appreciation for life.

Guidance for Health Care Professionals

This study presents a significant contribution to the existing literature as it is the first of its kind, to the best of our knowledge, to examine the sentiments and emotions of patients and their families related to sepsis events. By focusing on this previously unexplored aspect, the study provides valuable insights into the emotional impact of sepsis on individuals and their support networks for health care professionals. Our research reveals the distinct ways in which each patient's and their family members' experiences with sepsis shape their overall feelings. This individuality in the experiences of patients and their families highlights the need for a comprehensive approach that includes psychological support, encourages open dialogue, involves family members, and offers educational resources. Recognizing and addressing this individuality is crucial, as it ensures that each patient and family receives personalized and holistic support tailored to their unique journey through sepsis. By addressing the emotional needs of patients and their families, health care providers can effectively alleviate fear and sadness, promote patient well-being, and enhance satisfaction with the care received.

Limitations

Observational text analysis should be considered exploratory, as it relies on the interpretation of language patterns rather than direct measurements of emotions or experiences. As with any exploratory analysis, there are limitations to the method that should be considered. In this study, some data were missing, which meant that certain variables could not be analyzed, potentially limiting the scope of the findings. Additionally, some textual inference was completed, which means there is a possibility of error in interpreting the language patterns observed.

Responses to the blog post may originate from individuals who are not necessarily patients, are at the same or similar hospitals, of the same hospital size, or during similar times and can vary in length, among other factors that would typically result in more common responses. While this manuscript does not assert the existence of commonality among these responses, it is crucial to acknowledge that blog post data can exhibit more variability compared to other forms of electronic health record text data.

The initial story's impact might have shaped subsequent bloggers' narratives about their encounters, potentially biasing the spectrum of experiences shared toward those more adversely affected and potentially overshadowing milder cases in the discourse. These dynamics underscore the need for critical appraisal when interpreting these narratives to ensure a balanced understanding of the multifaceted experiences associated with sepsis events.

Further research and analysis are necessary to fully understand the relationship between patient outcomes and language use. While this study provides some insights into the language patterns associated with sepsis, additional research is needed to confirm and extend these findings. It is also important to note that lexical methods for analyzing sentiment, such as those used in this study, may not differentiate between authentic positive sentiments and sarcastic ones. Therefore, caution should be exercised when interpreting the sentiment analysis results.

Conclusions

This study highlights the toll sepsis plays on the emotions of patients, caregivers, spouses, children, and others. This sentiment analysis of patient- and family-related sepsis events can provide valuable insights into the emotional experiences of patients and their families during these events, which can guide health care providers in providing appropriate emotional support. By acknowledging and addressing the emotional impact of sepsis, health care providers can improve patient and family experiences and outcomes.

Acknowledgments

We would like to thank Centers for Disease Control and Prevention for sharing the data from the blog post.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Negative binomial least absolute shrinkage and selection operator regression model fit details and National Research Council of Canada emotions correlation matrix.
[DOCX File , 18 KB - nursing_v7i1e51720_app1.docx]

References

1. What is sepsis. Sepsis Alliance. URL: https://www.sepsis.org/sepsis-basics/what-is-sepsis/ [accessed 2023-05-31]
2. Tiru B, DiNino EK, Orenstein A, Mailloux PT, Pesaturo A, Gupta A, et al. The economic and humanistic burden of severe sepsis. Pharmacoeconomics 2015;33(9):925-937. [doi: 10.1007/s40273-015-0282-y] [Medline: 25935211]
3. Epstein RM, Street RL. The values and value of patient-centered care. Ann Fam Med 2011;9(2):100-103 [FREE Full text] [doi: 10.1370/afm.1239] [Medline: 21403134]
4. Reblin M, Uchino BN. Social and emotional support and its implication for health. Curr Opin Psychiatry 2008;21(2):201-205 [FREE Full text] [doi: 10.1097/YCO.0b013e3282f3ad89] [Medline: 18332671]
5. Jones C, Skirrow P, Griffiths RD, Humphris GH, Ingleby S, Eddleston J, et al. Rehabilitation after critical illness: a randomized, controlled trial. Crit Care Med 2003;31(10):2456-2461. [doi: 10.1097/01.CCM.0000089938.56725.33] [Medline: 14530751]
6. Nelson JE, Meier DE, Oei EJ, Nierman DM, Senzel RS, Manfredi PL, et al. Self-reported symptom experience of critically ill cancer patients receiving intensive care. Crit Care Med 2001;29(2):277-282. [doi: 10.1097/00003246-200102000-00010] [Medline: 11246306]
7. Wenrich MD, Curtis JR, Ambrozy DA, Carline JD, Shannon SE, Ramsey PG. Dying patients' need for emotional support and personalized care from physicians: perspectives of patients with terminal illness, families, and health care providers. J Pain Symptom Manage 2003;25(3):236-246 [FREE Full text] [doi: 10.1016/s0885-3924(02)00694-2] [Medline: 12614958]
8. Berry LL, Seiders K, Wilder SS. Innovations in access to care: a patient-centered approach. Ann Intern Med 2003;139(7):568-574. [doi: 10.7326/0003-4819-139-7-200310070-00009] [Medline: 14530228]
9. Bing L. Sentiment Analysis: Mining Opinions, Sentiments, and Emotions. 2nd Edition. Cambridge, England: Cambridge University Press; 2020.
10. Puchalski CM, Blatt B, Kogan M, Butler A. Spirituality and health: the development of a field. Acad Med 2014;89(1):10-16 [FREE Full text] [doi: 10.1097/ACM.0000000000000083] [Medline: 24280839]
11. Lautrette A, Darmon M, Megarbane B, Joly LM, Chevret S, Adrie C, et al. A communication strategy and brochure for relatives of patients dying in the ICU. N Engl J Med 2007;356(5):469-478 [FREE Full text] [doi: 10.1056/NEJMoa063446] [Medline: 17267907]
12. Giardina TD, Royse KE, Khanna A, Haskell H, Hallisy J, Southwick F, et al. Health care provider factors associated with patient-reported adverse events and harm. Jt Comm J Qual Patient Saf 2020;46(5):282-290 [FREE Full text] [doi: 10.1016/j.jcjq.2020.02.004] [Medline: 32362355]
13. Zunic A, Corcoran P, Spasic I. Sentiment analysis in health and well-being: systematic review. JMIR Med Inform 2020;8(1):e16023 [FREE Full text] [doi: 10.2196/16023] [Medline: 32012057]
14. Xavier T, Lambert J. Sentiment and emotion trends in nurses' tweets about the COVID-19 pandemic. J Nurs Scholarsh 2022;54(5):613-622 [FREE Full text] [doi: 10.1111/jnu.12775] [Medline: 35343050]
15. Sun N, Wei L, Shi S, Jiao D, Song R, Ma L, et al. A qualitative study on the psychological experience of caregivers of COVID-19 patients. Am J Infect Control 2020;48(6):592-598 [FREE Full text] [doi: 10.1016/j.ajic.2020.03.018] [Medline: 32334904]

16. Karl F. A family's perspective—"the brutality of sepsis will haunt us for the rest of our lives. Center for Disease Control and Prevention. 2014 Sep 16. URL: https://blogs.cdc.gov/safehealthcare/brutality-of-sepsis/ [accessed 2023-12-30]
17. Mohammad SM, Turney PD. NRC emotion lexicon. National Research Council of Canada. 2013. URL: https://nrc-publications.canada.ca/eng/view/object/?id=0b6a5b58-a656-49d3-ab3e-252050a7a88c [accessed 2020-12-15]
18. Tibshirani R. Regression shrinkage and selection via the lasso. J R Stat Soc Ser B Methodol 2018;58(1):267-288. [doi: 10.1111/j.2517-6161.1996.tb02080.x]
19. Cavanaugh JE, Neath AA. The Akaike information criterion: background, derivation, properties, application, interpretation, and refinements. WIREs Comp Stat 2019;11(3):e1460 [FREE Full text] [doi: 10.1002/wics.1460]
20. Plutchik R. The nature of emotions. American Scientist. URL: https://www.americanscientist.org/article/the-nature-of-emotions [accessed 2023-05-31]
21. Semeraro A, Vilella S, Ruffo G. PyPlutchik: visualising and comparing emotion-annotated corpora. PLoS One 2021;16(9):e0256503 [FREE Full text] [doi: 10.1371/journal.pone.0256503] [Medline: 34469455]
22. Apitzsch S, Larsson L, Larsson AK, Linder A. The physical and mental impact of surviving sepsis—a qualitative study of experiences and perceptions among a Swedish sample. Arch Public Health 2021;79(1):66 [FREE Full text] [doi: 10.1186/s13690-021-00585-5] [Medline: 33933171]
23. Mostel Z, Perl A, Marck M, Mehdi SF, Lowell B, Bathija S, et al. Post-sepsis syndrome—an evolving entity that afflicts survivors of sepsis. Mol Med 2019;26(1):6 [FREE Full text] [doi: 10.1186/s10020-019-0132-z] [Medline: 31892321]
24. Gallop KH, Kerr CEP, Nixon A, Verdian L, Barney JB, Beale RJ. A qualitative investigation of patients' and caregivers' experiences of severe sepsis. Crit Care Med 2015;43(2):296-307. [doi: 10.1097/CCM.0000000000000613] [Medline: 25251757]
25. Kang J, Yeon Jin J, Jun Hee J, Lee M. Risk factors for frailty in critical care survivors: a secondary analysis. Intensive Crit Care Nurs 2021;64:102981-102981. [doi: 10.1016/j.iccn.2020.102981]
26. Papathanassoglou ED, Patiraki EL. Transformations of self: a phenomenological investigation into the lived experience of survivors of critical illness. Nurs Crit Care 2003;8(1):13-21 [FREE Full text] [doi: 10.1046/j.1478-5153.2003.00004.x] [Medline: 12680514]
27. Lelubre C, Vincent JL. Mechanisms and treatment of organ failure in sepsis. Nat Rev Nephrol 2018;14(7):417-427. [doi: 10.1038/s41581-018-0005-7] [Medline: 29691495]
28. Ania-González N, Martín-Martín J, Amezqueta-Goñi P, Vázquez-Calatayud M. The needs of families who care for individuals with kidney failure on comprehensive conservative care: a qualitative systematic review. J Ren Care 2022;48(4):230-242 [FREE Full text] [doi: 10.1111/jorc.12415] [Medline: 35226408]
29. Rich S. Caregiver grief: taking care of ourselves and our patients. Int J Trauma Nurs 2002;8(1):24-28. [doi: 10.1067/mtn.2002.121332] [Medline: 11793009]
30. Keyes KM, Pratt C, Galea S, McLaughlin KA, Koenen KC, Shear MK. The burden of loss: unexpected death of a loved one and psychiatric disorders across the life course in a national study. Am J Psychiatry 2014;171(8):864-871 [FREE Full text] [doi: 10.1176/appi.ajp.2014.13081132] [Medline: 24832609]
31. Moskowitz A, Omar Y, Chase M, Lokhandwala S, Patel P, Andersen LW, et al. Reasons for death in patients with sepsis and septic shock. J Crit Care 2017;38:284-288 [FREE Full text] [doi: 10.1016/j.jcrc.2016.11.036] [Medline: 28013094]
32. Paul F, Rattray J. Short- and long-term impact of critical illness on relatives: literature review. J Adv Nurs 2008;62(3):276-292. [doi: 10.1111/j.1365-2648.2007.04568.x] [Medline: 18426451]
33. Davydow DS, Hough CL, Langa KM, Iwashyna TJ. Depressive symptoms in spouses of older patients with severe sepsis. Crit Care Med 2012;40(8):2335-2341 [FREE Full text] [doi: 10.1097/CCM.0b013e3182536a81] [Medline: 22635049]
34. Rosendahl J, Brunkhorst FM, Jaenichen D, Strauss B. Physical and mental health in patients and spouses after intensive care of severe sepsis: a dyadic perspective on long-term sequelae testing the actor-partner interdependence model. Crit Care Med 2013;41(1):69-75. [doi: 10.1097/CCM.0b013e31826766b0] [Medline: 23222259]
35. Vermunt LCAC, Buysse CMP, Joosten KFM, Hazelzet JA, Verhulst FC, Utens EMWJ. Recovery in parents of children and adolescents who survived septic shock caused by neisseria meningitidis: a cross-sectional study. Intensive Crit Care Nurs 2010;26(3):128-137. [doi: 10.1016/j.iccn.2010.01.001] [Medline: 20171889]

Abbreviations

CDC: Centers for Disease Control and Prevention
ED: emergency department
ICU: intensive care unit
IRR: incidence rate ratio
LASSO: least absolute shrinkage and selection operator
NRC: National Research Council Canada

Edited by E Borycki; submitted 09.08.23; peer-reviewed by P Valkonen, D Delnoij; comments to author 31.10.23; revised version received 24.01.24; accepted 07.02.24; published 01.04.24.

Please cite as:
Ntiamoah M, Xavier T, Lambert J
Sentiment Analysis of Patient- and Family-Related Sepsis Events: Exploratory Study
JMIR Nursing 2024;7:e51720
URL: https://nursing.jmir.org/2024/1/e51720
doi:10.2196/51720
PMID:38557694

Original Paper

Evaluation of Autonomic Nervous System Function During Sleep by Mindful Breathing Using a Tablet Device: Randomized Controlled Trial

Eiichi Togo[1*], PhD; Miki Takami[2*], PhD; Kyoko Ishigaki[2*], MD

[1]Department of Nursing, Faculty of Nursing, Hyogo University, Kakogawa City, Japan
[2]College of Nursing Art and Science, University of Hyogo, Akasi City, Japan
[*]all authors contributed equally

Corresponding Author:
Eiichi Togo, PhD
Department of Nursing, Faculty of Nursing, Hyogo University
2301
Hiraoka-cho Shinzaike
Kakogawa City, 675-0195
Japan
Phone: 81 794279516
Email: tougo@hyogo-dai.ac.jp

Abstract

Background: One issue to be considered in universities is the need for interventions to improve sleep quality and educational systems for university students. However, sleep problems remain unresolved. As a clinical practice technique, a mindfulness-based stress reduction method can help students develop mindfulness skills to cope with stress, self-healing skills, and sleep.

Objective: We aim to verify the effectiveness of mindful breathing exercises using a tablet device.

Methods: In total, 18 nursing students, aged 18-22 years, were randomly assigned and divided equally into mindfulness (Mi) and nonmindfulness (nMi) implementation groups using tablet devices. During the 9-day experimental period, cardiac potentials were measured on days 1, 5, and 9. In each sleep stage (sleep with sympathetic nerve dominance, shallow sleep with parasympathetic nerve dominance, and deep sleep with parasympathetic nerve dominance), low frequency (LF) value, high frequency (HF) value, and LF/HF ratios obtained from the cardiac potentials were evaluated.

Results: On day 5, a significant correlation was observed between sleep duration and each sleep stage in both groups. In comparison to each experimental day, the LF and LF/HF ratios of the Mi group were significantly higher on day 1 than on days 5 and 10. LF and HF values in the nMi group were significantly higher on day 1 than on day 5.

Conclusions: The correlation between sleep duration and each sleep stage on day 5 suggested that sleep homeostasis in both groups was activated on day 5, resulting in similar changes in sleep stages. During the experimental period, the cardiac potentials in the nMi group showed a wide range of fluctuations, whereas the LF values and LF/HF ratio in the Mi group showed a decreasing trend over time. This finding suggests that implementing mindful breathing exercises using a tablet device may suppress sympathetic activity during sleep.

Trial Registration: UMIN-CTR Clinical Trials Registry UMIN000054639; https://tinyurl.com/mu2vdrks

(JMIR Nursing 2024;7:e56616) doi:10.2196/56616

KEYWORDS

mindfulness; sleep; cardiac potential; low frequency; high frequency; mobile phone

Introduction

Recently, the spread of the internet and smartphones and the influence of companies operating around the clock have led to the rapid development of a society where people can be active at any time of the day or night. According to a survey by the Ministry of Health, Labor and Welfare, 37.5% (1000/2668) of men and 40.6% (1231/3033) of women sleep <6 hours, and 37.1% (82/221) of men and 37% (83/224) of women are in their

20s [1]. Approximately 37% (165/445) of university students in their 20s do not sleep sufficiently.

A study that investigated the relationship between sleep disturbances in university students and depression after graduation reported that those who developed sleep disturbances during their school years were at a higher risk of developing depression later in life [2]. Another study that investigated the association between sleep duration and impaired glucose tolerance found that sleeping for <6 hours was associated with an increased prevalence of diabetes [3]. Sleep disorders increase the risk of developing psychiatric disorders, cardiovascular diseases, and other physical diseases [4,5]. Therefore, as an issue to be considered in universities, improving the educational system for university students and providing interventions to improve sleep quality are necessary. The Ministry of Health, Labor and Welfare has established sleep guidelines for health promotion [6], and sleep-related consultations and support systems have been established at universities to help resolve sleep-related issues. VR use in adolescents with insomnia produces significant changes in heart rate, suggesting a relaxation effect [7]. Breathing interventions suggest that spontaneous slow breathing affects the parasympathetic nervous system [8], and breathing techniques may improve sleep quality and morning and evening cardiac vagal activity [9]. However, the impact of breathing on heart rate needs to be investigated via polysomnography to assess its effect on sleep, and its long-term efficacy in improving cardiovascular function is unknown [7,9]. Given these factors, sleep problems remain unresolved.

The mindfulness-based stress reduction (MBSR) method, developed by Kabat, has attracted attention [10]. MBSR involves developing mindfulness skills to help people cope with stress, improve self-healing skills, and sleep better. Studies on the effects of mindfulness on sleep have used subjective sleep rating scales [11,12] and cortisol levels during morning awakening during mindfulness practice [13]. The relationship between the practice of MBSR and the functioning of the autonomic nervous system during sleep remains poorly verified via physiological assessments. Autonomic function measurement using heart rate variability (HRV) analysis has been used to objectively assess sleep [14,15]. Mindfulness-based psychological interventions can reduce depressive symptoms [16].

The effects of mindfulness-based cognitive therapy in older adults with sleep disorders have been demonstrated objectively using polysomnography [17]. An unresolved issue is that studies using objective sleep measures, such as polysomnography, suggest that the effects of mindfulness on insomnia and sleep disorders are small compared with subjective reports [18]. Therefore, whether mindfulness-based interventions change sleep patterns or alter subjective sleep assessments remains unclear.

HRV analysis is effective in assessing sleep quality [19]. HRV analysis can enable an objective understanding of changes in the autonomic nervous system during sleep. Furthermore, wearable devices can assess pathological sleep conditions such as insomnia, sleep apnea, and hypertension [20]. Wearable devices can also assess sleep stages and disorders [21]. Based on the results of these studies, wearable devices have significant potential for use in sleep research and clinical practice. Furthermore, using wearable devices capable of measuring HRV during sleep is a viable method with sufficient validity for measuring the variability in sleep stages [22-24]. These studies have suggested that sleep assessment using wearable devices capable of measuring HRV is feasible.

Here, we hypothesized that participants who practiced mindful breathing techniques using a tablet device would show characteristics of autonomic nervous system function during sleep. This study aimed to verify the effects of mindfulness breathing exercises using a tablet device and capture changes in autonomic nervous system function.

Methods

Recruitment

In a study, 27 participants were evaluated for HRV during stable sleep [25]. This study was conducted with a sample size of >20 participants. In contrast, 15 participants were evaluated for sleep quality using HRV [26]. Further, 20 participants were evaluated for sleep using electroencephalography power spectral density [27]. The number of participants in this study was as follows: all previous studies had small sample sizes with <20 participants.

Therefore, based on previous studies, we hypothesized that differences between groups could be identified if we collected data from 18 participants.

With an expected dropout rate of 10%, the experiment was continued by collecting data from 10 participants in each group until data from 18 participants were available for analysis. In this study, the participants were 18 female nursing students at University A from the 1st to 4th year, aged 18-22 years. The participants were divided into 2 groups: a group that implemented (the Mi [mindfulness group]) and a group that did not implement mindfulness breathing exercises (the nMi [nonmindfulness group]). Each group consisted of 9 participants, and randomization was used to minimize the influence of bias in the number of participants and age differences between participants. To classify the participants into 2 groups, random numbers were assigned using the RAND function in the spreadsheet software Excel (Microsoft Corp). Participants were excluded from this study if they had previous meditation and mindfulness experience or had taken sleep-inducing drugs or other medications to assess the effects of mindful breathing techniques without error.

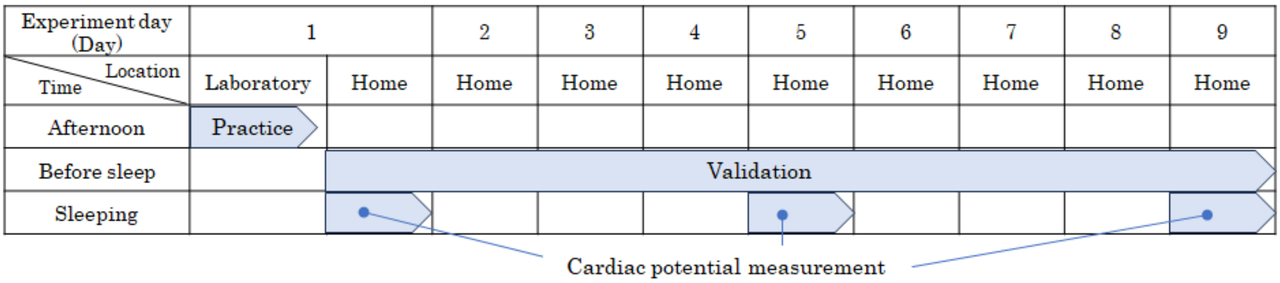
Exclusion criteria for health status were history of sleep disorders, use of sleep-inducing drugs, and inconsistent sleep-wake rhythms. Lifestyle exclusion criteria included those who worked part-time during nighttime hours and consumed alcohol or excess caffeine. Participants who met these conditions were excluded because they may have affected the effectiveness of the mindfulness breathing techniques.

Experimental Structure

Between May 2022 and November 2023, each student participated in this experiment.

On day 1 of the experiment, participants in the Mi group used the equipment and practiced mindful breathing exercises using a tablet device in a university laboratory. The nMi and control groups operated the equipment and practiced cross-gazing using a tablet device in a university laboratory. The laboratory practice was conducted in the afternoon to avoid the influence of the circadian cycle. The experimental structure consisted of 2 components: 1 "measurement" of cardiac potentials at home and the other "validation" of mindful breathing exercises or gazing at a cross on a personal computer screen (Figure 1). For the "measurement," autonomic function was measured during sleep on days 1, 5, and 9 for the Mi and nMi groups. For the "validation," the day 1 of the experiment was day 1, and for 9 consecutive weekdays, once a day at home before bedtime, the Mi group performed mindful breathing exercises, and the nMi group gazed at the crosshairs on the personal computer screen.

Figure 1. Experimental configuration. Practice: Mi group practicing mindful breathing exercises; nMi group practicing gazing at crosses. Validation: Mi group practicing mindful breathing exercises; nMi group practicing gazing at crosses.



Mindfulness

Mindfulness is described as "living consciously in the 'now' moment," being aware of the present and accepting experience as it is, without evaluation or judgment [10]. Mindfulness aims to maintain moment-to-moment awareness and detach oneself from strong attachments to beliefs, thoughts, and feelings [28].

In this study, based on the MBSR developed by Kabat, an original Access (Microsoft Corp) application for voice guidance of mindful breathing exercises was created and experimented with. On day 1 of the experiment, the participants were provided a verbal overview of mindfulness in the laboratory and practiced mindful breathing exercises following audio guidance. The mindfulness procedure in this study consisted of (1) relaxing the shoulders and assuming a sitting posture (meditation); (2) maintaining the sitting posture, breathing abdominally, and focusing on the flow of exhalation and inhalation (breathing exercises); and (3) focusing attention sequentially on the fingertips, back, belly, chest, neck, and head while remaining aware of the breath and feeling the sensations in those areas (body scan) [10].

On day 9 of the experiment, at the end, a questionnaire was administered regarding the effects of mindful breathing exercises and participants' intention to continue them. After explaining that the responses would be made confidential and statistically processed, the participants were asked to complete the questionnaire. The questionnaire included the following items regarding the effectiveness of mindful breathing exercises: "During the study, did implementing mindful breathing exercises have a positive effect on your sleep?" and asked them to respond on a 3-point scale (yes, no, or undecided). If the respondent answered "yes" to this question, she was asked, "What specific effects did it have?" and asked to describe the specific effects in free form.

Cardiac Potential Measurements

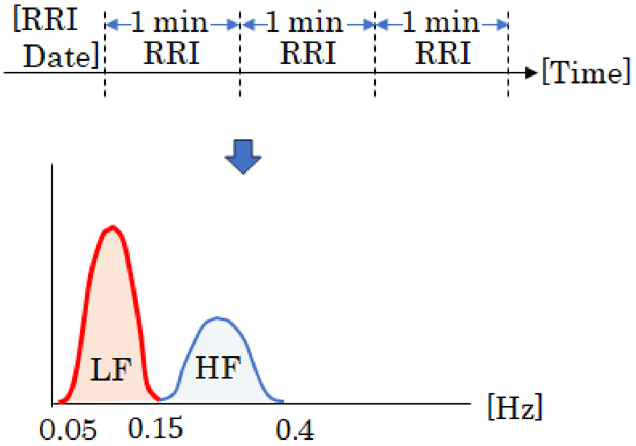
Measuring the power spectrum values of HRV has been used as a noninvasive quantitative assessment during sleep [29]. Therefore, in this study, a wearable biometric sensor device was used to noninvasively measure cardiac potential and pulse waves from heartbeats in an environment similar to daily life. For the cardiac potential measurement, the Silmee Bar type Lite, an affixed wearable biometric sensor manufactured by TDK Corporation, which can noninvasively assess autonomic nervous system function, was used. The wearable biometric sensor used in this study could obtain data without disturbing the participants' sleep [30]. For cardiac potential measurements, R-R intervals (RRI) were recorded at a sampling frequency of 1000 Hz. To remove body movement artifacts from the measurement data, the body movement error detection threshold of the RRI was set at 0.5 G. Measurements were made with a wearable biometric sensor attached approximately 3 cm below the middle of both clavicles to measure cardiac potentials close to the heart and reduce the influence of upper arm and chest muscle movement.

Sleep Analysis

In this study, Fast Fourier Transform was performed on the RRI of cardiac potential data during sleep using the Small_System manufactured by TDK Corporation. The low frequency (LF) components were separated into 0.05-0.15 and 0.15-0.40 Hz, with 1-min intervals, and the high frequency (HF) components were determined. The LF/HF ratio was calculated (Figure 2). The LF, HF, and LF/HF ratios are indices of HRV analysis and are used to assess autonomic function noninvasively. The LF component of HRV heart rate is jointly mediated by the sympathetic and parasympathetic nervous systems, whereas the HF component reflects only the parasympathetic nervous system, and the power ratio (LF/HF) reflects sympathetic activity [31,32]. The square root of the integral of the LF and HF power spectrum densities was calculated to suppress the variability and improve the accuracy of sleep determination. The time of sleep onset was estimated using Cole et al's [33] method using acceleration data to determine the time of sleep onset, and the sleep stage classification was estimated based on the autonomic balance during the period when sleep was determined via acceleration data [34]. In this study, the acceleration sampling frequency of the accelerometer of the measurement device Small_System was recorded and analyzed at 125 Hz.

Sleep stages were assessed based on the relationship between autonomic activity and sleep stage and were divided into the following three stages: (1) sleep with sympathetic nerve dominance (S sleep), (2) shallow sleep with parasympathetic nerve dominance (PS sleep [shallow]), and (3) deep sleep with parasympathetic nerve dominance (PS sleep [deep]) [34]. As the sleep stages used in this study were measured using nonmedical equipment, expressions such as S sleep and PS sleep were used.

Figure 2. Overview of LF and HF calculations from RRI data. HF: high frequency; LF: low frequency; RRI: R-R interval.



Statistical Analysis

Statistical analyses were performed for the total sleep time, sleep stage (S sleep, PS sleep [shallow], and PS sleep [deep]), LF value, HF value, and LF/HF ratios. The normality of the total sleep time, sleep stage, LF value, HF value, and LF/HF ratio was tested using the Shapiro-Wilk test and Q-Q plots. In this study, the mean (SD) of total sleep time, each sleep stage, LF value, HF value, and LF/HF ratio on days 1, 5, and 9 of both groups were used for quantitative evaluation. *t* Tests (2-tailed) were performed on the Mi and nMi groups for total sleep time and sleep time per sleep stage on each experimental day to compare the groups. Correlation coefficients were used to evaluate effect sizes. Multiple comparisons of total sleep time and sleep time for each sleep stage within each group were performed using 1-way ANOVA and the Games-Howell method.

To test the effect of mindful breathing techniques, group comparisons were made for LF values, HF values, and the LF/HF ratio on days 1, 5, and 9 in both groups using *t* tests. Further, 1-way ANOVA was also performed for LF values, HF values, and LF/HF ratios between conditions on days 1, 5, and 9 in each group, and multiple comparisons were performed using the Games-Howell method. The results were rechecked using the Bonferroni correction. Statistical significance was set at 0.05. SPSS Statistics (version 26; IBM Corp) was used for statistical analysis.

Ethical Considerations

All participants were fully informed of the purpose and objectives of this study, protection of their privacy, anticipated risks, the right to withdraw during this study, no disadvantages associated with this, publication of the results, guarantee of anonymity, and voluntary participation, and that the results would not be used for purposes other than research before this study commenced, and informed consent was obtained. The experiment was conducted in a private room, and efforts were made to protect the privacy of the participants. This study was approved by the Ethical Review Committee of the University of Hyogo and was conducted between May 2022 and December 2023 (21007) (Multimedia Appendix 1).

Results

Sleep Assessment Using a Questionnaire After Mindfulness Practice

Questionnaire test results were obtained from 6 of the 9 participants who practiced mindful breathing exercises using a tablet device. The valid response rate was 66.7% (6/9). All respondents answered “yes” to whether mindfulness meditation affected sleep quality. In free text responses, 1 respondent stated that she woke up feeling refreshed; 1 said that she felt calmer, which made it easier to sleep; 1 said that she was able to relax, get under the cover, sleep better, and was less likely to wake up in the middle of her sleep; and 2 said that they were able to fall asleep more easily.

Sleep Duration

In this study, the total sleep time and stage (S sleep, PS sleep [shallow], and PS sleep [deep] times) for the Mi and nMi groups were tested for normality using the Shapiro-Wilk test and Q-Q plot, and they followed a normal distribution.

Table 1 shows the mean and SD of total sleep time and stages (S sleep, PS sleep [shallow], and PS sleep [deep]) for both groups on each experimental day and the *t* test results for total sleep time and stages for both groups. The *t* test results were not significant.

Table 2 shows the results of multiple comparisons of the total and mean sleep times for each sleep stage for the Mi and nMi groups on each experimental day. On each experimental day, significant differences were found in the mean values of total sleep time and sleep time for each sleep stage in both groups and in comparing the mean values of sleep time between the sleep stages. On each experimental day, no significant differences were found between S and PS sleep (deep) in either group.

Table 1. Total sleep time and stage time on the measurement day (N=18).

	Mi[a], mean (SD)	nMi[b], mean (SD)	*t* Test		Pearson correlation coefficient	
			P value	Significance	*r*	*P* value
Day 1						
Total[c]	306 (107)	319 (109)	.80	ns[d]	0.369	.33
S sleep[e]	58 (39)	77 (26)	.25	ns	–0.001	>.99
PS (shallow)[f]	161 (83)	161 (64)	>.99	ns	0.346	.36
PS (deep)[g]	68 (43)	59 (30)	.61	ns	–0.174	.65
Day 5						
Total	381 (78)	332 (122)	.33	ns	0.387	.30
S sleep	81 (31)	48 (37)	.06	ns	–0.228	.56
PS (shallow)	203 (64)	180 (79)	.52	ns	0.422	.26
PS (deep)	67 (41)	56 (34)	.56	ns	–0.36	.34
Day 9						
Total	342 (111)	336 (108)	.92	ns	0.793	.01
S sleep	53 (37)	46 (32)	.67	ns	0.59	.09
PS (shallow)	177 (69)	141 (59)	.25	ns	–0.029	.94
PS (deep)	80 (26)	62 (24)	.14	ns	–0.245	.52

[a] Mi: mindfulness group.

[b] nMi: nonmindfulness group.

[c] Total: total sleep time.

[d] ns: not significant.

[e] S sleep: sleep with sympathetic nerve dominance.

[f] PS (shallow): shallow sleep with parasympathetic nerve dominance.

[g] PS (deep): deep sleep with parasympathetic nerve dominance.

Table 2. Association between total sleep time and stage using measurement date (N=18).

	P value	
	Mi[a]	nMi[b]
Day 1		
Total[c]		
S sleep[d]	3×10^{-4}[e]	5×10^{-4}[e]
PS (shallow)[f]	.027[g]	.01[g]
PS (deep)[h]	4×10^{-4}[e]	2×10^{-4}[e]
S sleep		
PS (shallow)	.028[g]	.017[g]
PS (deep)	.959 ns[i]	.55 ns
PS (shallow)		
PS (deep)	.05 ns	.005 ns
Day 5		
Total		
S sleep	3×10^{-6}[e]	3×10^{-4}[e]
PS (shallow)	4×10^{-4}[e]	.03[g]
PS (deep)	8×10^{-7}[e]	4×10^{-4}[e]
S sleep		
PS (shallow)	.001[e]	.004[e]
PS (deep)	.855 ns	.965 ns
PS (shallow)		
PS (deep)	5×10^{-4}[e]	.006[e]
Day 9		
Total		
S sleep	1×10^{-4}[e]	1×10^{-4}[e]
PS (shallow)	.01[g]	.002[e]
PS (deep)	3×10^{-4}[e]	2×10^{-4}[e]
S sleep		
PS (shallow)	.002[e]	.005[e]
PS (deep)	.29 ns	.62 ns
PS (shallow)		
PS (deep)	.01[g]	.017[g]

[a] Mi: mindfulness group.

[b] nMi: nonmindfulness group.

[c] Total: total sleep time.

[d] S sleep: sleep with sympathetic nerve dominance.

[e] *P*<.01.

[f] PS (shallow): shallow sleep with parasympathetic nerve dominance.

[g] *P*<.05.

[h] PS (deep): deep sleep with parasympathetic nerve dominance.

[i] ns: not significant.

Cardiac Potential Measurement

In this study, the LH values, HF values, and LF/HF ratios of the Mi and nMi groups were tested for normality using the Shapiro-Wilk test and Q-Q plots, and they followed a normal distribution.

Figure 3 shows an example of the time course of autonomic balance in LF and HF values and sleep time in each sleep stage, where PS sleep (deep) was observed immediately after sleep onset.

Table 3 shows the results of the 1-way ANOVA comparing the LH and HF values and the LF/HF ratio for each experimental day and Bonferroni correction. The threshold for the Bonferroni correction was set at α/k, where α is the significance level, and k is the number of comparisons. When multiple comparisons and 1-way ANOVA were conducted, and the threshold for Bonferroni correction was set to α/3, the results using multiple comparisons and Bonferroni correction were also significantly different, consistent with the original results.

The results of the 1-way ANOVA and *t* test for the mean LH value, HF value, and LF/HF ratio are shown in Figures 4A-4C. The horizontal axis shows the date of cardiac potential measurement in the Mi and nMi groups; the vertical axis shows the (A) LH value, (B) HF value, and (C) LF/HF ratio; the error bars in the graph show the SD of each value.

The results of this study showed that the mean LF and HF values of the Mi group were significantly higher on day 1 than on days 5 and 10 (*P*<.01) when comparing each experimental day. In contrast, the LF and HF values of the nMi group were significantly higher on day 1 than on day 5 (*P*<.01) and significantly lower on day 1 than on day 10 (*P*<.05). The LF/HF ratio of the Mi group showed a significant trend on day 1 compared with that on day 10 (*P*<.1) and on day 5 compared with that on day 10 (*P*<.05). The LF/HF ratio in the nMi group was significantly lower on day 1 than on day 5 (*P*<.05).

In a comparison between the groups, LF values on days 1 and 5 were significantly higher than those of the nMi group (*P*<.01); HF values on day 5 were significantly higher than those of the nMi group (*P*<.05); HF values on day 10 showed a significant trend compared to those of the nMi group (*P*<.1); and days 5 and 10 LF/HF ratios were significantly lower than those of the nMi group (*P*<.01).

Figure 3. Example of the autonomic balance in LF and HF values and the chronological changes in each sleep stage. HF: high frequency; LF: low frequency; PS sleep (deep): deep sleep with parasympathetic nerve dominance; PS sleep (shallow): shallow sleep with parasympathetic nerve dominance; S sleep: sleep with sympathetic nerve dominance.

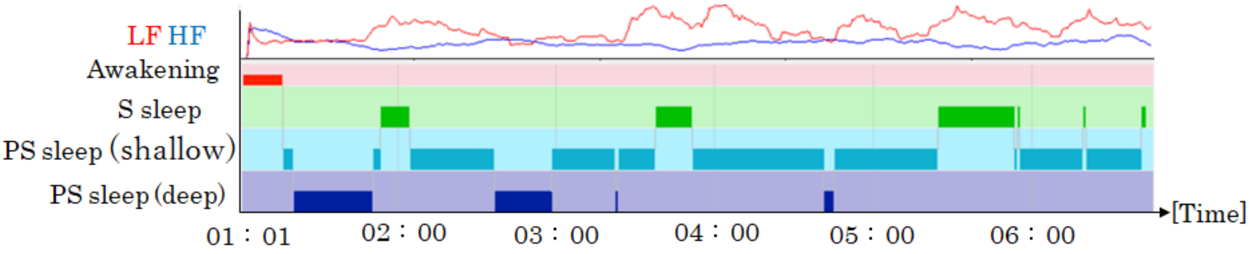


Table 3. Results of multiple comparisons of LH[a] values, HF[b] values, and LF/HF ratios.

	Mi[c]		nMi[d]	
	P value	Bonferroni	*P* value	Bonferroni
LF				
Day 1				
Day 5	5×10^{-9}[e]	2×10^{-8}[f]	5×10^{-7}[e]	15×10^{-6}[f]
Day 9	5×10^{-9}[e]	2×10^{-8}[f]	1×10^{-4}[e]	4×10^{-4}[f]
Day 5				
Day 9	5×10^{-9}[e]	2×10^{-8}[f]	5×10^{-9}[e]	15×10^{-8}[f]
HF				
Day 1				
Day 5	5×10^{-9}[e]	2×10^{-8}[f]	5×10^{-9}[e]	15×10^{-8}[f]
Day 9	5×10^{-9}[e]	2×10^{-8}[f]	.019	.056
Day 5				
Day 9	5×10^{-9}[e]	2×10^{-8}[f]	5×10^{-9}[e]	15×10^{-8}[f]
LF/HF ratio				
Day 1				
Day 5	.996	2.988	.032[g]	.097
Day 9	.051	2×10^{-1}	.81	2.429
Day 5				
Day 9	.039[g]	1×10^{-1}[h]	.16	.487

[a] LF: low frequency.

[b] HF: high frequency.

[c] Mi: mindfulness group.

[d] nMi: nonmindfulness group.

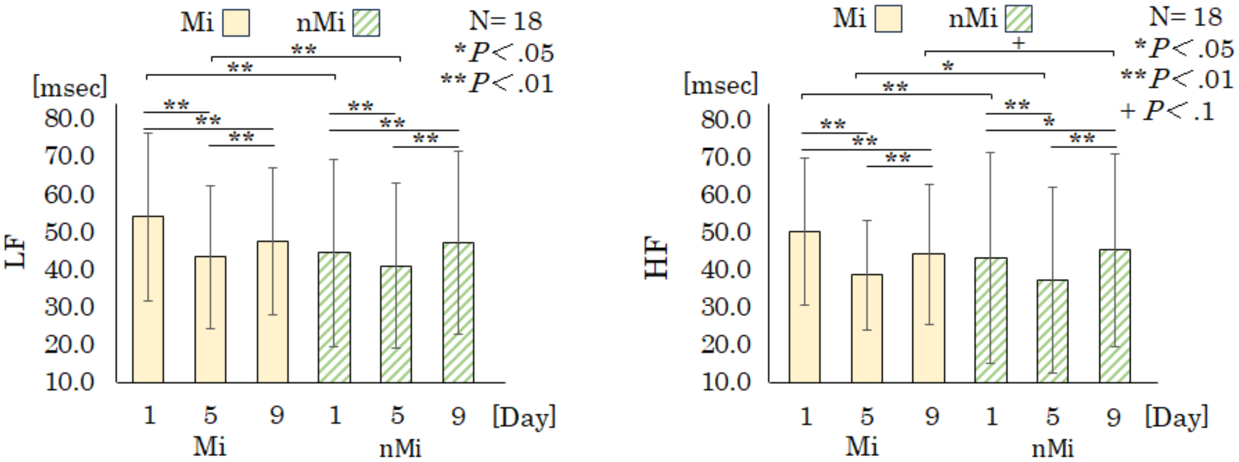
[e] *P*<.01.

[f] *P*<.003.

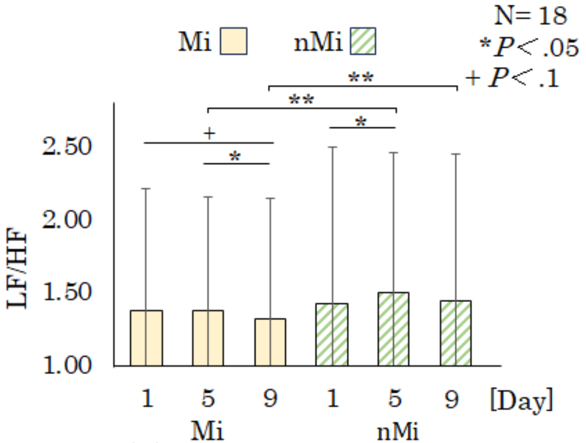
[g] *P*<.05.

[h] *P*<.017.

Figure 4. Cardiac potential results. HF: high frequency; LF: low frequency; Mi: mindfulness group; nMi: nonmindfulness group.



(A) Average of LF values (B) Average of HF values



(C) Average of LF/HF values

Discussion

Sleep Assessment Using a Questionnaire After Mindfulness Practice

This study analyzed the impact of mindful breathing exercises using a tablet device. The questionnaire had a low valid response rate (55.6%). However, of the participants who answered the questionnaire, 100% (n=18) answered that mindfulness meditation affected their sleep quality. In their free-text responses, participants stated that they awoke feeling refreshed and calmer, which made it easier to sleep, and felt that they slept better. Mindfulness is effective against insomnia and mental illness [35]. The results of a subjective evaluation of only those who performed mindful breathing exercises suggested that these exercises not only improved sleep quality but also had a positive effect on mood after waking and falling asleep.

Sleep Duration

The results of a *t* test comparing sleep duration and each sleep stage (S sleep, PS sleep [shallow], and PS sleep [deep]) showed no significant differences between the groups. This suggests that no significant difference exists in sleep duration between the groups.

Significant differences were found between the mean values of total sleep time and each sleep stage (S sleep, PS sleep [shallow], and PS sleep [deep]) of the groups on each experimental day. When each sleep stage was compared, significant differences were found in the duration of the sleep stages in both groups. Based on the results of this multiple comparison of the 2 groups, it is unclear from the comparison of the total sleep time and time at each sleep stage on each experimental day whether mindful breathing techniques were influential. Future research could assess the impact of mindful breathing techniques by more closely controlling the conditions and situations during sleep.

Cardiac Potential Measurements

The LF values in the Mi group were significantly lower on days 5 and 10 than on day 1. In evaluating autonomic function using HRV, the LF component reflects sympathetic and parasympathetic activities [31,32]. Mindfulness training decreases the resting LF component [36]. This suggests that suppressing sympathetic activity and activating parasympathetic activity during sleep may be involved during the experiment in the MI group that implemented mindfulness. The LF values in the nMi group were significantly higher on day 5 and lower on day 9 than those on day 1. This suggests that the sympathetic activity during sleep in the nMi group fluctuated during the experiment.

The LF values of the Mi group exhibited a decreasing trend, whereas those of the nMi group fluctuated. This difference may be owing to the difference in the intervention content between the groups. This suggests that activating parasympathetic nerve activity via mindful breathing exercises using the tablet device led to a decrease in LF values.

HF values in the Mi group were significantly higher on day 1 than on days 5 and 9. As the HF component reflects parasympathetic activity [32], parasympathetic activity was dominant on days 5 and 9 compared with the HF values on day 1 in the Mi group. The HF, which indicates parasympathetic activity, increases and affects HRV before and after mindfulness training [36]. These results suggest that mindful breathing exercises activate the parasympathetic system during sleep. The nMi group showed significantly higher HF on day 1 than on day 5 but significantly lower HF on day 1 than on day 9, suggesting fluctuations in parasympathetic activity [32]. This suggests the nMi group showed increased parasympathetic activity from days 1 to 5, followed by suppression on day 9.

The LF/HF ratio in the Mi group was significantly higher on day 9 than on day 1. In contrast, the nMi group showed significantly lower values on day 5 than on day 1. Autonomic control is an interaction rather than the activity of a continuum [37]. Implementing mindfulness leads to an increase in LF power [38]. Implementing mindfulness should have an attention-focusing and relaxation effect [10]. This suggests that continuous mindful breathing practices may calm the mind, alter the LF/HF ratio during sleep, and regulate the balance between sympathetic and parasympathetic nervous system activities.

Limitations

This study has few limitations. First, the sample size for this study was 9 for each group. This may have led to a decrease in the statistical power of studies assessing autonomic function during sleep. More reliable results can be obtained in the future by expanding the sample size. Second, the HF and LF values for the groups changed compared with those on day 1 but did not remain constant during the experiment. Although some of the implementation methods were standardized, such as the conditions of the participants and operation using the tablet terminal, a more detailed unification of the conditions is required to clarify the characteristics of autonomic nervous activity.

Conclusions

The results of this study suggest that implementing mindfulness leads to the simultaneous inhibition of parasympathetic activity and an increase in sympathetic activity. Inhibiting sympathetic activity may be reflected in the interaction between autonomic functions. In the Mi group, we observed a suppression of sympathetic activity in LF values and LF/HF ratios during the experiment; in the Mi group, under the conditions of this study, as hypothesized, implementing mindful breathing exercises using the tablet device reduced cardiac potentials, an indicator of autonomic function, has shown a change over time.

These results suggest that in the Mi group, mindful breathing exercises may influence HRV indices during sleep. Future research with larger sample sizes and long-term follow-ups could further validate these findings and inform targeted interventions for sleep-related issues.

Acknowledgments

This research was supported by a Japan Society for the Promotion of Science Grant-in-Aid for Scientific Research (21K10566).

Conflicts of Interest

None declared.

Multimedia Appendix 1
CONSORT-eHEALTH checklist (V 1.6.1).
[PDF File (Adobe PDF File), 1086 KB - nursing_v7i1e56616_app1.pdf]

References

1. Ministry of Health, Labour and Welfare. Report of the National Health and Nutrition Survey in 2048. 2020. URL: https://www.mhlw.go.jp/content/000711008.pdf [accessed 2023-08-01]
2. Chang PP, Ford DE, Mead LA, Cooper-Patrick L, Klag MJ. Insomnia in young men and subsequent depression. The Johns hopkins Precursors Study. Am J Epidemiol 1997;146(2):105-114. [doi: 10.1093/oxfordjournals.aje.a009241] [Medline: 9230772]
3. Gottlieb DJ, Punjabi NM, Newman AB, Resnick HE, Redline S, Baldwin CM, et al. Association of sleep time with diabetes mellitus and impaired glucose tolerance. Arch Intern Med 2005;165(8):863-867. [doi: 10.1001/archinte.165.8.863] [Medline: 15851636]
4. Tobaldini E, Costantino G, Solbiati M, Cogliati C, Kara T, Nobili L, et al. Sleep, sleep deprivation, autonomic nervous system and cardiovascular diseases. Neurosci Biobehav Rev 2017;74(Pt B):321-329. [doi: 10.1016/j.neubiorev.2016.07.004] [Medline: 27397854]
5. Nano MM, Fonseca P, Vullings R, Aarts RM. Measures of cardiovascular autonomic activity in insomnia disorder: a systematic review. PLoS One 2017;12(10):e0186716 [FREE Full text] [doi: 10.1371/journal.pone.0186716] [Medline: 29059210]

6. The 1st study group on revision of sleep guidelines for health promotion. Ministry of Health, Labour and Welfare (2023). 2023. URL: https://www.mhlw.go.jp/content/10904750/001126766.pdf [accessed 2023-08-01]
7. de Zambotti M, Yuksel D, Kiss O, Barresi G, Arra N, Volpe L, et al. A virtual reality-based mind-body approach to downregulate psychophysiological arousal in adolescent insomnia. Digit Health 2022;8:20552076221107887 [FREE Full text] [doi: 10.1177/20552076221107887] [Medline: 35733879]
8. Laborde S, Allen MS, Borges U, Dosseville F, Hosang TJ, Iskra M, et al. Effects of voluntary slow breathing on heart rate and heart rate variability: a systematic review and a meta-analysis. Neurosci Biobehav Rev 2022;138:104711. [doi: 10.1016/j.neubiorev.2022.104711] [Medline: 35623448]
9. Laborde S, Hosang T, Mosley E, Dosseville F. Influence of a 30-day slow-paced breathing intervention compared to social media use on subjective sleep quality and cardiac vagal activity. J Clin Med 2019;8(2):193 [FREE Full text] [doi: 10.3390/jcm8020193] [Medline: 30736268]
10. Kabat-Zinn J. Full Catastrophe Living: Using the Wisdom Books of Your Bodymind to Face Stress, Pain, Illness. New York, NY: Delacorte Press, Random House Publishing Group; 1990.
11. Conghui F, Ying X, Wei S, Jing W, Zhifang L, Qian Z. Effects of mindfulness-based stress reduction on mood disorders and sleep in patients with Alzheimer's disease in the context of COVID-19. J Diagn Concepts Pract 2022;21(01):46-51.
12. Jiang A, Rosario M, Stahl S, Gill JM, Rusch HL. The effect of virtual mindfulness-based interventions on sleep quality: a systematic review of randomized controlled trials. Curr Psychiatry Rep 2021;23(9):62 [FREE Full text] [doi: 10.1007/s11920-021-01272-6] [Medline: 34297230]
13. Brand S, Holsboer-Trachsler E, Naranjo JR, Schmidt S. Influence of mindfulness practice on cortisol and sleep in long-term and short-term meditators. Neuropsychobiology 2012;65(3):109-118. [doi: 10.1159/000330362] [Medline: 22377965]
14. Oriyama S, Miyakoshi Y, Kayahara M. Characteristics of sleep states, sleepiness and fatigue among nurses working in 12-hour double shifts. J Jpn Acad Nurs Sci 2019;39:19-28 [FREE Full text] [doi: 10.5630/jans.39.19]
15. Nano M, Fonseca P, Overeem S, Vullings R, Aarts RM. Lying awake at night: cardiac autonomic activity in relation to sleep onset and maintenance. Front Neurosci 2019;13:1405 [FREE Full text] [doi: 10.3389/fnins.2019.01405] [Medline: 32009886]
16. Firth J, Torous J, Nicholas J, Carney R, Pratap A, Rosenbaum S, et al. The efficacy of smartphone-based mental health interventions for depressive symptoms: a meta-analysis of randomized controlled trials. World Psychiatry 2017;16(3):287-298 [FREE Full text] [doi: 10.1002/wps.20472] [Medline: 28941113]
17. González-Martín AM, Aibar-Almazán A, Rivas-Campo Y, Marín-Gutiérrez A, Castellote-Caballero Y. Effects of mindfulness-based cognitive therapy on older adults with sleep disorders: a systematic review and meta-analysis. Front Public Health 2023;11:1242868 [FREE Full text] [doi: 10.3389/fpubh.2023.1242868] [Medline: 38179560]
18. Ong JC, Moore C. What do we really know about mindfulness and sleep health? Curr Opin Psychol 2020;34:18-22. [doi: 10.1016/j.copsyc.2019.08.020] [Medline: 31539830]
19. Tobaldini E, Nobili L, Strada S, Casali KR, Braghiroli A, Montano N. Heart rate variability in normal and pathological sleep. Front Physiol 2013;4:294 [FREE Full text] [doi: 10.3389/fphys.2013.00294] [Medline: 24137133]
20. Al Ashry HS, Ni Y, Thomas RJ. Cardiopulmonary sleep spectrograms open a novel window into sleep biology-implications for health and disease. Front Neurosci 2021;15:755464 [FREE Full text] [doi: 10.3389/fnins.2021.755464] [Medline: 34867165]
21. De Fazio R, Mattei V, Al-Naami B, De Vittorio M, Visconti P. Methodologies and wearable devices to monitor biophysical parameters related to sleep dysfunctions: an overview. Micromachines (Basel) 2022;13(8):1335 [FREE Full text] [doi: 10.3390/mi13081335] [Medline: 36014257]
22. Dodds KL, Miller CB, Kyle SD, Marshall NS, Gordon CJ. Heart rate variability in insomnia patients: a critical review of the literature. Sleep Med Rev 2017;33:88-100. [doi: 10.1016/j.smrv.2016.06.004] [Medline: 28187954]
23. Kuula L, Pesonen AK. Heart rate variability and firstbeat method for detecting sleep stages in healthy young adults: feasibility study. JMIR mHealth uHealth 2021;9(2):e24704 [FREE Full text] [doi: 10.2196/24704] [Medline: 33533726]
24. Correia ATL, Lipinska G, Rauch HGL, Forshaw PE, Roden LC, Rae DE. Associations between sleep-related heart rate variability and both sleep and symptoms of depression and anxiety: a systematic review. Sleep Med 2023;101:106-117. [doi: 10.1016/j.sleep.2022.10.018] [Medline: 36370515]
25. Kerkering EM, Greenlund IM, Bigalke JA, Migliaccio GCL, Smoot CA, Carter JR. Reliability of heart rate variability during stable and disrupted polysomnographic sleep. Am J Physiol Heart Circ Physiol 2022;323(1):H16-H23 [FREE Full text] [doi: 10.1152/ajpheart.00143.2022] [Medline: 35559723]
26. Herzig D, Eser P, Omlin X, Riener R, Wilhelm M, Achermann P. Reproducibility of heart rate variability is parameter and sleep stage dependent. Front Physiol 2018;8:1100 [FREE Full text] [doi: 10.3389/fphys.2017.01100] [Medline: 29367845]
27. Kuula L, Halonen R, Kajanto K, Lipsanen J, Makkonen T, Peltonen M, et al. The effects of presleep slow breathing and music listening on polysomnographic sleep measures—a pilot trial. Sci Rep 2020;10(1):7427 [FREE Full text] [doi: 10.1038/s41598-020-64218-7] [Medline: 32366866]
28. Ludwig DS, Kabat-Zinn J. Mindfulness in medicine. JAMA 2008;300(11):1350-1352. [doi: 10.1001/jama.300.11.1350] [Medline: 18799450]

29. Villa MP, Calcagnini G, Pagani J, Paggi B, Massa F, Ronchetti R. Effects of sleep stage and age on short-term heart rate variability during sleep in healthy infants and children. Chest 2000;117(2):460-466. [doi: 10.1378/chest.117.2.460] [Medline: 10669691]
30. Kondo K, Asawa T. Experimental study on sleep quality in naturally ventilated rooms under moderate climate conditions. Indoor Air 2023;2023:8853643 [FREE Full text] [doi: 10.1155/2023/8853643]
31. Pomeranz B, Macaulay RJ, Caudill MA, Kutz I, Adam D, Gordon D, et al. Assessment of autonomic function in humans by heart rate spectral analysis. Am J Physiol 1985 Jan;248(1 Pt 2):H151-H153. [doi: 10.1152/ajpheart.1985.248.1.H151] [Medline: 3970172]
32. Hayano J, Yuda E. Assessment of autonomic function by long-term heart rate variability: beyond the classical framework of LF and HF measurements. J Physiol Anthropol 2021;40(1):21 [FREE Full text] [doi: 10.1186/s40101-021-00272-y] [Medline: 34847967]
33. Cole RJ, Kripke DF, Gruen W, Mullaney DJ, Gillin JC. Automatic sleep/wake identification from wrist activity. Sleep 1992;15(5):461-469. [doi: 10.1093/sleep/15.5.461] [Medline: 1455130]
34. Suzuki T, Ouchi K, Kameyama K, Takahashi M. Development of a sleep monitoring system with wearable vital sensor for home use. 2009 Presented at: International Conference on Biomedical Electronics and Devices; 2009; Porto, Portugal p. 326-331. [doi: 10.5220/0001784203260331]
35. Peters AL, Saunders WJ, Jackson ML. Mindfulness-based strategies for improving sleep in people with psychiatric disorders. Curr Psychiatry Rep 2022;24(11):645-660 [FREE Full text] [doi: 10.1007/s11920-022-01370-z] [Medline: 36227451]
36. Krygier JR, Heathers JA, Shahrestani S, Abbott M, Gross JJ, Kemp AH. Mindfulness meditation, well-being, and heart rate variability: a preliminary investigation into the impact of intensive Vipassana meditation. Int J Psychophysiol 2013;89(3):305-313. [doi: 10.1016/j.ijpsycho.2013.06.017] [Medline: 23797150]
37. Berntson GG, Cacioppo JT, Quigley KS. Autonomic determinism: the modes of autonomic control, the doctrine of autonomic space, and the laws of autonomic constraint. Psychol Rev 1991;98(4):459-487. [doi: 10.1037/0033-295x.98.4.459] [Medline: 1660159]
38. Nijjar PS, Puppala VK, Dickinson O, Duval S, Duprez D, Kreitzer MJ, et al. Modulation of the autonomic nervous system assessed through heart rate variability by a mindfulness based stress reduction program. Int J Cardiol 2014;177(2):557-559. [doi: 10.1016/j.ijcard.2014.08.116] [Medline: 25179555]

Abbreviations

HF: high frequency
HRV: heart rate variability
LF: low frequency
Mi: mindfulness group
MBSR: mindfulness-based stress reduction
nMi: nonmindfulness group
PS sleep (deep): deep sleep with parasympathetic nerve dominance
PS sleep (shallow): shallow sleep with parasympathetic nerve dominance
RRI: R-R interval
S sleep: sleep with sympathetic nerve dominance

Edited by E Borycki; submitted 22.01.24; peer-reviewed by A Hassan, Q Chen, RS Gomaa Mahmoud; comments to author 03.04.24; revised version received 28.04.24; accepted 08.05.24; published 12.06.24.

Please cite as:
Togo E, Takami M, Ishigaki K
Evaluation of Autonomic Nervous System Function During Sleep by Mindful Breathing Using a Tablet Device: Randomized Controlled Trial
JMIR Nursing 2024;7:e56616
URL: https://nursing.jmir.org/2024/1/e56616
doi:10.2196/56616
PMID:38865177

Original Paper

mHealth Gratitude Exercise Mindfulness App for Resiliency Among Neonatal Intensive Care Unit Staff: Three-Arm Pretest-Posttest Interventional Study

Neil E Peterson[1], MSN, PhD; Michael Thomas[1], MSN, DNP; Stacie Hunsaker[1], MSN, DNP; Tevin Stewart[2], BS, MHA; Claire J Collett[1], BS

[1]College of Nursing, Brigham Young University, Provo, UT, United States
[2]Senda LLC, Seattle, WA, United States

Corresponding Author:
Neil E Peterson, MSN, PhD
College of Nursing
Brigham Young University
500 Spencer West Kimball Tower (KMBL)
Provo, UT, 84602
United States
Phone: 1 8014224893
Email: neil-peterson@byu.edu

Abstract

Background: Health care is highly complex and can be both emotionally and physically challenging. This can lead health care workers to develop compassion fatigue and burnout (BO), which can negatively affect their well-being and patient care. Higher levels of resilience can potentially prevent compassion fatigue and BO. Strategies that enhance resilience include gratitude, exercise, and mindfulness.

Objective: The purpose of this study was to determine if a 3-week daily resiliency practice, prompted via a gratitude, exercise, and mindfulness smartphone app, impacted the professional quality of life, physical activity, and happiness level of health care workers in a newborn intensive care unit setting.

Methods: In total, 65 participants from a level III newborn intensive care unit at a regional hospital in the western United States completed this study. The Professional Quality of Life Scale, Physical Activity Vital Sign, and Subjective Happiness Score instruments were used to evaluate the effects of the mobile health (mHealth) intervention. Further, 2-tailed dependent paired *t* tests were used to evaluate participant pre- and postintervention instrument scores. Multiple imputation was used to predict scores of participants who practiced an intervention but did not complete the 3 instruments post intervention.

Results: Dependent *t* tests using the original data showed that participants, as a whole, significantly improved in BO (t_{35}=2.30, P=.03), secondary trauma stress (STS; t_{35}=2.11, P=.04), and happiness (t_{35}=–3.72, P<.001) scores. Compassion satisfaction (CS; t_{35}=–1.94, P=.06) and exercise (t_{35}=–1.71, P=.10) were trending toward, but did not reach, significance. Using the original data, only the gratitude intervention group experienced significant improvements (CS, BO, and happiness), likely due to the higher number of participants in this group. Analysis using imputed data showed that participants, as a whole, had significant improvements in all areas: CS (t_{64}=–4.08, P<.001), BO (t_{64}=3.39, P=.001), STS (t_{64}=4.08, P<.001), exercise (t_{64}=–3.19, P=.002), and happiness (t_{64}=–3.99, P<.001). Looking at the intervention groups separately using imputed data, the gratitude group had significant improvements in CS, BO, STS, and happiness; the exercise group had significant improvements in STS and exercise; and the mindfulness group had significant improvements in CS and happiness.

Conclusions: Phone app delivery of resilience-enhancing interventions is a potentially effective intervention model for health care workers. Potential barriers to mHealth strategies are the technical issues that can occur with this type of intervention. Additional longitudinal and experimental studies with larger sample sizes need to be completed to better evaluate this modality.

(JMIR Nursing 2024;7:e54561) doi:10.2196/54561

KEYWORDS

burnout; compassion fatigue; compassion satisfaction; secondary trauma; trauma; satisfaction; compassion; gratitude; resilience; quality of life; QoL; mindfulness; meditation; exercise; happiness; mHealth; mobile health; app; apps; applications; neonatal intensive care unit; NICU; intensive care unit; ICU; intensive care; nurse; nurses; nursing; health care worker; health care workers; provider; providers; phone app; physical activity; resiliency; mobile phone

Introduction

Background

Being a nurse is physically and emotionally demanding. Enormous pressure, including overwork, frustration, isolation, and exhaustion from long shifts cause stress, anxiety, and depressive symptoms among health care workers. These psychological stressors not only affect health care workers' ability to provide competent care but could also have a lasting impact on overall well-being [1]. Compassion fatigue (CF), burnout (BO), and high stress are conditions that can become overwhelming burdens and can cause physical, mental, and emotional difficulties [2,3]. For example, nurses affected by CF may experience dissatisfaction with care, decreased empathy, intolerance to patients, medical mistakes, and leaving the profession [4]. CF and BO may cause a wide range of physical, emotional, and work-related problems that affect both the caregiver and the patient. Medication errors and overall patient safety perceived by nurses have been linked to CF and BO [5]. Nurses who exhibit these negative characteristics may reduce the quality of care, patient safety perceptions, and unit-level safety perceptions [6]. Additionally, elevated levels of BO have been associated with patient dissatisfaction and patient safety concerns [7]. Therefore, it is imperative to address BO and CF as they impact health care workers, patients, and health care systems.

Some nurses are naturally resilient and adapt to stressful work experiences well. Others struggle and strain and may benefit from positive psychology interventions that help build resilience. Resilience is a psychological attribute that is not only intrinsic but can also be learned. It has been recognized as one of the most critical factors in maintaining mental health and psychological well-being among health care workers [8]. Moreover, nurses with high psychological resilience can overcome adversity and adapt to pressures at work [9]. Research supports that individuals can improve their levels of happiness with various emotional management skills [10]. The focus of this study was to empower health care workers to learn skills that may help them cope with working in a high-stress, emotional environment.

Strategies

Self-care strategies can improve the personal and professional quality of life (ProQOL) of nurses and other health care staff. Further, 3 common interventions to help enhance happiness and resiliency levels include gratitude, exercise, and mindfulness.

First, the simple act of purposefully and consistently expressing gratitude has been found to help people have a greater sense of social cohesion, health, and wellness and is critical to improving well-being [11]. Researchers have known for a long time that expressing gratitude positively affects an individual's ability to cope and adapt to challenging circumstances [12]. Recent studies reaffirm that gratitude journals can help nurses by improving stress management skills and providing an outlet for self-reflection [13]. Not only does expressing gratitude have a profound effect on the individuals exercising it, but it also influences the people around that individual. Grateful people also improve the environment for others, effectively improving group happiness levels [14].

Second, the positive effects of physical activity on mental health are well-established. Research since the 1990s has established exercise as a simple and effective way to improve many aspects of mental health [15]. Health care givers benefit from exercise as they deal with work stress. Lack of regular exercise may predict the intention to leave work [16]. Recent evidence suggests physical activity can come in various forms, such as daily walks through a hospital garden during work breaks [17] or more structured exercise protocols as part of resilience training [18].

Third, nurses can directly benefit from learning and implementing stress management techniques. Mindfulness through guided meditation is 1 method that has a positive impact [19]. Mindfulness has been shown to help individuals become more self-aware, more open, more accepting of difficult situations, and have more peace. All of these qualities are essential in the prevention of stress and CF in health care workers. Mindfulness is an effective intervention to help improve the ProQOL of health care workers and, because of the link between BO and patient care, may result in more compassionate and patient-centered care [20].

Delivery of resiliency practices is traditionally done during in-person training. However, mHealth delivery of resiliency practices is another option that is effective in many areas including improving mental health and reducing BO in health care professionals [21]. The purpose of this study was to determine if a 3-week daily resiliency practice, prompted via a gratitude, exercise, and mindfulness smartphone app (GEM app), impacted ProQOL, physical activity, and the happiness level of health care workers in a newborn intensive care unit (NICU) setting.

Methods

Ethical Considerations

The Intermountain Healthcare's institutional review board completed and approved the human subjects research ethics review (1051038). Participation was voluntary and participants could withdraw at any time. Compensation of US $25 to a web-based shopping site was given to any participant who completed the prestudy questionnaires. Participants who also completed the poststudy questionnaires were entered into a drawing for a US $100 spa gift card. Participants were assigned code numbers for all data entry purposes. The participant-to-code number list was then destroyed after all study data had been collected. For participant protection, quantitative data are reported in aggregate.

Sample and Setting

Researchers partnered with a level III, 55-bed NICU at a large local hospital. Institutional review board approval was granted by the hospital system. The NICU had an estimated 160 staff members, counting full-time, part-time, and per diem staff. All adults aged 18 years and older who worked in the NICU with a smartphone compatible with the app were eligible to be in this study. G*Power (version 3.1.9.2; Heinrich-Heine-Universität Düsseldorf) [22] was used to estimate a sufficient sample size for using dependent paired *t* tests, assuming 2-tailed significance, with 80% power and α of .05 with effect size of 0.5. With these assumptions, and treating each group separately, 34 participants were needed for each intervention.

Data Collection

Recruitment and data collection occurred over 3 months. Before distributing the app, research staff attended several staff meetings to introduce this study to potential participants. Recruitment flyers were posted on the unit with a QR code to download the GEM app. All NICU employees received an email that described this study and included a link to download the iPhone or Android version of the GEM app. Potential participants downloaded the phone app and provided informed consent via the app. After providing consent, study participants completed basic demographic questions and 3 instruments: ProQOL scale, Physical Activity Vital Sign (PAVS), and Subjective Happiness Score (SHS). The GEM app then directed participants to choose 1 of 3 evidence-based resilience interventions: a daily gratitude journal, regular exercise, or mindfulness meditation. The GEM app provided participants daily notification reminders, at a time set by each participant on the app, to engage in their chosen resilience intervention. Participants charted daily completion of their chosen intervention in the GEM app. After 21 days, participants were then prompted to complete the ProQOL, PAVS, and SHS instruments again. The GEM app securely sent all data to a private database maintained by the hospital system.

Instruments

About ProQOL

ProQOL was used to measure both the negative and positive effects of helping others who experience suffering and trauma. ProQOL consists of 30 questions separated into 3 subscales compassion satisfaction (CS), BO, and secondary trauma stress (STS). STS is a measure for CF. The reliability of ProQOL is well-documented and has established its reliability with previous research. It reports a Cronbach score ranging from .71 to .88 [23].

About PAVS

PAVS is a validated tool that uses self-reporting to measure exercise levels [24]. PAVS consists of only two questions: (1) on average, how many days per week do you engage in moderate to strenuous physical activity (like a brisk walk)? and (2) on average, for how many minutes do you participate in physical activity at this level? Responses to these questions are then multiplied together to get an estimate of the total number of minutes of physical activity for an average week. Lower scores on the PAVS have been correlated with higher BMI and disease burden [25].

About SHS

SHS is a 4-item self-rated measure of general happiness. This instrument has good internal consistency with a Cronbach score ranging from .79 to .94. Test-retest reliability ranged from 0.55 to 0.90, and this instrument was found to have good construct validity [26].

Data Analysis

Demographics were analyzed using simple descriptive statistics with univariate analysis. Dependent paired *t* tests were done to determine whether the individual interventions impacted participant ProQOL, PAVS, and SHS scores. As this was a pilot study, we did not expect to be fully powered. Thus, missing instrument data were handled using multiple imputations and analyses using original data and imputed data were compared.

Results

Demographics

In total, 83 participants downloaded the GEM app and consented to participate in this study. Of those who consented, 65 participants completed their demographics, the 3 instruments, and selected an intervention. After this study, 29 participants did not fully complete the 3 instruments. More participants chose the gratitude intervention (n=32, 49%) than exercise (n=14, 22%) or mindfulness (n=19, 29%). All participants selecting an intervention were women and averaged 1.0 year (SD 8.8 years) of experience on the unit. On average, participants completed their daily intervention on 15.4 out of 21 (73%) days (Table 1).

Table 1. Demographics and study characteristics.

Characteristic	Participants, n (%)
Intervention	
Gratitude	32 (49)
Exercise	14 (22)
Mindfulness	19 (29)
Gender	
Women	65 (100)
Unit position	
Registered nurse	55 (85)
Health unit coordinator	5 (8)
Critical care technician	4 (6)
Occupational therapist	1 (2)
Age (y), mean (SD, minimum-maximum)	37.9 (10.9, 22-61)
Years working in the unit, mean (SD, minimum-maximum)	1.0 (8.8, 0-39)
Number of days doing intervention, mean (SD, minimum-maximum)	15.4 (7.7, 1-21)

Attrition and Missing Data

A high number of participants dropped out after downloading the app (21.7%). As this was a pilot study, the decision was made to compare the original data to an imputed data set as an estimate if participants had completed all questionnaires. SPSS (version 25; IBM Corp) was used to perform multiple imputation, using 5 iterations and auto method, on the 29 (44%) participants who practiced an intervention but did not fully complete the 3 instruments on follow-up at the end of this study. Dependent *t* tests were conducted on both the original and the imputed data (Table 2).

Table 2. Instrument scores by group.

Group	Original data					Multiple imputation data				
	Participants, n	Pre mean (SD)	Post mean (SD)	2-tailed *t* test[a] (*df*)	*P* value	Participants, n	Pre mean (SD)	Post mean (SD)	2-tailed *t* test (*df*)	*P* value
Gratitude group	18					32				
ProQOL[b]										
Comp. satis.[c]		38.8 (4.6)	40.4 (6.2)	–2.40 (17)	.05		38.3 (4.8)	40.1 (5.7)	–3.88 (31)	<.001
Burnout		24.3 (5.4)	21.9 (5.6)	2.12 (17)	.05		25.0 (5.2)	23.1 (5.5)	2.99 (31)	.005
2° trauma[d]		23.2 (5.6)	21.6 (5.2)	1.10 (17)	.29		24.4 (6.2)	22.1 (5.8)	2.68 (31)	.01
PAVS[e]										
MVPA[f] min/wk		86.9 (87.8)	117.5 (147.5)	–1.04 (17)	.32		100.5 (95.2)	130.3 (128.4)	–1.81 (31)	.08
SHS[g]										
Happiness		4.8 (1.3)	5.3 (1.3)	–4.04 (17)	<.001		4.8 (1.1)	5.2 (1.4)	–3.13 (31)	.004
Exercise group	7					14				
ProQOL										
Comp. satis.		45.0 (4.4)	44.7 (4.8)	0.16 (6)	.88		42.1 (6.7)	42.6 (6.7)	–0.51 (13)	.62
Burnout		19.7 (4.6)	19.7 (5.6)	0.00 (6)	1.00		23.2 (6.7)	22.2 (6.2)	1.20 (13)	.25
2° trauma		22.4 (6.0)	19.1 (6.1)	2.33 (6)	.06		23.8 (6.3)	21.1 (6.7)	3.52 (13)	.004
PAVS										
MVPA min/wk		74.3 (65.2)	125.7 (51.3)	–1.78 (6)	.13		68.6 (59.6)	108.5 (56.8)	–2.78 (13)	.02
SHS										
Happiness		5.5 (0.9)	5.5 (1.2)	0.00 (6)	1.00		5.1 (1.2)	5.2 (1.2)	–0.97 (13)	.35
Mindfulness group	11					19				
ProQOL										
Comp. satis.		36.7 (5.4)	38.0 (5.9)	–1.21 (10)	.26		37.3 (5.2)	38.9 (5.4)	–2.57 (18)	.02
Burnout		27.5 (6.2)	25.8 (5.5)	1.27 (10)	.23		26.5 (5.5)	25.4 (5.3)	1.27 (18)	.22
2° trauma		28.1 (7.2)	26.2 (7.2)	0.98 (10)	.35		27.4 (6.9)	25.5 (7.5)	1.68 (18)	.11
PAVS										
MVPA min/wk		90.5 (113.9)	10.0 (122.4)	–0.55 (10)	.59		107.6 (99.7)	127.4 (109.2)	–1.92 (18)	.07
SHS										
Happiness		4.2 (1.2)	4.6 (0.8)	–1.75 (10)	.11		4.6 (1.2)	5.0 (1.2)	–2.32 (18)	.03
Total, all groups	36					65				
ProQOL										
Comp. satis.		39.4 (5.6)	40.5 (6.2)	–1.94 (35)	.06		38.8 (5.6)	40.3 (6.2)	–4.08 (64)	<.001
Burnout		24.4 (6.0)	22.7 (5.9)	2.30 (35)	.03		25.0 (5.7)	23.6 (5.7)	3.39 (64)	.001
2° trauma		24.5 (6.5)	22.5 (6.4)	2.11 (35)	.04		25.1 (6.5)	22.9 (6.6)	4.08 (64)	<.001
PAVS										

Group	Original data					Multiple imputation data				
	Participants, n	Pre mean (SD)	Post mean (SD)	2-tailed t test[a] (df)	P value	Participants, n	Pre mean (SD)	Post mean (SD)	2-tailed t test (df)	P value
MVPA min/wk		85.6 (90.6)	113.8 (124.1)	–1.71 (35)	.10		95.7 (90.1)	124.8 (109.8)	–3.19 (64)	.002
SHS										
Happiness		4.7 (1.3)	5.1 (1.2)	–3.72 (35)	<.001		4.8 (1.2)	5.1 (1.3)	–3.99 (64)	<.001

[a] The t test was 2-tailed.

[b] ProQOL: Professional Quality of Life instrument with subscales of compassion satisfaction, burnout, and secondary trauma stress.

[c] Comp. satis.: compassion satisfaction.

[d] 2° Trauma: secondary trauma stress.

[e] PAVS: Physical Activity Vital Sign instrument.

[f] MVPA: moderate-to-vigorous physical activity, measured in minutes per week.

[g] SHS: Subjective Happiness Scale.

Overall Scores

In total, 36 participants had fully complete pre- and postdata in this study. Dependent t tests using the original data showed that this group significantly improved their BO (t_{35}=2.30, P=.03), STS (t_{35}=2.11, P=.04), and happiness (t_{35}=–3.72, P<.01) scores. CS (t_{35}=–1.94, P=.06) and exercise (t_{35}=–1.71, P=.10) were trending toward, but did not reach significance. Using the imputed data increased the usable sample size to 65. Analysis of this imputed data showed that all areas had significant improvement (Table 2).

Gratitude

In total, 32 participants selected the daily gratitude intervention. Of those 32, 18 had complete pre- and postdata. Dependent t tests using the original data showed this group significantly improved their CS (t_{17}=–2.14, P=.05), BO (t_{17}=2.12, P=.05), and happiness (t_{17}=–4.04, P<.001) scores. Using the imputed data increased the sample size to 32. CS (t_{31}=–3.88, P<.001), BO (t_{31}=2.99, P=.005), ST (t_{31}=2.68, P=.01), and happiness (t_{31}=–3.13, P=.004) all significantly improved. Exercise was trending toward, but did not reach, significance (t_{31}=–1.81, P=.08; see Table 2).

Exercise

Further, 14 participants selected the daily exercise intervention. Of those 14, 7 had complete pre- and postdata. Dependent t tests using the original data showed this group did not significantly change any of their scores on ProQOL, PAVS, or SHS though ST was almost significant (t_6=2.33, P=.06). Using the imputed data increased the sample size to 14. This resulted in significant improvements in ST (t_{13}=3.52, P=.004) and exercise (t_{13}=–2.78, P=.02) but not the other measures (Table 2).

Mindfulness

Further, 19 participants selected the daily mindfulness intervention. Of those 19, 11 had complete pre- and postdata. Dependent t tests using the original data showed that this group did not significantly change any of their scores on ProQOL, PAVS, or SHS. Using the imputed data increased the sample size to 19. This resulted in significant improvements in CS (t_{18}=–2.57, P=.02) and happiness (t_{18}=–2.32, P=.03). Exercise was trending toward, but did not reach, significance (t_{18}=–1.92, P=.07; Table 2).

Effect Sizes

Cohen d was calculated using original and imputed data to estimate the effect size of the GEM app as a whole (combining all intervention group data into one). Using the original data, effect sizes were generally in the low-to-medium range (CS=0.32, BO=0.38, STS=0.35, PAVS=0.29) with one in the medium-to-high range (SHS=0.62). Estimating the effect size using imputed data increased across most measures (CS=0.51, BO=0.42, STS=0.51, PAVS=0.40) except one (SHS=0.49).

Discussion

Principal Findings

Overall, this pilot study found that resiliency interventions delivered via mHealth technology are a promising way to improve the well-being of health care workers. When considering only participants who had complete pre- and postdata, only the gratitude intervention group had significant findings (CS, BO, and happiness). When analyzing the imputed data, all intervention groups had significant findings, with the gratitude group experiencing the most significant improvements. It is possible the higher number of participants contributed to the more significant findings of this group. Conversely, the exercise intervention group had the least number of participants. Further, one reason this group may have had fewer numbers is because of the perceived difficulty in comparison to other choices. This would resemble a similar experience by Torquati et al [27] who found nurses were more likely to focus on improving dietary choices rather than physical activity. Despite the lower numbers, those in the exercise group likely made an appropriate choice given that this group had lower average moderate-to-vigorous physical activity at baseline (74.3 min/wk) compared to the gratitude (86.9 min/wk) and mindfulness (90.5 min/wk) groups.

This study strengthens the research that novel delivery of resiliency practices is acceptable to clients and can be used to benefit workers in the high-stress health care environment. For example, Rao and Kemper [28] found that 1-time delivered online training modules for health care workers were well-received and were related to improved gratitude and compassion. Longer-term delivery can also be successful. In another study, a smartphone-delivered mindfulness practice over 3 months provided some benefit to novice nurses over in-person training [29]. Delivery of resiliency practices can also be successfully implemented in other ways. Using gamification and positive competition to recognize the good work of fellow health care coworkers improved gratitude and Press Ganey scores over 18 months [30]. Torquati et al [27] found some success in implementing a phone app combined with a Facebook group to motivate nurses to make positive dietary and physical activity changes over 3 months. While dietary changes were significantly improved, physical activity significantly worsened. Participants reported that trying to improve 2 behaviors at the same time was difficult. In the present study, participants could only choose 1 of the 3 resiliency interventions to follow. As the GEM app improves and research moves beyond the pilot stage, assessing if having multiple intervention offerings is counterproductive will be important to evaluate. Currently, adaptions are already being made to use the GEM app in different contexts, such as for patients who have traumatic brain injury and with millennial caregivers [31].

Researchers considering using mHealth to enhance their studies and improve client outcomes must realize and account for setbacks in preparation and implementation. Development of the GEM app took over double the anticipated amount of time to complete. Further, until recently, most app development had to be done separately for Apple iOS and Android. Now, common programming languages are appearing that make developing for both platforms at the same time possible. This also allows for apps to appear the same on both platforms. Since this was not a possibility when the GEM app was developed, the Apple iOS and Android apps differed in their appearance. The research team attended several staff meetings, posted flyers with QR codes that enabled participants to directly download the app to their phones, and were present in the unit break room at shift change for several days. Despite this preparation, multiple participants struggled with getting started. Having a preassigned research team member providing technical support and establishing an “app support email” was helpful, but this did not resolve all participant issues with the GEM app. Technical issues like this may have contributed to the number of participants who did not fully complete this study.

Imputing data is 1 way to “fill in the gaps” and give a statistical estimation. Although imputing less than 40% is optimal [32], some variables in this study needed up to 44.6% imputation. While this statistical procedure is acceptable for making estimations in a pilot study, going forward we will need to implement strategies to reduce the likelihood of needing this and increase power through adequate participants.

Conclusion

The purpose of this study was to teach nurses, and other health care staff, evidence-based self-care interventions. Overall, the 3-week daily resiliency practice delivered via the GEM app seemed to positively impact several well-being aspects in NICU health care workers. Practicing these evidence-based interventions can help individuals in similar high-stress work environments experience greater levels of well-being and resilience. While there are multiple positive studies demonstrating the benefits of these self-care interventions, many health care workers do not regularly practice them. This study shows the potential use of mHealth strategies to deliver and develop resiliency habits, such as through the GEM app. Enhancing health care staff resilience can reduce their risk for BO and improve well-being, while also potentially improving the quality of care provided to patients.

Acknowledgments

Funding for this study was provided by the Myrtie Fulton Endowed Mentorship Award, an intramural grant through Brigham Young University College of Nursing.

Data Availability

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

Conflicts of Interest

None declared.

References

1. Kang L, Li Y, Hu S, Chen M, Yang C, Yang BX, et al. The mental health of medical workers in Wuhan, China dealing with the 2019 novel coronavirus. Lancet Psychiatry 2020;7(3):e14 [FREE Full text] [doi: 10.1016/S2215-0366(20)30047-X] [Medline: 32035030]
2. Medina-Fernández J, Torres-Soto N, Casco-Gallardo K, Ruiz-Lara A, Martínez-Ramírez B, Fuentes-Fernández E. Fear and Coping with Death in Intensive Care Nurses: a Structural Model Predictor of Compassion Fatigue. Invest Educ Enferm 2023;41(1):e12 [FREE Full text] [doi: 10.17533/udea.iee.v41n1e12] [Medline: 37071867]

3. McKinless E. Impact of stress on nurses working in the district nursing service. Br J Community Nurs 2020;25(11):555-561. [doi: 10.12968/bjcn.2020.25.11.555] [Medline: 33161741]
4. Günüşen NP, Wilson M, Aksoy B. Secondary Traumatic Stress and Burnout Among Muslim Nurses Caring for Chronically Ill Children in a Turkish Hospital. J Transcult Nurs 2018;29(2):146-154. [doi: 10.1177/1043659616689290] [Medline: 28826329]
5. Sováriová Soósová M. Association between nurses' burnout, hospital patient safety climate and quality of nursing care. Cent Eur J Nurs Midw 2021;12(1):245-256 [FREE Full text] [doi: 10.15452/cejnm.2020.11.0039]
6. Dall'Ora C, Ball J, Reinius M, Griffiths P. Burnout in nursing: a theoretical review. Hum Resour Health 2020;18(1):41 [FREE Full text] [doi: 10.1186/s12960-020-00469-9] [Medline: 32503559]
7. Quigley DD, Slaughter ME, Qureshi N, Gidengil C, Hays RD. Associations of pediatric nurse burnout with involvement in quality improvement. J Pediatr Nurs 2023;70:e9-e16. [doi: 10.1016/j.pedn.2022.11.001] [Medline: 36402601]
8. Labrague LJ, De Los Santos JAA, Falguera CC. Social and emotional loneliness among college students during the COVID-19 pandemic: The predictive role of coping behaviors, social support, and personal resilience. Perspect Psychiatr Care 2021;57(4):1578-1584. [doi: 10.1111/ppc.12721] [Medline: 33410143]
9. Wang H, Rosa RDD. Situational Analysis of Influencing Factors of the Psychological Resilience of Junior Nurses at a Tertiary Hospital in Linfen City, Shanxi Province, China. Afr J Nurs Midwifery 2023;24(3):14. [doi: 10.25159/2520-5293/12200]
10. Terzi B, Polat Ş, Afşar Doğrusöz L. The relationships between novice nurses' emotions management skills and happiness levels: A cross-sectional study. Perspect Psychiatr Care 2022;58(4):3024-3033. [doi: 10.1111/ppc.13142] [Medline: 35932234]
11. Maksutova M, Kemp MT, Sharma SB, Shen M, Leininger L, Singer AA, et al. "You've Got Gratitude!"- A Multispecialty and Multi-institution Program Encouraging Expressions of Gratitude. J Surg Educ 2023;80(12):1741-1744. [doi: 10.1016/j.jsurg.2023.08.009] [Medline: 37723013]
12. Radloff LS. The CES-D Scale: a self-report depression scale for research in the general population. Appl Psychol Meas 1977;1(3):385-401. [doi: 10.1177/014662167700100306]
13. Cumella K. Gratitude journals can improve nurses' mental well-being. Nursing 2022;52(12):58-61. [doi: 10.1097/01.NURSE.0000884760.97338.8b] [Medline: 36394628]
14. Lyubomirsky S. The How of Happiness: A Practical Guide to Getting the Life You Want. London: Piatkus; 2010.
15. Stathopoulou G, Powers MB, Berry AC, Smits JAJ, Otto MW. Exercise interventions for mental health: a quantitative and qualitative review. Clin Psychol Sci Pract 2006;13(2):179-193. [doi: 10.1111/j.1468-2850.2006.00021.x]
16. Guo YF, Plummer V, Lam L, Wang Y, Cross W, Zhang JP. The effects of resilience and turnover intention on nurses' burnout: findings from a comparative cross-sectional study. J Clin Nurs 2019 Feb;28(3-4):499-508. [doi: 10.1111/jocn.14637] [Medline: 30091259]
17. Cordoza M, Ulrich RS, Manulik BJ, Gardiner SK, Fitzpatrick PS, Hazen TM, et al. Impact of nurses taking daily work breaks in a hospital garden on burnout. Am J Crit Care 2018 Nov;27(6):508-512. [doi: 10.4037/ajcc2018131] [Medline: 30385543]
18. Terkes N, Aksu NT, Yamac SU. The effect of an online-supervised exercise program in older people with diabetes on fasting blood sugar, psychological resilience and quality of life: A double blind randomised controlled trial. Int J Older People Nurs 2023;18(5):e12564 [FREE Full text] [doi: 10.1111/opn.12564] [Medline: 37559428]
19. Bellosta-Batalla M, Del Carmen Blanco-Gandía M, Rodríguez-Arias M, Cebolla A, Pérez-Blasco J, Moya-Albiol L. Brief mindfulness session improves mood and increases salivary oxytocin in psychology students. Stress Health 2020;36(4):469-477. [doi: 10.1002/smi.2942] [Medline: 32227624]
20. Knudsen RK, Gregersen T, Ammentorp J, Tousig CG, Timmermann C. Healthcare professionals' experiences of using mindfulness training in a cardiology department - a qualitative study. Scand J Caring Sci 2021;35(3):892-900. [doi: 10.1111/scs.12906] [Medline: 32852094]
21. Pospos S, Young IT, Downs N, Iglewicz A, Depp C, Chen JY, et al. Web-Based Tools and Mobile Applications To Mitigate Burnout, Depression, and Suicidality Among Healthcare Students and Professionals: a Systematic Review. Acad Psychiatry 2018;42(1):109-120 [FREE Full text] [doi: 10.1007/s40596-017-0868-0] [Medline: 29256033]
22. Faul F, Erdfelder E, Buchner A, Lang AG. Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses. Behav Res Methods 2009;41(4):1149-1160. [doi: 10.3758/BRM.41.4.1149] [Medline: 19897823]
23. Stamm BH. The concise ProQOL manual, 2nd Edition. Pocatello, ID: The ProQOL.org; 2010. URL: http://tinyurl.com/47wc76re [accessed 2024-02-09]
24. Ball TJ, Joy EA, Goh TL, Hannon JC, Gren LH, Shaw JM. Validity of two brief primary care physical activity questionnaires with accelerometry in clinic staff. Prim Health Care Res Dev 2015;16(1):100-108 [FREE Full text] [doi: 10.1017/S1463423613000479] [Medline: 24472569]
25. Ball TJ, Joy EA, Gren LH, Cunningham R, Shaw JM. Predictive Validity of an Adult Physical Activity "Vital Sign" Recorded in Electronic Health Records. J Phys Act Health 2016;13(4):403-408. [doi: 10.1123/jpah.2015-0210] [Medline: 26445164]

26. Lyubomirsky S, Lepper HS. A measure of subjective happiness: preliminary reliability and construct validation. Soc Indic Res 1999;46(2):137-155. [doi: 10.1023/A:1006824100041]
27. Torquati L, Kolbe-Alexander T, Pavey T, Leveritt M. Changing Diet and Physical Activity in Nurses: A Pilot Study and Process Evaluation Highlighting Challenges in Workplace Health Promotion. J Nutr Educ Behav 2018;50(10):1015-1025. [doi: 10.1016/j.jneb.2017.12.001] [Medline: 29650395]
28. Rao N, Kemper KJ. Online training in specific meditation practices improves gratitude, well-being, self-compassion, and confidence in providing compassionate care among health professionals. J Evid Based Complementary Altern Med 2017 Apr;22(2):237-241 [FREE Full text] [doi: 10.1177/2156587216642102] [Medline: 27055823]
29. Morrison Wylde C, Mahrer NE, Meyer RM, Gold JI. Mindfulness for novice pediatric nurses: smartphone application versus traditional intervention. J Pediatr Nurs 2017;36:205-212. [doi: 10.1016/j.pedn.2017.06.008] [Medline: 28888505]
30. Hamilton C, Osterhold H, Chao J, Chu K, Roy-Burman A. Gratitude and recognition in a hospital setting: addressing provider well-being and patient outcomes. Am J Med Qual 2018;33(5):554. [doi: 10.1177/1062860618772281] [Medline: 29717882]
31. Hebdon M, Thomas M, Peterson NE, Stewart E, Stewart T, Kent-Marvick J, et al. User-centered adaptation of an mHealth intervention for stress and emotional regulation in millennial caregivers. J Inf Nurs 2023;8(4):27.
32. Jakobsen JC, Gluud C, Wetterslev J, Winkel P. When and how should multiple imputation be used for handling missing data in randomised clinical trials - a practical guide with flowcharts. BMC Med Res Methodol 2017;17(1):162 [FREE Full text] [doi: 10.1186/s12874-017-0442-1] [Medline: 29207961]

Abbreviations

BO: burnout
CF: compassion fatigue
CS: compassion satisfaction
GEM app: gratitude exercise mindfulness app
NICU: newborn intensive care unit
PAVS: Physical Activity Vital Sign
ProQOL: professional quality of life
SHS: Subjective Happiness Score
STS: Secondary Trauma Stress

Edited by E Borycki, D Dordunoo; submitted 14.11.23; peer-reviewed by K Penberthy; accepted 20.01.24; published 16.02.24.

Please cite as:
Peterson NE, Thomas M, Hunsaker S, Stewart T, Collett CJ
mHealth Gratitude Exercise Mindfulness App for Resiliency Among Neonatal Intensive Care Unit Staff: Three-Arm Pretest-Posttest Interventional Study
JMIR Nursing 2024;7:e54561
URL: https://nursing.jmir.org/2024/1/e54561
doi:10.2196/54561
PMID:38363595

Original Paper

Nurses' Use of mHealth Apps for Chronic Conditions: Cross-Sectional Survey

Wa'ed Shiyab[1], RN, BN, MSciNurs; Kaye Rolls[1], RN, BAppsc, DNurs; Caleb Ferguson[1], RN, BSc, MHlth, PhD; Elizabeth Halcomb[1], RN, BN(Hons), PhD

School of Nursing, Faculty of Science, Medicine and Health, University of Wollongong, Wollongong, Australia

Corresponding Author:
Wa'ed Shiyab, RN, BN, MSciNurs
School of Nursing
Faculty of Science, Medicine and Health
University of Wollongong
Northfields Avenue
Wollongong, 2522
Australia
Phone: 61 42213784
Email: weys741@uowmail.edu.au

Abstract

Background: Mobile health (mHealth) is increasingly used to support public health practice, as it has positive benefits such as enhancing self-efficacy and facilitating chronic disease management. Yet, relatively few studies have explored the use of mHealth apps among nurses, despite their important role in caring for patients with and at risk of chronic conditions.

Objective: The aim of the study is to explore nurses' use of mHealth apps to support adults with or at risk of chronic conditions and understand the factors that influence technology adoption.

Methods: A web-based cross-sectional survey was conducted between September 2022 and January 2023. The survey was shared via social media and professional nursing organizations to Australian nurses caring for adults with or at risk of chronic conditions.

Results: A total of 158 responses were included in the analysis. More than two-thirds (n=108, 68.4%) of respondents reported that they personally used at least 1 mHealth app. Over half (n=83, 52.5% to n=108, 68.4%) reported they use mHealth apps at least a few times a month for clinical purposes. Logistic regression demonstrated that performance expectancy (P=.04), facilitating condition (P=.05), and personal use of mHealth apps (P=.05) were significantly associated with mHealth app recommendation. In contrast, effort expectancy (P=.09) and social influence (P=.46) did not have a significant influence on whether respondents recommended mHealth apps to patients. The inability to identify the quality of mHealth apps and the lack of access to mobile devices or internet were the most common barriers to mHealth app recommendation.

Conclusions: While nurses use mHealth apps personally, there is potential to increase their clinical application. Given the challenges reported in appraising and assessing mHealth apps, app regulation and upskilling nurses will help to integrate mHealth apps into usual patient care.

(JMIR Nursing 2024;7:e57668) doi:10.2196/57668

KEYWORDS

mHealth apps; adoption; smartphone; chronic conditions; nursing; technology; chronic; nurse; nurses; mHealth; mobile health; app; apps; use; cross-sectional; survey; surveys; questionnaire; questionnaires; mobile phone

Introduction

Chronic conditions account for 74% of all deaths globally [1]. Approximately 46% to 53% of adults in high-income countries have at least 1 chronic condition [2,3]. The high prevalence of chronic conditions contributes significantly to premature morbidity and mortality as well as poor quality of life [1,4]. Chronic conditions are also linked to high health care costs and resource consumption [5]. Self-management is a key strategy shown to improve outcomes and quality of life [6]. The growth of technology has changed how people can be supported to self-manage their chronic conditions [6,7]. Mobile health (mHealth) apps are an example of such technology.

In recent years, the use of mHealth apps has increased widely, driven by a global exponential increase in internet access, mobile phone ownership, and other smart technologies, such as wearables such as smartwatches and fitness trackers. It is estimated that in 2021, more than 350,000 mHealth apps were available from the Apple Store and Google Play [8]. Almost half of these apps were for chronic conditions, such as mental health, diabetes, and cardiovascular disease [8]. Apps offer a wide range of functionalities, including medication calculation, symptom monitoring and tracking, health data collection and monitoring, and access to health information [9]. Such functionality has widespread application and use in a range of chronic conditions.

Previous studies have suggested that mHealth apps could improve self-efficacy and adoption of healthy behaviors and empower individuals to engage more strongly in self-management [10,11]. The easy accessibility of mHealth apps makes them a viable adjunct to traditional health care by facilitating communication between patients and health care providers, especially when face-to-face visits are inaccessible [12]. The popularity of these apps was evident through the significant increase in downloads of exercise, mental health, and blood pressure management mHealth apps during the COVID-19 pandemic [8].

Despite the potential value of mHealth apps to improve patient care and health outcomes, the often slow progress of trials, along with the rapid changes in innovations, features, and functions of mHealth apps, make it difficult to keep the evidence up to date with the technology [13]. Additionally, mHealth apps need to be embedded in clinical practice to fully realize their efficacy [14]. While the role of mHealth apps in usual clinical practice is not well understood [15], a likely key to their maximum efficacy is uptake and engagement by the health care professionals providing care [16].

The unified theory of acceptance and use of technology (UTAUT) was used to guide this study in terms of understanding clinician engagement. The UTAUT is based on the assumption that there are 3 direct determinants of intention to use (performance expectancy, effort expectancy, and social influence) and 2 direct determinants of usage behavior (intention to use and facilitating condition) [17,18]. In total, 4 factors (gender, age, experience, and voluntariness of use) act as moderators and key features of the UTAUT [17,18]. These key principles guided the survey design.

Previous studies have explored the adoption of mHealth apps among health professionals such as doctors, pharmacists, and dieticians [9,19,20]. Despite nursing being the largest single health care profession globally [21] and being involved in delivering many interventions to support self-management, relatively few studies have explored the use of mHealth apps among nurses [19]. Previous studies of nurses have reported that the use of mHealth apps is relatively low, despite many nurses identifying that they are useful [22]. de Jong et al [23] report that nurses mainly use mHealth apps for checking medication information, reviewing laboratory tests, and communicating with other health care professionals and patients. However, being distracted by using their smartphone, concerns that patients might have negative feelings regarding device use, privacy, data security concerns, and lack of organizational support are perceived by nurses as key barriers to mHealth app use [23]. Gaining insight into nurses' engagement with the rapid advances of mHealth apps will help empower them to get the maximum benefit of such advances. This has the potential to enhance patient care, strengthen self-management support, and optimize health outcomes.

Methods

Objectives

This paper seeks to explore Australian nurses' use of mHealth apps to support adults with or at risk of chronic conditions and understand the factors that influence technology adoption.

Design

A web-based cross-sectional survey was conducted between September 2022 and January 2023 as the first phase of a concurrent mixed methods study. The second phase consisted of semistructured interviews with a subgroup of survey respondents. Given the depth of the data and the different foci, these interview data are reported separately.

Respondents

Diploma-prepared enrolled nurses, baccalaureate-prepared registered nurses, and master's-prepared nurse practitioners who identified as caring for adults with or at risk of chronic conditions across Australia were eligible to participate. Respondents were recruited through social media (Facebook and Twitter) and professional nursing organizations, such as the Australian College of Nursing, the Australasian Cardiovascular Nursing College, and the Australian Primary Health Care Nurses Association. Social media posts provided brief study information and the survey link. Follow-up and reminder posts were made at regular intervals [24]. Professional organizations advertised the study either via their email lists, social media pages, newsletters, or electronic communications.

Data Collection

The survey was web-based and delivered via REDCap (Research Electronic Data Capture; Vanderbilt University) [25]. The survey tool was developed by the research team based on expert knowledge and previous studies [9,20,22]. It consisted of 3 sections. The first section collected demographic and professional characteristics, including employment setting, age, gender, professional designation, work experience, location, education, clinical role, and specialty area.

The second section explored the use of mHealth apps for professional and clinical purposes. This section was based on previous surveys [9,20,22] and explored mHealth apps that are used by nurses for personal purposes, how respondents used mHealth apps for professional purposes, and whether respondents were asked to or recommended mHealth apps to patients.

The last section comprised a 38-item scale devised by Lim et al [20] (used with author permission). The first 19 items addressed factors influencing the adoption of mHealth apps in clinical work and the other 19 items addressed factors that affect the prescription of mHealth apps for patients. Each item is rated on a 5-point Likert scale, from 1=strongly disagree to 5=strongly agree. These items are based on the 4 constructs of the UTAUT, namely, performance expectancy, effort expectancy, social influence, and facilitating conditions [17] (Table S1 in Multimedia Appendix 1).

Validity and Reliability

The survey was assessed for face validity by a convenience sample of 5 nurses before dissemination. These nurses had expertise in survey design and the use of technology in health care and chronic conditions. The feedback they provided was used to amend the wording and format of the tool.

Lim et al [20] demonstrated acceptable reliability for the 38-item scale, with Cronbach α for each construct being 0.67-0.89. In this study, the Cronbach α for each construct was between 0.69 and 0.93, which indicates good reliability (Table S1 in Multimedia Appendix 1).

Ethical Considerations

The study was approved by the Human Research Ethics Committee of the University of Wollongong (approval 2022/202) in July 2022. Respondents were provided with an information sheet at the commencement of the survey and asked to check a box if they consented to participate. Participants were free to withdraw participation at any time during the survey, which can be done by ceasing the survey. However, once the survey was submitted the participants were not able to withdraw their responses as the data generated was deidentified. Any contact details that were provided in the survey were separated prior to analysis. Two AUD $100 vouchers were allocated to randomly selected participants who responded to the survey and were willing to be included in the prize draw. The value of the prize vouchers was sufficient to incentivize participation by compensating respondents for their time without being an inducement.

Data Analysis

The data were exported from REDCap into SPSS (version 28; IBM Corp) for analysis. Records were considered incomplete if more than half of the survey was not completed. Incomplete records were removed before analysis. Where less than half of the data were missing, the response was included, and the data were categorized as missing in the analysis.

Descriptive statistics were used to summarize the demographic and professional characteristics [26]. Age data were grouped based on standardized generational groups [27]. Logistic regression, using factors from the literature, was used to identify the factors that influence the adoption of mHealth apps. $P<.05$ was considered to be statistically significant.

Results

Respondents' Characteristics

Although 207 nurses responded to the survey, 49 (23.7%) surveys were incomplete and so were excluded. Therefore, 158 (76.3%) responses were included in the analysis. Most respondents were female (n=134, 84.8%), had completed a graduate diploma and above (n=112, 70.8%), and worked in a metropolitan area (n=100, 63.3%; Table 1). Slightly less than half of respondents (n=76, 48.1%) were from Generation X (43-58 years).

Table 1. Personal and professional characteristics (n=158).

Attribute	Values
Age (years), mean (SD)	46.7 (10.7)
Age group, n (%)	
Millennials (26-42 years)	50 (31.6)
Generation X (43-58 years)	76 (48.1)
Boomer (59-73 years)	20 (12.7)
Missing data	12 (7.6)
Education, n (%)	
Diploma or bachelor’s degree	46 (29.1)
Graduate certificate or diploma	49 (31)
Master’s degree	56 (35.4)
PhD degree	7 (4.4)
State, n (%)	
New South Wales	92 (58.2)
Victoria	26 (16.5)
Queensland	14 (8.9)
Western Australia	9 (5.7)
South Australia	5 (3.2)
Australian Capital Territory	5 (3.2)
Northern Territory	4 (2.5)
Tasmania	2 (1.3)
Missing data	1 (0.6)
Work location, n (%)	
Metropolitan or urban	100 (63.3)
Rural or regional	45 (28.5)
Remote area	5 (3.2)
Missing data	8 (5.1)
Professional designation, n (%)	
Registered nurse	80 (50.6)
Clinical nurse consultant	25 (15.8)
Clinical nurse specialist	17 (10.8)
Nurse practitioner	11 (7)
Clinical nurse educator	7 (4.4)
Enrolled nurse	6 (3.8)
Nurse manager	5 (3.2)
Multiple roles	14 (8.8)
Chronic condition, n (%)	
Cardiovascular disease	55 (34.8)
Diabetes mellitus	30 (19)
Multiple chronic conditions	18 (11.4)
Respiratory disease	16 (10.1)
Neurologic disease	13 (8.2)
Mental health condition	10 (6.3)

Attribute	Values
Missing data	1 (0.6)
Others	15 (9.5)
Employment setting, n (%)	
Acute care setting	51 (31)
General practice	38 (23.4)
Community health	32 (19.6)
Outpatient specialist service	28 (17.1)
Others	9 (5.7)

Of the 158 respondents, half (n=80, 50.6%) were registered nurses, with a further 33.6% (n=53) employed in advanced practice roles (eg, clinical nurse consultant, clinical nurse specialist, and nurse practitioner). Slightly less than a third (n=50, 31.7%) of respondents had worked in nursing for 20 years or less. Some (n=55, 34.8%) respondents primarily cared for patients with cardiovascular diseases, and 41.1% (n=65) provided chronic episodic care. Only 31% (n=51) of respondents worked in an acute hospital setting.

Personal mHealth App Use

Of the 158 respondents, most (n=108, 68.4%) reported that they personally used at least 1 mHealth app. The most popular mHealth apps used by respondents were physical activity trackers (n=77, 48.8%), mindfulness and meditation apps (n=45, 28.5%), symptom trackers (n=37, 23.5%), and diet trackers (n=34, 21.5%).

Personal use of mHealth apps was significantly associated with both age and gender (Table 2). Generation X (43-58 years) used mHealth apps 3 times more than boomers (59-73 years; *P*=.04), while millennials (22-42 years) used mHealth apps 5 times more than boomers (*P*=.008). Female respondents were twice as likely to use mHealth apps compared with male respondents (*P*=.04). Education and work location were not significantly associated with personal use of mHealth apps (*P*>.05).

Table 2. Predictors of mHealth[a] app personal use.

Factors	OR[b] (95% CI)	*P* value
Age group		
Millennials (22-42 years)	4.926 (1.524-15.920)	.01[c]
Generation X (43-58 years)	3.125 (1.069-9.135)	.04[c]
Boomers (59-73 years)	1 (—[d])	—
Sex		
Female	1 (—)	—
Male	.341 (.122-.956)	.04[c]
Education		
Undergraduate	1 (—)	—
Postgraduate	.998 (.417-2.389)	.99
Work location		
Remote area	1 (—)	—
Rural or regional	.434 (.039-4.803)	.49
Metropolitan or urban	.402 (.038-4.83)	.45

[a] mHealth: mobile health.

[b] OR: odds ratio.

[c] Significant values.

[d] Reference group.

mHealth App Use in Practice

Of the 158 respondents, only 2.5% (n=4) reported not having internet access, and 7% (n=11) of respondents reported that internet access is not provided by their employer. For clinical purposes, over half of the respondents reported they use mHealth apps at least a few times a month to communicate with other health professionals or colleagues (n=108, 68.4%); get information about medications or calculate dosages (n=99, 62.7%); access clinical guidelines, protocols, or reference sources (n=93, 58.9%); and interact with electronic medical records (n=83, 52.5%; Table 3).

Table 3. Clinical mHealth[a] app uses (n=158).

How often do you use a mHealth app	Never, n (%)	Less than once a month, n (%)	A few times a month, n (%)	Few times a week, n (%)	At least once a day, n (%)
To access a scientific journal	38 (24.1)	45 (28.5)	40 (25.3)	23 (14.6)	12 (7.6)
To access clinical guidelines, protocols, or reference sources	31 (19.6)	34 (21.5)	46 (29.1)	29 (18.4)	18 (11.4)
To get information about medications or calculate dosages	25 (15.8)	34 (21.5)	35 (22.2)	37 (23.4)	27 (17.1)
To interact with electronic medical records	61 (38.6)	14 (8.9)	10 (6.3)	16 (10.1)	57 (36.1)
To communicate with other health professionals or colleagues	33 (20.9)	17 (10.8)	23 (14.6)	34 (21.5)	51 (32.3)
To communicate with patients or their families	82 (51.9)	17 (10.8)	16 (10.1)	15 (9.5)	28 (17.7)
To book a shift or manage your roster	70 (44.3)	16 (10.1)	25 (15.8)	28 (17.7)	19 (12)

[a] mHealth: mobile health.

Respondents' perceptions toward using mHealth apps in clinical practice were variable. Approximately one-third of the 158 respondents agreed that performing tasks on mHealth apps is easy (n=56, 35.4%), that mHealth apps facilitate clinical decision-making (n=51, 32.3%), and that they can control the use of mHealth apps (n=51, 32.3%). These items reflect effort expectancy, performance expectancy, and facilitating conditions, respectively. The social influence of using mHealth apps was generally low (n=10, 6.3% to n=40, 25.3%). Only 10.2% (n=16) of respondents thought that mHealth apps could improve the quality of care, and 13.9% (n=22) agreed that information from mHealth apps is up-to-date (see Table S1 in Multimedia Appendix 2 for additional details).

mHealth App Recommendation

Of the 158 respondents, slightly fewer than half (n=74, 46.8%) reported that they recommend mHealth apps to patients at least once a month. Similarly, 64 (40.5%) respondents reported that they were asked for recommendations for mHealth apps at least once a month. Respondents reported not recommending mHealth apps for various reasons (Table 4). The most reported barriers were not being sure how to identify the quality of mHealth apps (n=65, 41.1%) and the lack of access to mobile devices or internet (n=53, 33.5%). The least commonly reported barriers were not being within their scope of practice (n=16, 11.1%) and privacy concerns (n=26, 16.5%).

Table 4. Barriers to mHealth[a] app recommendation (n=158).

Barriers	Values, n (%)
Not sure how to identify the quality of mHealth apps	65 (41.1)
Lack of access to mobile device or internet	53 (33.5)
Not confident in recommending mHealth apps	45 (28.5)
Unsure if mHealth apps improve health outcomes	42 (26.6)
Concern about the cost of apps	42 (26.6)
Patients are not interested	38 (24)
Concerns about liability if there are issues with using apps	31 (19.6)
I do not think patients can use apps	30 (19)
Never crossed my mind	27 (17.1)
Concerns about patient privacy	26 (16.5)
Not in my scope of practice	16 (11.1)
Other barriers	5 (3.2)

[a] mHealth: mobile health.

Factors that influence mHealth app recommendations were assessed based on the 4 constructs of the UTAUT. Slightly less than half of 158 respondents felt that mHealth apps could encourage patients to gain more health knowledge (n=77, 48.8%), and more than a third believed that mHealth apps improve chronic disease management (n=63, 39.9%) and patients' health (n=59, 37.5%). These 3 items all reflect performance expectancy. The social influence items were perceived as the lowest, with only 10.8% (n=17) of respondents reporting that patients adhered to the mHealth apps that they recommended to them, 12% (n=19) of respondents thought that the organization has a plan to implement mHealth app use for patients, and 13.3% (n=21) of respondents believed that the organization supports mHealth app recommendations (see Table S2 in Multimedia Appendix 2 for additional details).

Logistic regression demonstrated that performance expectancy (*P*=.04), facilitating condition (*P*=.05), and personal use of mHealth apps (*P*=.05) were significantly associated with mHealth app recommendation (Table 5). In contrast, effort expectancy (*P*=.09) and social influence (*P*=.46) did not have a significant influence (*P*>.05) on whether respondents recommended mHealth apps to patients.

Table 5. Predictors of mHealth[a] app recommendation.

Factors	OR[b] (95% CI)	*P* value
Personal use of mHealth app	2.668 (1.002-7.106)	.05[c]
Performance expectancy	2.384 (1.038-5.476)	.04[c]
Effort expectancy	.328 (.092-1.171)	.09
Social influence	1.553 (.481-5.014)	.46
Facilitating condition	3.743 (1.000-14.006)	.05[c]

[a] mHealth: mobile health.

[b] OR: odds ratio.

[c] Significant values.

Discussion

Principal Findings

This paper has explored the current use of mHealth apps among Australian nurses and the factors that influence technology adoption. Understanding the current situation regarding nurses' mHealth app use, preferences, and experiences given the recent rapid advancements in mHealth apps will inform future interventions, practices, and policies to support self-management for those living with chronic conditions. Strategies to empower nurses to maximize the benefit of mHealth apps will likely positively impact patient care and health outcomes [28].

Findings revealed that respondents' personal use of mHealth apps was similar to other health care providers, which ranged from 60% to 76% [29,30]. This highlights the widespread use and familiarity of health care providers with mHealth apps. It is noteworthy that, in this study, personal use of mHealth apps was found to be a significant predictor of their recommendation to patients. Other studies have also found that health professionals' personal use of mHealth apps significantly impacted their recommendations to patients [29,30]. The relationship between personal use and recommendation of mHealth apps suggests that it may be possible to leverage the pre-existing familiarity of health care providers with mHealth apps through workforce development [30]. This includes promoting the digital capabilities of nurses as a part of continuous professional development to adapt to a rapidly changing digital world [31]. In addition, encouraging knowledge-sharing and peer-to-peer learning can be a strategy to build digital literacy [32].

Despite the high personal use of mHealth apps, this study found that the inability to discern reliable apps and a lack of confidence in recommendations were the top barriers to mHealth app recommendations. Similar challenges were reported in previous studies, which reported unawareness of effective apps and sources to access them [9,22]. These barriers highlight the importance of mHealth app regulation, including involving the nurses in the whole process of mHealth app development [33], as well as the establishment of a rigorous framework for appraising mHealth apps, which could help nurses identify and differentiate high-quality apps for patient use [34]. On an individual level, Ferguson and Jackson [35] discussed criteria to evaluate app quality, and recently, more work has been done by the Australian Digital Health Agency to create a framework to help in the assessment of the quality and safety of mHealth apps [34]. This challenge is likely not confined to Australia. In their study of mHealth app regulation in 9 countries, Essén et al [36] found that all these countries have some initiatives, and despite the fact that the United Kingdom, Belgium, and Germany advanced in developing frameworks for app appraisal, they still struggle with implementation. Although the rapid developments in technology challenge policy makers and researchers, concerted efforts to create a unified and validated framework for app appraisal are still needed. Moreover, to maximize the benefit of such frameworks, nurses need to be provided with appropriate training to implement and use these frameworks in their practice [22].

Beyond the quality assessment frameworks to be used by individual clinicians, a further strategy to support app recommendation in clinical practice is a library that embraces safe and reliable apps and provides critical appraisals [9,22,37]. Regular reassessment of the quality of included apps is needed to keep such libraries up-to-date [34]. These measures could improve health care providers' confidence in recommending apps, which ultimately will reflect on the quality of care provided to patients [9,22].

Other predictors of mHealth app recommendation in this study were performance expectancy and facilitating conditions. Consistent with Lim et al [20], performance expectancy was found in this study to be significantly associated with app recommendation. Performance expectancy refers to the extent to which people believe that using technology will provide a gain in job performance [17]. Nurses' beliefs about the importance of mHealth apps in the management of patient conditions could positively influence them to recommend these apps to patients. Based on these findings, providing nurses with reliable evidence about the efficacy of mHealth apps will likely increase their rate of recommendation to patients [20]. Facilitating conditions, which encompass self-control over using apps, data security, time, and app affordability to patients [17], were also found to be significantly associated with app recommendation. This is a significant finding for mHealth app developers to give more attention to the app design. Secure, reliable, and trusted apps, with free or minimal cost, are more likely to be recommended to patients [20].

Limitations

This is one of the few studies that has explored the adoption of mHealth apps among nurses and the factors that are associated with such adoption. However, there are some limitations to this study. Given the inherent low response rate in survey research and survey fatigue, the sample size was modest. However, to improve the response rate, evidence-based strategies were followed for recruitment [24]. Despite the modest size, the sample did provide a spread of respondents across demographic groups and clinical settings. Another limitation is the absence of a validated tool to explore the adoption of mHealth apps, so the previous literature acted as a guide for the development of the survey tool. Finally, a bias may exist, as the sample might not be representative of the broader population of nurses. As in most survey research, the respondents might be more interested in the survey topic than those who declined to respond.

Conclusions

Overall, this research demonstrated that many nurses use mHealth apps personally, which increases the likelihood of adopting them in clinical practice and fosters patients' autonomy to self-manage their chronic conditions. However, given the large number of mHealth apps and the lack of regulation of these apps, nurses face challenges in integrating these apps into routine patient care. Targeting the barriers that nurses face would promote the integration of mHealth apps and harness their potential for the benefit of health care providers and patients. Nurses' involvement in any proposed solutions is essential.

Acknowledgments

The authors acknowledge the health professionals who completed the survey and the nursing professional organization that disseminated the survey. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. WS was supported by an Australian Government University Postgraduate Award from the University of Wollongong.

Authors' Contributions

WS led the development of the study, drafted the initial data collection tools, collected the data, and led the analysis. KR, CF, and EH provided critical feedback about the study design, data collection, analysis, and reporting. All authors have contributed to the preparation and review of the paper and agreed on the final version.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Unified theory of acceptance and use of technology (UTAUT) constructs reliability.
[DOCX File , 23 KB - nursing_v7i1e57668_app1.docx]

Multimedia Appendix 2
Factors influencing mobile health (mHealth) app recommendation and use in clinical practice.
[DOCX File , 29 KB - nursing_v7i1e57668_app2.docx]

References

1. World Health Organization. Noncommunicable diseases. 2023. URL: https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases [accessed 2024-01-15]
2. Chronic conditions and multimorbidity. Australian Institute of Health and Welfare. 2023. URL: https://aihw.gov.au/reports/australias-health/chronic-conditions-and-multimorbidity [accessed 2024-01-15]
3. Watson KB, Carlson SA, Loustalot F, Town M, Eke PI, Thomas CW, et al. Chronic conditions among adults aged 18-34 years—United States, 2019. MMWR Morb Mortal Wkly Rep 2022;71(30):964-970 [FREE Full text] [doi: 10.15585/mmwr.mm7130a3] [Medline: 35900929]
4. GBD 2017 Risk Factor Collaborators. Global, regional, and national comparative risk assessment of 84 behavioural, environmental and occupational, and metabolic risks or clusters of risks for 195 countries and territories, 1990-2017: a

systematic analysis for the Global Burden of Disease Study 2017. Lancet 2018;392(10159):1923-1994 [FREE Full text] [doi: 10.1016/S0140-6736(18)32225-6] [Medline: 30496105]

5. Hajat C, Stein E. The global burden of multiple chronic conditions: a narrative review. Prev Med Rep 2018;12:284-293 [FREE Full text] [doi: 10.1016/j.pmedr.2018.10.008] [Medline: 30406006]
6. Grady PA, Gough LL. Self-management: a comprehensive approach to management of chronic conditions. Am J Public Health 2014;104(8):e25-e31. [doi: 10.2105/AJPH.2014.302041] [Medline: 24922170]
7. Yi JY, Kim Y, Cho YM, Kim H. Self-management of chronic conditions using mHealth interventions in Korea: a systematic review. Healthc Inform Res 2018;24(3):187-197 [FREE Full text] [doi: 10.4258/hir.2018.24.3.187] [Medline: 30109152]
8. Digital health trends 2021: innovation, evidence, regulation, and adoption. IQVIA Institute for Human Data Science. 2021. URL: https://www.iqvia.com/insights/the-iqvia-institute/reports/digital-health-trends-2021 [accessed 2023-04-10]
9. Byambasuren O, Beller E, Glasziou P. Current knowledge and adoption of mobile health apps among Australian general practitioners: survey study. JMIR Mhealth Uhealth 2019;7(6):e13199 [FREE Full text] [doi: 10.2196/13199] [Medline: 31199343]
10. Lee JA, Choi M, Lee SA, Jiang N. Effective behavioral intervention strategies using mobile health applications for chronic disease management: a systematic review. BMC Med Inform Decis Mak 2018;18(1):12 [FREE Full text] [doi: 10.1186/s12911-018-0591-0] [Medline: 29458358]
11. Sittig S, Wang J, Iyengar S, Myneni S, Franklin A. Incorporating behavioral trigger messages into a mobile health app for chronic disease management: randomized clinical feasibility trial in diabetes. JMIR Mhealth Uhealth 2020;8(3):e15927 [FREE Full text] [doi: 10.2196/15927] [Medline: 32175908]
12. Fan K, Zhao Y. Mobile health technology: a novel tool in chronic disease management. Intell Med 2022;2(1):41-47 [FREE Full text] [doi: 10.1016/j.imed.2021.06.003]
13. Gallagher R, Zhang L. Evaluating mobile health technologies: does the traditional randomized controlled trial serve our needs? Eur J Cardiovasc Nurs 2021;20(6):623-626 [FREE Full text] [doi: 10.1093/eurjcn/zvab053] [Medline: 34269387]
14. Gordon WJ, Landman A, Zhang H, Bates DW. Beyond validation: getting health apps into clinical practice. NPJ Digit Med 2020;3:14 [FREE Full text] [doi: 10.1038/s41746-019-0212-z] [Medline: 32047860]
15. Rowland SP, Fitzgerald JE, Holme T, Powell J, McGregor A. What is the clinical value of mHealth for patients? NPJ Digit Med 2020;3:4 [FREE Full text] [doi: 10.1038/s41746-019-0206-x] [Medline: 31970289]
16. Shiyab W, Halcomb E, Rolls K, Ferguson C. The impact of social media interventions on weight reduction and physical activity improvement among healthy adults: systematic review. J Med Internet Res 2023;25:e38429 [FREE Full text] [doi: 10.2196/38429] [Medline: 36927627]
17. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. MIS Q 2003;27(3):425-478. [doi: 10.2307/30036540]
18. Taherdoost H. A review of technology acceptance and adoption models and theories. Procedia Manuf 2018;22:960-967 [FREE Full text] [doi: 10.1016/j.promfg.2018.03.137]
19. Gagnon MP, Ngangue P, Payne-Gagnon J, Desmartis M. m-Health adoption by healthcare professionals: a systematic review. J Am Med Inform Assoc 2016;23(1):212-220 [FREE Full text] [doi: 10.1093/jamia/ocv052] [Medline: 26078410]
20. Lim HM, Dunn AG, Ooi SMF, Teo CH, Abdullah A, Woo WJ, et al. mHealth adoption among primary care physicians in Malaysia and its associated factors: a cross-sectional study. Fam Pract 2021;38(3):210-217 [FREE Full text] [doi: 10.1093/fampra/cmaa103] [Medline: 32968795]
21. World Health Organization. State of the world's nursing 2020: investing in education, jobs and leadership. 2020. URL: https://www.who.int/publications/i/item/9789240003279 [accessed 2022-05-18]
22. Mayer MA, Blanco OR, Torrejon A. Use of health apps by nurses for professional purposes: web-based survey study. JMIR Mhealth Uhealth 2019;7(11):e15195 [FREE Full text] [doi: 10.2196/15195] [Medline: 31682587]
23. de Jong A, Donelle L, Kerr M. Nurses' use of personal smartphone technology in the workplace: scoping review. JMIR Mhealth Uhealth 2020;8(11):e18774 [FREE Full text] [doi: 10.2196/18774] [Medline: 33242012]
24. Shiyab W, Ferguson C, Rolls K, Halcomb E. Solutions to address low response rates in online surveys. Eur J Cardiovasc Nurs 2023;22(4):441-444 [FREE Full text] [doi: 10.1093/eurjcn/zvad030] [Medline: 36827086]
25. Harris PA, Taylor R, Minor BL, Elliott V, Fernandez M, O'Neal L, et al. The REDCap consortium: building an international community of software platform partners. J Biomed Inform 2019;95:103208 [FREE Full text] [doi: 10.1016/j.jbi.2019.103208] [Medline: 31078660]
26. Cooksey RW. Descriptive statistics for summarising data. In: Illustrating Statistical Procedures: Finding Meaning in Quantitative Data. Singapore: Springer; 2020:61-139.
27. Dimock M. Defining generations: where Millennials end and Generation Z begins. Pew Research Center. 2019. URL: https://www.pewresearch.org/fact-tank/2019/01/17/where-millennials-end-and-generation-z-begins [accessed 2022-05-18]
28. Ferguson C, Hickman L, Wright R, Davidson PM, Jackson D. Preparing nurses to be prescribers of digital therapeutics. Contemp Nurse 2018;54(4-5):345-349 [FREE Full text] [doi: 10.1080/10376178.2018.1486943] [Medline: 29940811]
29. Karduck J, Chapman-Novakofski K. Results of the clinician apps survey, how clinicians working with patients with diabetes and obesity use mobile health apps. J Nutr Educ Behav 2018;50(1):62-69.e1. [doi: 10.1016/j.jneb.2017.06.004] [Medline: 29325664]

30. Leigh S, Ashall-Payne L, Andrews T. Barriers and facilitators to the adoption of mobile health among health care professionals from the United Kingdom: discrete choice experiment. JMIR Mhealth Uhealth 2020;8(7):e17704 [FREE Full text] [doi: 10.2196/17704] [Medline: 32628118]
31. Australian Digital Health Agency. National nursing and midwifery digital health capability framework. 2020. URL: https://www.digitalhealth.gov.au/sites/default/files/2020-11/National_Nursing_and_Midwifery_Digital_Health_Capability_Framework_publication.pdf [accessed 2024-04-24]
32. Terry J, Davies A, Williams C, Tait S, Condon L. Improving the digital literacy competence of nursing and midwifery students: a qualitative study of the experiences of NICE student champions. Nurse Educ Pract 2019;34:192-198. [doi: 10.1016/j.nepr.2018.11.016] [Medline: 30579041]
33. Bakker CJ, Wyatt TH, Breth MC, Gao G, Janeway LM, Lee MA, et al. Nurses' roles in mHealth app development: scoping review. JMIR Nurs 2023;6:e46058 [FREE Full text] [doi: 10.2196/46058] [Medline: 37847533]
34. Australian Digital Health Agency. Assessment framework for mHealth apps. 2022. URL: https://www.digitalhealth.gov.au/about-us/strategies-and-plans/assessment-framework-for-mhealth-apps [accessed 2023-01-10]
35. Ferguson C, Jackson D. Selecting, appraising, recommending and using mobile applications (apps) in nursing. J Clin Nurs 2017;26(21-22):3253-3255. [doi: 10.1111/jocn.13834] [Medline: 28370697]
36. Essén A, Stern AD, Haase CB, Car J, Greaves F, Paparova D, et al. Health app policy: international comparison of nine countries' approaches. NPJ Digit Med 2022;5(1):31 [FREE Full text] [doi: 10.1038/s41746-022-00573-1] [Medline: 35304561]
37. Sarradon-Eck A, Bouchez T, Auroy L, Schuers M, Darmon D. Attitudes of general practitioners toward prescription of mobile health apps: qualitative study. JMIR Mhealth Uhealth 2021;9(3):e21795 [FREE Full text] [doi: 10.2196/21795] [Medline: 33661123]

Abbreviations

mHealth: mobile health
REDCap: Research Electronic Data Capture
UTAUT: unified theory of acceptance and use of technology

Edited by E Borycki; submitted 22.02.24; peer-reviewed by M Lee, A AL-Rumhi; accepted 07.04.24; published 29.05.24.

Please cite as:
Shiyab W, Rolls K, Ferguson C, Halcomb E
Nurses' Use of mHealth Apps for Chronic Conditions: Cross-Sectional Survey
JMIR Nursing 2024;7:e57668
URL: https://nursing.jmir.org/2024/1/e57668
doi:10.2196/57668
PMID:38809593

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

Mariwan Qadir Hamarash[1], MSc; Radhwan Ibrahim[2], PhD; Marghoob Hussein Yaas[1], PhD; Mohammed Faris Abdulghani[2], MSci; Osama Al Mushhadany[3], Prof Dr

[1]College of Nursing, Al-Kitab University, Kirkuk, Iraq
[2]College of Nursing, Ninevah University, Al Kafaat Second, Al Kindi St, Mosul, Iraq
[3]College of Medicine, Ninevah University, Mosul, Iraq

Corresponding Author:
Radhwan Ibrahim, PhD
College of Nursing, Ninevah University, , Al Kafaat Second, Al Kindi St, Mosul, , Iraq

Abstract

Background: Effective communication is vital in health care, especially for nursing students who are the future of health care delivery. In Iraq's nursing education landscape, characterized by challenges such as resource constraints and infrastructural limitations, understanding communication modalities is crucial.

Objective: This mixed methods study conducted in 2 nursing colleges aims to explore and compare the effectiveness of health communication on the web, through mobile health (mHealth) applications, and via social media among nursing students in Iraq. The research addresses a gap in understanding communication modalities specific to Iraq and explores the perspectives, experiences, and challenges faced by nursing students.

Methods: Qualitative interviews were conducted with a purposive sample (n=30), and a structured survey was distributed to a larger sample (n=300) representing diverse educational programs. The study used a nuanced approach to gather insights into the preferences and usage patterns of nursing students regarding communication modalities. The study was conducted between January 12, 2023, and May 5, 2023.

Results: Qualitative findings highlighted nursing students' reliance on the web for educational materials, the significant role of mHealth applications in clinical skill development, and the emergence of social media platforms as community-building tools. Quantitative results revealed high-frequency web use (276/300, 92%) for educational purposes, regular mHealth application usage (204/300, 68%) in clinical settings, and active engagement on social media platforms (240/300, 80%). Traditional methods such as face-to-face interactions (216/300, 72%) and practical experiences (255/300, 85%) were preferred for developing essential skills.

Conclusions: The study underscores nursing students' preference for an integrated approach, recognizing the complementary strengths of traditional and digital methods. Challenges include concerns about information accuracy and ethical considerations in digital spaces. The findings emphasize the need for curriculum adjustments that seamlessly integrate diverse communication modalities to create a dynamic learning environment. Educators play a crucial role in shaping this integration, emphasizing the enduring value of face-to-face interactions and practical experiences while harnessing the benefits of digital resources. Clear guidelines on professional behavior online are essential. Overall, the study expands the understanding of communication modalities among nursing students in Iraq and provides valuable insights for health care education stakeholders globally.

(JMIR Nursing 2024;7:e55744) doi:10.2196/55744

KEYWORDS

nursing education; nursing; nursing students; communication modalities; internet-based resources; nursing curriculum; mHealth clinical learning; mHealth; mobile health; social media

Introduction

Background

In the dynamic landscape of health care, effective communication stands as a cornerstone for both health care professionals and patients alike. The ability to convey information, build trust, and establish meaningful connections is particularly vital for nursing students, who serve as the future backbone of health care delivery [1,2]. The evolving nature of health care delivery necessitates a keen understanding of diverse communication modalities among these aspiring health care professionals [3]. As digital natives, nursing students find themselves at the crossroads of traditional methods and cutting-edge technologies, a juncture that not only significantly influences their education but also shapes the trajectory of their future practice [4].

In the context of Iraq, nurses are required to possess language proficiency and undergo training in cultural customs and beliefs to effectively deliver care to a diverse patient population. Furthermore, the inclusion of support services, such as dieticians, in the care plan is essential to address relevant cultural considerations [5-7].

In the global context, the study's focus expands beyond the borders to the unique health care landscape of Iraq. The health care system in Iraq grapples with a range of challenges, including resource constraints, infrastructural limitations, and the aftermath of conflict [8,9]. Understanding the gap in communication modalities among nursing students in Iraq becomes crucial, as it provides insights into the specific challenges faced by these students within the broader context of developing health care infrastructure.

This study, therefore, seeks to explore and compare the effectiveness of health communication on the web, through mobile health (mHealth) applications, and via social media among nursing students in Iraq. We aim to juxtapose these digital methods against traditional communication approaches, shedding light on the specific challenges and opportunities that arise within the unique health care landscape of Iraq. By delving into the distinctive perspectives, experiences, and challenges faced by nursing students in Iraq, we aspire to uncover insights that not only contribute to the broader discourse on health care communication and education but also offer targeted recommendations for improving nursing education in Iraq's specific context.

Previous studies may have examined general communication practices in health care or nursing education, but they often overlook the nuanced sociocultural and infrastructural factors present in Iraq. These factors could significantly impact the choice and effectiveness of communication modalities among nursing students in the region. In addition, as technology and digital resources become increasingly integrated into health care delivery worldwide, understanding how nursing students in Iraq navigate and use these tools within their specific context is essential.

The gap in the study lies in the limited research that specifically addresses the communication modalities used by nursing students in Iraq. As the health care landscape undergoes transformations, understanding how nursing students navigate and use communication tools becomes pivotal. By addressing this gap, we not only contribute to the global understanding of health care communication but also provide valuable insights for stakeholders in Iraq's health care education and delivery system, fostering a foundation for more effective and contextually relevant nursing education programs.

Objective

The objective of this study is to investigate and compare the effectiveness of health communication modalities, including the web, mHealth applications, and social media, among nursing students in Iraq. Specifically, the research aims to juxtapose these digital communication methods against traditional approaches, shedding light on the unique challenges and opportunities within the health care landscape of Iraq. By delving into the distinctive perspectives, experiences, and challenges faced by nursing students in Iraq, the study seeks to provide comprehensive insights that not only contribute to the broader discourse on health care communication and education but also offer targeted recommendations for improving nursing education in Iraq's specific context. The primary goal is to bridge the existing gap in research by specifically addressing the communication modalities used by nursing students in Iraq, recognizing the transformative nature of the health care landscape, and providing valuable insights for stakeholders in Iraq's health care education and delivery system, thereby enhancing the global understanding of health care communication and offering contextually relevant recommendations for more effective nursing education programs in Iraq.

Methods

Overview

To capture the nuanced perspectives of nursing students, a mixed methods approach was used in 2 nursing colleges affiliated with different universities in Iraq—Ninevah University in Mosul and Al-Kitab University in Kirkuk. This approach involved the integration of qualitative and quantitative data collection strategies. The study intentionally focused on nursing students enrolled in various educational programs, encompassing diploma, associate degree, and bachelor's degree programs. This diverse sampling aimed to ensure a comprehensive representation of perspectives within the study's scope.

Qualitative Phase

Semistructured interviews were conducted with a purposive sample of nursing students (n=30) from various educational institutions. The interviews focused on understanding how nursing students perceive and engage with health communication methods, exploring their preferences, challenges, and experiences. Open-ended questions encouraged participants to share anecdotes and reflections on the impact of different communication modalities in their educational journey.

Quantitative Phase

To complement the qualitative insights, a structured survey was distributed to a larger sample of nursing students (n=300). The survey included Likert-scale questions and multiple-choice items to quantify the frequency and preferences regarding the use of web, mHealth applications, social media, and traditional communication methods in their education. Questions also addressed perceived effectiveness, challenges, and ethical considerations associated with each modality.

The chosen sample sizes of 30 for interviews and 300 for surveys in this study were determined based on principles of qualitative and quantitative research methodology, as well as considerations specific to the research objectives and population.

Validity and Reliability of Survey Instrument

Steps were taken to ensure the validity and reliability of the survey instrument. Before distribution to the larger sample, the survey underwent a pilot study involving a small group of nursing students (n=20) from similar educational backgrounds. The pilot study aimed to assess the clarity, relevance, and comprehensibility of the survey questions. Feedback from the pilot study participants was used to refine and finalize the survey instrument, enhancing its validity and reliability for the main data collection phase.

Data Analysis

Qualitative data from interviews were transcribed and analyzed using thematic analysis to identify key themes and patterns. Quantitative data from the surveys were subjected to descriptive statistical analysis, providing a quantitative overview of nursing students' preferences and perceptions.

Integration of Findings

The qualitative and quantitative findings were triangulated to provide a comprehensive understanding of nursing students' perspectives on health communication methods. By integrating both types of data, we aimed to offer a robust and multifaceted exploration of the comparative effectiveness of web-based, mHealth, and social media communication versus traditional methods, as perceived by nursing students.

Ethical Considerations

The ethical aspects of this study were carefully addressed during the qualitative data collection phase. Prior to their involvement, all nursing student participants received comprehensive information regarding the research's objectives, procedures, and potential risks and benefits, and they provided written informed consent. Strict measures were implemented to maintain confidentiality, ensuring that participants' responses remained anonymous, and their privacy was protected. Participants were explicitly informed of their autonomy to withdraw from the study at any point without facing any repercussions to their academic standing or relationships. Postinterview debriefing procedures were established to provide support or counseling resources to participants in case of distress. The study protocol, including ethical considerations, underwent thorough review and approval by the institutional ethics board at the College of Nursing-Nineveh University (NUR-IRB-23. October-18th NO:25). Throughout the data collection process, researchers maintained reflexivity by critically reflecting on their biases and potential influences on participants' responses, thus upholding the study's integrity.

Results

Qualitative Findings

Utilization of Web-Based Resources

Nursing students overwhelmingly expressed a reliance on the web for accessing educational materials, research studies, and e-learning platforms. The flexibility and accessibility of web-based resources were highlighted, allowing students to engage with content at their own pace.

mHealth Applications in Clinical Learning

mHealth applications played a significant role in clinical skill development, with students using apps for medication management, patient assessment, and real-time data retrieval. Challenges were noted, including concerns about the accuracy of information within some applications and variations in app reliability.

Social Media as a Community-Building Tool

Social media platforms were instrumental in fostering a sense of community among nursing students. Peer support, information sharing, and collaborative learning were cited as key benefits. Ethical considerations, such as maintaining professionalism on social media, were acknowledged as important aspects of digital interaction.

Value of Traditional Methods

Face-to-face interactions, classroom discussions, and hands-on clinical experiences were deemed essential for honing communication skills. Mentorship from experienced health care professionals during traditional interactions was emphasized as invaluable.

Quantitative Findings

Frequency of Web Use

In total, 92% (276/300) of surveyed nursing students reported using the web daily for educational purposes. The majority (234/300, 78%) indicated that web-based resources were their primary source of information.

mHealth Application Usage Patterns

In total, 68% (204/300) of nursing students reported using mHealth applications in clinical settings at least once a week. Medication reference apps (138/300, 45%) and patient education apps (96/300, 32%) were among the most frequently used.

Social Media Engagement

In total, 80% (240/300) of participants were active on social media platforms related to nursing education. Facebook (138/300, 45%) and Instagram (90/300, 30%) were the most commonly used platforms for academic purposes.

Traditional Methods Preferences

In total, 72% (216/300) of nursing students found face-to-face interactions with educators to be highly effective. Practical, hands-on experiences in clinical settings were rated as very important by 85% (255/300) of participants.

Common Themes Across Qualitative and Quantitative Data

Integration Preferences

Nursing students expressed a preference for an integrated approach, combining traditional methods with digital technologies for a comprehensive learning experience.

Information Validation

Both qualitative and quantitative data revealed concerns about the accuracy of information, with students emphasizing the importance of verifying web-based content.

Balancing Ethical Considerations

Nursing students acknowledged the need for clear guidelines on professional behavior in digital spaces and the importance of maintaining patient privacy and confidentiality (Table 1).

Table . Navigating communication avenues in nursing education: an in-depth exploration of modalities and preferences (n=300).

Communication modality	Frequency of use, n (%)	Primary purpose	Usage in clinical settings, n (%)	Most frequently used apps, n (%)	Social media engagement, n (%)	Preferred traditional methods, n (%)
Web	Daily (n=276, 92%)	Educational	—[a]	—	—	—
mHealth applications	At least weekly (n=204, 68%)	Clinical	Medication reference (n=135, 45%)	Patient education (n=96, 32%)	—	—
Social media	Active (n=240, 80%)	Academic	—	—	Facebook (n=135, 45%)	Instagram (n=90, 30%)
Traditional methods	—	—	—	—	—	Face-to-face (n=216, 72%)
Not applicable	—	—	—	—	—	Practical, hands-on (n=255, 85%)

[a] Not applicable.

Discussion

Principal Findings

The main findings of this study reveal a dynamic interplay between traditional and digital health communication modalities among nursing students in Iraq. Specifically, the study highlights the significant reliance on digital resources such as the web, mHealth applications, and social media platforms for educational purposes, while also recognizing the enduring value of traditional methods such as face-to-face interactions and practical experiences in clinical settings. This underscores the need for a nuanced and integrated approach to nursing education that effectively combines both traditional and digital modalities to prepare the next generation of health care professionals.

Integration Preferences

The preference for an integrated approach to learning among nursing students emerges as a pivotal finding, shedding light on their nuanced perspectives toward communication modalities. This inclination toward integration indicates a sophisticated understanding among nursing students, recognizing the symbiotic relationship between traditional and digital methods in the educational landscape. This revelation aligns with contemporary pedagogical theories that emphasize the importance of adapting education to the evolving needs and preferences of the learners.

IIn the Philippines, research indicated that technology-enhanced nursing education was more effective than conventional methods [10, 11]. Arunasalam [12] highlighted that nursing students encountered frustration with information and communication technology (ICT) usage, primarily due to a lack of support from faculty and staff. This aligns with the findings by Webb et al [13], where Austria identified technological delay, insufficient government support, limited exposure, and a dependence on technology as primary challenges faced by users in the realm of ICT in nursing education .

A study conducted in Egypt by Fernandes et al [14] revealed a set of challenges confronted by nursing students in using ICT, including issues such as slow or poor web speed and access (84.3%), inadequate ICT facilities (80.4%), difficulties in accessing required information (68.7%), and the high cost of web subscriptions (68.5%). This collective evidence underscores that, despite the well-documented advantages of integrating ICT into nursing education, there persist inherent challenges that impede its seamless incorporation.

Complementary Strengths of Traditional and Digital Methods

The recognition of complementary strengths between traditional and digital methods in nursing education reflects a mature and nuanced approach toward shaping the learning experiences of future health care professionals. The integration of both modalities creates a synergistic educational environment that leverages the unique advantages offered by each approach.

Traditional Methods

Traditional methods, characterized by face-to-face interactions and hands-on practical experiences, play an integral role in the development of essential interpersonal and clinical skills among nursing students [15]. Face-to-face interactions with educators provide a platform for immediate feedback, mentorship, and the cultivation of effective communication. Practical experiences in clinical settings not only reinforce theoretical knowledge but also foster critical thinking, decision-making, and a deep understanding of patient care [16,17].

Digital Methods

Simultaneously, digital methods represented by the web, mHealth applications, and social media bring distinct benefits to nursing education. The web serves as a vast repository of information, offering accessibility to a wealth of resources and facilitating self-directed learning. mHealth applications contribute to the enhancement of clinical skills by providing real-time data, medication references, and patient education tools. Social media platforms create virtual communities, fostering collaborative learning, knowledge sharing, and a sense of camaraderie among nursing students [18-20].

Synergy and a Well-Rounded Skill Set

The synergy achieved by combining traditional and digital methods allows nursing students to harness the best of both worlds. Traditional methods provide the foundational skills and human touch necessary for effective patient care, while digital methods offer efficiency, accessibility, and the ability to stay abreast of the latest developments in health care. This symbiotic relationship promotes a well-rounded skill set that is crucial for nursing students as they transition into their future roles in health care [21].

Balanced Approach and Core Values

The inclination toward a balanced approach in nursing education underscores the pivotal importance of preserving the core values embedded in traditional methods. As technology continues to reshape education in the digital age, nursing students recognize that the enduring value of face-to-face interactions with educators and practical, hands-on experiences is indispensable for fostering comprehensive clinical competence and holistic patient care.

Preserving Core Values

The emphasis on a balanced approach reflects a commitment to preserving the core values that have long been integral to nursing education. Face-to-face interactions with educators provide a unique opportunity for immediate feedback, mentorship, and the cultivation of interpersonal skills. These interactions contribute to the development of empathy, a foundational element in patient-centered care. Practical, hands-on experiences are essential for translating theoretical knowledge into real-world applications, fostering critical thinking, and instilling a deep understanding of the complexities of patient care [22,23].

Indispensable Components of Nursing Education

Face-to-face interactions and practical experiences are considered indispensable components of nursing education. They go beyond the acquisition of technical skills, playing a critical role in developing effective communication skills, teamwork, and the ability to navigate complex health care scenarios. The immersive nature of hands-on experiences allows nursing students to engage with the emotional and humanistic aspects of patient care, contributing to the holistic development of future health care professionals [24,25].

Enduring Value in the Digital Age

In the digital age, where technological advancements offer new possibilities in education, nursing students emphasize the enduring value of these foundational elements. While recognizing the benefits of technology-enhanced learning, they underscore the irreplaceable role of face-to-face interactions and practical experiences in shaping their identities as empathetic and skilled caregivers. This sentiment aligns with broader discussions in education literature that emphasize the importance of balancing technological advancements with traditional pedagogical approaches to foster holistic development in students [26,27].

Leveraging Integration in Curriculum Design

Educators wield a pivotal role in shaping the learning experiences of nursing students, and the insights derived from this study underscore the imperative of crafting a curriculum that seamlessly integrates diverse communication modalities. By integrating technology-enhanced learning tools, web-based resources, and digital simulations into traditional classroom settings, educators can foster a dynamic and engaging learning environment. This pedagogical approach not only aligns with the current findings but also resonates with existing literature that underscores the critical importance of technology integration in nursing education.

Creating a Dynamic Learning Environment

The integration of various communication modalities into curriculum design creates a dynamic learning environment that caters to the diverse learning preferences and technological competencies of nursing students. By incorporating technology-enhanced learning tools, educators can enhance the accessibility of educational content, promote interactive learning experiences, and facilitate real-time engagement with evolving health care concepts [28,29].

Enhancing Student Engagement

Technology integration has been shown to enhance student engagement, a critical factor in the overall success of nursing education. Web-based resources, interactive simulations, and collaborative digital platforms provide avenues for active participation, fostering a sense of ownership over the learning process. The integration of technology not only captures the interest of tech-savvy students but also accommodates various learning styles, ensuring a more inclusive and participatory educational experience [30,31].

Preparation for the Evolving Health Care Landscape

A curriculum that embraces technology integration is essential for preparing nursing students for the ever-evolving health care landscape. The incorporation of digital simulations, telehealth experiences, and exposure to emerging technologies aligns with the contemporary demands of health care practice. It equips students with the technological proficiency and adaptability required in modern health care settings, ensuring that they are well positioned to navigate the complexities of their future roles [32,33].

Leveraging Integration in Curriculum Design

Educators wield a pivotal role in shaping the learning experiences of nursing students, and the insights derived from this study underscore the imperative of crafting a curriculum that seamlessly integrates diverse communication modalities [34]. By integrating technology-enhanced learning tools, web-based resources, and digital simulations into traditional classroom settings, educators can foster a dynamic and engaging learning environment. This pedagogical approach not only aligns with the current findings but also resonates with existing literature that underscores the critical importance of technology integration in nursing education [35].

Creating a Dynamic Learning Environment

The integration of various communication modalities into curriculum design creates a dynamic learning environment that caters to the diverse learning preferences and technological competencies of nursing students. By incorporating technology-enhanced learning tools, educators can enhance the accessibility of educational content, promote interactive learning experiences, and facilitate real-time engagement with evolving health care concepts [26,36].

Enhancing Student Engagement

Technology integration has been shown to enhance student engagement, a critical factor in the overall success of nursing education. Web-based resources, interactive simulations, and collaborative digital platforms provide avenues for active participation, fostering a sense of ownership over the learning process [37]. The integration of technology not only captures the interest of tech-savvy students but also accommodates various learning styles, ensuring a more inclusive and participatory educational experience [38,39].

Preparation for the Evolving Health Care Landscape

A curriculum that embraces technology integration is essential for preparing nursing students for the ever-evolving health care landscape. The incorporation of digital simulations, telehealth experiences, and exposure to emerging technologies aligns with the contemporary demands of health care practice. It equips students with the technological proficiency and adaptability required in modern health care settings, ensuring that they are well positioned to navigate the complexities of their future roles [40].

Balancing Ethical Considerations

The discourse on ethical considerations in the digital realm within the context of nursing education resonates with the broader ethical conversation in health care. The acknowledgment by nursing students of the need for clear guidelines on professional behavior in digital spaces aligns with the increasing recognition of the ethical implications associated with the use of social media and mHealth applications. It is imperative that educational programs incorporate components addressing the ethical responsibilities of health care professionals in web-based environments, emphasizing the crucial aspects of privacy, confidentiality, and maintaining the highest standards of professionalism.

Growing Recognition of Ethical Implications

In the digital age, health care professionals, including nursing students, find themselves navigating a complex landscape where ethical considerations intertwine with technological advancements. The acknowledgment of the need for clear guidelines reflects a growing awareness among nursing students about the potential ethical pitfalls associated with social media interactions, the use of mHealth applications, and other web-based platforms. These platforms, while offering opportunities for communication and information-sharing, also pose ethical challenges related to patient privacy, boundaries, and the responsible use of technology in health care [40].

Educational Imperative

The integration of ethical considerations into nursing education is an imperative response to the evolving health care landscape [34]. Educational programs must proactively address the ethical responsibilities of health care professionals in digital spaces, ensuring that nursing students are well equipped to navigate the ethical complexities that may arise in their future practice [41]. This involves providing comprehensive training on maintaining patient confidentiality, safeguarding privacy, and upholding the highest standards of professionalism in the digital realm [34,42-44].

Components of Ethical Education

The ethical education of nursing students in the digital era should encompass the following components:

- *Privacy and confidentiality*: Emphasizing the importance of safeguarding patient information and maintaining confidentiality in web-based communications.
- *Professionalism*: Instilling a sense of professionalism in digital interactions, setting boundaries, and ensuring that web-based behavior aligns with established ethical standards.
- *Informed consent*: Educating students about the importance of obtaining informed consent when using digital platforms for patient engagement or sharing health care information.
- *Navigating ethical dilemmas*: Providing guidance on how to navigate ethical dilemmas that may arise in the context of social media, mHealth applications, and other web-based environments.

Implications for Nursing Education

The findings of this study offer several implications for nursing education, particularly in the context of Iraq's health care landscape. Educators should recognize and capitalize on the positive aspects of digital technologies, such as web-based resources, mHealth applications, and social media, by strategically incorporating them into the curriculum. This integration should be purposeful and aligned with specific learning objectives and competencies, ensuring that digital tools enhance the educational experience rather than serve as distractions. Educators can achieve this by designing interactive web-based modules, using evidence-based mHealth applications for skill development, and creating web-based discussion forums on social media platforms to facilitate peer learning and knowledge exchange.

Moreover, educators should emphasize the development of critical thinking skills among nursing students to navigate the digital information landscape effectively. This involves teaching students to critically evaluate web-based sources, discern credible information from misinformation, and apply evidence-based practices in their clinical decision-making processes. Incorporating case studies or simulated scenarios that require students to analyze and interpret digital health information can further enhance their critical thinking abilities in the context of health care communication.

Practical experiences in clinical settings remain irreplaceable for nursing students' education. While digital tools can enhance certain aspects of learning, the hands-on application of theoretical knowledge in real-world scenarios is essential for building clinical competence and effective communication skills. Educators should continue to prioritize and innovate in clinical education, ensuring that students have ample opportunities for direct patient care experiences, interprofessional collaboration, and mentorship from experienced clinicians. Simulated clinical scenarios using technology-enabled simulation platforms can also complement traditional clinical experiences, providing students with a safe and controlled environment to practice and refine their skills before entering real clinical settings.

In summary, educators in nursing education should adopt a balanced approach that seamlessly integrates diverse communication modalities into the curriculum. This involves leveraging the strengths of digital technologies while preserving the enduring value of hands-on clinical experiences. By implementing specific strategies and best practices for incorporating digital tools and fostering critical thinking skills, educators can better prepare nursing students for the demands of contemporary health care practice in Iraq and beyond.

Limitations of the Study

The findings of this study, conducted in 2 nursing colleges in Iraq, offer valuable insights into communication modalities among nursing students. However, several limitations impact the generalizability of the findings. These include the study's focus on specific institutions, a relatively small and homogeneous sample size, reliance on self-reported data that may introduce bias, a limited time frame, and contextual factors unique to Iraq's health care and educational landscape. Caution should be exercised when applying these findings to broader populations or contexts. Further research with larger, more diverse samples, conducted across multiple regions and institutions, is needed to provide a comprehensive understanding of health care communication among nursing students in Iraq and beyond.

Future Directions

The study's findings pave the way for future research avenues. Longitudinal studies could track nursing students' evolving perspectives over the course of their education and subsequent professional practice. Exploring the impact of interventions designed to enhance information literacy and ethical awareness among nursing students in the digital realm would also be valuable. In addition, investigations into the experiences of nursing educators in integrating diverse communication modalities could provide a holistic understanding of the challenges and opportunities in nursing education.

Conclusions

This study provides a rich foundation for understanding health communication preferences among nursing students. As technology continues to evolve, nursing education must adapt to prepare students for the complexities of modern health care. A thoughtful integration of traditional and digital communication methods will not only enhance educational outcomes but also contribute to the development of well-rounded, technologically literate, and ethically conscious nursing professionals.

Acknowledgments

The authors extend their sincere appreciation to the institutional review boards of Ninevah University and Al-Kitab University for their support and supervision throughout the research process. Special thanks are also due to the nursing students from both universities who generously participated in this study, as well as to the panel of experts who provided valuable validation of the study tools.

Data Availability

The data sets used and analyzed during this study are available from the corresponding author upon reasonable request.

Authors' Contributions

MQH and MFA contributed to conceptualization, methodology, formal analysis, investigation, data curation, writing, reviewing, and editing of the original draft. OAM and MHY contributed to conceptualization, investigation, and editing. MFA contributed to supervision and project administration. All the authors have read and agreed to the published version of the manuscript. MQH, RHI, and MFA were responsible for designing and conducting the study, as well as the acquisition, analysis, and interpretation of data. OAM and MHY developed the study tools. RHI drafted the first version of the manuscript. MFA and MHY were involved in the data analysis and interpretation. MQH and RHI made substantial contributions to the study design and interpretation. All authors critically revised the manuscript, and all authors approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

Conflicts of Interest

None declared.

References

1. Eastern Mediterranean Public Health Network (EMPHNET). Toward public health resilience in the Eastern Mediterranean Region: findings from the seventh Eastern Mediterranean Public Health Network Regional Conference. Interact J Med Res 2023 Mar 9;12:e36356. [doi: 10.2196/36356] [Medline: 36892927]
2. Vadakalu Elumalai K, Sankar JP, Kalaichelvi· R, et al. Factors affecting the quality of e-learning during the COVID-19 pandemic from the perspective of higher education students. JITE: Res 2021;19:731-753. [doi: 10.28945/4628]
3. Arunasalam ND, Burton R. Investigating Malaysian nurses' perspectives of intercultural teaching in transnational higher education learning environments. Nurse Educ Today 2018 Oct;69:165-171. [doi: 10.1016/j.nedt.2018.07.011]
4. Attia YK, Ibrahim RH. Difficulties experienced in clinical learning settings for nurses in Iraq: perspectives of nursing administrators and nursing instructors. Inform Med Unlocked 2023;38:101229. [doi: 10.1016/j.imu.2023.101229]
5. Ayaya GI. Online support for students with diverse learning needs at an inclusive private school in South Africa. E-Learning Dig Media 2024 May;21(3):273-291. [doi: 10.1177/20427530231156179]
6. Lawal Bello U. Challenges of information and communication technology utilization among undergraduate community health nursing students in Tanta University, Egypt. AJNS 2017;6(3):274. [doi: 10.11648/j.ajns.20170603.26]
7. Brunner M, McGregor D, Keep M, et al. An eHealth capabilities framework for graduates and health professionals: mixed-methods study. J Med Internet Res 2018 May 15;20(5):e10229. [doi: 10.2196/10229] [Medline: 29764794]
8. De Gagne JC, Koppel PD, Park HK, et al. Nursing students' perceptions about effective pedagogy: netnographic analysis. JMIR Med Educ 2021 Jun 22;7(2):e27736. [doi: 10.2196/27736] [Medline: 34156337]
9. De Sutter E, Geerts D, Yskout K, et al. Testing and practical implementation of a user-friendly personalized and long-term electronic informed consent prototype in clinical research: mixed methods study. J Med Internet Res 2023 Dec 19;25:e46306. [doi: 10.2196/46306] [Medline: 38113088]
10. Penaflor-Espinosa MJB. Technology integration in nursing education: its implications to colleges of nursing in Western Visayas, Philippines. IJHIT 2016 Sep 30;9(9):375-392 [FREE Full text] [doi: 10.14257/ijhit.2016.9.9.35]
11. Pugoy R, Ramos RC, Figueroa Jr RB, et al. Augmented reality in nursing education: addressing the limitations of developing a learning material for nurses in the Philippines and Thailand. Int J Dev E Learn 2016;2:13 [FREE Full text]
12. Arunasalam N. Technology-enhanced learning in transnational higher education. Br J Nurs 2016 Nov 24;25(21):1201-1205. [doi: 10.12968/bjon.2016.25.21.1201] [Medline: 27882796]
13. Webb L, Clough J, O'Reilly D, Wilmott D, Witham G. The utility and impact of information communication technology (ICT) for pre-registration nurse education: a narrative synthesis systematic review. Nurse Educ Today 2017 Jan;48:160-171. [doi: 10.1016/j.nedt.2016.10.007] [Medline: 27816862]
14. Fernandes B, Neelakantan L, Shah H, et al. Evidencing the impact of web-based coproduction with youth on mental health research: qualitative findings from the MindKind study. JMIR Public Health Surveill 2023 Jun 19;9:e42963. [doi: 10.2196/42963] [Medline: 37335609]
15. George AS, George AH, Baskar T. Exploring the potential of prompt engineering in India: a study on the future of AI-driven job market and the role of higher education. PUIRP 2023;1(2):34-57. [doi: 10.5281/zenodo.10121998]
16. Goodman P, Edge B, Agazio J, Prue-Owens K. Cultural awareness: nursing care of Iraqi patients. J Transcult Nurs 2015 Sep;26(4):395-401. [doi: 10.1177/1043659614524794] [Medline: 24810515]
17. Nadhim Hasan N, Hasan Mohammed I, Ahmed Mahmood Y. Communication skills among nursing staff at Azadi Teaching Hospital. Al-Kitab J Pure Sci 2019;3(2):62-70. [doi: 10.32441/kjps.03.02.p5]
18. Herbst R, Rybak T, Meisman A, et al. A virtual reality resident training curriculum on behavioral health anticipatory guidance: development and usability study. JMIR Pediatr Parent 2021 Jun 29;4(2):e29518. [doi: 10.2196/29518] [Medline: 34081601]
19. Jeyakumar T, Ambata-Villanueva S, McClure S, Henderson C, Wiljer D. Best practices for the implementation and sustainment of virtual health information system training: qualitative study. JMIR Med Educ 2021 Oct 22;7(4):e30613. [doi: 10.2196/30613] [Medline: 34449402]
20. Jin J, Bridges SM. Educational technologies in problem-based learning in health sciences education: a systematic review. J Med Internet Res 2014 Dec 10;16(12):e251. [doi: 10.2196/jmir.3240] [Medline: 25498126]
21. Joseph R. Basic qualitative design: faculty experiences in technology integrated faculty development for IPE [Dissertation]. : Capella University; 2023 URL: https://eric.ed.gov/?id=ED635946 [accessed 2024-10-13]
22. King DL, Billieux J, Mueller K, Delfabbro PH. Clinical interventions for technology-based problems. In: Mental Health in a Digital World: Academic Press; 2022:435-457. [doi: 10.1016/B978-0-12-822201-0.00016]
23. Lall P, Rees R, Law GCY, Dunleavy G, Cotič Ž, Car J. Influences on the Implementation of mobile learning for medical and nursing education: qualitative systematic review by the digital health education collaboration. J Med Internet Res 2019 Feb 28;21(2):e12895. [doi: 10.2196/12895] [Medline: 30816847]

24. Lefebvre C, Mesner J, Stopyra J, et al. Social media in professional medicine: new resident perceptions and practices. J Med Internet Res 2016 Jun 9;18(6):e119. [doi: 10.2196/jmir.5612] [Medline: 27283846]
25. Leung J, Som A, McMorrow L, et al. Rethinking the difficult patient: formative qualitative study using participatory theater to improve physician-patient communication in rheumatology. JMIR Form Res 2023 Mar 6;7:e40573. [doi: 10.2196/40573] [Medline: 36877547]
26. Lifländer M, Ylinen S. Preceptors' experience on their support and training at the pediatric and adolescent clinic—Turku University Hospital. 2023. URL: https://urn.fi/URN:NBN:fi:amk-2023120835285 [accessed 2024-10-13]
27. Magagna W, Wang N, Peck K. Current and future trends in life sciences training: questionnaire study. JMIR Med Educ 2020 Apr 24;6(1):e15877. [doi: 10.2196/15877] [Medline: 32329739]
28. Masya L, Shepherd HL, Butow P, et al. Impact of individual, organizational, and technological factors on the implementation of an online portal to support a clinical pathway addressing psycho-oncology care: mixed methods study. JMIR Hum Factors 2021 Apr 14;8(2):e26390. [doi: 10.2196/26390] [Medline: 33851926]
29. Adnan Mirdan A, KhadherBaiez Y. Evaluation of factors that impact female nurses job performance at Kirkuk hospitals. Al-Kitab J Pure Sci 2019;3(2):29-51. [doi: 10.32441/kjps.03.02.p3]
30. Rolls K, Hansen M, Jackson D, Elliott D. How health care professionals use social media to create virtual communities: an integrative review. J Med Internet Res 2016 Jun 16;18(6):e166. [doi: 10.2196/jmir.5312] [Medline: 27328967]
31. Saravanakumar A, Raja G, Sivakumar P. Transforming education: perceptions and challenges of technology-enabled teacher education programmes. Open Access Res J Eng Technol 2023;5(2):001-007. [doi: 10.53022/oarjet.2023.5.2.0077]
32. Sharma S. Cultivating pedagogical sustainability in early education. Int J Manag Educ Sustain Dev 2023;6(6):13-23 [FREE Full text]
33. Siebert JN, Lacroix L, Cantais A, Manzano S, Ehrler F. The impact of a tablet app on adherence to American Heart Association guidelines during simulated pediatric cardiopulmonary resuscitation: randomized controlled trial. J Med Internet Res 2020 May 27;22(5):e17792. [doi: 10.2196/17792] [Medline: 32292179]
34. Tibble H, Mueller T, Proud E, et al. Real-world severe COVID-19 outcomes associated with use of antivirals and neutralising monoclonal antibodies in Scotland. NPJ Prim Care Respir Med 2024 Jun 28;34(1):17. [doi: 10.1038/s41533-024-00374-x] [Medline: 38942748]
35. Sulaiman MH, Jasim MS, Ahmed AA, Ahmed AA, Ibrahim RH, Al-Mashhadany OI. A winning formula for nursing education: effective study strategies and techniques. Teach Learn Nurs 2023 Oct;18(4):e142-e145. [doi: 10.1016/j.teln.2023.05.001]
36. Tate E. Nursing students' experiences using therapeutic communication techniques: a basic qualitative study [Dissertation].: Capella University; 2023. URL: https://www.proquest.com/openview/a376650d8474212f342f3cbcd31080f0/1?pq-origsite=gscholar&cbl=18750&diss=y [accessed 2024-11-12]
37. Egilsdottir H. Using mobile learning to enhance nursing students' competence and confidence in performing basic physical assessment skills: an exploratory sequential mixed methods study [Thesis]. : University of South-Eastern Norway; 2024 URL: https://hdl.handle.net/11250/3104898 [accessed 2024-11-12]
38. Tolppa T, Pari V, Pell C, et al. Determinants of implementation of a critical care registry in Asia: lessons from a qualitative study. J Med Internet Res 2023 Mar 6;25:e41028. [doi: 10.2196/41028] [Medline: 36877557]
39. Valdez Soto M, Balls-Berry JE, Bishop SG, et al. Use of Web 2.0 social media platforms to promote community-engaged research dialogs: a preliminary program evaluation. JMIR Res Protoc 2016 Sep 9;5(3):e183. [doi: 10.2196/resprot.4808] [Medline: 27613231]
40. Yaas MH, Hamarash MQ, Almushhadany OI, Ibrahim RH, Jassim RS. Assessing the effectiveness of clinical rotations in preparing undergraduate nursing students for practice: mixed study. MJN 2023;15:87-99. [doi: 10.31674/mjn.2023.v15i02.010]
41. Arunasalam N. A Defining Moment: Transnational Nursing Education: Transnational Press London; 2017.
42. Zhang X, Xue Y, Su X, et al. A transfer learning approach to correct the temporal performance drift of clinical prediction models: retrospective cohort study. JMIR Med Inform 2022 Nov 9;10(11):e38053. [doi: 10.2196/38053] [Medline: 36350705]
43. Hamarash MQ, Yaas MH, Almushhadany OI, Ibrahim RH. Preceptoring of graduate nursing students in Iraq. Adv Med Educ Pract 2023;14:1025-1034. [doi: 10.2147/AMEP.S418824] [Medline: 37766737]
44. Wu H, Aziz AR, Dehghan M, Ahmadi Lari L, Al-Amer R, Zakeri MA. Use of complementary and alternative medicine for reducing fear of cancer recurrence among cancer survivors: does it work? Asia Pac J Oncol Nurs 2023 Oct;10(10):100278. [doi: 10.1016/j.apjon.2023.100278] [Medline: 37731732]

Abbreviations

ICT: information and communication technology

Edited by E Borycki; submitted 22.12.23; peer-reviewed by H Mahmood, SA Mukhtar; revised version received 23.02.24; accepted 13.09.24; published 19.11.24.

Please cite as:
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 Nursing 2024;7:e55744
URL: https://nursing.jmir.org/2024/1/e55744
doi:10.2196/55744

Review

Digital Health Education and Training for Undergraduate and Graduate Nursing Students: Scoping Review

Manal Kleib[1], BScN, MN, MBA, PhD; Antonia Arnaert[2], PhD; Lynn M Nagle[3], PhD; Shamsa Ali[1], MN, RN; Sobia Idrees[1], MN; Daniel da Costa[4], MN; Megan Kennedy[5], BA, MLIS; Elizabeth Mirekuwaa Darko[1], MN

[1]Faculty of Nursing, University of Alberta, Edmonton, AB, Canada
[2]Ingram School of Nursing McGill University, Montreal, QC, Canada
[3]Faculty of Nursing, University of New Brunswick, Fredericton, NB, Canada
[4]Ingram School of Nursing, McGill University, Montreal, QC, Canada
[5]Geoffrey & Robyn Sperber Health Sciences Library,, University of Alberta, Edmonton, AB, Canada

Corresponding Author:
Shamsa Ali, MN, RN
Faculty of Nursing
University of Alberta
Edmonton Clinic Health Academy
11405 87 Ave NW
Edmonton, AB, T6G 1C9
Canada
Phone: 1 587 937 0313
Email: shamsa1@ualberta.ca

Abstract

Background: As technology will continue to play a pivotal role in modern-day health care and given the potential impact on the nursing profession, it is vitally important to examine the types and features of digital health education in nursing so that graduates are better equipped with the necessary knowledge and skills needed to provide safe and quality nursing care and to keep abreast of the rapidly evolving technological revolution.

Objective: In this scoping review, we aimed to examine and report on available evidence about digital health education and training interventions for nursing students at the undergraduate and graduate levels.

Methods: This scoping review was conducted using the Joanna Briggs Institute methodological framework and the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews). A comprehensive search strategy was developed and applied to identified bibliographic databases including MEDLINE (Ovid; 1946 to present), Embase (Ovid; 1974 to present), CINAHL (EBSCOhost; 1936 to present), ERIC (EBSCOhost; 1966 to present), Education Research Complete (EBSCOhost; inception to present), and Scopus (1976 to present). The initial search was conducted on March 3, 2022, and updated searches were completed on January 11, 2023, and October 31, 2023. For gray literature sources, the websites of select professional organizations were searched to identify relevant digital health educational programs or courses available to support the health workforce development. Two reviewers screened and undertook the data extraction process. The review included studies focused on the digital health education of students at the undergraduate or graduate levels or both in a nursing program. Studies that discussed instructional strategies, delivery processes, pedagogical theory and frameworks, and evaluation strategies for digital health education; applied quantitative, qualitative, and mixed methods; and were descriptive or discussion papers, with the exception of review studies, were included. Opinion pieces, editorials, and conference proceedings were excluded.

Results: A total of 100 records were included in this review. Of these, 94 records were identified from database searches, and 6 sources were identified from the gray literature. Despite improvements, there are significant gaps and limitations in the scope of digital health education at the undergraduate and graduate levels, consequently posing challenges for nursing students to develop competencies needed in modern-day nursing practice.

Conclusions: There is an urgent need to expand the understanding of digital health in the context of nursing education and practice and to better articulate its scope in nursing curricula and enforce its application across professional nursing practice roles at all levels and career trajectories. Further research is also needed to examine the impact of digital health education on improving patient outcomes, the quality of nursing care, and professional nursing role advancement.

International Registered Report Identifier (IRRID): RR2-10.11124/JBIES-22-00266

(JMIR Nursing 2024;7:e58170) doi:10.2196/58170

KEYWORDS

curriculum; digital health; health informatics; nursing education; nursing students; undergraduate; graduate

Introduction

Background

The World Health Organization (WHO) emphasized the important role of information and communication technologies (ICTs) in facilitating eHealth services and urged health systems to embrace emerging technologies such as artificial intelligence (AI) and big data analytics, considering their potential to radically change health outcomes. However, this requires intentional investments in people and processes as well as national-level strategies to realize the vision of a digitalized health sector [1]. Correspondingly, as the largest group of health care professionals, "there is an urgent need for the nursing workforce to acquire the skills and competencies to deliver high-quality, safe, optimized person-centred care in a digital health environment and to lead and participate in digital health initiatives, decision-making, and evaluation" [2].

Digital health is a new and evolving term that is often used interchangeably with other terms including *eHealth*, *mobile health*, *virtual care*, and *telehealth* to name a few [3]. These terms have evolved over time and can be understood by examining the eras of the industrial revolution impacting society, including health care. During the periods from 1950 to 1960 (Mainframe Computer Era) and 1970 to 2000 (Health IT Era), technological development was in its infancy, as such health care systems focused on the basic use of IT systems to manage enterprise information and logistics. The eHealth Era (2000-2020) witnessed an expansive use of ICTs such as electronic health records (EHRs) and increased consumer engagement in decision-making and self-care through digital technologies such as apps and personal health records [3]. In this period, terms such as *mHealth* and *eHealth* were popular. Services such as telehealth were also available but mostly as specialized and organization-based platforms. Telehealth refers to the "delivery and facilitation of health and health-related services including medical care, provider and patient education, health information services, and self-care via telecommunications and digital communication technologies. Examples of the technologies used in telehealth include but are not limited to live video conferencing, mobile health apps, 'store and forward' electronic transmission, and remote patient monitoring" [4]. The period between 2020 and beyond marked the Digital Health Era, which is anticipated to revamp health care as a result of the integration of more sophisticated technologies including AI, robotics, machine learning, the Internet of Things, virtual reality, and wearables. These advancements are shifting the focus of health care from the provider to a person-centered model and creating opportunities to improve health services modalities, system performance, therapeutics and treatments, and all aspects of health care [3]. During this period, the term *virtual care* emerged during the COVID-19 pandemic. Virtual health denotes the facilitation of the delivery of care services through any remote interactions between patients and health care providers and between health care providers themselves, whether synchronous or asynchronous, using ICTs [5].

Although some progress has been achieved in increasing nurses' digital health capacity, the expanded and rapid integration of technological innovations in health care has created challenges for nursing educators and nursing programs to keep pace and ensure that nurses are well prepared to lead the digital transformation impacting professional practice roles and patient care [6-9]. In addition, while most nursing students have strong basic digital literacy skills, these skills do not necessarily translate into effective use of digital health technologies in the context of patient care [8,10,11]. Sometimes, assumptions about the use of technology in the academic setting put nursing students at a disadvantage, resulting in missed learning opportunities for students to develop competency in working with digital health technologies available in the clinical environment [8,12]. In Canadian nursing, approaches currently applied for preparing students at the undergraduate level in digital health are mainly focused on integrating informatics within existing courses; however, this integration is mostly inconsistent and sporadic [8,13,14]. Similar to the Canadian context, in other countries, the nursing informatics (NI) competencies, which should serve as a guiding framework for content integration in nursing curricula and as standards for professional practice requirements in the workplace, have limited to no focus on emerging technologies [15-17]. Furthermore, the adoption of these NI competencies in the workplace and their impact on patient outcomes remain largely unknown [8,18].

Nursing education is a key pathway for preparing nurses to assume professional roles in diverse practice settings. Providing nurses and nursing students with a comprehensive education in digital health should be an urgent priority, so they are better equipped with the necessary knowledge and skills needed to provide safe and quality nursing care and to keep abreast of the rapidly evolving technological revolution. This is also important so that nurses are better able to support patients and families as they navigate the health system and make decisions about using these technologies for health promotion and chronic disease management and to ensure that digital health services and technologies brought into the health care system are equitable, bias free, and accessible [2,9].

To identify current approaches for digital health education at the undergraduate and graduate nursing education levels, a preliminary search of available literature was conducted to identify prior work on this topic, and several reviews were retrieved. Some reviews focused on NI and digital health competency frameworks and the integration of NI into nursing curricula [15,16,18,19]. Other reviews addressed the learning outcomes of digital learning interventions in higher education [20] and technological literacy in nursing education [21]. The remaining reviews examined the influence of AI on different domains of nursing [22] and the effectiveness of telehealth educational interventions in graduate nursing education [23]. Another search was conducted on December 1, 2023, to identify if new reviews have been published since the initial search was conducted on January 5, 2022, and a scoping review protocol was found in CINAHL Plus database that focused on NI education in undergraduate nursing education [24].

On the basis of the evidence available on the digital health education for nursing students, we believe a gap exists in the literature, particularly assessing the current state with respect to how nursing education at the undergraduate and graduate nursing levels addresses digital health education about existing and emerging technologies. Therefore, this scoping review aimed to report on evidence available about digital health education and training interventions for nursing students at the undergraduate and graduate levels.

Review Question

The review aimed to answer the following question: what are the types and features of digital health education and training interventions currently available to guide teaching and curricular integration or education about digital health for nursing students at the undergraduate and graduate levels? More specifically, this review analyzed and synthesized information on the following elements: (1) the definitions of digital health and learning objectives and topic content addressed in the digital health intervention; (2) the instructional strategies used and their delivery processes; (3) the pedagogical theories or frameworks used; and (4) the outcomes measured and evaluation or assessment strategies used for measuring them.

Methods

The scoping review was conducted following the Joanna Briggs Institute methodology [25] and in line with the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) [26]. The review followed a priori protocol [27].

Search Strategy

A health sciences librarian developed a comprehensive search strategy according to the PRISMA-S (Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Searching) [28]. To ascertain the feasibility and testability of the search strategy, an initial search was conducted in CINAHL (EBSCOhost) as published in the study protocol [27]. All identified databases were searched, and the search strategy was adapted as appropriate. The following bibliographic databases were searched from inception to present: MEDLINE (Ovid; 1946 to present), Embase (Ovid; 1974 to present), CINAHL (EBSCOhost; 1936 to present), ERIC (EBSCOhost; 1966 to present), Education Research Complete (EBSCOhost; inception to present), and Scopus (1976 to present; Multimedia Appendix 1). The search used subject headings, wherever available, and appropriate keywords to capture relevant peer-reviewed literature. The search strategy was derived from two main concepts: (1) *digital health*, applying descriptors associated with the term such as virtual, telehealth, or remote delivery to capture the most relevant literature and (2) *nursing education*, both undergraduate and graduate level, as well as competencies and curricula. A multidatabase search was completed for ERIC and Education Research Complete, as these databases were available on the same platform, and the search strategy for these databases did not include any subject headings.

Only studies published from 2012 to 2023 were included because the authors wanted to capture current and relevant articles. Also included were studies published in the English language, as the authors speak only English. The non–peer-reviewed materials such as notes, editorials, letters, books, and book chapters were removed from the results, as they had limited information to contribute to the findings and discussion. The initial database searches were conducted on March 3, 2022, and updated searches were completed on January 11, 2023, and October 31, 2023. The same search strategy was used for each updated search to ensure consistency and identify any recently published papers. For gray literature sources, select relevant organizational sources were identified and searched for information regarding the digital health education programs that were being offered to gain insights on which topics were addressed and the target audiences for such education. Limiting this search to a few organizations was intentional, considering the volume of information that can be found on the web.

Eligibility Criteria

Participants

This scoping review considered studies that included nursing students at the undergraduate or graduate levels admitted to public or private institutions. Furthermore, the review included students enrolled in undergraduate or graduate nursing programs, qualifying graduates for various nursing roles such as generalist entry-to-practice programs for registered nurses, licensed practical nurses or registered practical nurses, nurse practitioners (NPs), and registered psychiatric nurses. Empirical studies that reported on digital health education for qualified nurses working in practice settings and studies that reported on students in other health-related professions (eg, medicine, pharmacy, physiotherapy) or allied health staff (eg, health care aids) were excluded because these professions are not the subject of interest in this review.

Concept

The primary concepts of significance to the review are digital health education and training for nursing students. Other related concepts included are instructional strategies, delivery processes, pedagogical theory and frameworks, and evaluation strategies. Since the use of different technologies in health professionals' education exists, the authors contend that the use of technologies for learning and teaching purposes differs from the use of digital health technologies for care delivery. Consequently, studies that focused on the use of instructional technologies, such as PowerPoint, simulation, and virtual reality for teaching or learning purposes in the classroom or laboratory or for learning about general clinical nursing skills, as opposed to education, learning, and training for acquisition of digital health knowledge and competence, were excluded. Studies that only examined an aspect of digital capabilities or NI competency, such as computer or information literacy, and focused on NI competency without explicitly linking the concept to digital health were excluded. Studies that focused on aspects of medical technologies, such as computed tomography scans and in vitro fertilization, were also excluded.

Context

This review considered studies that examined digital health education for nursing students admitted to educational institutions (colleges or universities) at undergraduate and graduate programs or both. There was no limit on the geographical location of the published studies, as the authors wanted to be comprehensive in their search and provide an in-depth analysis of the literature from multiple geographical locations.

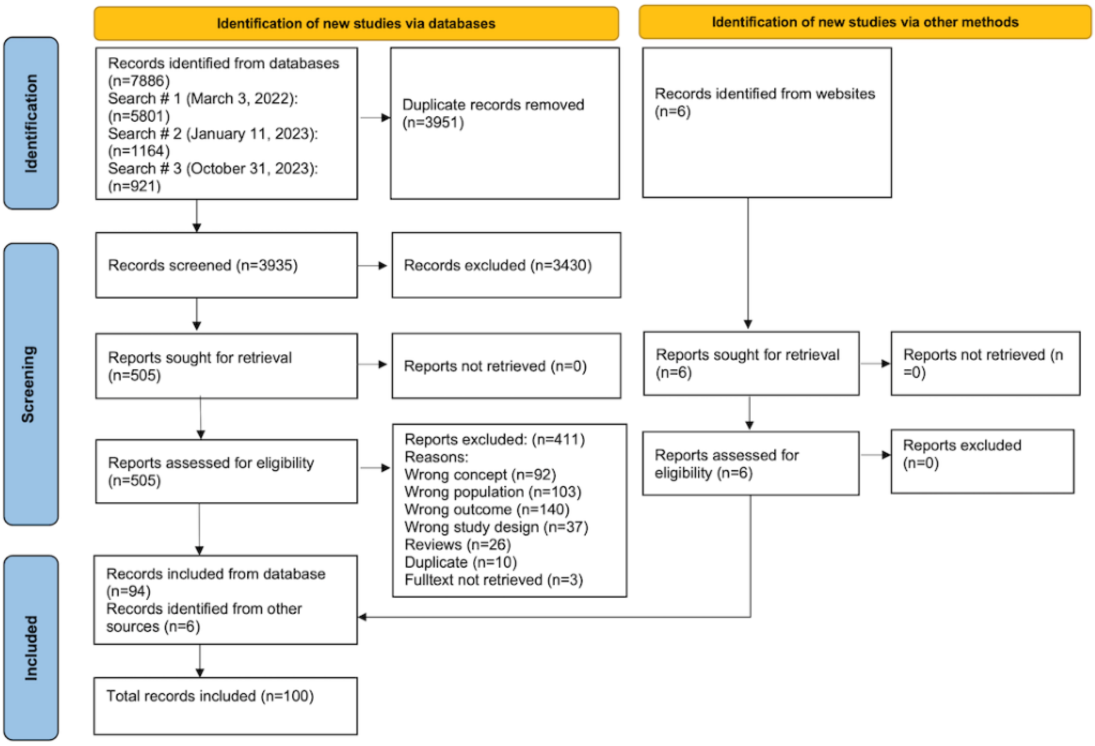
Types of Sources

This scoping review considered all methodological and theoretical papers, including quantitative, qualitative, and mixed methods study designs. Systematic, scoping, integrative, umbrella, and narrative review studies were excluded but these types of studies were referred to in the *Discussion* section to provide further information. In addition, opinion pieces, editorials, and conference proceedings were also excluded due to the insufficient information these sources offer to contribute to the evidence available. Furthermore, a hand-search of reference lists of the included studies to search for missing studies was planned but not completed due to the large volume of searches retrieved. Selected gray literature sources were searched for additional evidence and insights.

Study and Source of Evidence Selection

Retrieved records were exported in complete batches into the Mendeley reference manager software (Mendeley Ltd) to generate bibliographies and the Covidence software (Veritas Health Innovation) for deduplication and to enable the screening process. To increase the reliability of the screening process, 2 reviewers (SI and SA) independently determined the eligibility of articles against the inclusion and exclusion criteria using a 2-stage screening process consisting of a title and abstract scan followed by a full-text review. All disagreements were resolved in consultation with other reviewers (M Kleib and EMD). The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) chart was used to document inclusion and exclusion decisions and ensure transparency and rigor in reporting (Figure 1) [29,30]. Where full-text articles were excluded, reasons were provided for the exclusion (Multimedia Appendix 2).

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



Data Extraction

Two independent reviewers (SI and SA) extracted data from the included studies and recorded it into an open-access Google spreadsheet. The included studies were extracted based on the extraction table as published in the a priori protocol [27]. To enhance reliability, the independent reviewers piloted the extraction table on 10 records (qualitative, quantitative, and mixed method study designs), and after comparing results, no further modifications were made to the extraction table. For each record, the following information was extracted: record information (ie, author or authors, year of publication, and study aim or purpose); population or sample (nursing students or level); context (country or program); concept (digital health existing and emerging technologies, the definition of digital health if provided, instructional strategy used and delivery process [eg, lecture, video, case-based scenario, pedagogical theory or framework, outcomes measured [eg, knowledge gain], assessment methods, or approaches [eg, instrument or tool, quizzes]); key findings; and recommendations. Any disagreements were resolved with other reviewers (M Kleib and EMD).

Data Analysis and Interpretation

Basic descriptive statistics (ie, percentages or proportions) were applied to analyze and report key characteristics of studies included in the review. Using an iterative, descriptive approach, abstracted data from the included studies were examined for similarities and differences to identify patterns and facilitate thematic grouping of findings to answer the research questions. All members of the research team engaged in the discussion of the results and agreed upon the adequacy of the proposed thematic grouping. Where appropriate, a tabular format was used to provide a visual representation of the findings [25,31]. Appendices were used to provide access to information relevant to the conduct of this review and facilitate future research. Quality appraisal of the included studies was not completed, as it is not a requirement for scoping reviews.

Results

Study Inclusion

As shown in the PRISMA chart (Figure 1), combining all 3 searches together, we identified a total of 7886 studies. After removing duplicates and completing the first-level and second-level screening, 94 (1.19%) records were included from the database searches. Furthermore, 6 sources from the gray literature were included. These pertained to educational resources published on the websites of select organizations, including Digital Health Canada, Coursera, Healthcare Information and Management Systems Society, Canadian Nursing Informatics Association, Canadian Association of Schools of Nursing, and the Open WHO (Multimedia Appendix 3 [12,13,32-123]). In total, 100 records were included in this review.

Characteristics of Included Studies

Of the 94 included studies from databases, the majority (n=67, 71%) were published within the last 5 years (2019-2023). Studies were mainly conducted in the United States (n=69, 73%) followed by Canada (n=8, 9%). The remaining were a few studies (n=17, 18%) from New Zealand, the United Kingdom, Australia, South Korea, Japan, Singapore, Norway, Democratic People's Republic of Korea, and Saudi Arabia. The research populations in these studies included representations from nursing students at the undergraduate and graduate levels and decision makers in charge of planning educational offerings. There were no studies involving licensed practical nurse students or their educational preparation in digital health.

Review Findings

Table 1 provides a visual presentation of the range of studies included in this review classified according to the type and focus of the research study and the level of nursing education (undergraduate and graduate) in order to facilitate the reporting of the findings according to the review questions. Detailed abstraction tables of all the included studies from databases are available in Multimedia Appendix 4. The review of the 6 websites comprising the gray literature sources is also provided in Multimedia Appendix 3.

The included literature sources revealed a proliferation of educational offerings (Multimedia Appendix 4), and these sources were examined to identify whether or not authors have included a definition of digital health. A few studies involving undergraduate-level [13,104] and graduate-level education [83,84] cited the definition by Healthcare Information and Management Systems Society, which defined *digital health* as a health care delivery system that “connects and empowers people and populations to manage health and wellness through technology. Care is augmented by accessible and supportive provider teams working within flexible, integrated, interoperable, and digitally enabled care environments that strategically leverage digital tools, technologies, and services to transform care delivery” [124]. The definition of digital health proposed by the WHO, including the initial one in the draft of the global digital health strategy document published in 2019 or the one reported in final document, is as follows: “the field of knowledge and practice associated with the development and use of digital technologies to improve health. Digital health expands the concept of eHealth to include digital consumers, with a wider range of smart and connected devices. It also encompasses other uses of digital technologies for health such as the Internet of Things, advanced computing, big data analytics, artificial intelligence including machine learning, and robotics” [1].

Table 1. Overview of the records included in the review (n=100).

	Reference
Database sources (n=94)	
Interventional studies (n=61)	
Undergraduate	
Telehealth (n=11)	[32-42]
EHR[a] training (n=10)	[73-82]
NI[b] (n=2)	[85,86]
Graduate	
Telehealth (n=30)	[43-72]
EHR (n=2)	[87,88]
Digital health (n=2)	[83,84]
NI (n=4)	[89-92]
Curriculum status and integration (n=14)	[13,93-105]
Proposed strategies for integration (n=19)	[12,106-123]
Gray literature sources (n=6)	—[c]

[a] EHR: electronic health record.

[b] NI: nursing informatics.

[c] Not applicable.

Digital Health and NI Educational Interventions at the Undergraduate Level

Overview

At the undergraduate level, the main focus of the education delivered was on telehealth and telenursing [32-42] and competency development in using the EHR through simulated EHRs [73-82]. In total, 2 studies focused on NI education [85,86]. Of note, some of these interventions were implemented or developed in response to the COVID-19 pandemic [32-36,40].

Interventions Focused on Telehealth Education

The scope of the telehealth theoretical education in the included studies varied but mainly focused on the prepreparation for the telehealth simulation. In 1 study, a range of topics including telehealth etiquette, professionalism, peripherals, technologies, documentation, billing, collaboration, and history taking were taught [33], using different teaching modalities to deliver the content such as online modules [33], e-book, and video [32]. One study reported the use of a telehealth clinical placement experience [34], another study applied a web-based clinical experience [36], and the remaining studies applied different simulation activities [32,33,35,37-42].

Integration of simulation experiences was mostly as a stand-alone intervention; a few studies reported integration as part of an existing course. These studies integrated the simulation experiences as part of a rotation practice [38], course assignment [33], and as part of a clinical course [37,40]. Simulation was delivered mainly via teleconferencing and online technologies such as Zoom and Google Hangouts [32,33,35,36,40-42]. A few studies used a telehealth robot [33] or a telepresence robot [38,39]. The simulation experiences varied in length from 1 hour to a few hours, facilitated by using scenarios, standardized patients, briefing, and debriefing. Authors used different professional practice frameworks such as the American Association of Colleges of Nursing Essentials [33,40], National Organization of Nurse Practitioner Faculties [33], and Quality and Safety Education for Nurses [37] and best practices and theoretical frameworks for conducting simulation such as the International Nursing Association of Clinical Simulation and Learning and Promoting Excellence and Reflective Learning through Simulation method for debriefing [33,36,37].

A quantitative quasi-experimental design with a pretest-posttest [32,33,38] or posttest-only [39] and mixed methods research [34] approaches were mostly used to measure a variety of outcomes including knowledge, confidence, attitudes, communication, and overall experiences. Some studies also sought to determine the usability of the telehealth robot [33,39] or feasibility of the telehealth experience [35,36]. In addition to using pretest-posttest assessments, some authors used Objective Structured Clinical Examinations [32,35], knowledge tests [33,40], reflection [34,36,41], and focus group interviews [34,37,42]. Despite the inherent limitations of the study designs used, the interventions delivered yielded positive outcomes and students' experiences and feedback. Two studies [32,38] reported a statistically significant change in the outcomes measured.

Interventions Focused on EHR Education

For studies involving EHR-related education, authors applied a variety of research designs mainly to pilot academic EHRs including mixed methods [74,75,80], case study [77], correlational design [81], surveys [73,76,78], think-aloud method [79], and focus groups [82]. Integration was mostly as a stand-alone intervention; a few studies reported integration as part of the first-year nursing clinical course [73], a clinical course [76], or as part of a fundamentals of nursing course [81]. A key aspect of using the simulated EHRs focused on developing documentation skills [73-75,79,82]. Case scenarios were used in most interventions; some included an additional didactic content [73] or provided orientation through videos, webinars, and opportunities to practice [74,75,81,82]. A few studies related the intervention to the required professional NI competencies or educational theories supporting simulation activities [75,80]. Outcomes of interest in these studies included knowledge, confidence, attitudes, satisfaction, experience, and perceived NI competency. Statistically significant findings were reported in some of these interventions [73,75,76]. Some studies also sought to evaluate the feasibility and suitability of the simulated record for use in a nursing program [74,75,78,79].

Interventions Focused on NI Education

In total, 2 studies addressed NI education [85,86]. Of these, 1 study applied a controlled interventional design to measure knowledge gain, attitudes toward the EHR, and perceived confidence following the completion of 2 learning modules on NI delivered via in-person lectures and online using vodcasts [86]. The other study used a 1-group pretest-posttest design following a 2-day online NI educational program and measuring perceived NI competency [85]. Both interventions were informed by professional practice standards or competencies and relevant educational theory, yielding a statistically significant improvements in the outcomes measured [85,86].

Digital Health and NI Educational Interventions at the Graduate Level

Overview

Of the 38 studies identified in this category, 30 (79%) focused on telehealth interventions [43-72], 2 (5%) addressed digital health [83,84], 2 (5%) focused on EHRs [87,88], and 4 (11%) studies focused on NI education [89-92]. Of note, interventions focused on telehealth education were mostly delivered without situating this knowledge or skills within the broader digital health or NI context, despite some studies indicating the increased use of technology in the context of nursing practice. In addition, some of these studies were implemented or developed in response to the COVID-19 pandemic [43-45,47-49,51,53,55,57-59,71,83,84].

Most studies (32/38, 84%) enhanced the intervention design by incorporating theoretical and pedagogical frameworks such as Bandura’s self-efficacy theory [66,70]; Kolb’s Cycle of Experiential Learning [49,72]; Ericsson’s and Smith Expertise theory [68]; the Ottawa Model for Research [71]; the Plan-Do-Study-Act cycle [66]; the Technology Acceptance Model [60]; Roy’s Adaptation Model [59]; problem-based learning [62], Bloom’s Taxonomy [66,91]; Adult Learning Theories [89]; Nursing Education Healthcare Informatics Framework [92]; Technology Informatics Guiding Education Reform Competencies [92]; and professional standards and competencies, telehealth competencies, and best practices for simulation-based research [43-45,47,49,51-53,55-59, 61,63-65, 67,72,83,84,91].

Interventions Focused on Telehealth Education

Integration was mostly as a stand-alone intervention; however, a good number of studies reported integration as part of an existing theory or clinical course [44,45,47,48,50,51,53, 61-63,66,68,72]; theory courses included health policy, role transition course, advanced health assessment course, and bio-physical and integrated clinical diagnosis course. Of note, only a few studies engaged students in their final clinical practicum course in a telehealth clinical rotation experience [61]. Other students experienced telehealth during a clinical rotation [46] or as part of a clinical experience [69]. Telehealth education was delivered using a variety of educational modalities or strategies including didactic education (online modules and lectures, reading materials, videos, narrated lectures, and self-directed modules) with simulation scenarios and standardized patients [43-45,47,49,51,52,55,57, 58,62-64,67-70,72]; asynchronous and synchronous simulation using teleconferencing tools and interactivities with or without didactic education [51,52,58,59,63,65,71]; telehealth self-paced learning with discussion [48]; guest speaker lectures with self-paced modules, lectures, and videoconferencing demos [66,125]; simulation with a telehealth robot with an iPad and or a telehealth cart [54,55,64]; simulation with students acting as patients or providers [54,55,58,60]; telehealth as a clinical rotation [46,72]; telehealth Objective Structured Clinical Examinations and clinical examinations [47,63,65,67]; telehealth curriculum with supporting competencies [56]; telehealth focused on specific skills (eg, consultation, e-visit, triage) [50,54,55,60,64,65,68]; and partnership with clinical organizations [61,69].

The duration of telehealth simulation intervention varied from a few hours to days. Regarding topics covered in telehealth education, some studies reported on topics included, such as a broad overview of telehealth, technologies used in delivering telehealth, ways to engage with patients, telehealth competencies, laws and regulations related to telehealth practice, digital professionalism, and licensure requirements [56-58,64,66-72].

Researchers designed the interventional studies using different methods including mixed methods [43,55], pretest-posttest design [71], descriptive design [54], quasi-experimental design [44,50], formative and summative evaluation introduced as educational activities [45,48,51,53], program evaluations [46,47,49,56,63,65,69], pilot studies [43,52,55,57,59,60, 62,64,67,68], and quality improvement projects [58,66,71]. Some studies applied pretest-posttest assessments or pretest-posttest surveys to measure a variety of outcomes including knowledge, beliefs, confidence and comfort levels, interest in telehealth, attitudes, preparedness, and satisfaction with the learning [44-48,50,52,56,64,66,68,72], proficiency and competence in performing skills, clinical decision-making, working collaboratively with members of the health team, communication, providing care virtually, opinions, and experience of learning. In addition, some researchers evaluated the usability of telehealth technologies applied in simulation and simulation effectiveness [55]. Majority of these studies reported improvements after the intervention and positive student feedback; however, these measurements were either limited by the study design applied or the small sample size due to the heterogeneity of designs used (see Multimedia Appendix 4 for more details).

Interventions Focused on Digital Health

Only 2 studies [83,84] have actually used the term *digital health* and intentionally developed educational strategies to deliver such education to the students of the doctor of nursing practice program [83]. Of these studies, 1 study reported on developing an elective course on digital health that comprised 5 units [83], and the second study incorporated mind maps within a practicum experience to expose students to digital health technologies used in practice [84]. In this same study, the authors also reported that prior NI courses existed in the curriculum.

Interventions Focused on EHR Education

In total, 2 studies published by the same authors [87,88] reported on EHR-related learning by exposing students to simulated EHRs using an assignment strategy, with case scenarios integrated within health IT and NI courses, and assessing perceived NI competency. The initial evaluation [87] included an assessment of NI competence within the same group following the intervention; however, the second evaluation incorporated a control group [88].

Interventions Focused on NI Education

In total, 4 studies [89-92] reported on NI education; 1 (25%) study provided didactic education in the form of an online learning module [89]; 1 (25%) study developed a 4-week clinical practicum experience for using the electronic medical record [90]; and 2 (50%) studies reported on developing online courses in NI [91,92], but these were conducted in 2013 and 2014.

Studies Reporting on Status of Curricular Integration

In total, 14 studies [13,93-105] focused on determining the status of digital health or NI integration in undergraduate and graduate nursing curricula using mainly survey designs [94,96,97,100,101,103,105]. Four studies focused on telehealth integration [93-96]. Of these, 2 studies included NP curricula [93,95], one applying an evaluation of a web-based telehealth (module-based) course [93] and the other reporting on program evaluation [95] following curriculum mapping, integration, and obtaining students' feedback through comparing pretest-posttest surveys. The remaining 2 studies [94,96] used cross-sectional surveys of nursing programs involving both undergraduate- and graduate-level students, and both studies revealed variable levels of integration.

A total of 9 studies examined NI integration in nursing curricula using different methods including Delphi survey [97], internet search [98,100,103], case study [99], questionnaires [101], curriculum review [102], and mixed methods approach examining both NI and digital health [13,104], and 1 study examined the status of academic EHR use [105]. Variability was noted across these studies, but overall, some studies (4/9, 44%) that have implemented NI or digital health have noted improvement in students' learning outcomes after integration [93,95,98,99].

Proposed Strategies for Enhancing Digital Health and NI Education

A total of 14 studies [12,106-123] provided a discussion of strategies that could be used by nurse educators or nursing programs to strengthen undergraduate and graduate nursing education including AI competencies to inform undergraduate and graduate education [106], role of clinical preceptors in helping students learn about digital health [12], guidelines for health informatics [107], different telehealth educational strategies including how to incorporate or level telehealth competencies in the curriculum [108-112], strategies for NI education or curricular leveling [113-120], and EHR simulations [121,122]. Furthermore, 1 study focused on digital health and technology competency [123].

Gray Literature Findings

A review of the websites of 6 organizations revealed an increase in the offering of educational programs and courses related to digital health, with some of them focused on emerging technologies. An overview of these findings is available in Multimedia Appendix 3.

Discussion

Principal Findings

The purpose of this review was to map the literature on digital health education, training courses, or other pedagogical interventions used for undergraduate and graduate nursing students and to inform the development of future educational interventions. Despite improvements, there are significant gaps and limitations in the scope of digital health education at the undergraduate and graduate levels, consequently posing challenges for nursing students to develop competencies needed in modern-day nursing practice.

In defining digital health, a few studies used the term *digital health* or provided educational strategies and content that capture the broad focus of digital health in nursing education. Several studies included in this review were conducted in the wake of the COVID-19 pandemic. The increased use of virtual care and telehealth practice mainly occurred at the graduate NP practice level, and both modalities are subsumed under digital health. Yet, the authors of these studies did not situate this education within the broader area of digital health or eHealth. Furthermore, the current educational approaches regarding digital health education are primarily focused on developing dimensions of NI competencies, that is, skills for using digital health technologies such as EHRs and telehealth.

According to the 2022 Nurse Practitioner Role Core Competencies in the United States, domain 8 Technology and Information Literacy includes 5 indicators focused on the application of ICTs [126]. These are also aligned to the American Association of Colleges of Nursing Essentials and Advanced-level Nursing Education, which emphasizes ICTs and informatics processes under domain 8 and provides 5 indicators, for example, indicator 8.4f: "employ electronic health, mobile, health, and telehealth systems to enable quality, ethical, and efficient patient care" may explain the focus on telehealth education at the NP education level within the included studies [126]. These guidelines also do not use the terminology of *digital health*. In Canada, the Canadian Nurse Practitioner Core Competency Framework, published in 2010, has an indicator 1.11: "Adheres to federal and provincial/territorial legislation, policies, and standards related to privacy, documentation, and information management (this also applies to verbal, written or electronic records)" [127], but no reference to digital health or NI was made.

Only two studies (2/38, 5%) focused on digital health as a concept to teach nursing students, with an increasing volume of studies on telehealth or telenursing education (30/38, 79%). Contrary to the findings of this review, the review by Foster and Adams [128] indicated inadequate research studies on telehealth education. The disparity in the findings could partly be due to the difference in the search periods, as our review included studies conducted before, during, and after the COVID-19 pandemic when the use of telehealth began to increase. Despite the difference in the findings, both reviews address the importance of timing and indicate the attention and relevance of telehealth education within nursing. Although most of the educational interventions about digital health at the graduate level addressed telehealth, the integration and education about telehealth are still inadequate as identified in this review and prior reviews [129]. In addition, a recent national survey conducted by Eckoff et al [94], which examined the telehealth education in both prelicensure and graduate nursing education, also revealed inconsistency and limited education about telehealth.

No studies indicated teaching NI or digital health as a unique course within the nursing curriculum. In addition, despite the increased attention to the potential impact of AI on nursing education and practice, no interventional studies that addressed AI education at the undergraduate or graduate levels were found. Only 1 study [106] identified AI competencies to guide nursing education in Canada despite urgent calls for providing formal training and education of health care providers and nurses at the basic and advanced levels in AI. The proliferation of AI technologies in nursing education and clinical practice shows the need for proactive measures to integrate AI education and its related competencies in nursing education [22,130].

With respect to the scope of educational strategies currently being used, these included didactic approaches such as training sessions or webinars, online modules, prerecorded lectures, PowerPoint presentations, and video clips; experiential approach that mostly applies simulation encounters along with debriefing, guided exercises, and opportunities for question or answer; or a combination of both. To enhance students' experiential learning, the educational strategies were delivered through online and face-to-face means [131]. The choice of these strategies was largely based on the objectives of the study and the interventional design applied. More advanced educational strategies, such as virtual and augmented reality, are limited in teaching nursing students about digital health and NI. As these technologies become more mainstream, it is anticipated that future research will shed light on the value and effectiveness of these strategies in nursing education, specifically in the digital health education [8,9]. It is promising to see that educators and scholars have shared their expertise and the strategies that they have applied in their programs for integrating digital health and NI; this could serve to encourage educators to consider applying these strategies within their programs or day-to-day teaching in order to improve graduate outcomes and increase their capacity for optimal practice in digital health care environments.

It is noted that the theoretical education about digital health and NI as core concepts in the nursing curricula remains variable and is mostly focused on the skills component as opposed to providing comprehensive and foundational knowledge that would help students understand the full picture of the digital health revolution. This was also corroborated by the findings from studies that examined the status of NI and digital health integration in nursing curricula, demonstrating variable levels of integration at both the undergraduate and graduate levels. These findings suggest that digital health and NI are not yet a priority in nursing education; however, studies reviewed were mostly survey studies examining the state of education at a point in time.

Several papers in the included studies have incorporated theoretical, conceptual, pedagogical, and professional standards in designing their interventions. Using such frameworks is highly recommended because it provides an evidence-based approach for planning, implementation, and evaluation of the educational intervention [132]. It also enables researchers to expand on the body of knowledge available to inform nursing education and practice based on best practices for knowledge generation. Incorporating theory in the intervention design also increases the intervention fidelity; however, the effectiveness of these interventions can be limited by a small sample size and the lack of experimental control in measuring the outcomes of interest.

The evaluative strategies used in these studies depended on the study design and the expected outcomes. Although not all the included studies assessed an intervention, some studies used a single, multiple, or a combination of assessment strategies or tools to undertake summative or formative assessment to determine the effectiveness of the intervention. Therefore, the assessment served as the measurement of the intervention done or the process instituted. Similar to the findings of Hui et al [131], authors of studies included in this scoping review also identified multiple and written assessment tasks as evaluative strategies used in assessing telehealth education implemented in a health curriculum. Of note is that some studies (35/61, 57%) that used theoretical frameworks for the intervention design also developed assessment strategies or used existing validated instruments to evaluate or measure outcomes.

Concerning the outcome measures examined, the outcome measure for undergraduate and graduate levels had some similarities and differences. Regarding the similarities, students at the undergraduate and graduate levels were assessed on their levels of competencies related to an educational intervention. However, at the graduate level, in addition to the competencies identified at the undergraduate level, the expectations and outcomes measured were more complex and advanced. After completing graduate-level education, graduate students are expected to assume leadership with the delivery and implementation of telehealth; hence, the education and training at the graduate level on telehealth is more comprehensive, and the educational interventions were often designed in alignment with advanced practice standards and competencies as well as frameworks such as the telehealth competence framework [133].

With respect to the results from the gray literature, it is interesting to note that different organizations in the United States and Canada provided a wide range of courses in different areas of practice related to digital health (Multimedia Appendix 3). This may reflect an increased interest in digital health or a demand among health care professionals or their employers for such information. This is encouraging and can be used as a guidepost for nursing educational programs with respect to the importance and scope of content that can be incorporated into formal nursing education at the undergraduate and graduate levels. While these educational offerings primarily target health care professionals in practice, they can also be used by students particularly at the graduate level. It can also serve as a resource for nurse educators or practitioners to pursue continuing education or increase their knowledge in areas that are evolving rapidly in health care, such as AI; for example, the WHO course named *Ethics and Governance of AI for Health* is one example.

The limitations in the scope of the digital health education both at the undergraduate and graduate levels could be attributed, in part, to the fact that digital health as a field is still evolving. The definition of digital health may not necessarily be known or used by nursing scholars, and the term is also new and will likely further evolve as technology advances in the years to come. Although this may pose challenges for nurse educators and programs to clearly articulate the scope of digital health education in nursing curricula, standardization in either the definition or the dimensions of digital health education should not be perceived as a barrier for nursing programs and educators to begin teaching their students about digital health.

Nursing education programs and educators are encouraged to integrate what is known about digital health as it applies to nursing in their curricula and to keep abreast of the developments in this field so that nurses are not left behind. In addition, upgrading existing NI competency standards, particularly, from the entry level to practice level, in order to account for developments in the field of digital health and providing resources for nurse educators on how to operationalize these indicators in their day-to-day teaching are needed to expedite this process of integration. As the field will continue to evolve, periodic revisions of the NI competency standards should also be considered.

Implications

The dynamic nature of the health care system continuously evolving as a result of technological advancement demands that nursing students have opportunities to develop a baseline knowledge and competency in digital health and to cultivate this knowledge through continuing education upon becoming independent practitioners. From an equity perspective, all nursing students should have the opportunity to receive comprehensive digital health education because they represent the future health care workforce that is already faced with significant challenges to overcome including aging population, technological disruption, globalization, population displacement, and climate change to name a few [2]. As such, digital health education should not be a side topic in the nursing curriculum or be taught on a need-to-know basis, but rather it should be comprehensively embedded throughout all levels of nursing education and nursing career trajectories.

This scoping review provided important insights into the current state of digital health education and the modalities available for teaching nursing students. In light of the gaps and limitations identified in this review, enhancing the digital health education for nurses and nursing students should be a policy priority. A comprehensive education about digital health should provide foundational knowledge in core concepts relative to the existing and new digital health care technologies and create opportunities for learners to continuously reflect on their practice as well as be able to identify areas for growth and development as the digital health ecosystem evolves. Upgrading nursing education by introducing new strategies, such as virtual and augmented reality and AI generative platforms, to deliver and augment learning allows nursing students to think critically about these technologies and, by extension, other similar applications that will eventually make their way into clinical practice [124,134]. Follow-up studies may also be beneficial to determine the impact of digital health and informatics education in the workplace.

Conclusions

As the digital health ecosystem continues to evolve, nursing education and practice must evolve too. There is an urgent need to expand the understanding of digital health in the context of nursing education and practice and to better articulate its scope in nursing curricula and enforce its application across professional nursing practice roles at all levels and career trajectories. Further research is also needed to examine the impact of digital health education on improving patient outcomes, the quality of nursing care, and professional nursing role advancement.

Acknowledgments

M Kleib received Seed Social Sciences and Humanities Research Council (SSHRC) through the University of Alberta Vice Provost Office for Research to support this research, and M Kleib and AA received funding through an SSHRC IDG grant; a portion of this funding was used to pay for research assistantship costs.

Authors' Contributions

M Kleib, AA, and LMN conceptualized the project idea, developed the initial draft, and discussed and interpreted the findings. SA, SI and M Kennedy contributed to data searches, abstraction, analysis, and reviewing and editing the final paper.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Search strategy.
[DOCX File , 32 KB - nursing_v7i1e58170_app1.docx]

Multimedia Appendix 2
List of excluded studies.
[DOCX File , 64 KB - nursing_v7i1e58170_app2.docx]

Multimedia Appendix 3
Abstraction tables.
[DOCX File , 100 KB - nursing_v7i1e58170_app3.docx]

Multimedia Appendix 4
Organizations providing digital health education.
[DOCX File , 23 KB - nursing_v7i1e58170_app4.docx]

Multimedia Appendix 5
PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist.
[PDF File (Adobe PDF File), 114 KB - nursing_v7i1e58170_app5.pdf]

References

1. Global strategy on digital health 2020-2025. World Health Organization. URL: https://cdn.who.int/media/docs/default-source/documents/gs4dhdaa2a9f352b0445bafbc79ca799dce4d.pdf?sfvrsn=f112ede5_75 [accessed 2024-02-01]
2. Position statement. International Council of Nurses. URL: https://www.icn.ch/what-we-do/position-statements [accessed 2024-02-01]
3. Snowdon AW. Digital health ecosystems: a strategy for transformation of health systems in the post-pandemic future. In: Nursing and Informatics for the 21st Century - Embracing a Digital World, Book 1. Boca Raton, FL: Productivity Press; 2022.
4. What is telehealth? NEJM Catalyst. 2018 Feb 1. URL: https://catalyst.nejm.org/doi/full/10.1056/CAT.18.0268 [accessed 2024-06-05]
5. Shaw J, Jamieson T, Agarwal P, Griffin B, Wong I, Bhatia RS. Virtual care policy recommendations for patient-centred primary care: findings of a consensus policy dialogue using a nominal group technique. J Telemed Telecare 2018 Oct;24(9):608-615. [doi: 10.1177/1357633X17730444] [Medline: 28945161]
6. Spatharou A, Hieronimus S, Jenkins J. Transforming healthcare with AI: the impact on the workforce and organizations. McKinsey & Company. 2020 Mar 10. URL: https://www.mckinsey.com/industries/healthcare/our-insights/transforming-healthcare-with-ai [accessed 2024-06-05]
7. O'Connor S, Leonowicz E, Allen B, Denis-Lalonde D. Artificial intelligence in nursing education 1: strengths and weaknesses. Nurs Times 2023;119:10 [FREE Full text]
8. Kleib M, Nagle L, Furlong KE, Paul P, Duarte Wisnesky U, Ali S. Are future nurses ready for digital health?: informatics competency baseline assessment. Nurse Educ 2022 Mar 25;47(5):E98-104 [FREE Full text] [doi: 10.1097/NNE.0000000000001199] [Medline: 35324499]
9. Booth RG, Strudwick G, McBride S, O’Connor S, Solano López AL. How the nursing profession should adapt for a digital future. BMJ 2021 Jun 14;373:n1190 [FREE Full text] [doi: 10.1136/bmj.n1190]
10. Brown J, Morgan A, Mason J, Pope N, Bosco A. Student nurses' digital literacy levels: lessons for curricula. Comput Inform Nurs 2020 Mar 13;38(9):451-458 [FREE Full text] [doi: 10.1097/CIN.0000000000000615] [Medline: 33955370]
11. van Houwelingen CT, Ettema RG, Kort HS, Ten Cate OT. Internet-generation nursing students' view of technology-based health care. J Nurs Educ 2017 Dec 01;56(12):717-724 [FREE Full text] [doi: 10.3928/01484834-20171120-03] [Medline: 29206261]
12. Subramanian S, Kleib M. Leveraging clinical preceptorship to enhance nursing students' readiness in digital health. Qual Adv Nurs Educ 2023;9(3) [FREE Full text] [doi: 10.17483/2368-6669.1412]

13. Nagle LM, Kleib M, Furlong K. Digital health in Canadian schools of nursing part A: nurse educators' perspectives. Qual Adv Nurs Educ 2020;6(1) [FREE Full text] [doi: 10.17483/2368-6669.1229]
14. Chauvette A, Kleib M, Paul P. Developing nursing students' informatics competencies - a Canadian faculty perspective. Int J Nurs Educ Scholarsh 2022 Jun 14;19(1) [FREE Full text] [doi: 10.1515/ijnes-2021-0165] [Medline: 35697520]
15. Kleib M, Chauvette A, Furlong K, Nagle L, Slater L, McCloskey R. Approaches for defining and assessing nursing informatics competencies: a scoping review. JBI Evid Synth 2021 Apr;19(4):794-841. [doi: 10.11124/JBIES-20-00100] [Medline: 33625068]
16. Nazeha N, Pavagadhi D, Kyaw BM, Car J, Jimenez G, Tudor Car LT. A digitally competent health workforce: scoping review of educational frameworks. J Med Internet Res 2020 Nov 05;22(11):e22706 [FREE Full text] [doi: 10.2196/22706] [Medline: 33151152]
17. Longhini J, Rossettini G, Palese A. Digital health competencies among health care professionals: systematic review. J Med Internet Res 2022 Aug 18;24(8):e36414 [FREE Full text] [doi: 10.2196/36414] [Medline: 35980735]
18. Harerimana A, Wicking K, Biedermann N, Yates K. Nursing informatics in undergraduate nursing education in Australia before COVID-19: a scoping review. Collegian 2022 Aug;29(4):527-539 [FREE Full text] [doi: 10.1016/j.colegn.2021.11.004] [Medline: 34867065]
19. Forman TM, Armor DA, Miller AS. A review of clinical informatics competencies in nursing to inform best practices in education and nurse faculty development. Nurs Educ Perspect 2019 Nov 12;41(1):E3-E7 [FREE Full text] [doi: 10.1097/01.nep.0000000000000588]
20. Sormunen M, Heikkilä A, Salminen L, Vauhkonen A, Saaranen T. Learning outcomes of digital learning interventions in higher education: a scoping review. Comput Inform Nurs 2021 Aug 04;40(3):154-164 [FREE Full text] [doi: 10.1097/CIN.0000000000000797] [Medline: 34347644]
21. Nes AA, Steindal SA, Larsen MH, Heer HC, Lærum-Onsager E, Gjevjon ER. Technological literacy in nursing education: a scoping review. J Prof Nurs 2021;37(2):320-334 [FREE Full text] [doi: 10.1016/j.profnurs.2021.01.008] [Medline: 33867086]
22. Buchanan C, Howitt ML, Wilson R, Booth RG, Risling T, Bamford M. Predicted influences of artificial intelligence on nursing education: scoping review. JMIR Nurs 2021;4(1):e23933 [FREE Full text] [doi: 10.2196/23933] [Medline: 34345794]
23. Gartz J, O'Rourke J. Telehealth educational interventions in nurse practitioner education: an integrative literature review. J Am Assoc Nurse Pract 2021 Nov 1;33(11):872-878 [FREE Full text] [doi: 10.1097/jxx.0000000000000488]
24. Reid L, Button D, Breaden K, Brommeyer M. Nursing informatics and undergraduate nursing curricula: a scoping review protocol. Nurse Educ Pract 2022 Nov;65:103476 [FREE Full text] [doi: 10.1016/j.nepr.2022.103476] [Medline: 36356324]
25. Peters MD, Godfrey CM, McInerney P, Munn Z, Kahlil H, Trico AC. Chapter 11: scoping reviews. In: Aromataris E, Munn Z, editors. JBI Manual for Evidence Synthesis. Adelaide, Australia: Joanna Briggs Institute; 2020.
26. Tricco A, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Ann Intern Med 2018 Oct 02;169(7):467-473 [FREE Full text] [doi: 10.7326/M18-0850] [Medline: 30178033]
27. Kleib M, Arnaert A, Nagle LM, Ali S, Idrees S, Kennedy M, et al. Digital health education and training for undergraduate and graduate nursing students: a scoping review protocol. JBI Evid Synth 2023 Jul 01;21(7):1469-1476 [FREE Full text] [doi: 10.11124/JBIES-22-00266] [Medline: 36728743]
28. Rethlefsen ML, Kirtley S, Waffenschmidt S, Ayala AP, Moher D, Page MJ, et al. PRISMA-S: an extension to the PRISMA statement for reporting literature searches in systematic reviews. Syst Rev 2021 Jan 26;10(1):39 [FREE Full text] [doi: 10.1186/s13643-020-01542-z] [Medline: 33499930]
29. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021 Mar 29;372:n71 [FREE Full text] [doi: 10.1136/bmj.n71] [Medline: 33782057]
30. Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) statement. PRISMA. URL: https://www.prisma-statement.org/ [accessed 2024-05-31]
31. Pollock D, Peters M, Khalil H, McInerney P, Alexander L, Tricco AC, et al. Recommendations for the extraction, analysis, and presentation of results in scoping reviews. JBI Evid Synth 2023 Mar 01;21(3):520-532 [FREE Full text] [doi: 10.11124/JBIES-22-00123] [Medline: 36081365]
32. Moore J, Jairath N, Montejo L, O'Brien S, Want D. Telehealth simulation: effect on nurse learner knowledge, confidence, and attitudes. Nurs Educ Perspect 2024;45(2):106-108. [doi: 10.1097/01.NEP.0000000000001137] [Medline: 37235551]
33. Eckhoff DO, Diaz DA, Anderson M. Using simulation to teach intraprofessional telehealth communication. Clin Simul Nurs 2022 Jun;67:39-48 [FREE Full text] [doi: 10.1016/j.ecns.2022.03.006]
34. Brownie SM, Chalmers LM, Broman P, Andersen P. Evaluating an undergraduate nursing student telehealth placement for community-dwelling frail older people during the COVID-19 pandemic. J Clin Nurs 2023 Jan;32(1-2):147-162. [doi: 10.1111/jocn.16208] [Medline: 35018676]
35. Ochs N, Franco H, Gallegos B, Baba D, Crossland J. Telehealth in nursing education: navigating the new normal. Nursing 2022 Mar 01;52(3):12-14 [FREE Full text] [doi: 10.1097/01.NURSE.0000820044.72197.f9] [Medline: 35196275]

36. Victor J, Hauze C, Ruppert W, Turnitza J. Telehealth simulation: an online clinical experience. Nurse Educ 2021;46(4):204-206. [doi: 10.1097/NNE.0000000000000916] [Medline: 32773526]
37. Powers K, Neustrup W, Thomas C, Saine A, Sossoman LB, Ferrante-Fusilli FA, et al. Baccalaureate nursing students' experiences with multi-patient, standardized patient simulations using telehealth to collaborate. J Prof Nurs 2020;36(5):292-300 [FREE Full text] [doi: 10.1016/j.profnurs.2020.03.013] [Medline: 33039061]
38. Lister M, Vaughn J, Brennan-Cook J, Molloy M, Kuszajewski M, Shaw RJ. Telehealth and telenursing using simulation for pre-licensure USA students. Nurse Educ Pract 2018 Mar;29:59-63 [FREE Full text] [doi: 10.1016/j.nepr.2017.10.031] [Medline: 29180228]
39. Molloy M, Shaw RJ, Vaughn J, Hueckel R. An innovative use of telepresence robots for educating healthcare professional. Stud Health Technol Inform 2016;225:989-990. [Medline: 27332446]
40. Thomas RM, Moore LP, Urquhart BB, Harris S, Davis S, Farmer J, et al. Use of simulated telenursing with standardized patients to enhance prelicensure nursing education. Nurse Educ 2023;48(6):E191-E195 [FREE Full text] [doi: 10.1097/NNE.0000000000001410] [Medline: 37000901]
41. Watkins SM, Jarvill M, Wright V. Simulated telenursing encounters with standardized participant feedback for prelicensure nursing students. Nurse Educ 2022;47(2):125-126 [FREE Full text] [doi: 10.1097/NNE.0000000000001100] [Medline: 34657108]
42. Reierson I, Solli H, Bjørk IT. Nursing students' perspectives on telenursing in patient care after simulation. Clin Simul Nurs 2015 Apr;11(4):244-250 [FREE Full text] [doi: 10.1016/j.ecns.2015.02.003]
43. LaManna JB, Eckhoff DO, Duncan J. Applying nurse practitioner student reflections in design of telehealth curricula. J Nurse Pract 2022 Sep 07;19(1):104416 [FREE Full text] [doi: 10.1016/j.nurpra.2022.07.024]
44. Jones H, Ammerman B, Joiner K, Lee D, Bigelow A, Kuzma E. Evaluating an intervention of telehealth education and simulation for advanced practice registered nurse students: a single group comparison study. Nurs Open 2023 Jun;10(6):4137-4143 [FREE Full text] [doi: 10.1002/nop2.1620] [Medline: 36693008]
45. Baliko B, Raynor P, Cox D, Tavakoli A. Developing family nurse practitioner student competencies: a two-part mental health-focused telehealth education activity. J Prof Nurs 2023;49:33-39 [FREE Full text] [doi: 10.1016/j.profnurs.2023.08.009] [Medline: 38042559]
46. French R, Lyons E, Schachter A, Treston JA, Marshall A, Lattimer J, et al. "Because of this rotation, this is what I want to do": implementation and evaluation of a telehealth opioid use disorder clinical placement for nurse practitioner students. J Am Assoc Nurse Pract 2023 Dec 01;35(12):826-834 [FREE Full text] [doi: 10.1097/JXX.0000000000000949] [Medline: 37756445]
47. Chrostowski SK, Tietze M. Using a telemedicine cart for an Objective Structured Clinical Examination (OSCE) in nurse practitioner education. Clin Simul Nurs 2022 Sep;70:21-27. [doi: 10.1016/j.ecns.2022.06.002]
48. Chike-Harris KE, Lauerer J, Powers A, Stanley A. Telehealth professionalism education for advanced practice nursing students. Nurs Educ Perspect 2022 Dec 18;43(6):382-383 [FREE Full text] [doi: 10.1097/01.NEP.0000000000000910] [Medline: 34798643]
49. Berrier F, Hellier S. Addressing telehealth education in a family nurse practitioner program through simulation-based learning. J Am Assoc Nurse Pract 2022 Nov 01;34(11):1204-1211. [doi: 10.1097/JXX.0000000000000764] [Medline: 36001797]
50. VanGraafeiland B, Busch DW, Mudd SS, McIltrot K, Brown K, Abshire Saylor MA, et al. A mock telephone triage experience for nurse practitioner students. J Nurse Pract 2022 Mar;18(3):320-323. [doi: 10.1016/j.nurpra.2021.10.023]
51. Lattner C, Badowski D, Otremba D, Gieger J, Klass J. Creating an asynchronous telehealth simulation for advance nursing practice students. Clin Simul Nurs 2022 Feb;63:5-9 [FREE Full text] [doi: 10.1016/j.ecns.2021.11.005] [Medline: 35069937]
52. Emerson MR, Buchanan L, Golden A. Telehealth simulation with graduate nurse practitioner students. Nurse Educ 2021 Apr 22;46(2):126-129 [FREE Full text] [doi: 10.1097/NNE.0000000000000843] [Medline: 33755385]
53. Chike-Harris K, Garber K, Brooks P, Williams A. Integration of telehealth policy education into an existing advanced practiced nurse practitioner policy course. J Nurs Educ 2021 Jan 01;60(1):57. [doi: 10.3928/01484834-20201217-13] [Medline: 33400811]
54. Ball S, Hanks J, Potthoff M, Connelly S. A pediatric telehealth simulation for prelicensure and advanced practice nursing students. Nurs Educ Perspect 2021;42(6):E181-E182. [doi: 10.1097/01.NEP.0000000000000743] [Medline: 34581309]
55. LaManna JB, Eckhoff DO, Duncan J, Anderson M. Nurse practitioner student perceptions of a pilot simulated gerontologic telehealth visit. J Nurs Educ 2021 Jul;60(7):408-413. [doi: 10.3928/01484834-20210616-10] [Medline: 34232822]
56. Arends R, Gibson N, Marckstadt S, Britson V, Nissen MK, Voss J. Enhancing the nurse practitioner curriculum to improve telehealth competency. J Am Assoc Nurse Pract 2021 May 01;33(5):391-397. [doi: 10.1097/JXX.0000000000000303] [Medline: 31577665]
57. Love R, Carrington JM. Introducing telehealth skills into the Doctor of Nursing Practice curriculum. J Am Assoc Nurse Pract 2020 Oct 07;33(11):1030-1034. [doi: 10.1097/JXX.0000000000000505] [Medline: 33038114]
58. Cassiday OA, Nickasch BL, Mott JD. Exploring telehealth in the graduate curriculum. Nurs Forum 2021 Jan;56(1):228-232 [FREE Full text] [doi: 10.1111/nuf.12524] [Medline: 33205442]

59. Wesemann D, Posey K, Wilson C. Clinical simulation to evaluate students' intraprofessional telehealth skills between multiple university campuses. Clin Simul Nurs 2021 May;54:35-39 [FREE Full text] [doi: 10.1016/j.ecns.2021.01.011]
60. Knight EP, Prettyman AV. Rural telehealth team education for baccalaureate and nurse practitioner students. J Nurs Educ 2020 May 01;59(5):274-277. [doi: 10.3928/01484834-20200422-07] [Medline: 32352542]
61. Gibson N, Arends R, Voss J, Marckstadt S, Nissen MK. Reinforcing telehealth competence through nurse practitioner student clinical experiences. J Nurs Educ 2020 Jul 01;59(7):413-417. [doi: 10.3928/01484834-20200617-12] [Medline: 32598014]
62. Robinson-Reilly M, Irwin P, Coutts R, Slattery N. Adding telehealth simulation into NP programs. Nurse Pract 2020 Mar;45(3):44-49. [doi: 10.1097/01.NPR.0000653956.29721.1a] [Medline: 32068657]
63. Phillips TA, Munn AC, George TP. Assessing the impact of telehealth objective structured clinical examinations in graduate nursing education. Nurse Educ 2020;45(3):169-172. [doi: 10.1097/NNE.0000000000000729] [Medline: 31335622]
64. Chike-Harris KE, Harmon E, van Ravenstein K. Graduate nursing telehealth education: assessment of a one-day immersion approach. Nurs Educ Perspect 2020;41(5):E35-E36. [doi: 10.1097/01.NEP.0000000000000526] [Medline: 31232882]
65. Quinlin L, Clark Graham M, Nikolai C, Teall AM. Development and implementation of an e-visit objective structured clinical examination to evaluate student ability to provide care by telehealth. J Am Assoc Nurse Pract 2020 Apr 16;33(5):359-365. [doi: 10.1097/JXX.0000000000000409] [Medline: 32304481]
66. List BA, Saxon R, Lehman D, Frank C, Toole KP. Improving telehealth knowledge in nurse practitioner training for rural and underserved populations. J Nurs Educ 2019 Jan 01;58(1):57-60. [doi: 10.3928/01484834-20190103-10] [Medline: 30673094]
67. Smith TS, Watts P, Moss JA. Using simulation to teach telehealth nursing competencies. J Nurs Educ 2018 Oct 01;57(10):624-627. [doi: 10.3928/01484834-20180921-10] [Medline: 30277549]
68. Merritt LS, Brauch AN, Bender AK, Kochuk D. Using a web-based e-visit simulation to educate nurse practitioner students. J Nurs Educ 2018 May 01;57(5):304-307. [doi: 10.3928/01484834-20180420-10] [Medline: 29718522]
69. Erickson CE, Fauchald S, Ideker M. Integrating telehealth into the graduate nursing curriculum. J Nurse Pract 2015 Jan;11(1):e1-e5. [doi: 10.1016/j.nurpra.2014.06.019]
70. Rutledge CM, Haney T, Bordelon M, Renaud M, Fowler C. Telehealth: preparing advanced practice nurses to address healthcare needs in rural and underserved populations. Int J Nurs Educ Scholarsh 2014 Jan 14;11:1-9. [doi: 10.1515/ijnes-2013-0061] [Medline: 24423469]
71. Parmeter S, Foronda C, Lee J. Improving telenursing skills through simulation-based education. J Dr Nurs Pract 2023 Jun 27;16(2):93. [doi: 10.1891/JDNP-2022-0021] [Medline: 37369454]
72. Burt L, Kilroy S. Nurse practitioner student perceptions of a multimodal telemedicine clinical course. Nurse Educ 2021;46(5):E122-E126. [doi: 10.1097/NNE.0000000000001019] [Medline: 33935267]
73. Mollart L, Noble D, Mereles A, Mallyon J, Irwin P. The impact of using an academic electronic medical record program on first-year nursing students’ confidence and skills in using E-documentation: a quasi-experimental study. Aust J Adv Nurs 2023 Sep 28;40(3). [doi: 10.37464/2023.403.1078]
74. Hong S, Cho I, Park M, Lee JY, Lee J, Choi M. Simulation education incorporating academic electronic medical records for undergraduate nursing students: a pilot study. Healthc Inform Res 2022 Oct;28(4):376-386 [FREE Full text] [doi: 10.4258/hir.2022.28.4.376] [Medline: 36380434]
75. Kleib M, Jackman D, Duarte Wisnesky U, Ali S. Academic electronic health records in undergraduate nursing education: mixed methods pilot study. JMIR Nurs 2021 Apr 27;4(2):e26944 [FREE Full text] [doi: 10.2196/26944] [Medline: 34345797]
76. Repsha C, Morse B, Lee SE, Katz J, Burrows E, Teates J. Use of a simulated electronic health record to support nursing student informatics knowledge and skills. Comput Inform Nurs 2020 Feb;38(2):55-59 [FREE Full text] [doi: 10.1097/CIN.0000000000000618] [Medline: 32028282]
77. Elliott K, Marks-Maran D, Bach R. Teaching student nurses how to use electronic patient records through simulation: a case study. Nurse Educ Pract 2018 May;30:7-12 [FREE Full text] [doi: 10.1016/j.nepr.2018.02.003] [Medline: 29459316]
78. Choi M, Park JH, Lee HS. Nursing students' satisfaction with mobile academic electronic medical records for undergraduate clinical practicum. Stud Health Technol Inform 2016;225:1005-1006. [Medline: 27332454]
79. Choi M, Lee HS, Park JH. Usability of academic electronic medical record application for nursing students' clinical practicum. Healthc Inform Res 2015 Jul;21(3):191-195 [FREE Full text] [doi: 10.4258/hir.2015.21.3.191] [Medline: 26279956]
80. Titzer JL, Swenty CF, Mustata Wilson G. Interprofessional education: lessons learned from conducting an electronic health record assignment. J Interprof Care 2015;29(6):536-540 [FREE Full text] [doi: 10.3109/13561820.2015.1021000] [Medline: 25955409]
81. Warboys I, Mok WY, Frith KH. Electronic medical records in clinical teaching. Nurse Educ 2014;39(6):298-301 [FREE Full text] [doi: 10.1097/NNE.0000000000000072] [Medline: 25073041]
82. Kowitlawakul Y, Wang L, Chan SW. Development of the electronic health records for nursing education (EHRNE) software program. Nurse Educ Today 2013 Dec;33(12):1529-1535. [doi: 10.1016/j.nedt.2012.12.001] [Medline: 23273687]
83. Beasley B, Reeves N, Riley E. Introduction to digital health course. J Prof Nurs 2023;49:64-69. [doi: 10.1016/j.profnurs.2023.09.002] [Medline: 38042564]

84. Seckman C, Van de Castle B. Understanding digital health technologies using mind maps. J Nurs Scholarsh 2021 Jan;53(1):7-15. [doi: 10.1111/jnu.12611] [Medline: 33259152]
85. Almarwani AM, Yacoub MI. Examining the effect of an educational program on nursing students' informatics competencies. Nurs Educ Perspect 2023;44(6):E59-E61. [doi: 10.1097/01.NEP.0000000000001106] [Medline: 36792354]
86. Kleib M, Olson K. Evaluation of an informatics educational intervention to enhance informatics competence among baccalaureate nursing students. Knowl Manage E Learn Int J 2015 Sep;7(3):395-411 [FREE Full text] [doi: 10.34105/j.kmel.2015.07.026]
87. Choi J, Bove L, Tarte V. Nursing informatics competency after experiencing simulated electronic health records: descriptive study. Stud Health Technol Inform 2021 Dec 15;284:143-147. [doi: 10.3233/SHTI210686] [Medline: 34920491]
88. Choi J, Bove LA, Tarte V, Choi WJ. Impact of simulated electronic health records on informatics competency of students in informatics course. Healthc Inform Res 2021 Jan;27(1):67-72 [FREE Full text] [doi: 10.4258/hir.2021.27.1.67] [Medline: 33611878]
89. Galacio B. Expanding the informatics competencies of nurse practitioners through online learning. Comput Inform Nurs 2022 Sep 01;40(9):606-614 [FREE Full text] [doi: 10.1097/CIN.0000000000000864] [Medline: 35485946]
90. Lokmic-Tomkins Z, Brar S, Lin N, Khor M, Mathews K, Lawlor K. Advancing nursing informatics through clinical placements: pilot study. Stud Health Technol Inform 2021 Dec 15;284:98-102 [FREE Full text] [doi: 10.3233/SHTI210678] [Medline: 34920483]
91. Beckham R, Riedford K. Evolution of a graduate-level informatics course for the noninformatics specialist nurse. J Nurse Pract 2014 Jun;10(6):387-392. [doi: 10.1016/j.nurpra.2014.03.012]
92. McBride SG, Tietze M, Fenton MV. Developing an applied informatics course for a doctor of nursing practice program. Nurse Educ 2013;38(1):37-42. [doi: 10.1097/NNE.0b013e318276df5d] [Medline: 23222633]
93. Hamilton W, Walters C, Howington Z. A Mixed-method pilot project: the evaluation of telehealth training in a college of nursing. Nurs Educ Perspect 2023 May 08. [doi: 10.1097/01.NEP.0000000000001140] [Medline: 37154739]
94. Eckhoff DO, Guido-Sanz F, Anderson M. Telehealth across nursing education: findings from a national study. J Prof Nurs 2022;42:308-314 [FREE Full text] [doi: 10.1016/j.profnurs.2022.07.013] [Medline: 36150875]
95. Chike-Harris KE. Telehealth education of nurse practitioner students. J Nurse Pract 2021 Jan 22;17(3):310-316 [FREE Full text] [doi: 10.1016/j.nurpra.2020.12.029]
96. Ali NS, Carlton KH, Ali OS. Telehealth education in nursing curricula. Nurse Educ 2015;40(5):266-269 [FREE Full text] [doi: 10.1097/NNE.0000000000000149] [Medline: 25689080]
97. Park M, Dlamini BB, Kim J, Kwak MJ, Cho I, Choi M, et al. Development of a standardized curriculum for nursing informatics in Korea. Healthc Inform Res 2022 Oct;28(4):343-354 [FREE Full text] [doi: 10.4258/hir.2022.28.4.343] [Medline: 36380431]
98. Shobuzawa S, Endo Y, Yamanouchi K. Availability of nursing informatics education for master's programs in nursing administration at graduate schools of nursing in Japan. Stud Health Technol Inform 2021 Dec 15;284:44-46 [FREE Full text] [doi: 10.3233/SHTI210660] [Medline: 34920466]
99. O'Connor S, LaRue E. Integrating informatics into undergraduate nursing education: a case study using a spiral learning approach. Nurse Educ Pract 2021 Jan;50:102934 [FREE Full text] [doi: 10.1016/j.nepr.2020.102934] [Medline: 33278702]
100. Bove LA. Integration of informatics content in baccalaureate and graduate nursing education: an updated status report. Nurse Educ 2020;45(4):206-209 [FREE Full text] [doi: 10.1097/NNE.0000000000000734] [Medline: 31498198]
101. Jeon E, Kim J, Park HA, Lee JH, Kim J, Jin M, et al. Current status of nursing informatics education in Korea. Healthc Inform Res 2016 Apr;22(2):142-150 [FREE Full text] [doi: 10.4258/hir.2016.22.2.142] [Medline: 27200224]
102. Stephens-Lee C, Lu DF, Wilson KE. Preparing students for an electronic workplace. Online J Nurs Inform 2013 Oct;17(3) [FREE Full text]
103. Hunter K, McGonigle D, Hebda T. The integration of informatics content in baccalaureate and graduate nursing education: a status report. Nurse Educ 2013;38(3):110-113 [FREE Full text] [doi: 10.1097/NNE.0b013e31828dc292] [Medline: 23608911]
104. Nagle LM, Kleib M, Furlong K. Digital health in Canadian schools of nursing—part B: academic nurse administrators' perspectives. Qual Adv Nurs Educ 2020;6(3) [FREE Full text] [doi: 10.17483/2368-6669.1256]
105. Raghunathan K, McKenna L, Peddle M. Utilisation of academic electronic medical records in pre-registration nurse education: a descriptive study. Collegian 2022 Oct;29(5):645-653 [FREE Full text] [doi: 10.1016/j.colegn.2022.03.005]
106. Lattuca M, Maratta D, Beffert U, Chevrier A, Winer L. Healthcare AI: a revised Quebec framework for nursing education. Qual Adv Nurs Educ 2023 Oct 13;9(3). [doi: 10.17483/2368-6669.1408]
107. Honey M, Collins E, Britnell S. Education into policy: embedding health informatics to prepare future nurses-New Zealand case study. JMIR Nurs 2020 Jan 09;3(1):e16186 [FREE Full text] [doi: 10.2196/16186] [Medline: 34345779]
108. Bobek H. Teaching strategies for online nurse practitioner physical assessment and telehealth education. Nurs Clin North Am 2022 Dec;57(4):589-598 [FREE Full text] [doi: 10.1016/j.cnur.2022.07.003] [Medline: 36280297]
109. Dzioba C, LaManna J, Perry C, Toerber-Clark J, Boehning A, O'Rourke J, et al. Telehealth competencies: leveled for continuous advanced practice nurse development. Nurse Educ 2022;47(5):293-297. [doi: 10.1097/NNE.0000000000001196] [Medline: 35404870]

110. Taylor J, Fuller B. The expanding role of telehealth in nursing: considerations for nursing education. Int J Nurs Educ Scholarsh 2021 Jul 06;18(1). [doi: 10.1515/ijnes-2021-0037] [Medline: 34225397]
111. Fronczek AE, Rouhana NA, Kitchin JM. Enhancing telehealth education in nursing: applying King's conceptual framework and theory of goal attainment. Nurs Sci Q 2017 Jul;30(3):209-213 [FREE Full text] [doi: 10.1177/0894318417708418] [Medline: 28899265]
112. Guenther J, Branham S, Calloway S, Hilliard W, Jimenez R, Merrill E. Five steps to integrating telehealth into APRN curricula. J Nurse Pract 2021 Mar;17(3):322-325 [FREE Full text] [doi: 10.1016/j.nurpra.2020.12.004] [Medline: 33746648]
113. Vottero B. Teaching informatics to prelicensure, RN-to-BSN, and graduate level students. Nurse Educ 2017;42(5S Suppl 1):S22-S26 [FREE Full text] [doi: 10.1097/NNE.0000000000000414] [Medline: 28832458]
114. Weiner E, Trangenstein P, Gordon J, McNew R. Integrating informatics content into the nursing curriculum. Stud Health Technol Inform 2016;225:302-306. [Medline: 27332211]
115. Jenkins ML. Informatics essentials for DNPs. Stud Health Technol Inform 2018;250:55-57. [Medline: 29857370]
116. Wolf DM, Morouse KM. Using blogs to support informatics nurses' curriculum needs. Online J Nurs Inform 2015;19(2) [FREE Full text]
117. Frisch N, Borycki E. A framework for leveling informatics content across four years of a Bachelor of Science in Nursing (BSN) curriculum. Stud Health Technol Inform 2013;183:356-366. [Medline: 23388314]
118. Spencer JA. Integrating informatics in undergraduate nursing curricula: using the QSEN framework as a guide. J Nurs Educ 2012 Dec;51(12):697-701. [doi: 10.3928/01484834-20121011-01] [Medline: 23061435]
119. Swenty CL, Titzer JL. A sense of urgency: integrating technology and informatics in advance practice nursing education. J Nurse Pract 2014 Nov;10(10):e57-e67. [doi: 10.1016/j.nurpra.2014.07.034]
120. Titzer JL, Swenty CF. Integrating an academic electronic health record in a nursing program: creating a sense of urgency and sustaining change. Nurse Educ 2014;39(5):212-213. [doi: 10.1097/NNE.0000000000000064] [Medline: 25137446]
121. Eardley D, Matthews K, DeBlieck CJ. Quality improvement project to enhance student confidence using an electronic health record. J Nurs Educ 2021 Jun;60(6):337-341. [doi: 10.3928/01484834-20210520-07] [Medline: 34077320]
122. Sorensen J, Campbell L. Curricular path to value: integrating an academic electronic health record. J Nurs Educ 2016 Dec 01;55(12):716-719. [doi: 10.3928/01484834-20161114-10] [Medline: 27893909]
123. Kunkel D, Tietze M, Wilson M, Fant CT, Rivard MJ, Belchez CA, et al. Creating case studies for digital health and technology competency in nursing. Nurse Educ 2024;49(1):31-35. [doi: 10.1097/NNE.0000000000001458] [Medline: 37229722]
124. Snowdon A. Digital health: a framework for healthcare transformation white paper. Healthcare Information and Management Systems Society. 2020 Apr 13. URL: https://tinyurl.com/3k8sxb7m [accessed 2024-02-01]
125. Chike-Harris KE, Garber K, Derouin A. Telehealth educational resources for graduate nurse faculty. Nurse Educ 2021;46(5):295-299 [FREE Full text] [doi: 10.1097/NNE.0000000000001055] [Medline: 34238795]
126. NONPF nurse practitioner role core competencies table. National Organization of Nurse Practitioner Faculties. URL: https://cdn.ymaws.com/www.nonpf.org/resource/resmgr/competencies/20220825_nonpf_np_role_core_.pdf [accessed 2024-02-20]
127. Canadian nurse practitioner core competency framework. Canadian Nurses Association. 2010 May. URL: https://hl-prod-ca-oc-download.s3-ca-central-1.amazonaws.com/CNA/2f975e7e-4a40-45ca-863c-5ebf0a138d5e/UploadedImages/documents/Competency_Framework_2010_e.pdf [accessed 2024-02-20]
128. Foster M, Lioce L, Howell Adams M. Telehealth in nursing education: a systematic review. J Nurs Educ 2021 Nov;60(11):633-635 [FREE Full text] [doi: 10.3928/01484834-20210913-06] [Medline: 34723739]
129. Chike-Harris KE, Durham C, Logan A, Smith G, DuBose-Morris R. Integration of telehealth education into the health care provider curriculum: a review. Telemed J E Health 2021 Feb;27(2):137-149. [doi: 10.1089/tmj.2019.0261] [Medline: 32250196]
130. O'Connor S, Yan Y, Thilo FJ, Felzmann H, Dowding D, Lee JJ. Artificial intelligence in nursing and midwifery: a systematic review. J Clin Nurs 2023 Jul;32(13-14):2951-2968. [doi: 10.1111/jocn.16478] [Medline: 35908207]
131. Hui K, Haines C, Bammann S, Hallandal M, Langone N, Williams C, et al. To what extent is telehealth reported to be incorporated into undergraduate and postgraduate allied health curricula: a scoping review. PLoS One 2021 Aug 19;16(8):e0256425 [FREE Full text] [doi: 10.1371/journal.pone.0256425] [Medline: 34411171]
132. Grant C, Osanloo A. Understanding, selecting, and integrating a theoretical framework in dissertation research: creating the blueprint for your “House”. Adm Issues J Connect Educ Pract Res 2014;4(2):12-26 [FREE Full text] [doi: 10.5929/2014.4.2.9]
133. Rutledge CM, O'Rourke J, Mason AM, Chike-Harris K, Behnke L, Melhado L, et al. Telehealth competencies for nursing education and practice: the four P's of telehealth. Nurse Educ 2021;46(5):300-305 [FREE Full text] [doi: 10.1097/NNE.0000000000000988] [Medline: 33481494]
134. Castonguay A, Farthing P, Davies S, Vogelsang L, Kleib M, Risling T, et al. Revolutionizing nursing education through Ai integration: a reflection on the disruptive impact of ChatGPT. Nurse Educ Today 2023 Oct;129:105916 [FREE Full text] [doi: 10.1016/j.nedt.2023.105916] [Medline: 37515957]

Abbreviations

AI: artificial intelligence
EHR: electronic health record
ICT: information and communication technology
NI: nursing informatics
NP: nurse practitioner
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PRISMA-S: Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Searching
PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews
WHO: World Health Organization

Edited by E Borycki; submitted 08.03.24; peer-reviewed by T Hebda, M Brommeyer, L Powell; accepted 04.05.24; published 17.07.24.

Please cite as:
Kleib M, Arnaert A, Nagle LM, Ali S, Idrees S, Costa DD, Kennedy M, Darko EM
Digital Health Education and Training for Undergraduate and Graduate Nursing Students: Scoping Review
JMIR Nursing 2024;7:e58170
URL: https://nursing.jmir.org/2024/1/e58170
doi:10.2196/58170
PMID:39018092

Original Paper

Exploring Student Perspectives and Experiences of Online Opportunities for Virtual Care Skills Development: Sequential Explanatory Mixed Methods Study

Lorelli Nowell[1], PhD; Sara Dolan[1], PhD; Sonja Johnston[2], PhD; Michele Jacobsen[2], PhD; Diane Lorenzetti[3], PhD; Elizabeth Oddone Paolucci[3], PhD

[1]Faculty of Nursing, University of Calgary, Calgary, AB, Canada
[2]Werklund School of Education, University of Calgary, Calgary, AB, Canada
[3]Cumming School of Medicine, University of Calgary, Calgary, AB, Canada

Corresponding Author:
Lorelli Nowell, PhD
Faculty of Nursing
University of Calgary
2500 University Drive NW
Calgary, AB, T2N 1N4
Canada
Phone: 1 4036209822
Email: lnowell@ucalgary.ca

Abstract

Background: Caring profession students require skills and competencies to proficiently use information technologies for providing high-quality and effective care. However, there is a gap in exploring the perceptions and experiences of students in developing virtual care skills within online environments.

Objective: This study aims to better understand caring professional students’ online learning experiences with developing virtual care skills and competencies.

Methods: A sequential explanatory mixed methods approach, integrating both a cross-sectional survey and individual interviews, was used to better understand caring professional students’ online learning experiences with developing virtual care skills and competencies.

Results: A total of 93 survey and 9 interview participants were drawn from various faculties, including students from education, nursing, medicine, and allied health. These participants identified the barriers, facilitators, principles, and skills related to learning about and delivering virtual care, including teaching methods and educational technologies.

Conclusions: This study contributes to the growing body of educational research on virtual care skills by offering student insights and suggestions for improved teaching and learning strategies in caring professions’ programs.

(JMIR Nursing 2024;7:e53777) doi:10.2196/53777

KEYWORDS

virtual care; online teaching and learning; mixed methods research; virtual care; development; mixed method study; online; care; student; students; online learning; virtual learning; interview; experience; educational; technology; nursing; medicine; allied health; teaching

Introduction

Background

The COVID-19 pandemic created a prime opportunity for higher-education institutions to reevaluate how online education is provided. More specifically, the pandemic considerably changed the ways in which education and care are provided across the caring professionals including teachers, physicians, nurses, and allied health professionals. It has become essential to ensure that caring professionals have the required skills and competencies to adapt and navigate this new virtual care landscape. The pandemic also uncovered a range of virtual care skills and competencies that caring professions students will need to thrive, reflecting a new era where remote care is often facilitated by information technologies to facilitate high-quality and effective care.

Traditionally, caring profession students have learned the required skills and competencies of their profession through in-person lectures, in-class group experiences, and work-integrated placements with educators and professionals (eg, kindergarten to 12th-grade classrooms, hospital settings, and counseling centers) [1,2]. The COVID-19 pandemic accelerated a shift to virtual learning and caring contexts, where students both learned about their profession and cared for the public, using information technologies for effective training [3-5].

Virtual care is care provided through digital online collaboration platforms where caring professionals use interpersonal and technological skills to provide care to clients in a virtual setting, including a variety of activities such as telemedicine, distance consultation, remote counseling, and online education. The authors conducted a recent systematic review, which identified that students value the benefits of and are eager to learn how to use digital technologies in preparation for their future roles in caring professional practice [6]. The review highlighted that student learning was best supported when online learning activities and technology aligned and closely replicated real-world situations [6]. Furthermore, students who engaged in online learning about virtual care were more likely to incorporate virtual care into their future professional practice [6].

Objectives

Despite these findings, there remains a need to identify the teaching and learning conditions that may optimize e-learning experiences to support caring profession students in developing virtual care skills and competencies [6]. More research is needed to explore the perceptions and experiences of students in developing virtual care skills within online environments. We therefore conducted a study to answer the following research questions:

1. How do caring professions students *describe* the components of current online teaching and learning innovations that support their development of virtual care skills and competencies?
2. What are caring professions students' *experiences and perceptions* of online learning opportunities for developing their virtual care skills and competencies?
3. What are the *facilitators and barriers* to creating and engaging in online learning opportunities to support student's development of virtual care skills and competencies?

Methods

Design

We used a sequential explanatory mixed methods approach for data collection, analysis, and integration of quantitative and qualitative data [7,8]. We used a cross-sectional survey and individual interviews to understand caring professional students' online learning experiences with developing virtual care skills and competencies. Integration between the 2 phases occurred when the survey responses were used to identify potential participants for follow-up interviews. This process involved analyzing the survey data to purposively sample interview participants that represented diverse perspectives and characteristics of interest. Subsequently, the qualitative interviews provided a deeper, context-rich understanding of the survey findings, allowing for a more comprehensive exploration.

Sample and Participants

Voluntary participation was sought from students in caring professions, encompassing education, medicine, nursing, and allied health, within a midsized research-intensive institution located in western Canada.

Data Collection

We developed an online survey following well-established methods [9] to examine components of current e-learning opportunities, explore students' perceptions and experiences of these opportunities, and identify the facilitators and barriers to engaging in online learning that support the development of virtual care skills and competencies. The survey was informed by a systemic review previously completed by the authors [6]. To our knowledge, no previously validated tools have been published that could be used to answer our research questions. To ensure measurement-related validity (face and content), the survey was piloted with 10 caring profession students who did not subsequently participate in the formal study. Their suggested edits were incorporated before survey distribution [7,10,11]. Survey items were a mix of Likert, closed-ended, and open-ended questions including demographic questions and questions about educational experience, instructional methods, satisfaction and effectiveness of technologies and educational methods, and preparedness to provide virtual care. Surveys were distributed securely online using Qualtrics (Qualtrics International Inc), and students were recruited via university email, Twitter, Instagram, and Facebook [12,13]. Due to individual faculty policies, only students from education, nursing, and medicine were sent a recruitment email directly. Social media recruitment targeted students from the caring profession faculties of education, medicine, nursing, and allied health within this western Canadian university (approximately 8000 students). Informed consent was assumed if the survey was completed. All survey participants were also asked to provide an email address if they were interested in participating in a follow-up interview. Interviews were conducted to better understand students' perceptions and experiences vis-à-vis the research questions.

A semistructured interview guide was developed based on the findings from the authors' published systematic review and online survey responses. While no theoretical frameworks were used in the creation of the interview guide, the categories, domains, and concepts identified in the systematic review helped inform the interview questions. All survey participants who provided their email were contacted to participate in a 30- to 60-minute interview conducted via Zoom (Zoom Video Communications). Before each interview, oral consent was obtained and documented. The interviews were audio recorded and transcribed verbatim.

Data Analysis

Closed-ended online survey responses were downloaded from Qualtrics and imported into the SPSS (version 28; IBM Corp). The characteristics of the study population (eg, age, gender, faculty, and experience) were analyzed using descriptive statistics. Differences in the distribution across the data set were summarized and displayed in tabular and graphical formats [11]. In addition, univariate analyses were conducted on continuous data where appropriate [11]. Several 1-way ANOVA tests were completed to assess potential differences in satisfaction and preparedness scores based on various demographic factors, including gender, age, faculty, or experience with online teaching and learning technologies. To analyze the relationships with age, participant ages were grouped into 5 categories: ≤19, 20 to 29, 30 to 39, 40 to 49, and ≥50 years, making the data more readable and more amenable to post hoc analysis should significance be found.

All open-ended online survey responses and interview transcripts were assigned unique identifiers and imported into NVivo software (version 14; QSR International) for qualitative data management. Qualitative data were analyzed thematically via induction to transform data from individual sources to common themes [14,15]. To familiarize ourselves with the data, the entire qualitative data set was initially read independently by 2 researchers (LN and SD) who met regularly to discuss, develop, and ensure mutual understanding and agreement of the initial codes. Detailed categorical code descriptions were created using NVivo software. Each data set was independently examined within NVivo by the same 2 researchers who coded sections of text, and the independent data files were merged to assess alignment and divergence. Any divergence between the researchers was discussed and resolved without the use of a third party. Larger team meetings were held with all authors to examine and further refine patterns in the data and confirm themes and subthemes. Written memos and meeting minutes were used to record our data analysis process. We followed the Standards for Reporting Qualitative Research (SRQR) in our research and reporting processes [16].

Ethical Considerations

We were granted permission to conduct this research through the University of Calgary's Conjoint Health Research Ethics Board (REB22-1054). Students were invited to participate voluntarily, with the assurance that their involvement in the survey would be anonymous and would not impact their standing at the university. Completion of the survey was considered as implied consent. For the interviews, all participants provided informed verbal consent before engaging in an interview. These interviews were conducted by a graduate student who did not know and was not responsible for teaching the participants. The audio recordings were professionally transcribed and then anonymized by the graduate student before sharing any data with the larger research team. To further maintain participant anonymity, unique identifiers were assigned to each participant, and the data were aggregated accordingly.

Rigor

Several techniques were used to ensure rigor in our study. Regular team meetings created occasions for debriefing, reflexivity, and purposeful questioning of our interpretations [17]. A detailed audit trail including codebooks, meeting minutes, and shared files was maintained to document all study decisions [18]. While 2 researchers coded all qualitative data, all decisions about themes and subthemes were assessed by the larger research team. We returned to the raw survey and interview data to further verify our findings and ensure that our findings adequately displayed the student participants' voices [17].

Results

Participant Demographics

A total of 107 students started the survey, and 93 (86.9%) completed the survey. Of the 93 survey participants, 15 (16%) agreed to be contacted for a follow-up interview, of which 9 (10%) responded and completed an interview. Table 1 presents the participant demographics for the survey and interviews.

Table 1. Participant demographics.

Demographic subcategory	Survey participants (n=93), n (%)	Interview participants (n=9), n (%)
Age group (y)		
<20	11 (12)	0 (0)
20-29	39 (50)	2 (22)
30-39	22 (24)	2 (22)
40-49	14 (15)	2 (22)
≥50	5 (5)	3 (33)
Not disclosed	2 (2)	0 (0)
Gender		
Man	15 (16)	2 (22)
Woman	74 (80)	7 (78)
Gender diverse[a]	4 (4)	0 (0)
Faculty		
Education	22 (24)	2 (22)
Medicine	27 (29)	0 (0)
Nursing	42 (45)	7 (78)
Allied health	2 (2)	0 (0)
Experience (self-report)		
Beginner	13 (14)	1 (11)
Intermediate	33 (35)	2 (22)
Expert	47 (51)	6 (67)

[a] Gender diverse includes gender fluid, nonbinary, queer, and individuals who prefer not to disclose due to the need for maintaining anonymity, especially with small numbers.

Quantitative Results

Student survey respondents (n=89) reported that the faculty used a variety of online instructional methods and various teaching and caring technologies to help develop students' virtual care skills. For instance, the most-reported instructional technology that respondents (n=93) reported being exposed to included audio conferencing and videoconferencing (n=50, 54%), online learning systems (n=50, 54%), and online media (n=35, 38%). Other instructional technology included simulated health records (n=25, 28%) and telehealth monitoring systems (n=5, 1%). Similarly, the most frequently reported instructional methods included online modules (n=77, 83%), reflection on learning (n=66, 71%), and online discussion boards (n=65, 70%). Other instructional methods included consultation with clients (n=25, 27%) and demonstration of remote care (n=8, 9%).

Students were asked how satisfied they were with the online teaching and learning strategies that were used to help them develop virtual care skills. Of the students who responded to the question (n=89), only 9 (10%) indicated that they were not satisfied, with others indicating they were satisfied (n=20, 23%) or somewhat satisfied (n=60, 67%). Students were also asked how prepared they felt to use virtual care skills in their future practice. Of the students who responded to the question (n=64), 11 (17%) indicated they were not prepared, with other indicating they were prepared (n=22, 25%) or somewhat prepared (n=52, 58%). The ANOVA test results did not reveal any statistically significant differences among the groups (gender, age, faculty, and experience) for both satisfaction and preparedness scores. The full ANOVA test results and exact *P* values are presented in Table 2.

Table 2. ANOVA results.

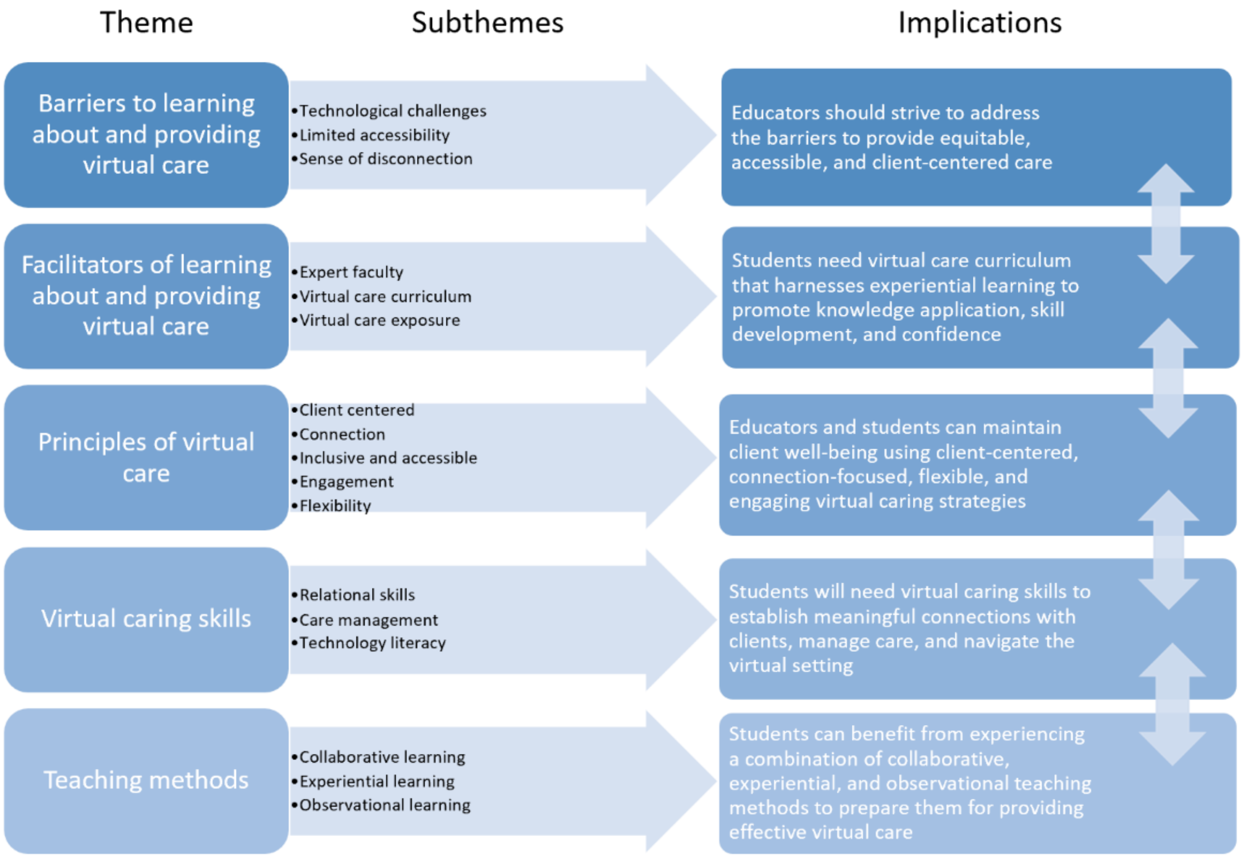
Scores and groups	*F* test (*df*)	Mean square	*P* value
Satisfaction			
Gender	1.514 (2)	0.470	.23
Faculty	1.806 (3)	.552	.15
Experience	0.106 (2)	.034	.90
Age	1.353 (4)	.396	.26
Preparedness			
Gender	0.026 (2)	.011	.98
Faculty	1.642 (3)	.673	.19
Experience	0.144 (2)	.063	.87
Age	1.380 (4)	.569	.25

Qualitative Findings

Overview

Figure 1 provides a high-level overview of the 5 themes and their corresponding 16 subthemes derived from the qualitative data, along with potential implications. These findings are explored in further depth in the sections that follow. Overall, interview participants lacked exposure to a robust virtual care curriculum. These findings represent their perspectives on the limited exposure that they did have and perspectives on what could be valuable to students in the future. Participants' limited exposure to virtual care learning varied as participants were recruited from different faculties and programs. Students reflected on how learning in an online setting had helped them to gain or enhance virtual care skills.

Figure 1. Overview of themes, subthemes, and implications.



Educators should strive to address the barriers to provide equitable, accessible, and client-centered care

Students need virtual care curriculum that harnesses experiential learning to promote knowledge application, skill development, and confidence

Educators and students can maintain client well-being using client-centered, connection-focused, flexible, and engaging virtual caring strategies

Students will need virtual caring skills to establish meaningful connections with clients, manage care, and navigate the virtual setting

Students can benefit from experiencing a combination of collaborative, experiential, and observational teaching methods to prepare them for providing effective virtual care

Barriers to Learning About and Providing Virtual Care

Students identified several barriers to online learning related to developing virtual care skills for their future practice: technological challenges, limited accessibility, and a sense of disconnection.

Technological Challenges

Interviewees identified several key challenges to their active participation in online learning aimed at fostering virtual care skills and competencies. These challenges included streaming problems, difficulties navigating new technologies, and the unreliability of the technology. Students expressed their struggles with web-based learning platforms, which can often be unpredictable and unreliable:

> *The system would kick the whole class out and people would have to log back in again if too many people tried to turn their cameras on. Even in cases where people were trying to fight against that black screen, sometimes the technology would fail and then you'd be stuck in the same situation.* [P6, interview, education student]

Technology challenges further impacted the students' ability to provide virtual care to clients. Students commented that in addition to learning how to use the technology themselves, they needed to guide clients using unfamiliar technology. In addition, they needed to accommodate technology failures when they occurred:

> *Navigating or teaching clients how to navigate which platforms to use... some clients aren't well-versed in using this platform, I think that's definitely a barrier.* [P1, interview, nursing student]

Students commented on the time implications when technology failed to work:

> *One of the things that we use here in my community is telehealth, but even that can be terribly complicated... you get together and then the technology does not work and then everybody has to plan again.* [P3, interview, nursing student]

Challenges with technology clearly impacted students' learning as well as their ability to provide excellent and timely care to their clients.

Limited Accessibility

Issues with accessibility, particularly inadequate internet connections, hindered students from engaging in learning opportunities that are crucial for developing essential virtual care skills. One student stated as follows:

> *If my wifi cut out, I would completely miss what somebody said. And the bigger of a group you have, the more technological barriers we faced with maybe not the best sound quality or somebody's camera maybe not working.* [P8, interview, nursing student]

One student discussed the challenge of providing virtual care to a population that might lack access to the technology used by providers. The student emphasized the necessity of being adaptable and responsive to the diverse needs of clients:

> *For example, text messaging can be a good thing. It's shown in the literature and different studies that being able to stay connected with a client through text messaging that's been set up that you're going to text them twice a week as a check-in, for example, was one of the things that came up. Well, that's great if, of course, your client has a cell phone, or has reliable access. So, then you look at what are the client strengths? Do they have access to a cell phone? If they don't, well then that's not going to work, so you're going to need to come up with something else.* [P3, interview, nursing student]

Inadequate access to mobile devices and robust internet connections can impact student learning and the types of care they can provide to clients.

Sense of Disconnection

Students were worried that providing care in a virtual environment could restrict their ability to develop human connections with clients or provide specific therapeutic services that require in-person interaction. For example, therapeutic touch is an important caring skill used in face-to-face interactions:

> *Because in person you can make physical contact, obviously therapeutic and appropriate with a person, versus online. I can't really hug my computer. It's more difficult to display that physical human connection. I mean, sure, you can express empathy through your words and your intent, but that's a little bit different than that face-to-face value. So, I could see that as another barrier.* [P8, interview, nursing student]

Students who were learning to both provide care and teach in online settings spoke of the lack of personal connection and the challenge of establishing a sense of community with their clients as significant barriers to the provision of care:

> *...[N]obody turned their camera on. It just felt like I was lecturing to my computer screen alone in a room... it wasn't a strong community... I tried to get them to turn their cameras on, but I just couldn't break that wall down.* [P6, interview, education student]

Another student spoke about the complexity of providing appropriate personalized care over the phone, noting they were unable to connect with clients by reading their body language:

> *I do work at a crisis center where I am over the phone, and we don't have that face-to-face interaction. And then I work in the emergency department in mental health. And so, a lot of the body language, the information you can collect when you have a patient in person is very different than the information that you need to collect over the phone.* [P9, interview, nursing student]

The importance of creating meaningful connections with clients was confirmed by other student respondents who noted that "being online detracts from the real human experience" (P83, survey, medical student)" and confirmed the challenges associated with "convey[ing] compassion online and… develop[ing] relationships with large online groups" (P8, survey, nursing student)."

Facilitators of Learning About and Providing Virtual Care

Students identified several facilitators of online learning related to developing virtual care skills for future practice, including expert faculty, virtual care curriculum, and virtual care exposure.

Expert Faculty

Expert faculty are needed to facilitate the learning of virtual care skills. While students indicated that the faculty should be skilled in educating in online environments to provide a smooth, engaging atmosphere for students, they also reported that their experience varied by the educator:

> *Some were excellent at facilitating ways to participate online and others didn't have the skills needed to build an online community of learners.* [P44, survey, education student]

Students also noted that it is important for faculty to be "competent in using online technology and be held accountable to upload information and provide feedback in a timely manner being available to students as needed" (P56, survey, nursing student). Students discussed the potential benefit of having the faculty who have experience in providing virtual care and the opportunity for faculty members to reach out to other departments for expert guidance regarding teaching virtual skills in online environments, with 1 student stating as follows:

> *...[T]hat mentorship component is when you are following... a mentor who's in that field who can help you relate to the material that you're learning, I find that to be really helpful, the interactive component of it.* [P9, interview, nursing student]

As noted by student participants, expert faculty can also role model and encourage online etiquette, foster psychological safety in the classroom, and ensure that there are interactive activities to facilitate a shared experience.

Virtual Care Curriculum

Students indicated a genuine desire for a virtual care curriculum; however, none of the interviewed participants had received robust virtual care training in their programs of study, such as a virtual care course. Some participants indicated that the topic would be brought up as a discussion around different ways that professionals may interact with clients rather than a devoted topic. Participants thought it would be beneficial if their professional educational programs provided a virtual care course or threaded a virtual care curriculum to address topics such as relevant technology, information on remote care equipment (eg, telemonitoring devices), rapport building in the virtual setting, and limitations of virtual care. Students urged that virtual care is a reality that needs to be addressed in professional educational programs that teach caring skills. Students in this study expressed a clear desire to learn how to teach remotely. One student remarked as follows:

> *Oh, definitely have a remote teaching course... how to navigate Zoom as an instructor or in Google Classroom... how to navigate some of the online assessments... That would be awesome. I would totally take that course* [P4, interview, education student]

As another student confirmed as follows:

> *[W]e focus so much on the bedside nursing, on the clinician approach to care, that we forget about the tremendous opportunities that come about with remote care as well as the need to have healthcare workers in the remote care setting.* [P8, interview, nursing student]

Virtual Care Exposure

Students conveyed the desire to be exposed to virtual care during their educational programs by shadowing a virtual care provider, practicing virtual care skills with clients, viewing online virtual care demonstrations, or role-playing and simulating virtual care environments where they could demonstrate their virtual care competencies in a psychologically safe environment. Exposure to individuals working in remote health care settings was viewed as highly beneficial and most effective when students understand the diverse scope of practice:

> *I feel like having more individuals who work in the remote setting and being able to shadow them or have a clinical rotation in a remote setting would definitely help if it was more inclusive of the broad scope of practice of healthcare practitioners.* [P8, interview, nursing student]

Survey respondents provided additional statements suggesting specific educational strategies that could be implemented to enhance learning in online settings, such as "some virtual simulations would be a great addition to the tools already used" (P61, survey, nursing student), "Exposure and experience with various technologies, and careful consideration of the intended goals and benefits/detriments of using these technologies" (P9, survey, education student), and "I wish educators focused more on demonstrations and explaining how this will work in 'the real world'" (P10, survey, nursing student)." According to the students, the more exposure to virtual care, the better, and thoughtfully integrating practical experiences with technology can support more effective online learning.

Principles of Virtual Care

We identified 5 principles of virtual care: client centered, connection, inclusive and accessible, engagement, and flexibility. These principles reflect what students reported as important factors in their ability to learn about and demonstrate caring skills in a virtual environment.

Client Centered

Students recognized the value of client-centered learning for their transition to caring practice. Students expressed that when learning in an online environment, they wanted to feel cared for and that their well-being was a priority; this translated to experiences they wanted to create for their current and future virtual clients. Students expressed how the client-centered approach involves individually assessing client needs and adapting to effectively meet them within the online environment:

> *Understanding how we can adapt and meet client needs better just in the environment alone I think is something else that I kind of have taken away from that experience.* [P1, interview, nursing student]

Online learning throughout the pandemic also helped students recognize that people are complex and more than a name or diagnosis:

> *I think the pandemic and online learning pulled back that veil a bit and showed how complex people are. I hope that an awareness of that complexity and the needs that come with being whole people... carries forward in teaching both online and in person.* [P6, interview, education student]

One student further identified how being client centered could also inform the questions that they may ask and the care they may provide for future remote clients:

> *Not just seeing a person as a diagnosis but seeing them as so much more. Seeing is how their community, the people in their lives affect their quality of life and wellbeing, as well as the resources they have access to or don't have access to, and making meaningful changes to them in a remote setting.* [P8, interview, nursing student]

The pandemic raised a newfound awareness of human complexity and integrating a more holistic approach to both online and in-person teaching was viewed as valuable by students. Students emphasized the importance of seeing the "human" as a dynamic member of a larger system. Hence, caring for people necessitates recognizing individual and systemic influences of care.

Connection

Students expressed the importance of connection during their online learning. They emphasized the value of relationship building and discussed how a lack of connection can adversely impact engagement. They appreciated the faculty who invested time in checking in with them and became acquainted with them as individuals. They viewed this ability to connect as an important skill to develop in themselves. Other students noted that taking the time to build community was essential for building connections with both colleagues and clients:

> *Online learning really showed me the value of slowing down a little bit. While still getting through all the content you need to get through in a good way, it's okay to also have moments... that are just about community building... and checking in with people.* [P6, interview, education student]

They expressed that relationships were built through shared experiences:

> *I have found that relationship building is key... these relationships are what stimulate not only engagement with the material but also motivation to participate and apply what one is learning.* [P15, survey, nursing student]

Students prioritized connection as part of their virtual learning and virtual care practices.

Inclusive and Accessible

Students remarked on the extent to which educational technology has made learning and caring more inclusive and accessible. Students noted how educational technology has created new ways of engagement, particularly benefiting those who may have previously been excluded:

> *Online and virtual open up opportunities to learn and interact in multiple ways such as text alongside audio. This has meant people with disabilities could join and participate more.* [P67, survey, medical student]

It has also allowed those students who live outside of urban centers or who are balancing various life priorities to learn in new ways:

> *It has made it so I as a working mother of 2 children can continue my education without feeling I must put these other things in my life on hold. Online teaching has meant I get to pursue my career aspirations sooner than I ever expected. It is very exciting for me.* [P15, survey, nursing student]

Students also reflected on how virtual care has provided a means for clients outside of large urban areas to access care that they may not have been able to previously:

> *It tends to be a lot more accessible for clients... we can adapt and meet client needs better just in the environment alone I think is something else that I kind of have taken away from that experience.* [P1, interview, nursing student]

Students recognized and appreciated the transformative impact of educational technology, particularly online and virtual platforms; this technology has made learning and caring more inclusive, accessible, and equitable, benefiting learners with diverse life commitments and clients residing in rural locations.

Engagement

Students conveyed the belief that engagement is a key principle in online learning of virtual care skills. Students expressed that engagement could be achieved in many ways including engaging in in-class activities and group work, having breakout rooms, leaving time for student questions, sharing experiences, role-playing, and using multimodal content. One student remarked on how they observed an educator modeling an engaging strategy and that they considered how they would use that strategy in their own practice of virtual care:

> *I learned a lot about different ways... to be present... through the use of my voice and through the use of my face and the video.* [P2, interview, nursing student]

One student discussed how a professor embraced innovation to enhance engagement in the virtual setting during the challenging early days of the COVID-19 pandemic:

> *Because I was taking a class online that was land-based learning. That's a really hard topic to transition to online because you're off the land in some ways while still being connected to the land in others. The instructor did this really innovative and fascinating thing where they would independently on their own safely go out onto the land and they'd take videos and make little audio recordings of their encounters with the land to show how we can still be land-based even when we're not together in the same space.* [P6, interview, education student]

Flexibility

Students identified flexibility as an essential principle in learning and applying virtual care skills. Students noted how the inherent nature of online learning provided them with the necessary flexibility to learn content and skills at their own pace and schedule, a skill that can be carried forward to their virtual care practice. Some students noted that the flexibility in online learning allowed them to learn optimally in a way that best suited them:

> *Online learning means I can learn at my own pace in an environment that is more comfortable and therefore more conducive to learning. Without the time pressure, I could redo things that I struggled with and go faster through other parts.* [survey respondent]

Students observed flexibility in virtual care when their educators offered flexible communication, flexible office hours, and the freedom to choose assignment topics within the course objectives. This flexibility empowered students to engage more effectively and tailor their learning experience to their unique needs and interests:

> *There's more onus placed on the student to learn. What's beautiful about that, I think, is that, at least from my experience, the learning really was driven by me. There's a certain topic or there's a certain parameter around what my learning was about or what I was to achieve, but how I went about doing that, the questions I asked, that really became a personal journey for me rather than fulfilling somebody else's preset plan for my learning.* [P5, interview, nursing student]

That same student went on to use that modeled behavior to inform the development of their own virtual care and teaching skills:

> *I think that there is still similarities there in terms of even just communication, and how is that shaped or modified, or even bettered because of my experience of being a student and my own personal journey with learning. But then be able to communicate better with my students as a result of that rather than a prescript, predetermined pathway. And giving my students that opportunity as well to explore the world according to them, really.* [P5, interview, nursing student]

Students associated flexibility in access, choice of topics, meeting times, and personalization with optimal online learning and virtual care practice.

Virtual Care Skills

Students identified many essential skills needed to provide virtual care. The skills were divided into 3 main categories: relational skills, care management skills, and technology literacy.

Relational Skills

Relational skills such as communication, relationship building, ensuring psychological safety, and conveying empathy were viewed as essential for providing care in virtual settings. Students expressed the importance of paying attention to nonverbal cues, voice tone, and active listening when working in virtual contexts:

> *I think it definitely did help to develop communication techniques over the phone that were mostly verbal, because we lost the aspect of most of the time having non-verbal communication and the ability to build rapport face-to-face. So I think just in terms of dialogue and building rapport over just purely verbal communication, I would say it definitely was beneficial in having more practice to do that.* [P1, interview, nursing student]

As another student confirmed as follows:

> *I do find that my skills that I've learned and communication skills that I've learned doing the online Zoom classes, I've been able to utilize some of those skills with delivering remote care to patients...my learning that I've done in my program, I've been able to put directly to use at work. It's been very helpful.* [P7, interview, nursing student]

One student conveyed the significance of small relational moments in building a community during the pandemic:

> *It actually became about connection and community as well, because I don't know...I can't speak for anyone else during the pandemic or in that particular time, but classes, online classes, were really my point of seeing other people outside my immediate bubble when we were all in isolation. Those opportunities to connect and chat in those breakout rooms, both about course content and not about course content, were really nice opportunities at the time.* [P6, interview, education student]

Students discussed the importance of establishing rapport and building relationships with clients. They remarked on how this was challenging but essential to demonstrating virtual care. One student shared how online learning enhanced the ability to build rapport and relationships with clients:

> *We talked about the rapport building and that relational aspect to remote care that I think is really important, that I think online learning really hones those skills. It does also help with the assessment skills.* [P9, interview, nursing student]

Students expressed the significance of cultivating psychological safety when delivering virtual care, as this would allow the client to feel more comfortable and at ease during the care process:

> *I think it would be really helpful to have a better understanding of creating an online learning environment that's conducive to safety, to people feeling safe enough to ask questions, express values, and be clear about assumptions and be open. So just really helping to create that.* [P2, interview, nursing student]

Furthermore, students desired more opportunities to learn how to convey empathy in the virtual setting. One student described why they thought conveying empathy was important:

> *I might not be able to offer therapeutic touch for somebody who's grieving, but I can show as much empathy as possible and possibly recommend them to additional resources. Because I feel like as people, it's fundamentally important to validate how individuals feel and work toward improving their health. And I mean in a remote setting, that might take a few times, a few follow-ups just as in a physical setting, but you can make progress too.* [P8, interview, nursing student]

Care Management

Virtual care management requires critical thinking, organization, advocacy, adaptability, client education, assessment, documentation, and problem-solving, all important skills for students to develop. Students discussed the skills involved in organizing client care and serving as advocates to access resources in virtual care environments:

> *I think definitely, especially in this current environment of nursing that I'm in, you take on more responsibilities in terms of organizing and advocating for patients. So especially with remote care, I think that aspect of taking clerical roles on top of nursing while still providing adequate and best practice nursing care. I think that's something that had I not had remote learning, I would've been less practiced in.* [P1, interview, nursing student]

Students also reflected on the skills that they needed to complete comprehensive client assessments in the virtual setting. They noted that as professionals, they needed to be skilled in asking the right questions and knowing when to dig a little deeper:

> *I think it made my assessments more comprehensive. Instead of just focusing on a person physically, there are a lot of questions that you can ask them that are objective that you don't need to see a person face to face to ask, that you could quite literally do through a chat if you needed to. And I think it really honed in on, how do I put this, your ability to use resources to the best of your ability.* [P8, interview, nursing student]

Students expressed that adaptably was very important in the virtual setting. One student described how their educators' adaptability provided benefits to their online learning during the early days of the pandemic and inspired them to mirror this behavior as one education student shared:

> *One of my professors, the methodologies course professor, also changed one of the learning tasks when we shifted online and shifted it from a research paper into a research presentation and had us partner up with someone in the class. It made it much more dialogic as opposed to written. I think this helped them both because they were transitioning their class online, which comes with a lot of logistical headaches and logistical work. It helped them cut down on their marking a little bit or change the way that they had to mark, and then it also allowed us to make sure we had someone we were regularly connecting with and dealing with the content with. So, that was nice. I would use those types of strategies moving forward.* [P6, interview, education student]

Technology Literacy

Technology literacy was noted as key to students' ability to perform virtual care. Students indicated that they needed to learn and gain confidence in using various virtual care technology platforms. In addition, one student discussed how technology literacy was an asset in their work within health care and education:

> *So, with the remote care of patients, I found I'm much more comfortable with using the remote technology. So, it's given me that comfort and it's also given me the comfort of walking patients and their families through the remote technology and being able to access, walk them through how to access the chat functions or even able getting them to use their camera to show me specific things has been helpful.* [P7, interview, nursing student]

Students expressed the need to understand the legal and ethical implications of providing virtual care, including aspects of adequate documentation and privacy concerns:

> *Yeah, I think how to navigate some of the pitfalls and how to navigate some of the challenges to providing this type of care. I mean, I think there's some issues around legalities and managing information that aren't necessarily addressed clearly in your teaching and learning.* [P2, interview, nursing student]

Teaching Methods

Students discussed many teaching methods that their instructors used that helped them develop virtual care skills. These teaching methods were divided into 3 main categories: collaborative learning, experiential learning, and observational learning.

Collaborative Learning

Collaborative learning was found to contribute to students' development of virtual care skills. Students discussed how class discussions and group work enriched their educational experience, emphasizing the positive impact of collaborative approaches:

> *I find I learn best through discussions and problem solving with other people. So I like it when we get projects to work on in smaller groups and then go back to a larger group online to present our work that we've worked together on in smaller groups.* [P7, interview, nursing student]

Underscoring the value of interdisciplinary collaboration in enhancing the skills related to providing virtual care, one student remarked on the benefits of participating in an interprofessional education sessions:

> *In previous terms we've done interviews with simulated patients where we collected health*

> *information, then worked with other students from other healthcare teams. I think that was really helpful in teaching. I think more of those interprofessional exercises would be really helpful going forward, just to kind of see how would you then work with another healthcare provider to provide care from different locations remotely. I think that would be helpful in continuing to do, and if not doing more.* [P1, interview, nursing student]

Experiential Learning

Experiential learning was noted by students to be important in developing virtual care skills. Specifically, students stated that engaging with virtual simulations, participating in role-play, and analyzing case-study scenarios significantly contributed to their understanding and acquisition of virtual care skills:

> *The learning opportunity for me was actually doing the role playing with my peers, but my teaching opportunity was also facilitating that role play online because during the pandemic, that was the only way that we were meeting with patients and clients out in the world. So it was that interaction online, learning that in the classroom to sort of set that skill set, get that skill set up to speed, so that when you're actually interacting with that individual online in a virtual caring situation, there's that transference of knowledge into what it is we were actually doing, what the students would be preparing for, for their clinical.* [P5, interview, nursing student]

Some students highlighted the benefit of a virtual practicum experience, where they had the opportunity to interact with actual clients in a virtual setting:

> *We had an assignment to interview someone with diabetes, we used videoconferencing to take a history from them, and received simulated medical records.* [P85, survey, medical student]
>
> *It would be lovely if it was a specific course on remote care, that would be fantastic. But if not a specific course, at least a few class days spent on perhaps assessing a patient remotely, like assess learning using either actual patients or acting patients and having the students have to learn how to or have to do a head-to-toe assessment or some sort of assessment on a patient who actually is remote just to get the practice of it.* [P7, interview, nursing student]

Observational Learning

Students discussed how they were able to learn virtual care skills by observing faculty and practicing professional work within a virtual setting:

> *Demonstration throughout clerkship has shown the many positives and negatives of virtual care.* [P86, survey, medical student]

In addition, an interview participant remarked on how they learned skills by observing others provide education in a virtual setting and thought about how they might use that in their own practice:

> *[Y]ou've had someone do a presentation and they just presented, their presentation skills were unique and interesting, and it's something that you could learn to build on for yourself. I think you take away a lot from that, having that place to sandbox you're learning and then bringing it into your formalized teaching or care practice that you're doing remotely.* [P2, interview, nursing student]

This observational learning played a crucial role in student skill development.

Synthesis of Findings

In our quantitative survey analysis, we observed that most respondents (80/89, 90%) expressed some level of satisfaction with the online teaching and learning strategies that were used to help them gain virtual care skills. These results are congruent with the qualitative findings that indicated that while students reported primarily positive learning experiences, they also saw potential for improvement. For example, many students suggested incorporating more virtual care exposure in their programs of study to further develop virtual care skills.

In the quantitative survey, students reported varying levels of preparation , which was also corroborated by our qualitative data. Although some students had some exposure to virtual care curricula and practical experience, others reported minimal exposure and offered suggestions to better prepare future students to learn and work in virtual environments. All students emphasized the importance of virtual care skills in quickly changing caring environments.

In our quantitative survey, students identified various teaching methods that helped them to learn virtual care skills. These quantitative results aligned partially with our qualitative findings. We have provided a joint display to further describe the integration of these results in Table 3.

Table 3. Joint display of teaching method data (n=93).

Qualitative themes	Quantitative data, n (%)	Participant quote	Interpretation
Collaborative learning			
Participants indicated that online discussion boards were used to develop their virtual care skills.	65 (70)	“We learn through reflection and that can easily be done virtually and on discussion boards.” [P22, survey, allied health]	Discussion boards were mentioned in the surveys and interviews as a way to collaborate with other students and faculty. Although it is a widely used teaching method, many students valued synchronous online discussions and group work as a way to collaborate and build connections.
Experiential learning			
Participants indicated that they were able to consult with clients to enhance their virtual care skills.	23 (25)	“Those are kind of things that I didn’t have any skills with when I graduated nursing, so that’s something I had to learn with experience and just on the job. So just giving the nursing students practice with these kinds of phone calls from either fake patients or families with scenarios of what’s going on, and have the nurse think about what advice they should give. And yeah, practicing doing virtual head to toe assessments, or not virtual, but yeah, online head to toe assessments of patients.” [P7, interview, nursing student]	Students expressed their desire for practical experience with virtual care while in their program; however, most students did not get the opportunity for this experience. Educational leaders should make an effort to provide virtual care practical experience to best prepare students for the challenges they will meet in the workplace.
Observational learning			
Participants indicated that they had had the opportunity to watch a demonstration of virtual care.	19 (20)	“Most of my learning has been from watching physicians do virtual care.” [P80, survey, medical student]	Students benefited from seeing practicing professionals demonstrate proper virtual care; however, only a small percentage were provided that opportunity. This gap can be addressed by offering virtual care practicums or having faculty demonstrate effective virtual care.
Divergence (no theme)			
Participants indicated that online modules were used to further their learning of virtual care skills.	77 (83)	—[a]	Although online modules can be helpful and are widely used to organize course content, students value the education more when there is an effort made to ensure learning has collaborative, experiential, and observational elements.
Participants indicated that reflection was used to help develop virtual care skills.	66 (71)	—	Although most survey respondents identified reflection on learning as a teaching method that helped them learn virtual care skills, this is not something that was explicitly discussed in the interviews and qualitative survey responses. This could be because many of the teaching methods proposed inherently use reflection (eg, simulation, discussion boards, group discussion).

[a] Not available.

Discussion

Principal Findings

In this mixed methods study, our primary objective was to explore the experiences and perspectives of caring profession students concerning online learning opportunities aimed at enhancing their virtual care skills and competencies. We sought to uncover both the facilitators and barriers to creating and engaging in such online learning opportunities. We conducted surveys and interviews with caring profession students from education, medicine, nursing and allied health disciplines across a midsized research-intensive educational institution located in western Canada. While no statistically significant differences were noted in satisfaction scores or preparedness scores based on gender, age, faculty, or experience with online teaching and learning technologies, the survey combined with the interview data revealed a number of interesting findings.

Students identified several barriers to effective online learning in the context of developing virtual care skills for future practice. These difficulties comprised challenges with technology, lack of accessibility, and lack of personal connection. Providing virtual care has undoubtedly revolutionized caring professions while also raising challenges that can act as barriers to effective virtual care delivery. Challenges with technology can be a significant hurdle, especially in cases where not all students or clients have access to reliable internet connections or the necessary devices for virtual care [19,20]. Although not explicitly mentioned by student participants, these challenges can disproportionately affect vulnerable populations, hindering their ability to provide and receive adequate care [20]. Moreover, technical glitches and software issues can disrupt virtual appointments, causing frustration and potentially compromising client safety. The lack of accessibility to virtual care may also be problematic. Some students and clients may require special accommodations, such as sign-language interpreters or Braille interfaces, which may not be readily available in virtual settings. This lack of inclusivity may lead to suboptimal learning and care for those with disabilities or language barriers. Finally, the limitations on personal connection in virtual care can potentially impede the caring relationship [21]. The physical distance can make it challenging for caring professionals to establish rapport, interpret nonverbal cues, and provide empathetic care. Students and clients may also feel isolated or detached from their educators or care providers, which can affect the quality of their learning or caring experiences. While virtual care offers many advantages, it is imperative to consider and address these barriers to ensure equitable, accessible, and client-centered care for all. Educators, students, administrators, policy makers, and caring professionals must work together to bridge these gaps and harness technology to optimize its full potential in virtual care learning and delivery. Ultimately, a more concerted effort can lead to a future where virtual care is maximized to benefit both students and their recipients of care.

Facilitating the development of virtual care skills in caring profession students requires a multifaceted approach that includes reliable technology infrastructures, expert faculty, a comprehensive remote care curriculum, and ample remote care exposure. Postsecondary educational institutions need to provide the technologies required for robust online learning environments. Expert faculty can play a pivotal role in guiding students toward mastering virtual care skills. Drawing from their wealth of knowledge and clinical expertise, experienced educators can provide valuable insights, feedback, and real-world scenarios to nurture students' empathy and communication, as well as help students understand the nuances of delivering compassionate care in remote settings. Well-designed remote care curricula are needed to not only cover the technical aspects of virtual care but also emphasize the importance of empathy, active listening, and cultural sensitivity. Such curricula should provide case studies, simulations, and role-playing exercises to allow students to practice and refine their virtual care skills in controlled environments [22]. Caring professional students must have ample opportunities for remote care exposure. This may include clinical rotations, internships, or practical experiences where students interact with patients virtually under expert faculty guidance. These hands-on experiences allow students to apply their theoretical knowledge, develop their virtual care skills, and gain confidence in providing compassionate care through digital platforms [23,24]. When combined, these elements can effectively work together to prepare future caring professionals to deliver high-quality, client-centered care irrespective of the mode of communication.

In a virtual environment, mastering caring skills becomes even more crucial, and several key factors should guide the learning and demonstrating of these skills in practice [25]. Participants in this study identified five principles of virtual care: (1) client centered, (2) connection, (3) inclusive and accessible, (4) engagement, and (5) flexibility. Prioritizing the needs and preferences of the student or client is paramount. Virtual care should be tailored to the individual's unique circumstances and requirements to ensure that their concerns, values, and goals remain centered [26]. Caring professionals must actively engage with clients to foster trust and rapport through effective communication and active listening. Showing empathy and a caring demeanor can help strengthen this connection, and ensuring that virtual care is accessible to all is essential [27]. This may include accommodating individuals with disabilities, providing language translation services, and addressing cultural sensitivities to ensure that every student and client feels included and valued. While maintaining engagement in a virtual environment can be challenging due to distractions and technology-related issues, caring professionals can use strategies to keep clients actively involved in their care, promoting adherence to care plans and shared decision-making. Flexibility is also essential in adapting to the unique circumstances of each student and client. Virtual care providers should be ready to adjust their approach, timing, and content to meet the evolving needs of their clients, allowing for personalized care plans [28]. Client-centered, connection-focused, inclusive, accessible, engagement-driven, and flexible virtual care practices are critical components for effectively demonstrating caring skills. These factors can ensure that caring professionals can deliver compassionate, high-quality care in the digital realm, maintaining the dignity and well-being of their clients while adapting to the ever-evolving landscape of virtual care delivery.

Although student participants provided thoughtful responses, their limited exposure to virtual care may have hindered their ability to give informed perspectives. When considering these perspectives, it is important to reflect on the guidelines offered by professional organizations and the government to identify areas that may not have been captured in student interviews. The College of Physicians and Surgeons of Alberta has published principles for virtual care including providing high-quality care, upholding ethical and legal standards, ensuring the appropriateness of the use of virtual care as well as patient privacy and confidentiality [29]. The government of Canada's Virtual Care Policy Framework has four policy pillars, including (1) community and patient-centered approaches; (2) equitable access to care; (3) provider incentive and payment; and (4) appropriateness and quality of care, provider change management, and licensure [30]. In addition, the American Telemedicine Association has published principles for virtual health providers, including upholding legal and ethical standards, upholding the standard of care regardless of care modality, maintaining appropriate licensure, mitigating threats to confidentiality and patient safety, and avoiding misleading advertisements [31]. Although there are organizations that support online education practices, they do not speak to the concept of virtual care through education, indicating a potential gap in guidance for this caring profession. Although student participants offered valuable insights into more individual-level concerns, they may not have been exposed to practical system concerns such as legal and ethical standards, appropriateness of care modality, equity, cybersecurity, and provider payment structures. These may also be considered as important content areas when developing a curriculum to prepare students for practice.

To deliver effective virtual care, students in caring professions need to cultivate a combination of relational skills, care management skills, and technology literacy. These skills are indispensable in ensuring high-quality, client-centered care in virtual care environments. Building strong relationships is important in providing virtual care, and caring professionals must excel in active listening, empathy, and effective communication to establish trust, understand client's needs, and provide emotional support remotely [32-36]. These skills enable caring professionals to connect with clients on a personal level and deliver compassionate, comforting care. In virtual settings, effective care management can involve comprehensive assessment, treatment planning, and monitoring. Caring profession students need to develop skills in remote assessment, risk evaluation, and care coordination to become adept at developing individualized care plans, setting goals, and tracking progress while addressing any challenges that arise in the virtual care environment. A strong foundation in technology literacy is essential for navigating the digital tools and platforms used in virtual care [37-39]. Caring professionals should be proficient in using virtual connection software, electronic records, and other digital tools to facilitate consultations, securely access client data, and ensure compliance with privacy regulations. Being technology savvy not only improves efficiency but also enhances the overall client experience by minimizing technical disruptions during virtual appointments. The development of relational skills, care management skills, and technology literacy is crucial for students in the caring profession to excel in providing virtual care, establish meaningful connections with clients, manage care effectively in remote settings, and leverage technology to benefit the clients they care for.

In this study, students identified three impactful educational approaches that significantly contribute to the development of virtual care skills: (1) collaborative learning, (2) experiential learning, and (3) observational learning. Collaborative learning, whether through group discussions, case studies, or collaborative projects, offers students a platform to exchange ideas, insights, and feedback. Engaging in discussions with peers exposes students to diverse client scenarios, fosters empathy, and facilitates a deeper understanding of different perspectives on care. It also encourages students to collectively engage in problem-solving, stimulating the creation of innovative strategies for delivering compassionate care in virtual settings. Learning by doing is another way to master virtual care skills. Practical experiences, such as virtual clinical simulations or telehealth practice sessions, enable students to apply their theoretical knowledge in real-world scenarios [22]. Through these hands-on experiences, students can practice active listening, effective communication, and empathetic responses while addressing the needs of virtual patients. Experiential learning builds confidence and hones the skills necessary for effective virtual care delivery [39]. Students can gain insights into best practices for virtual care by observing skilled practitioners during virtual consultations. This observational learning allows them to identify effective communication techniques and develop empathetic responses and strategies for building patient rapport, which they can then integrate into their own practice. Finally, a combination of collaborative, experiential, and observational learning may provide a well-rounded education that equips students with the virtual care skills needed in contemporary virtual environments. These approaches can encourage active engagement, practical application, and exposure to best practices, ultimately preparing students to deliver compassionate and effective care in virtual environments.

Strengths and Limitations

This study used a sequential explanatory mixed methods design, offering a robust exploration of virtual care skill development within a specific educational institution. The inclusion of participant learners from diverse caring professions provided a rich array of perspectives, enriching the comprehensiveness of the study. Using surveys and interviews, the study integrated both quantitative and qualitative data, allowing for a deeper understanding of students' experiences and perspectives in developing competencies related to virtual care. However, the limitations of our study suggest the need for some caution when interpreting our findings. The study's focus on a single institution could potentially constrain the generalizability of our findings to broader settings, as the findings may be specific to that particular institution. In addition, the participant pool being drawn from a single institution might introduce a lack of diversity in perspectives, impacting the external validity and transferability of our findings to a more varied population.

Furthermore, it is possible student respondents may have interpreted the terms in the survey regarding virtual care differently than the research team intended, as the terms were not explicitly defined. Most survey respondents (89/93, 96%) reported teaching methods that were used to enhance their virtual care skills. Given the lack of a formal virtual care curriculum discussed by the students in interviews, our qualitative sample might be biased. Despite these limitations, our study serves as a foundational exploration of virtual care skill development, encourages further research in this area, and promises potential advancements in understanding and improving the delivery of virtual care in educational settings.

Conclusions

Caring professionals require specialized knowledge and skills to deliver high-quality, effective virtual care; however, little is known about what is needed to teach students in this skill set. Our study highlights the barriers, facilitators, and principles of learning virtual care skills while also identifying pertinent skills and impactful teaching methods. This study contributes to the growing body of educational research regarding virtual care skills by providing insights into student perspectives and offering suggestions for optimizing teaching and learning strategies within caring professions' educational programs.

Conflicts of Interest

None declared.

References

1. Bogo M. Field education for clinical social work practice: best practices and contemporary challenges. Clin Soc Work J 2015 Mar 18;43(3):317-324. [doi: 10.1007/s10615-015-0526-5]
2. Future skills center. Co-operative Education and Work-Integrated Learning Canada. URL: https://www.cewilcanada.ca/ [accessed 2020-12-18]
3. Dewart G, Corcoran L, Thirsk L, Petrovic K. Nursing education in a pandemic: academic challenges in response to COVID-19. Nurse Educ Today 2020 Sep;92:104471 [FREE Full text] [doi: 10.1016/j.nedt.2020.104471] [Medline: 32502723]
4. Roskvist R, Eggleton K, Goodyear-Smith F. Provision of e-learning programmes to replace undergraduate medical students' clinical general practice attachments during COVID-19 stand-down. Educ Prim Care 2020 Jul;31(4):247-254 [FREE Full text] [doi: 10.1080/14739879.2020.1772123] [Medline: 32469632]
5. van Nuland S, Mandzuk D, Tucker Petrick K, Cooper T. COVID-19 and its effects on teacher education in Ontario: a complex adaptive systems perspective. J Educ Teach 2020 Aug 06;46(4):442-451 [FREE Full text] [doi: 10.1080/02607476.2020.1803050]
6. Nowell L, Dhingra S, Carless-Kane S, McGuinness C, Paolucci A, Jacobsen M, et al. A systematic review of online education initiatives to develop students remote caring skills and practices. Med Educ Online 2022 Dec;27(1):2088049 [FREE Full text] [doi: 10.1080/10872981.2022.2088049] [Medline: 35694798]
7. Creswell JW, Creswell JD. Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. Thousand Oaks, CA: Sage Publications; 2018.
8. Tashakkori A, Teddlie C. Handbook of Mixed Methods in Social & Behavioral Research. Thousand Oaks, CA: Sage Publications; 2010.
9. Rattray J, Jones MC. Essential elements of questionnaire design and development. J Clin Nurs 2007 Feb;16(2):234-243 [FREE Full text] [doi: 10.1111/j.1365-2702.2006.01573.x] [Medline: 17239058]
10. DeVon HA, Block ME, Moyle-Wright P, Ernst DM, Hayden SJ, Lazzara DJ, et al. A psychometric toolbox for testing validity and reliability. J Nurs Scholarsh 2007 May 23;39(2):155-164. [doi: 10.1111/j.1547-5069.2007.00161.x] [Medline: 17535316]
11. Polit DF, Beck CT. Nursing Research: Generating and Assessing Evidence for Nursing Practice. Philadelphia, PA: Lippincott Williams & Wilkins; 2020.
12. Topolovec-Vranic J, Natarajan K. The use of social media in recruitment for medical research studies: a scoping review. J Med Internet Res 2016 Nov 07;18(11):e286 [FREE Full text] [doi: 10.2196/jmir.5698] [Medline: 27821383]
13. Yuan P, Bare MG, Johnson MO, Saberi P. Using online social media for recruitment of human immunodeficiency virus-positive participants: a cross-sectional survey. J Med Internet Res 2014 May 01;16(5):e117 [FREE Full text] [doi: 10.2196/jmir.3229] [Medline: 24784982]
14. Braun V, Clarke V. Using thematic analysis in psychology. Qual Res Psychol 2006 Jan;3(2):77-101. [doi: 10.1191/1478088706qp063oa]
15. Nowell LS, Norris JM, White DE, Moules NJ. Thematic analysis. Int J Hum Comput Interact 2017 Oct 02;16(1):160940691773384 [FREE Full text] [doi: 10.1177/1609406917733847]
16. O'Brien BC, Harris IB, Beckman TJ, Reed DA, Cook DA. Standards for reporting qualitative research: a synthesis of recommendations. Acad Med 2014 Sep;89(9):1245-1251 [FREE Full text] [doi: 10.1097/ACM.0000000000000388] [Medline: 24979285]
17. Morse JM. Critical analysis of strategies for determining rigor in qualitative inquiry. Qual Health Res 2015 Sep;25(9):1212-1222 [FREE Full text] [doi: 10.1177/1049732315588501] [Medline: 26184336]
18. Carnevale FA. Authentic qualitative research and the quest for methodological rigour. Can J Nurs Res 2002 Sep;34(2):121-128. [Medline: 12425004]
19. Kuntz J, Manokore V. “i did not sign up for this”: student experiences of the rapid shift from in-person to emergency virtual remote learning during the COVID pandemic. High Learn Res Commun 2022 Jul 01;12:110-146 [FREE Full text] [doi: 10.18870/hlrc.v12i0.1316]
20. Ortega G, Rodriguez JA, Maurer LR, Witt EE, Perez N, Reich A, et al. Telemedicine, COVID-19, and disparities: policy implications. Health Policy Technol 2020 Sep;9(3):368-371 [FREE Full text] [doi: 10.1016/j.hlpt.2020.08.001] [Medline: 32837888]
21. English W, Robinson J, Gott M. Health professionals' experiences of rapport during telehealth encounters in community palliative care: an interpretive description study. Palliat Med 2023 Jul 02;37(7):975-983 [FREE Full text] [doi: 10.1177/02692163231172243] [Medline: 37129344]

22. Lister M, Vaughn J, Brennan-Cook J, Molloy M, Kuszajewski M, Shaw RJ. Telehealth and telenursing using simulation for pre-licensure USA students. Nurse Educ Pract 2018 Mar;29:59-63. [doi: 10.1016/j.nepr.2017.10.031] [Medline: 29180228]
23. Brownie SM, Chalmers LM, Broman P, Andersen P. Evaluating an undergraduate nursing student telehealth placement for community-dwelling frail older people during the COVID-19 pandemic. J Clin Nurs 2023 Jan 11;32(1-2):147-162. [doi: 10.1111/jocn.16208] [Medline: 35018676]
24. Moore S, Hong J. Designing a virtual practicum to prepare teachers for online instruction: developing an online field experience. Int J Des Learn 2022 Nov 08;13(2):70-86. [doi: 10.14434/ijdl.v13i2.33417]
25. Wittmeier KD, Hammond E, Tymko K, Burnham K, Janssen T, Pablo AJ, et al. "Another tool in your toolkit": pediatric occupational and physical therapists' perspectives of initiating telehealth during the COVID-19 pandemic. Phys Occup Ther Pediatr 2022 Apr 24;42(5):465-481 [FREE Full text] [doi: 10.1080/01942638.2022.2065898] [Medline: 35466859]
26. Marquez CM. Mobile health can be patient-centered and help solve inequality issues in Brazil's Unified Health System. Front Public Health 2023 Apr 27;11:1032412 [FREE Full text] [doi: 10.3389/fpubh.2023.1032412] [Medline: 37181694]
27. Annaswamy TM, Verduzco-Gutierrez M, Frieden L. Telemedicine barriers and challenges for persons with disabilities: COVID-19 and beyond. Disabil Health J 2020 Oct;13(4):100973 [FREE Full text] [doi: 10.1016/j.dhjo.2020.100973] [Medline: 32703737]
28. Rogers-Shaw C, Carr-Chellman DJ, Choi J. Universal design for learning: guidelines for accessible online instruction. Adult Learn 2017 Oct 17;29(1):20-31 [FREE Full text] [doi: 10.1177/1045159517735530]
29. Advice to the profession of virtual care. College of Physicians & Surgeons of Alberta. URL: https://cpsa.ca/wp-content/uploads/2020/06/AP_Virtual-Care-1.pdf [accessed 2024-04-29]
30. Virtual care- policy framework: a product of the federal, provincial, and territorial virtual care/digital table. Health Canada. 2021. URL: https://www.canada.ca/content/dam/hc-sc/documents/corporate/transparency/health-agreements/bilateral-agreement-pan-canadian-virtual-care-priorities-covid-19/policy-framework/policy-framework-eng.pdf [accessed 2024-04-29]
31. The ATA's principles of practice for virtual health providers. American Telemedicine Association. 2022. URL: https://www.americantelemed.org/wp-content/uploads/2022/07/ATA-Provider-Principals-v2.pdf [accessed 2024-04-29]
32. Goldingay S, Boddy J. Preparing social work graduates for digital practice: ethical pedagogies for effective learning. Aust Soc Work 2016 Dec 11;70(2):209-220. [doi: 10.1080/0312407X.2016.1257036]
33. Liu C, Scott KM, Lim RL, Taylor S, Calvo RA. EQClinic: a platform for learning communication skills in clinical consultations. Med Educ Online 2016 Jul 29;21(1):31801 [FREE Full text] [doi: 10.3402/meo.v21.31801] [Medline: 27476537]
34. Pullen RL, Silvers CA. Helping students embrace HIT. Nurs Manage 2018 Dec;49(12):17-21. [doi: 10.1097/01.NUMA.0000547841.89245.bd] [Medline: 30499855]
35. Rutledge C, Hawkins EJ, Bordelon M, Gustin TS. Telehealth education: an interprofessional online immersion experience in response to COVID-19. J Nurs Educ 2020 Oct 01;59(10):570-576. [doi: 10.3928/01484834-20200921-06] [Medline: 33002163]
36. Bautista CA, Huang I, Stebbins M, Floren LC, Wamsley M, Youmans SL, et al. Development of an interprofessional rotation for pharmacy and medical students to perform telehealth outreach to vulnerable patients in the COVID-19 pandemic. J Interprof Care 2020;34(5):694-697. [doi: 10.1080/13561820.2020.1807920] [Medline: 32917114]
37. Tømte C, Enochsson A, Buskqvist U, Kårstein A. Educating online student teachers to master professional digital competence: the TPACK-framework goes online. Comput Educ 2015 May;84:26-35 [FREE Full text] [doi: 10.1016/j.compedu.2015.01.005]
38. He Y. Universal design for learning in an online teacher education course: enhancing learners' confidence to teach online. J Online Learn Teach 2014;10(2):298 [FREE Full text]
39. Wong R, Ng P, Spinnato T, Taub E, Kaushal A, Lerman M, et al. Expanding telehealth competencies in primary care: a longitudinal interdisciplinary simulation to train internal medicine residents in complex patient care. J Grad Med Educ 2020 Dec;12(6):745-752 [FREE Full text] [doi: 10.4300/JGME-D-20-00030.1] [Medline: 33391599]

Abbreviations

SRQR: Standards for Reporting Qualitative Research

Edited by E Borycki; submitted 18.10.23; peer-reviewed by M Alam, B Lesselroth; comments to author 03.04.24; revised version received 11.05.24; accepted 05.07.24; published 21.08.24.

Please cite as:
Nowell L, Dolan S, Johnston S, Jacobsen M, Lorenzetti D, Oddone Paolucci E
Exploring Student Perspectives and Experiences of Online Opportunities for Virtual Care Skills Development: Sequential Explanatory Mixed Methods Study
JMIR Nursing 2024;7:e53777
URL: https://nursing.jmir.org/2024/1/e53777
doi:10.2196/53777
PMID:39167789

Original Paper

Experiences of Using a Digital Guidance and Assessment Tool (the Technology-Optimized Practice Process in Nursing Application) During Clinical Practice in a Nursing Home: Focus Group Study Among Nursing Students

Hege Mari Johnsen[1*], BSc, RN, MSc, PhD; Andréa Aparecida Gonçalves Nes[2,3*], BSc, RN, MSc, PhD; Kristine Haddeland[4*], BSc, RN, MSc, PhD

[1]Department of Health and Nursing Science, University of Agder, Grimstad, Norway
[2]Lovisenberg Diaconal University College, Oslo, Norway
[3]Department of Caring and Ethics, Faculty of Health Sciences, University of Stavanger, Stavanger, Norway
[4]Department of Health and Nursing Science, University of Agder, Kristiansand, Norway
[*]all authors contributed equally

Corresponding Author:
Hege Mari Johnsen, BSc, RN, MSc, PhD
Department of Health and Nursing Science, University of Agder
Jon Lilletuns vei 9
Grimstad, 4879
Norway
Phone: 47 97515773
Email: hege.mari.johnsen@uia.no

Abstract

Background: Nursing students' learning during clinical practice is largely influenced by the quality of the guidance they receive from their nurse preceptors. Students that have attended placement in nursing home settings have called for more time with nurse preceptors and an opportunity for more help from the nurses for reflection and developing critical thinking skills. To strengthen students' guidance and assessment and enhance students' learning in the practice setting, it has also been recommended to improve the collaboration between faculties and nurse preceptors.

Objective: This study explores first-year nursing students' experiences of using the Technology-Optimized Practice Process in Nursing (TOPP-N) application in 4 nursing homes in Norway. TOPP-N was developed to support guidance and assessment in clinical practice in nursing education.

Methods: Four focus groups were conducted with 19 nursing students from 2 university campuses in Norway. The data collection and directed content analysis were based on DeLone and McLean's information system success model.

Results: Some participants had difficulties learning to use the TOPP-N tool, particularly those who had not attended the 1-hour digital course. Furthermore, participants remarked that the content of the TOPP-N guidance module could be better adjusted to the current clinical placement, level of education, and individual achievements to be more usable. Despite this, most participants liked the TOPP-N application's concept. Using the TOPP-N mobile app for guidance and assessment was found to be very flexible. The frequency and ways of using the application varied among the participants. Most participants perceived that the use of TOPP-N facilitated awareness of learning objectives and enabled continuous reflection and feedback from nurse preceptors. However, the findings indicate that the TOPP-N application's perceived usefulness was highly dependent on the preparedness and use of the app among nurse preceptors (or absence thereof).

Conclusions: This study offers information about critical success factors perceived by nursing students related to the use of the TOPP-N application. To develop similar learning management systems that are usable and efficient, developers should focus on personalizing the content, clarifying procedures for use, and enhancing the training and motivation of users, that is, students, nurse preceptors, and educators.

(JMIR Nursing 2024;7:e48810) doi:10.2196/48810

KEYWORDS

application; assessment of clinical education; AssCE; clinical education assessment tool; electronic reports; feedback; guidance model; smartphone; Technology-Optimized Practice Process in Nursing; TOPP-N; information system success model; nurse; nursing; allied health; education; focus group; focus groups; technology enhanced learning; digital health; content analysis; student; students; nursing home; long-term care; learning management; mobile phone

Introduction

Background

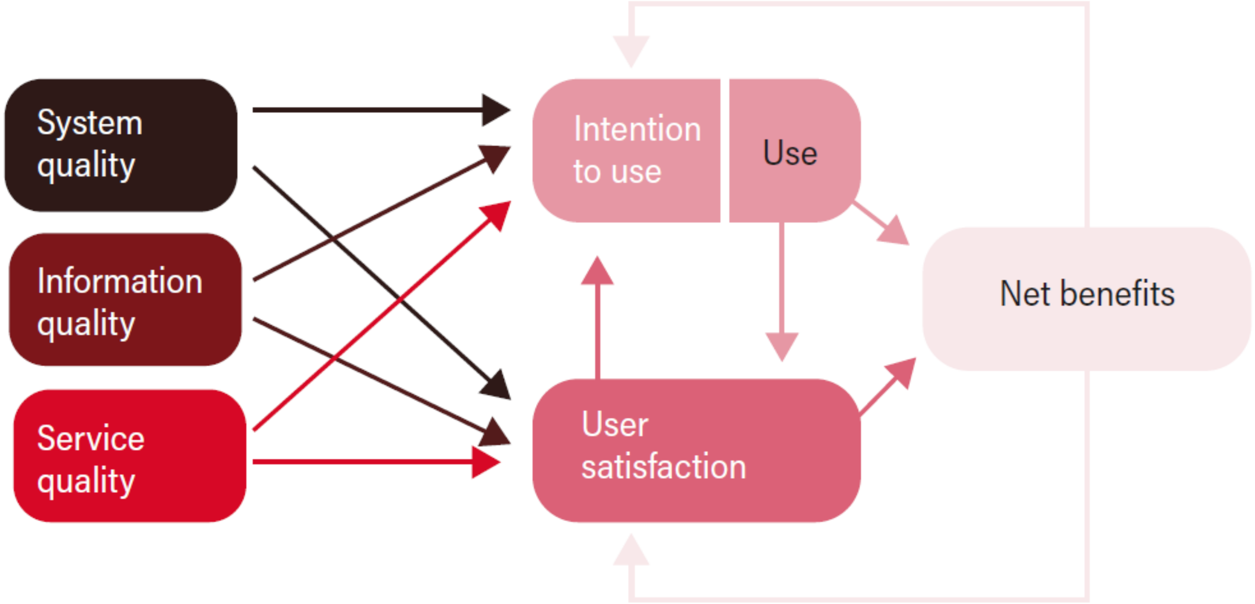
During an undergraduate program in nursing, learning in clinical practice, such as a nursing home, is crucial [1,2]. Of the 180 credits required in Norway's undergraduate nursing program, 90 credits are derived from clinical practice supervised by registered nurses (hereafter referred to as nurses) [3]. Research on nursing students' learning in clinical practice has shown that access to qualified guidance from nurses is essential to their learning [4-6]. Students have reported dissatisfaction with the limited amount of time spent with nurses in the nursing home setting [7] and have expressed a need for more professional reflection and help from the nurses to develop critical thinking skills [2,8]. Several studies also recommend better collaboration between faculties and nurses to strengthen guidance and assessment to enhance students' learning in a practice setting [2,5,8-11].

The use of mobile technology is becoming an important part of nursing education [12]. According to Li et al [12], the flexibility and interactivity of mobile apps for learning may positively influence students' motivations. Further, Shajani et al [13] suggest that digital evaluation tools (in the form of mobile apps or desktop applications) may provide timely and specific in-self-reflection and instructor feedback and are easily accessible. The digital guidance and assessment tool Technology-Optimized Practice Process in Nursing (TOPP-N) was developed to meet some of the challenges described above and is available in app and web versions [14]. Its purpose is to support students, nurses, and faculties in the guidance process in clinical practice, to improve communication and collaboration between the 3 parties [14], to ensure the quality of the students' achievement of learning outcomes, and to enable following up on them regardless of geographic distance. Importantly, the tool also aims to improve the guidance competence of nurses. Unlike other digital tools to assess students' achievement in clinical practice [13,15], TOPP-N facilitates the entire guidance and assessment process, not merely the midterm and final assessments.

TOPP-N may be viewed as a learning management system (LMS). From a learner-centered perspective, LMSs are described as platforms that function as mediums that may assist learners to gather, construct, and share knowledge [16,17]. The failure of LMS initiatives in higher-education institutions is often attributed to underestimating the significance of critical factors that influence the success of LMS adoption when designing and evaluating such systems [16,18]. Hence, it is important to identify factors critical to the successful acceptance of an LMS, such as TOPP-N. Perceived usefulness and ease of use are among the main constructs that influence an individual's behavioral intention and actual use of a system [17,19].

In our context, we were especially interested in how the students experienced the ease of use, the content, the user support, and the usefulness of the application version of TOPP-N. Thus, the most applicable theoretical framework to our study was the information system (IS) success model developed by Delone and McLean [20] (D&M), which offers a framework of the most critical factors contributing to IS success model in various contexts [17,20]. The framework was first introduced in 1992 but was revised and published in an updated version in 2003 [20]. This framework includes 6 dimensions: system quality, information quality, service quality, use, intention to use, user satisfaction, and net benefits (Figure 1).

Figure 1. The updated Delone and Mclean Information System Success Model [21].



System quality indicates desirable characteristics of an IS, such as ease of learning, ease of use (usability), intuitiveness, flexibility, reliability, response times, availability, and desirable characteristics. Information quality indicates the characteristics of system outputs, such as relevance, completeness, accuracy, conciseness, personalization, understandability, timeliness, and security. Service quality refers to the quality of the support that the system users receive from the service providers, which could entail information technology support as well as other types of user support and empathy from staff personnel. Use (behavior) refers to the degree and manner in which the IS or its features are used, for example, the amount, frequency, use patterns, appropriateness, and purpose of use. Intentions to use the system refer to users' attitudes toward using and reusing the system. User satisfaction refers to users' overall opinions about the system. Finally, net benefits refer to the benefits resulting from using the IS, such as impacts on individual users, groups, organizations, industries, and nations [20,21].

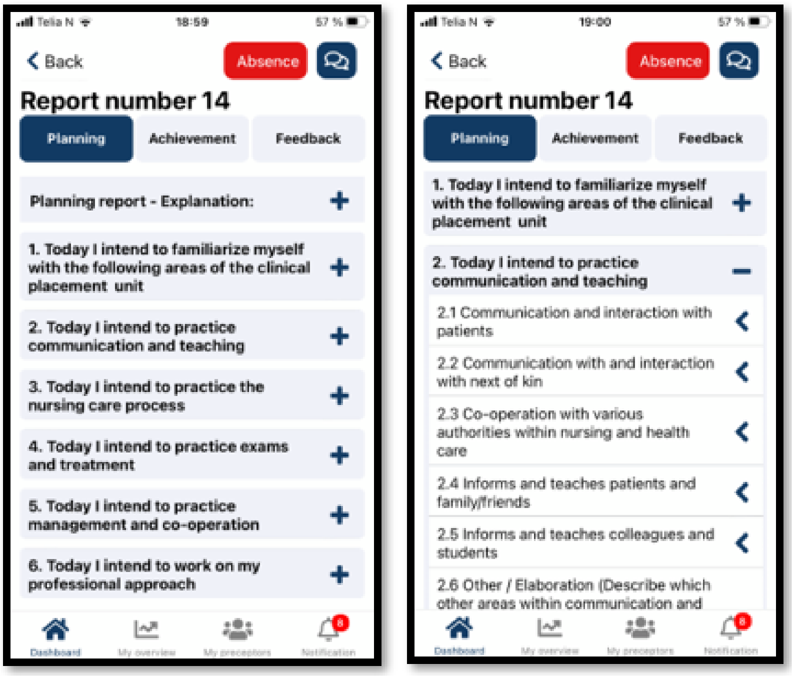
As shown in Figure 1, the D&M model views IS success as a multidimensional, interdependent construct and uses arrows to describe associations among the dimensions. For example, the quality dimensions (information quality, system quality, and service quality) will singularly or jointly affect subsequent use and user satisfaction. The intention to use and use, user satisfaction, and net benefits dimensions measure IS success or effectiveness. Further, intention to use (attitude) links with use (behavior). According to D&M [20], positive experiences with use will lead to greater user satisfaction and will increase the intention to use. Net benefits emerge because of use and user satisfaction. Whether the experience of benefits is positive or negative, it will lead to increased or decreased intention to use and user satisfaction [20]. D&M [20] recommend that the application context of the D&M model dictate the appropriate specification and application, as well as the various weights assigned to the dimensions of system quality, information quality, and service quality. In this study, *net benefits* describe the individual impacts or perceived usefulness of the app.

In recent reviews of the application of D&M's IS model [22,23], we have found no other studies that have applied the framework to evaluate a similar app for guidance and assessment of students during clinical practice in health education. Further, there is a lack of qualitative studies based on this framework in an educational context [23]. Hence, the aim of this study was to use the D&M framework to explore first-year nursing students' experiences of using the TOPP-N application for guidance and assessment in clinical practice in nursing homes.

TOPP-N Application

To ensure coherence between learning activities, learning outcomes, and assessment, the processes in TOPP-N are based on constructive alignment [24] and promote metacognition to stimulate nursing students' development of critical thinking [25]. To achieve this, TOPP-N provides both a guidance module and an assessment module. In the guidance module, the students fill out planning reports (Figure 2) and achievement reports (Figure 3). The former improves students' awareness of the learning objectives and helps them focus on learning activities that contribute to achieving the learning outcomes. The latter stimulates students to reflect on what they have learned. The content is based on AssCE (Assessment of Clinical Education [26]). AssCE is a research-based and validated assessment instrument.

Figure 2. Example of a Technology-Optimized Practice Process in Nursing (TOPP-N) planning report (mobile version screenshot).



Report number 14

Planning report - Explanation: +

1. Today I intend to familiarize myself with the following areas of the clinical placement unit +

2. Today I intend to practice communication and teaching +

3. Today I intend to practice the nursing care process +

4. Today I intend to practice exams and treatment +

5. Today I intend to practice management and co-operation +

6. Today I intend to work on my professional approach +

Report number 14

1. Today I intend to familiarize myself with the following areas of the clinical placement unit +

2. Today I intend to practice communication and teaching −

2.1 Communication and interaction with patients

2.2 Communication with and interaction with next of kin

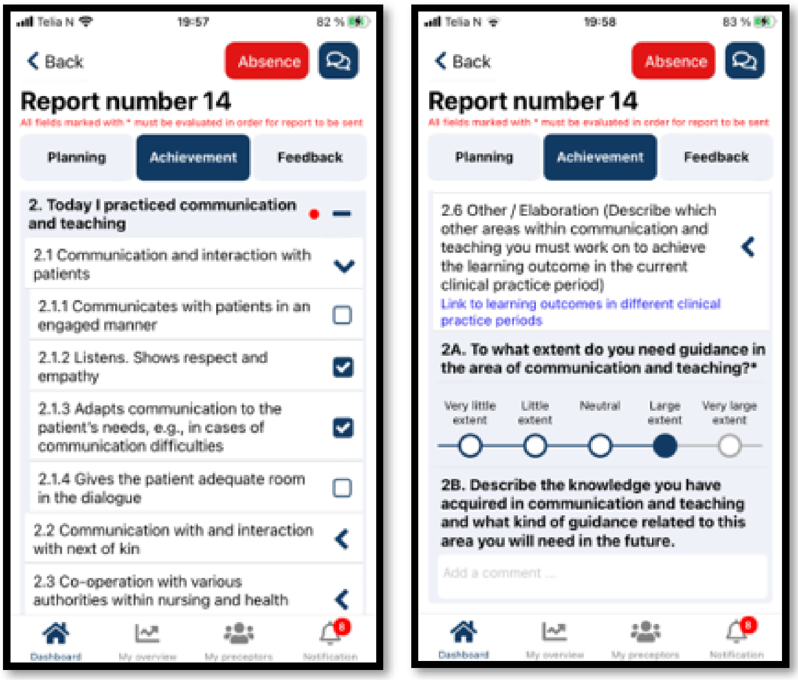
2.3 Co-operation with various authorities within nursing and health care

2.4 Informs and teaches patients and family/friends

2.5 Informs and teaches colleagues and students

2.6 Other / Elaboration (Describe which other areas within communication and

Figure 3. Example of a Technology-Optimized Practice Process in Nursing (TOPP-N) achievement report (mobile version screenshot).



Report number 14

All fields marked with * must be evaluated in order for report to be sent

2. Today I practiced communication and teaching −

2.1 Communication and interaction with patients

2.1.1 Communicates with patients in an engaged manner ☐

2.1.2 Listens. Shows respect and empathy ☑

2.1.3 Adapts communication to the patient's needs, e.g., in cases of communication difficulties ☑

2.1.4 Gives the patient adequate room in the dialogue ☐

2.2 Communication with and interaction with next of kin

2.3 Co-operation with various authorities within nursing and health

Report number 14

All fields marked with * must be evaluated in order for report to be sent

2.6 Other / Elaboration (Describe which other areas within communication and teaching you must work on to achieve the learning outcome in the current clinical practice period)

Link to learning outcomes in different clinical practice periods

2A. To what extent do you need guidance in the area of communication and teaching?*

○ Very little extent ○ Little extent ○ Neutral ● Large extent ○ Very large extent

2B. Describe the knowledge you have acquired in communication and teaching and what kind of guidance related to this area you will need in the future.

Add a comment ...

The reports are stored on a server and, together with the nurses' daily personal guidance, form the basis for feedback from the nurses for the individual students. A free-text field gives students and nurses the opportunity to elaborate on the answers and communicate directly with one another. The nurse educators at the faculties responsible for the students can access reports and feedback overviews at any time and, consequently, support the students and nurses as necessary. Thus, the guidance during clinical practice is thoroughly documented and provides a better basis for student assessment [27,28]. AssCE [26] is integrated within the assessment module and is used at the students' midterm and final evaluations. As shown in Textbox 1 [26], AssCE has 21 assessment points under 5 main areas: (1) communication and teaching, (2) the nursing care process, (3) examinations and treatments, (4) work management and cooperation, and (5) professional attitude.

Figure 4 shows an example of an assessment point in TOPP-N with grading and explanatory text.

Textbox 1. Main areas and assessment criteria factors in the Assessment of Clinical Education instrument [26].

Main areas and assessment criteria

I. Communication and teaching

- Communication and interaction with patients
- Communication with and encounter with family and friends
- Cooperation with various authorities within nursing and health care
- Informs and teaches patients and family or friends
- Informs and teaches colleagues and students

II. The nursing care process

- Describes patients' nursing care needs
- Plans and prioritizes nursing-care interventions
- Carries out nursing-care interventions
- Follows up on needs or problems and nursing-care interventions
- Reports, documents, and record keeping

III. Examinations and treatments

- Participates in and carries out examinations and treatments
- Administers medications

IV. Work management and cooperation

- Plans, organizes, allocates, and follows up on work assignments
- Cooperates
- Readiness to act
- Safety awareness

V. Professional approach

- Scientific awareness
- Ethical awareness
- Self-knowledge
- Thoroughness, reliability, and judgment
- Independence

Figure 4. Example of an assessment point in Technology-Optimized Practice Process in Nursing (TOPP-N) with grading and explanatory text (web version screenshot).

andreaprofessora

All fields marked with * MUST be rated by the student, supervisor and teacher, AND the student must also comment

1. Communication and teaching *

1.1 Communication and interaction with patients*

INADEQUATE ACHIEVEMENT OF GOALS:
Goals not achieved

GOOD ACHIEVEMENT OF GOALS:
Communicates with patients in an engaged manner. Listens. Shows respect and empathy.

VERY GOOD ACHIEVEMENT OF GOALS:
Adapts communication to the patient's needs, e.g., in cases of communication difficulties. Gives the patient adequate room in the dialogue.

Inadequate Good Very good

○ ○ ○ ○ ○ ○ ○ ○ ○

Comments from educator

Add a comment ...

Comments from preceptor

Add a comment ...

Comments from student

Add a comment ...

Methods

Study Design and Method

This study used an explorative qualitative design and used focus groups (FGs) to collect data. According to Krueger and Casey [29], FGs can capture the diverse range of participants' perspectives or feelings about a topic. This method also promotes a synergy that goes beyond individual interviews. The study was conducted in line with the COREQ (Consolidated Criteria for Reporting Qualitative Research) checklist [30] (Multimedia Appendix 1).

Participants

A convenience sampling method was used to recruit first-year undergraduate nursing students. Before they started using the app in clinical practice, they attended a 1-hour digital course on the app and its use. In addition to receiving course material, the participants had access to instruction videos through the TOPP-N login page and had access to a paper-based brochure with a short user instruction. The participants attended 8 weeks of clinical practice in community services and were placed at 4 different sites (nursing homes or short-term rehabilitation units). During that period, 31 first-year nursing students used the application, and all were invited to participate in the study. The last author contacted the nurse educators (n=4) responsible for the nursing students' clinical practice, who further invited all the students to participate. A total of 19 students voluntarily participated, and no one who wanted to participate was excluded. The participants had never used the application before the study. Four FGs were conducted, with a different number of participants in each group. One reason for the difference in the number of participants was that the recruitment and interviews were conducted immediately after a reflection group meeting with the students and their nurse educator responsible for their clinical practice. These reflection groups varied in the number of participants. Another reason was that participation in the study was voluntary, and all participants who wanted to participate were included.

Data Collection

The FGs were conducted in March and April 2022. The first and last authors planned to conduct all the FGs, but the second was conducted by the last author alone for logistical reasons. A semistructured interview guide with 17 primary questions was used (Multimedia Appendix 2 [30]), including demographic questions and questions based on the theoretical framework of D&M. Before the data collection, one coauthor who had contributed to developing the application evaluated the interview guide for relevance and clarity. The guide was also reviewed by nurse educators (other than the ones responsible for the nursing students' clinical practice) who had contributed to planning the use of the application to follow up on the students' clinical practice. Because of the reviews, a question about how users compared TOPP-N with other assessment forms was removed, as this was their first clinical placement and they had never used anything but TOPP-N. The interviews were held in meeting rooms on the 2 universities' campuses. The FGs were audio recorded and lasted from 41 to 62 minutes (52 min on average, SD 10).

Data Analysis

The last author transcribed all the interviews, which were then subjected to combined inductive and deductive analysis. The first author initially coded all the transcribed data inductively, after which the coded meaning units were sorted according to the categories of the IS success model model by means of directed or deductive content analysis [31,32]. Directed content analysis ideally includes both deductive and inductive analysis [31,32], so the deductive analysis was followed by an inductive process in which subcategories were identified within each predefined category. All the authors read the transcribed data and discussed the findings of the deductive and inductive analyses until they reached consensus. Table 1 provides an example of the analytic process.

Table 1. An example from the analysis process.

Meaning unit	Condensed meaning unit	Code	Subcategory	Predefined category
In the reports, you are asked to deal with all the learning outcomes each week. But if it was decided which outcomes to focus on the various weeks, then you didn't have to deal with everything all the time.	If learning outcomes were predefined for the various weeks, then you would not have to deal with all the outcomes each time.	Desire for predefined areas for the various periods	Amount and relevance of learning objectives	Information quality

Ethical Considerations

This study was approved by the Norwegian Centre for Research Data (607,252) and followed national ethical research guidelines [33]. All the participants received verbal and written information about the study and FGs in advance and signed informed consent forms before the FGs started. Each participant was assigned a number in case further information was required. To maintain confidentiality, the last author kept the names and participant numbers separately and stored all personal information in a secure location. None of the authors were in a teacher-student relationship with the participants and had not physically met the students before the actual interviews.

Results

Findings

The characteristics of the 19 participants in the 4 FGs are shown in Table 2. The participants included 16 women and 3 men, and the median age was 20 years. They were approximately equally distributed between the 2 different campuses, and most of them had attended the digital course about TOPP-N before using it in clinical practice. However, only 6 of the participants had used the instructional videos about TOPP-N. A total of 11 participants used TOPP-N on mobiles and PCs; 7 used it on mobiles only; and 1 participant used TOPP-N on both mobile and PCs and tablets.

Table 2. Study participant demographics in the different focus groups (FGs; n=19).

	FG 1 (n=7)	FG 2 (n=3)	FG 3 (n=6)	FG 4 (n=3)
Sex, n				
Female	6	2	5	3
Male	1	1	1	0
Age (y), median (IQR)	22 (19-30)	19 (19-22)	20 (19-24)	20 (20-21)
University campus				
A	0	0	Yes	Yes
B	Yes	Yes	0	0
Attended digital course, n				
Yes	6	2	5	3
No	1	1	1	0
Used instructional videos, n				
Yes	0	1	5	0
No	7	2	1	3
Use of platform, n				
Mobile only	5	0	2	0
Mobile and PC	2	2	4	3
Mobile, PC, and tablet	0	1	0	0

Textbox 2 describes the main findings identified in this study. The findings related to each subcategory are further described below. The texts in italics are authentic statements of the respondents.

Textbox 2. Overview of identified subcategories related to each predefined main category of the information systems success model.

System quality

- Ease of use
- Desirable functionality

Information quality

- Amount and relevance of learning objectives
- Completeness and understanding of learning objectives

Service quality

- Instruction and information
- Follow-up and guidance
- User support

Use and intention to use the app

- Patterns of use
- Intention to continue using the app

User satisfaction

- Perceived benefits of using the app
- Perceived disadvantages of using the app

Impact on guidance, assessment, and competence

- Feedback
- Visualization of competence

System Quality

Ease of Use

Most of the participants who had attended the digital course believed it was easy to learn how to use the app, and some said that they learned to use the app through "learning by doing" and "trial and failure." As one participant commented, "The application itself is very self-explanatory. If you have tried it once and figured out how to write a report, then you know how to do the next report" (participant 7, FG 1). The few participants who had not attended the digital course (or attended only part of it) found the app difficult to learn and required guidance from fellow students.

The participants perceived that the user interface and use of the app were quite similar on a PC and a mobile phone but mentioned that the text box for writing comments was very small on the mobile app, forcing them to scroll up and down on their mobile when providing comments. In addition, some participants commented that it was cumbersome to switch between the mobile phone and computer, as they could not be logged in at the same time on both platforms. However, the participants described the autosave function as an advantage:

> *Say that you don't complete the report...then it is saved until the next time you access it and complete it. I thought that was very good.* [Participant 3, FG 3]

Regarding completion of the achievement report, some of the students had trouble figuring out how to view the difference in grading achievement between a student and a preceptor. However, most of the participants said that using the app became easier after once using the planning and achievement part of the guidance module and after attending their first midterm evaluation using the assessment module.

Desired Functionality

The participants wished that the list of learning objectives would be adjusted depending on their personal achievements. For example, the learning objectives they had ticked off in the planning and achievement report one week would disappear from the planning report's list of learning objectives the next week:

> *Now, we start over for each report in the application. And we must base further reports on our own memory in relation to what we have ticked off previously...You can do it systematically yourself, but a tip for further development of the application is that it systematises it for you.* [Participant 5, FG 3]

With this kind of functionality, they could also observe their progress. As one put it, "It would have been a little more fun if the planning reports were a little shorter each time, because then we might have had a little more motivation to manage to get through everything!" (participant 2, FG 2). The things that they said could disappear from the planning reports included, for example, learning objectives about knowing the physical surroundings and routines at their clinical practice site.

One participant suggested that it should also be possible to receive alerts (ie, reminders to complete the planning and achievement reports on time) without opening the app (as was possible with other apps on their phone).

Information Quality

Amount and Relevance of Learning Objectives

Most of the participants felt that the list of learning objectives in the planning report was useful, as they were reminded of various things they needed to focus on during their clinical practice. However, the list of learning objectives in the planning report was also perceived as overwhelming by many of the participants and, for some, impossible to achieve. Many participants pointed out that not all the learning objectives were relevant to their level and clinical practice.

The participants appreciated the ability to choose an individual number of learning objectives from the list, and many commented that they wished the list of learning objectives in the planning report was predefined according to their level (first year) and included a checklist of the procedures relevant to their clinical practice. It was also suggested that some subitems (eg, under communication) could have been merged into fewer items.

Several participants also mentioned the challenge of planning learning outcomes, as the week never turned out as planned. One participant explained it this way:

> *Nursing is actually a very unstructured profession. Suddenly, something happens, and you have to change your whole day! Or the plan for your day. So, it was a bit difficult to plan.* [Participant 1, FG 4]

All the participants found it useful that the learning objectives they had picked for a week were highlighted in yellow in the guidance module's achievement report, which clarified the objectives requiring comment in the achievement report. The participants also appreciated that they could add new learning objectives to the achievement report, as it often happened that their plan changed or they had performed more activities than planned.

Completeness and Understanding of Learning Objectives

Most participants appreciated the ability to add free text, particularly in the planning and achievement reports, as they could specify their learning objectives and explain why other objectives were not relevant. As one participant put it, "The best thing about TOPP-N was that we could write comments" (participant 2, FG 1). Likewise, all the participants appreciated receiving free-text comments from their preceptors in the achievement report, saying that these comments made their preceptor's evaluation and feedback more specific and complete:

> *It was good that we received feedback on all the objectives we had ticked off, too. That there was specific feedback, not just summarizing.* [Participant 6, FG 3]

After filling out the assessment form in the assessment module, many participants experienced that they, their preceptor, and the teacher had somewhat different understandings of some learning objectives, specifically those related to handling acute situations and communicating with patients and their relatives.

In regard to noting the achieved goals in the assessment form, many participants regretted not having the option to choose "not conducted" or "not applicable," as the only available option was "insufficient." One participant argued that this term was quite negative and could easily impact students' self-esteem. It was suggested that users should be able to grade only the achievement based on performed activities instead of providing a grade for all the learning objectives. However, most of the participants said that they appreciated the ability to add a free-text comment in the assessment form to specify their achievement (or lack thereof) during the midterm and final evaluation.

The participants agreed that the number of grading points (9) in the assessment form was appropriate. Many students said that they were motivated by the ability to view the difference in grading of achievement between themselves and the preceptor, as the preceptor generally graded them higher than they graded themselves.

Service Quality

Instruction and Information

Some of the participants said that they had trouble keeping up during the digital course, partly because the lecturer talked a bit fast and they had not yet accessed the application themselves. One participant complained:

> *"We couldn't follow along inside the application at the same time. And that made it a little difficult".* [Participant 2, FG 4]

Only a few participants had used the available instructional videos (Table 1), the brochure, or the slideshow received through email. One who had read the brochure said, "I read the brochure. Then I understood how to use the reports—that we should plan first, then execute afterwards and then send the achievement report to get feedback" (participant 3, FG 1). Another who had viewed the instructional videos said:

> *"They were very easy to follow, so I got it [how to use the application] right away".* [Participant 2, FG 2]

Follow-Up and Guidance

Some of the participants planned their week together with their preceptor and agreed with their preceptor on how many learning outcomes to focus on. As one commented:

> *We usually sit down with our preceptor at the start of the week and talk a bit about what we want to focus on that week. Doing it this way has worked really well...so she can facilitate what I plan.* [Participant 6, FG 3]

Not all the participants received feedback on their achievement reports from their preceptor through the application, however. One participant commented:

> *Our preceptor has not familiarised (herself) with that application at all. She doesn't know how it works, and, technically, she's not good. She said she had received training, but still we have not received a response to any of the reports we have written.* [Participant 3, FG 2]

The participants who received feedback on their achievement reports found weekly written feedback very useful, but one said, "I think it might be a bit too often to have such feedback once a week" (participant 2, FG 3). Some participants noted that their preceptor's follow-up varied; in 1 week, they might receive comments on some or almost all the learning outcomes in the achievement report, while in another week they received only a summarized comment. The students also observed that the number of comments in the assessment module decreased from the first to the last week, but most participants said that they received comments on all the learning outcomes from their preceptors at their midterm and final evaluations. However, not all the copreceptors had access to the application, which raised obstacles to its use. One said, "I've been with a secondary preceptor a lot, but she doesn't have access to TOPP-N, so she doesn't really know what I'm up to" (participant 7, FG 1). Furthermore, the participants speculated that inconsistency in follow-up through the application could be explained by the preceptor's lack of competence in using it, a lack of time to fill in the great number of learning outcomes, or the fact that most communication was in person.

User Support

None of the participants required technical support from the application developers, but 2 participants said that their preceptors needed support to access the application:

> *There were some initial difficulties with getting to log in. It took a while for the preceptor to get started on it.* [Participant 5, FG 1]

Most participants received support for using the application from fellow students. Three students who lived together during their clinical practice also helped one another understand the general learning outcomes and reminded one another to fill in the achieved learning outcomes.

Use and Intention to Use the Application

Patterns of Use

In regard to the choice of platform, several participants commented that they chose to use a PC the first time they logged in to register and when they had to write a great deal of text in the guidance and assessment module, but all the participants said that they preferred using the application on their mobile phone. As one participant put it:

> *It was easiest to have it on the mobile. If you're sitting on the bus on the way home after practice, it's much easier to pick up your mobile phone than pick up your PC. And, if you have two minutes during your lunch break, you can go in and double-check something, or, if your preceptor asks about something, it's easy to find out on your mobile.* [Participant 7, FG 1]

Regarding using the application's guidance module, most of the participants filled in the 2 related reports (planning and achievement) once a week. Some of the participants filled in the planning reports according to the whole list of available learning objectives, while others chose only the most relevant ones each week. Not all left free-text comments in the planning or achievement reports.

Many participants said that they did not fill in the reports during their days in clinical practice, with one explaining that the priority was spending valuable time on nursing tasks rather than on using the application. Some filled in both reports at the same time, while others stopped using the planning and achievement reports when they noticed that their preceptors did not view them. Other students who did not receive feedback on their achievement reports continued using them for their own sakes, as they provided an overview of goals to focus on.

In most cases, the midterm and final evaluation were done in person in practice, in which case the nurse educator used a computer to view the grading and add a final judgment with comments. Only a few participants used the opportunity to follow the adjustments made by the nurse educator on their own mobile phones, and not everyone knew about this option. One participant who had a digital evaluation appreciated the ability to view the interface and the changes made on the teacher's computer. All the participants used the application's assessment module, and they were required to fill out the assessment form to prepare for their midterm and final evaluations, but the amount of free text provided in this context varied among the participants.

None of the participants used the function of sending messages to their preceptor or teacher within the application. They explained that one had to enter the application to use this function, so messages could be easily overlooked if they were not logged in. Therefore, both students and preceptors preferred using text messages on their mobile phones.

Intention to Continue Using the Application

Most of the participants indicated that they would continue using the application if the list of learning objectives in the guidance module could be better adjusted to their individual clinical practice and level. They also noted that it would be easy to continue using the application when both students and preceptors were more familiar with it.

One participant expressed skepticism about using such an application, arguing that the application should supplement and not replace face-to-face conversations with preceptors. The participant explained that much communication is lost when one relies only on written words.

User Satisfaction

Perceived Benefits of the Application

Several participants remarked that they liked the application's concept, with one saying, "I really like the concept or idea of TOPP-N" (participant 3, FG 2) and another adding,

> *I really liked that it was digital! That we didn't have to "hold a pile of paper" and look after it. It is very*

> *easy for papers to disappear or to be destroyed, folded or put somewhere where you can't find it again. So, it was very good that we had everything on our mobile. I really liked that!* [Participant 1, FG 4]

Other advantages experienced by the participants included, for example, that the list of learning outcomes in the planning report reminded them of what to focus on in that period. As one participant explained, "I'm a big fan of setting concrete goals, because then it's much easier to work towards them" (participant 5, FG 3). Because the planned outcomes were visible, both students and preceptors became more conscious of them. In relation to student awareness, one participant commented:

> *There were actually a lot of items to go through. Both main and subitems. But I feel that, if you spend some time on it, you have better control over what you expect to go through during the week...Then you sort of see what you've mastered so far and what you want to improve.* [Participant 1, FG 2]

The students perceived that, by continually receiving comments or grading before the evaluations, they could better prepare for what was coming and have less fear of possible unpleasant surprises.

Perceived Disadvantages of the Application

Among the disadvantages mentioned by the participants was that the list of learning outcomes could be "overwhelming," "too general," and "not specific for their practice or level of education." As one student put it, "What was most difficult about using the application were the learning outcome goals that were there. Because the goals were so big!" (participant 2, FG 4).

Many participants also found it a bit "time-consuming" to fill in all the learning objectives in the planning report, achievement report, and assessment form. The one who had spent the longest time filling out the assessment form said, "I think I spent about one hour or one and a half hours on the report; I got a bit frustrated" (participant 7, FG 1). A disadvantage mentioned by another participant was that relying on an app for guidance and assessment could add screen time and reduce face-to-face communication with the preceptor.

Impact on Guidance, Assessment, and Competence

Feedback

Many students noted that making the planned learning outcomes visible through the application made their preceptor more aware of them. As one participant commented, "Yes...that was an advantage. Because, if we had ticked something off, our preceptor saw it and tried to get us to do it" (participant 3, FG 4). The participants also agreed that using the application provided more comprehensive and continuous feedback and guidance. "In a way, you get a little more follow-up then and a reminder" (participant 4, FG 1). Some pointed out, however, that the application's usefulness depended on equal commitment from the student and the preceptor. One participant who did not receive feedback on the achievement report said:

> *"I think I would have gotten even more out of it if our preceptor had been as active as us".* [Participant 3, FG 3]

Visualization of Competence

Many participants found the application useful for visualizing their own competence: "It is a useful tool in that you have marked which areas you have been through. And it is useful to be able to go through it afterwards" (participant 5, FG 3). The students said that receiving comments or grading from the preceptors on their achievements each week, rather than only on the actual evaluations, made them more aware of their level of competence:

> *It was reassuring to get feedback during practice and to know a little about how you are doing.* [Participant 3, FG 4]

Another participant described the personal impact of using the application:

> *I actually think it was very useful. You sort of got an overview of where both you and your preceptor think you stand. You are often a bit strict with yourself, and then you see that your preceptor means something else. That you can actually do more than you think. So, I felt that, by using the application, you became a little more motivated, and (I) thought that I can actually do this!* [Participant 3, FG 3]

Similarly, several participants expressed that receiving positive feedback on their competence through the application had a positive impact on their motivation and self-esteem.

Discussion

Principal Findings

This study explored first-year nursing students' experiences of using TOPP-N for guidance and assessment in clinical practice in nursing homes. The findings are discussed in relation to the categories and their relationships in the D&M model.

System Quality

Usability, which describes the ease of using a system's user interface [34], is an important indicator of a system's quality [20], as a system's perceived ease of use is among the main elements that influence behavioral intention and actual use of it [17,20]. Most participants in our study found TOPP-N easy to use, but those who had not attended the course struggled a bit when first using it. This was also the result of a feasibility study by Zlamal et al [28], in which some students found it challenging to log into TOPP-N and know what to fill out and when. Based on the findings of this study, we recognize that the available sources of information in the application should be made more visible in an updated version. This aligns with Nielsen's [34] suggestion for user interface design: "Information required to use the design should be visible or easily retrievable when needed." A system's ability to provide desired functionalities and characteristics is another important element of usability [20,34]. The participants noted some functionalities that the application lacked, including the recall and removal of learning objectives that they had already reached, the ability to place an icon on their phone screen (as with other phone apps) to alert them about messages from the nurse preceptor or nurse educator, and the ability to be simultaneously logged in on multiple platforms. According to Nielsen [34], allowing personalization and tailoring of content makes user interfaces more flexible and efficient to use. In light of developments in artificial intelligence and machine learning, it should be possible to personalize the list of learning objectives, but the ability to log in at the same time on different platforms is limited by data security requirements. However, all the students appreciated the flexibility of having TOPP-N on their phone, as it could be used wherever and whenever they wished without their computer. Hence, despite the lack of some desired functionalities, our findings support a positive relationship between system quality and user satisfaction, in line with D&M [20] and Petter et al [21].

Information Quality

As in the study of Zlamal et al [28], we identified some misunderstandings related to using the planning function of TOPP-N. For example, some participants believed that they had to fill in the whole list of available learning objectives offered by the application when planning or evaluating their achievement in TOPP-N. However, participants appreciated the ability to choose an individual number of learning objectives from the list and write individual comments. This ability to personalize the list of learning objectives is in line with Nielsen's [34] user interface design principles. One advantage of TOPP-N is that students can individualize the list of learning objectives and implement tailored learning activities and assessment criteria, supporting both constructive alignment—to ensure coherence between learning activities, learning outcomes, and assessment [24]—and TOPP-N's metacognition approach, which aims to stimulate nursing students' development of critical thinking [25]. Critical thinking is a crucial skill in a constantly changing profession that deals with the complexity of modern health care demands [27].

Many students wished that the list of learning objectives in the planning report had been predefined according to their clinical practice context and level of education (first year). Their suggestions are in line with information quality indicators, such as "relevance" and "timeliness," as described by D&M [20] and Petter et al [21]. Considering the rapidly growing older population's increased need for complex medical and palliative care [6], learning objectives better adjusted to the nursing home context would address the growing need for nursing competence in caring for older adults. However, one advantage of having common learning objectives in TOPP-N is that the application is applicable in many different contexts. In addition, providing common learning objectives promotes the achievement of the desired learning outcomes and the expected competence level for each clinical practice. Furthermore, adjusting the list of learning objectives to a specific educational level would ignore the fact that nursing students' individual levels of knowledge, skills, and experience may differ.

The participants also wished that the application included a checklist of the procedures relevant to their clinical practice, but Engström et al [35] argue that, if an assessment tool is used more as a checklist, it will have little value for enhancing students' learning. In other words, if clinical skills or tasks dominate, there is a risk of losing focus on caring-related knowledge and understanding. However, the various clinical placements can provide students with checklists as a supplement to the content in TOPP-N.

According to D&M [20] and Petter et al [21], "completeness" and "accuracy" are 2 important indicators of a system's information quality. As in the study of Aase et al [10], some of our participants experienced that students, preceptors, and teachers had different understandings of some learning objectives and concepts. According to Nielsen [34], an IS's words, phrases, and concepts should be familiar to users, but the challenge of changing the phrases and content in TOPP-N is that the application is based on the assessment tool AssCE, whose purpose is to promote a standardized language and content [35]. A potential solution could be for nurse educators, nurse preceptors, and nursing students to agree on the included concepts and phrases before using the application as demonstrated by the participants in Aase et al [10]. Otherwise, the participants seemed satisfied with the information quality in TOPP-N.

Service Quality

Service quality embraces all the support that system users receive when using the application [20,21]. Our findings indicate that the digital course about the TOPP-N application should include a practical part where the students can follow along inside the app during the course. In addition, the link to available instruction videos should be made more visible.

Qualified guidance from nurses is essential to nurse students' learning [4-6], and good collaboration between students, preceptors, and nurse educators is essential to achieving a sound, objective assessment of students' learning outcomes [10,35]. As in the study of Zlamal et al [28], our participants experienced that some preceptors had little knowledge and competence in using TOPP-N. The students perceived this negatively and suggested that training for those who use TOPP-N should be improved, especially in cases involving more than one supervisor. The need for additional time for training in the use of digital evaluation tools among nursing instructors was also pointed out in the study of Shajani et al [13]. Furthermore, our findings show that the guidance and support (or lack thereof) received from their nurse preceptors influenced students' motivation, self-effort, and perceived usefulness. This is in line with Frøiland et al [6], who propose that the supervisory relationship and the role of the nurse preceptor are of utmost significance in influencing students' learning experiences. Thus, in contrast to previous studies of the D&M model [22], ours shows that service quality was particularly important to the student's use of the application, user satisfaction, and perceived usefulness. As suggested by Jeyaraj [22], this may be explained by the context in which the model was applied (nursing education) and the specific service provision (guidance and support). Our findings support evidence [6] that suggests that targeted efforts to enhance mentorship practices in nursing homes are needed to maximize the learning potential in this context.

Use and Intention to Use

The participants in our study preferred to use TOPP-N on their mobile phone, as they could log in at all times, and access was perceived as faster. This accords with the research of Zlamal et al [28], Li et al [12], and Shajani et al [13], who found that using mobile apps is easy to access and can increase students' motivation for self-study. However, our participants' choice of platform depended on the task to be done. For example, a computer was preferred during the midterm and final assessments to obtain a better overview of the student's achievement.

The use of the planning reports varied among the participants and was influenced by the feedback on the reports (or lack of feedback). As in the Zlamal et al [28] study, our participants' own motivation or motivation by others (nurse preceptors, nurse educators, or fellow students) was an important facilitator of their intention to use the application. This aligns with the theory of adult learning [36], which proposes that learning is dependent on both intrinsic and extrinsic motivation. It also supports the theory of user acceptance of technology [17], which proposes that user acceptance of new technology can be influenced by personal factors (eg, self-efficacy, experience, and computer anxiety) as well as environmental ones (including social influence). Hence, the findings indicate that it is important that nurse educators and faculty facilitate increased motivation and proper use of the application among the nurse students and preceptors. As noted by D&M [20], a system's use must be appropriate to achieve the expected impacts. Proper use could be enhanced if the guidelines for use better match what is manageable in a busy, everyday routine in clinical practice.

User Satisfaction

Overall, the participants were quite satisfied with the app, but, like those in the Zlamal et al [28] study, our students expressed that using TOPP-N was quite time-consuming, which was experienced as a disadvantage. According to Nielsen [34], the time required to engage with a digital program (ie, efficiency) is a usability attribute that influences motivation and the intention to use the program. TOPP-N's efficiency can probably be improved by better personalizing the application's content, as suggested by the participants. Personalization of the list could also make it easier for the nurse preceptors to obtain an overview of students' learning objectives, which could improve the usability of the application and increase the preceptors' intention to use it.

In line with findings from Jeyaraj's [22] critical metareview, all 3 D&M quality dimensions (system quality, information quality, and service quality) seemed to impact our participants' satisfaction with the application. Confirming the finding of Li et al [12], however, the students expressed that the application should be a supplement and not a replacement, and TOPP-N aims to be a supplement that enhances the quality of guidance and assessment during clinical practice [14].

Perceived Usefulness

Learning at clinical practice sites, such as a nursing home, is vital [1,2], and self-awareness, or thinking about one's own thinking (metacognition), is an important element in bridging knowledge and cognition in learning [37]. Because TOPP-N is based on the concepts of metacognition and critical thinking [14], we were happy that the students recognized that, by making the planned learning outcomes visible, the application made both students and their supervisors more conscious of them. By doing so, it enabled continuous, comprehensive feedback and guidance from preceptors. These findings are in line with research [15,27,28,35] showing that using AssCE provides superior continuity in student guidance and assessment and supports students' clinical learning. Our findings also indicate that the information quality of a system, such as TOPP-N, is strongly associated with individual impacts [20,21]. In addition, our findings support the notion that ongoing feedback during clinical practice (formative assessment) is fundamental to students' professional development, as it provides direction and nurtures confidence, motivation, and self-esteem [10,14].

Perceived usefulness is among the main elements that influence individuals' behavioral intentions and actual use of a system [17,19,20]. Our findings show that the perceived usefulness of the application depended on equal commitment from the student and the preceptor, which aligns with the D&M model [20,21] and research [5,10,11,35] and suggests that service quality—regarding collaboration with nurse preceptors (or its absence)—crucially influences individual impacts, such as students' clinical learning outcomes. Our findings also imply that nurse students' experiences of TOPP-N's positive or negative outcomes will increase or decrease their intention to use it, as well as their user satisfaction [20]. Thus, our findings support the D&M success model [20,21], suggesting that the 6 dimensions of success are interrelated rather than independent, with each dimension required to ensure the perceived usefulness or success of TOPP-N. However, nursing students' learning in clinical practice may also be influenced by the characteristics of the nursing home's ward environment, such as the pedagogical atmosphere, management support, and qualified nurse preceptors [6]. This was not investigated in this study.

Strengths and Limitations of This Study

The values of trustworthiness in qualitative analyses, such as credibility, dependability, and transferability [38], were protected by our chosen qualitative design. To ensure credibility and dependability, a validated IS success model was used to explore nursing students' experiences of using a mobile app (TOPP-N) for guidance and assessment during clinical practice in a nursing home. To capture the diversity of participants' feelings and perspectives on the application, FGs were chosen for data collection. However, FGs may have limitations [29]. For example, some participants may comment on all questions, while others may comment several times on a single issue. The FGs had a different number of participants, and the sample size in each interview may have influenced how much each participant contributed to the data collection. We took this into consideration during the analysis and when presenting the findings by ensuring a balanced presentation of experiences and comments from the participants. The total sample of 19 participants provided substantial insights into the perceptions of the participants, and we reached a point where we had sufficient data to draw the necessary conclusions [39].

The main categories of the directed analysis were based on the dimensions of the D&M model. Aware that using a directed approach can blind researchers to the possible presence of other main categories in the text [31], the authors kept an open mind during the analysis process so as not to overlook other main categories or subcategories in the data. All the authors were involved in the discussion and in reaching consensus, but no additional main categories were identified.

Regarding trustworthiness and transferability, the authors have described the context, participants, and research process thoroughly, making it possible to replicate the methodology in similar studies. All the authors are female academics in nursing education and have expertise in qualitative analysis.

A limitation of the study that influenced participants perceptions of the usefulness of TOPP-N was that some preceptors had not familiarized themselves with the application. In addition, not all the copreceptors managed to access the application, which raised obstacles. All preceptors were invited to attend a 1-hour digital course about TOPP-N and its use. In addition, they received the video recording of the course and information through email. The brochure was also available at the 4 clinical practice sites. In retrospect, we recognize that we should have asked for confirmation that the preceptors had viewed the course material and the available information.

Conclusions

The aim of using TOPP-N as a guidance and assessment tool is to increase the quality, flexibility, and efficiency of clinical practice in the undergraduate program in nursing [14]. Based on the findings, it appears that the application has the potential to improve users' quality of learning by enhancing metacognition and critical thinking skills. However, the perceived usefulness depends on students' own motivation and the collaboration and support of nurse preceptors. Students found using the mobile app for guidance and assessment to be very flexible, but they were less satisfied with the amount of time it took to fill in the reports. Improvements should focus on personalizing the content, clarifying procedures for use, and enhancing the training and motivation of both students and preceptors to make the application more efficient.

The application and its implementation process will be improved based on the findings of this study before it is used in other contexts and in further research (ie, a qualitative study with a focus on mental health). Our findings can alert developers and researchers in other educational contexts to the critical factors in the successful acceptance of similar LMSs.

Acknowledgments

The authors thank the participating nursing students, who kindly took the time to share their experiences with us. They also thank the nurse educators who helped us recruit students for the interviews. The authors have not used generative AI in any portion of the manuscript. The language of the manuscript was edited by Scribendi Inc.

Data Availability

The qualitative data set is in Norwegian and is not publicly available to protect the anonymity of the participants. On a reasonable request, data may be available from the corresponding author. In that case, the integrity and anonymity of the participants will be maintained.

Authors' Contributions

All authors, HMJ, AAGN, and KH, fulfill the journal's authorship policy and have approved the final manuscript. KH and HMJ collected the data. KH transcribed all the data. All authors conducted the data analysis and contributed to the manuscript preparation.

Conflicts of Interest

This study is financed by the Norwegian Agency for International Cooperation and Quality Enhancement in Higher Education. The funding source has not been involved in the study design; in the collection, analysis, and interpretation of the data; in the writing of the manuscript; or in the decision to submit the manuscript for publication.

Multimedia Appendix 1
The COREQ (Consolidated Criteria for Reporting Qualitative Research) checklist.
[PDF File (Adobe PDF File), 193 KB - nursing_v7i1e48810_app1.pdf]

Multimedia Appendix 2
Interview guide.
[PDF File (Adobe PDF File), 20 KB - nursing_v7i1e48810_app2.pdf]

References

1. Aamlid H, Tveit B. Simulation as a joint learning activity in clinical placement-interaction between first-year nursing students and qualified nurses. J Clin Nurs 2022 Jan;31(1-2):250-261. [doi: 10.1111/jocn.15903] [Medline: 34101278]

2. Bjørk IT, Berntsen K, Brynildsen G, Hestetun M. Nursing students' perceptions of their clinical learning environment in placements outside traditional hospital settings. J Clin Nurs 2014 Oct;23(19-20):2958-2967 [FREE Full text] [doi: 10.1111/jocn.12532] [Medline: 24460862]
3. Jacobsen TI, Onshuus K, Frisnes H, Thorsen GM. Nursing students’ experiences with clinical placement in a marginal Norwegian nursing home learning environment. Int Pract Develop J 2020;10(1):1-14 [FREE Full text] [doi: 10.19043/ipdj.101.007]
4. Gonella S, Brugnolli A, Terzoni S, Destrebecq A, Saiani L, Zannini L, SVIAT Team. A national study of nursing homes as learning environments according to undergraduate nursing student's perspective. Int J Older People Nurs 2019 Sep;14(3):e12245 [FREE Full text] [doi: 10.1111/opn.12245] [Medline: 31148416]
5. Husebø AM, Storm M, Våga BB, Rosenberg A, Akerjordet K. Status of knowledge on student-learning environments in nursing homes: a mixed-method systematic review. J Clin Nurs 2018 Apr;27(7-8):e1344-e1359 [FREE Full text] [doi: 10.1111/jocn.14299] [Medline: 29399921]
6. Frøiland CT, Husebø AM, Akerjordet K, Kihlgren A, Laugaland K. Exploring mentorship practices in clinical education in nursing homes: a qualitative mixed-methods study. J Clin Nurs 2022 Apr;31(7-8):895-908 [FREE Full text] [doi: 10.1111/jocn.15943] [Medline: 34278645]
7. Cooke J, Greenway K, Schutz S. Learning from nursing students' experiences and perceptions of their clinical placements in nursing homes: an integrative literature review. Nurse Educ Today 2021 May;100:104857. [doi: 10.1016/j.nedt.2021.104857] [Medline: 33714854]
8. Brynildsen G, Bjørk IT, Berntsen K, Hestetun M. Improving the quality of nursing students' clinical placements in nursing homes: an evaluation study. Nurse Educ Pract 2014 Nov;14(6):722-728 [FREE Full text] [doi: 10.1016/j.nepr.2014.09.004] [Medline: 25306396]
9. Snoeren M, Volbeda P, Niessen TJ, Abma TA. Dutch care innovation units in elderly care: a qualitative study into students' perspectives and workplace conditions for learning. Nurse Educ Pract 2016 Mar;17:174-181 [FREE Full text] [doi: 10.1016/j.nepr.2015.11.005] [Medline: 26694313]
10. Aase I, Akerjordet K, Crookes P, Frøiland CT, Laugaland KA. Exploring the formal assessment discussions in clinical nursing education: an observational study. BMC Nurs 2022 Jun 16;21(1):155 [FREE Full text] [doi: 10.1186/s12912-022-00934-x] [Medline: 35710411]
11. Tørring B, Jensen T. Udfordringer i samarbejdet omkring klinisk uddannelse i sygeplejerskeuddannelsen. Nordisk Sygeplejersken 2022 Apr 11;12(1):1-15 [FREE Full text] [doi: 10.18261/nsf.12.1.3]
12. Li KC, Lee LY, Wong SL, Yau IS, Wong BT. Effects of mobile apps for nursing students: learning motivation, social interaction and study performance. Open Learn J Distance eLearn 2018 Mar 22;33(2):99-114 [FREE Full text] [doi: 10.1080/02680513.2018.1454832]
13. Shajani Z, Laing CM, O'Rae A, Burkett J, Peters K. Utilization and perception of a digital clinical tracking tool in undergraduate nursing education. Teach Learn Nurs 2024 Jul;19(3):e494-e499 [FREE Full text] [doi: 10.1016/j.teln.2024.02.009]
14. Nes AA, Zlamal J, Linnerud SC, Steindal SA, Solberg MT. A technology-supported guidance model to increase the flexibility, quality, and efficiency of nursing education in clinical practice in Norway: development study of the TOPP-N application prototype. JMIR Hum Factors 2023 Feb 03;10:e44101 [FREE Full text] [doi: 10.2196/44101] [Medline: 36735289]
15. Nordhagen SS, Grethe Kydland A, Solbakken FM, Rustad I, Høvik MH, Struksnes S. Elektronisk studentvurdering i praksisstudier. Fremmer det kvalitet og effektivitet? Uniped 2021 Mar 29;44(1):75-89 [FREE Full text] [doi: 10.18261/issn.1893-8981-2021-01-07]
16. Çelik K, Ayaz A. Validation of the Delone and McLean information systems success model: a study on student information system. Educ Inf Technol 2021 Nov 15;27(4):4709-4727 [FREE Full text] [doi: 10.1007/S10639-021-10798-4]
17. Al-Nuaimi MN, Al-Emran M. Learning management systems and technology acceptance models: a systematic review. Educ Inf Technol 2021 Apr 23;26(5):5499-5533 [FREE Full text] [doi: 10.1007/S10639-021-10513-3]
18. Alsabawy AY, Cater-Steel A, Soar J. Determinants of perceived usefulness of e-learning systems. Comput Human Behav 2016 Nov;64:843-858 [FREE Full text] [doi: 10.1016/j.chb.2016.07.065]
19. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q 1989 Sep;13(3):319. [doi: 10.2307/249008]
20. Delone WH, McLean ER. The DeLone and McLean model of information systems success: a ten-year update. J Manag Inf Syst 2003;19(4):9-30 [FREE Full text] [doi: 10.1080/07421222.2003.11045748]
21. Petter S, DeLone W, McLean E. Measuring information systems success: models, dimensions, measures, and interrelationships. Eur J Inf Syst 2017 Dec 19;17(3):236-263 [FREE Full text] [doi: 10.1057/ejis.2008.15]
22. Jeyaraj A. DeLone and McLean models of information system success: critical meta-review and research directions. Int J Inf Manage 2020 Oct;54:102139 [FREE Full text] [doi: 10.1016/j.ijinfomgt.2020.102139]
23. Sabeh HN, Husin MH, Kee DM, Baharudin AS, Abdullah R. A systematic review of the DeLone and McLean model of information systems success in an e-learning context (2010–2020). IEEE Access 2021;9:81210-81235 [FREE Full text] [doi: 10.1109/access.2021.3084815]

24. Biggs J. Enhancing teaching through constructive alignment. High Educ 1996 Oct;32(3):347-364 [FREE Full text] [doi: 10.1007/bf00138871]
25. Magno C. The role of metacognitive skills in developing critical thinking. Metacogn Learn 2010 Mar 31;5(2):137-156 [FREE Full text] [doi: 10.1007/s11409-010-9054-4]
26. Löfmark A, Mårtensson G. Validation of the tool assessment of clinical education (AssCE): a study using Delphi method and clinical experts. Nurse Educ Today 2017 Mar;50:82-86 [FREE Full text] [doi: 10.1016/j.nedt.2016.12.009] [Medline: 28033551]
27. Zlamal J, Roth Gjevjon E, Fossum M, Trygg Solberg M, Steindal SA, Strandell-Laine C, et al. Technology-supported guidance models stimulating the development of critical thinking in clinical practice: mixed methods systematic review. JMIR Nurs 2022 Jun 07;5(1):e37380 [FREE Full text] [doi: 10.2196/37380] [Medline: 35671078]
28. Zlamal J, Roth Gjevjon E, Fossum M, Steindal SA, Nes AA. A technology-supported guidance model to support the development of critical thinking among undergraduate nursing students in clinical practice: concurrent, exploratory, flexible, and multimethod feasibility study. JMIR Form Res 2023 Apr 26;7:e43300 [FREE Full text] [doi: 10.2196/43300] [Medline: 37099377]
29. Krueger RA, Casey MA. Focus Groups: A Practical Guide for Applied Research. 5th edition. Thousand Oaks, CA: Sage Publications; 2015.
30. Tong A, Sainsbury P, Craig J. Consolidated criteria for reporting qualitative research (COREQ): a 32-item checklist for interviews and focus groups. Int J Qual Health Care 2007 Dec;19(6):349-357 [FREE Full text] [doi: 10.1093/intqhc/mzm042] [Medline: 17872937]
31. Hsieh HF, Shannon SE. Three approaches to qualitative content analysis. Qual Health Res 2005 Nov;15(9):1277-1288 [FREE Full text] [doi: 10.1177/1049732305276687] [Medline: 16204405]
32. Elo S, Kääriäinen M, Kanste O, Pölkki T, Utriainen K, Kyngäs H. Qualitative content analysis: a focus on trustworthiness. SAGE Open 2014 Feb 11;4(1):215824401452263 [FREE Full text] [doi: 10.1177/2158244014522633]
33. General guidelines for research ethics. The Norwegian National Research Ethics Committees. 2019. URL: https://www.forskningsetikk.no/en/guidelines/general-guidelines/ [accessed 2024-02-18]
34. Nielsen J. Usability 101: introduction to usability. Nielsen Norman Group. 2012. URL: https://www.nngroup.com/articles/usability-101-introduction-to-usability/ [accessed 2024-02-18]
35. Engström M, Löfmark A, Vae K, Mårtensson G. Nursing students' perceptions of using the Clinical Education Assessment tool AssCE and their overall perceptions of the clinical learning environment - a cross-sectional correlational study. Nurse Educ Today 2017 Apr;51:63-67 [FREE Full text] [doi: 10.1016/j.nedt.2017.01.009] [Medline: 28130975]
36. Abela J. Adult learning theories and medical education: a review. Malta Med J 2009;21(1):11-18 [FREE Full text]
37. Higgs J, Jones MA. Clinical decision making and multiple problem space. In: Higgs J, Jones MA, Loftus S, Christensen N, editors. Clinical Reasoning in the Health Professions. 3rd edition. London, UK: Butterworth Heinemann; 2008:3-17.
38. Graneheim UH, Lundman B. Qualitative content analysis in nursing research: concepts, procedures and measures to achieve trustworthiness. Nurse Educ Today 2004 Feb;24(2):105-112 [FREE Full text] [doi: 10.1016/j.nedt.2003.10.001] [Medline: 14769454]
39. Malterud K, Siersma VD, Guassora AD. Sample size in qualitative interview studies: guided by information power. Qual Health Res 2016 Nov;26(13):1753-1760 [FREE Full text] [doi: 10.1177/1049732315617444] [Medline: 26613970]

Abbreviations

AssCE: Assessment of Clinical Education
COREQ: Consolidated Criteria for Reporting Qualitative Research
D&M: DeLone and McLean
FG: focus group
IS: information system
LMS: learning management system
TOPP-N: Technology-Optimized Practice Process in Nursing

Edited by E Borycki; submitted 08.05.23; peer-reviewed by S Funghetto, T Hebda, UM Kinnunen; comments to author 05.06.24; revised version received 09.06.24; accepted 04.08.24; published 10.09.24.

Please cite as:
Johnsen HM, Nes AAG, Haddeland K
Experiences of Using a Digital Guidance and Assessment Tool (the Technology-Optimized Practice Process in Nursing Application) During Clinical Practice in a Nursing Home: Focus Group Study Among Nursing Students
JMIR Nursing 2024;7:e48810
URL: https://nursing.jmir.org/2024/1/e48810
doi:10.2196/48810
PMID:39255477

Original Paper

In-Home Respite Care Services Available to Families With Palliative Care Needs in Quebec: Novel Digital Environmental Scan

Aimee Castro[1*], RN, MSCN; Gabrielle Lalonde-LeBlond[1*], BSc; Zelda Freitas[2,3], SW; Antonia Arnaert[1], RN, PhD; Vasiliki Bitzas[1,4], RN, PhD; John Kildea[5], PhD; Karyn Moffatt[6], PhD; Devon Phillips[7], BFA; Lorne Wiseblatt[8], MD; Audrey-Jane Hall[9], RN, MBA; Véronique Després[10], BSW; Argerie Tsimicalis[1,11], RN, PhD

[1]Ingram School of Nursing, McGill University, Montreal, QC, Canada
[2]Professional Practice Directorate of Rehabilitation and Multidisciplinary Services, CIUSSS West-Central Montreal, Montreal, QC, Canada
[3]School of Social Work, McGill University, Montreal, QC, Canada
[4]Geriatrics and Palliative Care, CIUSSS West-Central Montreal, Montreal, QC, Canada
[5]Medical Physics Unit, McGill University, Montreal, QC, Canada
[6]School of Information Studies, McGill University, Montreal, QC, Canada
[7]Palliative Care McGill, McGill University, Montreal, QC, Canada
[8]McGill University Health Centre, Montreal, QC, Canada
[9]Palliative Home-Care Society of Greater Montreal, Montreal, QC, Canada
[10]St-Raphaël Palliative Care Home and Day Centre, Montreal, QC, Canada
[11]Nursing Research, Shriners Hospitals for Children-Canada, Montreal, QC, Canada
[*]these authors contributed equally

Corresponding Author:
Aimee Castro, RN, MSCN
Ingram School of Nursing
McGill University
680 Sherbrooke Street West #1800
Montreal, QC,
Canada
Phone: 1 5143984144
Email: aimee.castro2@mail.mcgill.ca

Abstract

Background: Caregiving dyads in palliative care are confronted with complex care needs. Respite care services can be highly beneficial in alleviating the caregiving burden, supporting survivorship and dying at home. Yet, respite care services are difficult to locate and access in the province of Quebec, Canada, particularly when navigating ubiquitous sources of online health information of varying quality.

Objective: This project aimed to (1) compile a list of at-home palliative respite care services in Quebec, Canada; (2) describe key accessibility features for each respite care service; (3) identify accessibility gaps and opportunities; and (4) describe a novel method for conducting environmental scans using internet search engines, internet-based community health databases, and member checking.

Methods: A novel environmental scan methodology using 2 internet-based targeted databases and 1 internet search engine was conducted. Results were screened and data were extracted, descriptively analyzed, and geographically schematized.

Results: A total of 401 services were screened, and 52 at-home respite care services specific to palliative populations were identified, compiled, and analyzed. These respite care services were characterized by various types of assistance, providers, fees, and serviced geographical regions. Accessibility was explored through the lens of service amenability, availability, eligibility, and compatibility. The data revealed important barriers to accessing respite care services, such as a lack of readily available information on service characteristics, limited availability, and a time-consuming, technical search process for potential respite care users and clinicians to identify appropriate services.

Conclusions: Both methodological and contextual knowledge have been gained through this environmental scan. Few methodologies for conducting internet-based environmental scans have been clearly articulated, so we applied several learnings from other scans and devised a methodology for conducting an environmental scan using the mixed methods of internet search engines, internet-based community health databases, and member checking. We have carefully reported our methods, so that others conducting community health environmental scans may replicate our process. Furthermore, through this scan, we identified assorted respite care services and pinpointed needs in the provision of these services. The findings highlighted that more easily accessible and centralized information about respite care services is needed in Quebec. The data will enable the creation of a user-friendly tool to share with community support services across Quebec and ultimately help alleviate the added burden caregivers and clinicians face when looking for respite care services in fragmented and complex digital spaces.

(JMIR Nursing 2024;7:e53078) doi:10.2196/53078

KEYWORDS

respite care; palliative care; caregiving; environmental scan; digital methodology; accessibility

Introduction

Overview

Palliative caregiving is a particularly intensive form of caregiving. Respite care is one of the essential services helping to support informal caregivers (ie, generally individuals with a preexisting relationship to the care recipient, with no additional training, and contributing unpaid work), and care recipients, particularly those in the palliative stage of care [1]. The goal of respite care is to provide short-term relief to informal caregivers and care recipients from their dyadic care-giving and care-receiving relationship by allowing both parties to spend time away from each other, interact with others, and perform activities that they enjoy or need to do [2-4]. During respite, another person acts as the care recipient’s temporary caregiver [2,4]. Respite can be accessed via a variety of service provisions (eg, palliative care, hospice day centers, and home care), offered in different settings (at home, in a facility, in the hospital, and in the community) and provided by an array of health care personnel to individuals coping with disabilities or illnesses [2,3,5,6].

For dyads in a palliative stage of care, respite care often contributes to supporting death in the home setting, which most patients prefer, all the while improving both parties’ psychosocial well-being and quality of life [2,6-9]. Additionally, these services are linked to decreased hospital admissions, health care costs, and use of aggressive care at the end of life [8,10]. In fact, dyads coping with terminal illnesses and needing palliative care support are increasingly requesting respite care services in Canada [3,10,11]. Despite these benefits, there seems to be no clear, comprehensive, and easily accessible information on overall or specific resources offered in Quebec.

In Canada, and particularly in Quebec, the provision of respite care falls outside the Canadian Health Act, which governs health care provision across Canada. As a result, a patchwork of services, funded through a variety of public, private-for-profit, and private nonprofit initiatives, is offered to nearly 1.5 million informal caregivers and care recipients in Quebec [12]. Government guides direct caregivers to their local Centres intégrés de santé et de services sociaux (in English: integrated health and social services centers) and Centres intégrés universitaires de santé et de services sociaux (in English: integrated university health and social services centers) for details on respite care services as opposed to specific agencies [13]. Additionally, some nonprofit organizations offer web portals for searching respite care services within their target population, such as Portail Répit for caregivers of children living with disabilities. The lack of a seamless respite care access pathway results in a lengthy, multistep process to access services—a process that can be overwhelming for exhausted palliative care dyads, and time-consuming for nurses, who typically oversee respite care service coordination and home care service provision.

Difficulties encountered while searching, locating, and accessing respite care impose an additional, undesirable burden on informal caregivers seeking respite [11,14]. Even with internet access at home, nearly a quarter of Canadians, particularly those most likely to resort to at-home health care services, have very limited internet use and digital skills [15-17]. Consequently, individuals with varying levels of digital literacy (ie, the ability to successfully use and navigate the internet and the associated apps or devices), are stranded to identify a search strategy by themselves [17]. The paucity of relevant information and difficulties in finding available services specific to individual needs may render respite care services inaccessible [7,8,18-20]. Considering the overall preference for death at home, and challenges associated with palliative caregiving, addressing access to information and support services, such as respite care, is essential to ensure all parties are supported through this phase of care.

Objectives

This environmental scan study aimed to identify and describe the characteristics of in-home respite care services currently available to caregiving dyads with palliative care needs in the French-speaking province of Quebec, by (1) mapping a current list of in-home palliative respite care services available to adults in Quebec; (2) describing and analyzing key offerings and accessibility features for each service; (3) identifying gaps and opportunities to increase accessibility and usage of these services; and (4) describing a methodology for conducting environmental scans using various internet-based sources and member checking.

Methods

Overview

Environmental scans methodologically support the systematic collection and analysis of information and services available within a specific environment for addressing the needs of a specific population. While no standard approach exists, this design often relies on searching beyond the academically published literature to identify all currently available programs [21-25]. Environmental scan strategies consist of combining sources of information consolidated from grey literature, internet search engines, and stakeholder consultations to identify all up-to-date and accessible services of a specific type available in a given geographic region [21]. This project implemented a novel environmental scan methodology to compile existing respite care services for individuals with palliative care needs in Quebec.

The novel and iterative strategy we developed consisted of (1) conducting a comprehensive search of internet-based respite and health care databases and internet search engines, (2) identifying and screening results for eligibility, (3) extracting and compiling the data, (4) seeking expert consultations, (5) analyzing the data, and (6) synthesizing the results into a coherent report on respite care services in Quebec. The general framework for scoping reviews by Peters et al [26], was taken into consideration, as were the methods used by related environmental scans, which tended to use analog paper sources and grey literature, rather than digital and internet-based resources [23,27].

Ethical Considerations

As this was a grey literature–based study and no human or animal participants were involved, ethics approval was not required.

Eligibility Criteria

The eligibility of respite care services was determined through a 2-step process. First, for respite care services to be considered eligible for this environmental scan, they had to be (1) offered in Quebec, (2) coordinated by an official organization, (3) offered in-person, and (4) offered as a stand-alone service. Home support services that did not specifically mention the concept of respite were excluded, along with Google ads. Remote respite care services (eg, video camera “nanny cams”) and informal respite care provided by family, friends, or self-employed individuals were not considered, as well as services only available when participating in the organization’s broader activities [1].

Second, eligible respite care services were further screened to identify a subgroup of services that (1) were offered in the family’s home and (2) indicated that services were either destined for a population in palliative care or at the end of life or that specialized services for persons in palliative care or at the end of life were offered in conjunction with general respite care.

Internet-Based Search of Respite Care Services

Respite care services were identified by (1) searching internet-based respite and health care databases and (2) searching the most commonly used internet search engine. The search strategies and methodology were created in collaboration with an expert librarian and reviewed by consulting coauthors to ensure that the keywords used were most appropriate for the Quebec context. Examples of keywords used in these search strategies included “respite care,” “short-term care,” and “home caregiving” (see Table 1 for the full list of keywords).

Table 1. Keywords related to the main research question and concept of respite care; keywords were translated from English to French by a bilingual member of the research team, with the corroborating assistance of DeepL Translator (DeepL SE) [28].

Original English keywords	Translated French keywords
Respite care	Soins de répit; service de répit; soins de relève; service de relève
Respite	Répit; relève
Short-term care; short term care	Soins à court terme; soins de courte durée
Sitting service	Service de garde
Adult day-care; adult day care; adult daycare	Soins de jour pour adulte
Day respite facility	Établissement de répit de jour; centre de répit de jour; maison de répit de jour
Hospice at home; home-based palliative care; home hospice	Soins palliatifs à domicile
Hospice day centre; palliative day centre	Centre de jour de soins palliatifs; centre de jour palliatif
Home care; Homecare; home caregiving	Soins à domicile; assistance à domicile
Caregiving help	Aide aux proches aidants; aide aux aidants
Help for caregivers	Aide pour proches aidants; aide pour aidants

Step 1: Searching Internet-Based Respite and Health Care Databases

Overview

A bilingual, French and English, search was conducted using web resource databases intended for caregivers and patients and that are relevant to the subject of caregiving support and respite care in Quebec—the Canadian Cancer Society Community Services Locator and the resource directory for L'Appui Proche Aidants, an organization supporting informal caregiving in Quebec [29,30]. Our search strategy slightly differed from 1 database to the next due to their unique search functionalities.

Canadian Cancer Society Community Services Locator

This database was searched using the keywords found in Textbox 1, with Quebec, Canada, listed as the location. No specific search parameters or limitations were applied, and the results were sorted by relevance.

Textbox 1. Search permutation for Google search; "Keyword" was replaced by each keyword listed in Table 1. Quebec, Montreal, Sherbrooke, Trois-Riviere, Chicoutimi, Saint-Jerome, and Saint-Jean-sur-Richelieu were selected due to being populous regions in the province of Quebec.

> For English keywords: "Keyword" AND ("palliative" OR "hospice" OR "dying" OR "end-of-life") AND (Quebec OR Montreal OR Sherbrooke OR Trois-Rivieres OR Chicoutimi OR Saint-Jerome OR Saint-Jean-sur-Richelieu)
>
> For French keywords: "Keyword" AND ("palliatif" OR "mourant" OR "mourir" OR "fin de vie") AND (Québec OR Montréal OR Sherbrooke OR Trois-Rivières OR Chicoutimi OR Saint-Jérôme OR Saint-Jean-sur-Richelieu)

L'Appui Resource Directory

This database was searched using the "Search by Service" function along with selecting the subcategory listed in the database filters of "respite care services offered in the home." This directory does not allow for a province-wide search. Thus, the most populated postal codes for each of Quebec's 18 health regions were used to facilitate the search for services across Quebec [31,32]. The results were automatically sorted from closest to farthest away from the postal code.

Step 2: Searching an Internet Search Engine

Google, the most popular search engine option in Canada, was used on a private browsing window to further identify respite care services [33]. The following search permutation (see Textbox 1) was selected based on its ability to return a high number of relevant results.

Before conducting each search, Google settings were adjusted to deactivate results personalization based on prior activity, location, and stored data. Such adjustments reduce the probability of previous search activities by the researcher, or their location, affecting the results of the search [34]. Google alerts for once-a-month returns were also created for the keyword combinations to identify new results after the initial search period.

Step 3: Screening

Based on preliminary searches, the 2 caregiving support databases, and particularly the 1 internet search engine, yielded a large number of results. In order to screen a feasible number of relevant results, we reviewed the first 100 results for each search, which accounts for the first 10 pages of results on Google with default settings [35,36]. In general, users interact most with first page results, with few visiting or clicking the following pages' results [37]. Therefore, our approach goes beyond the typical use of internet search engines.

Duplicates were removed, and each returned result's home page was previewed for eligibility. Search results that did not meet the eligibility criteria, such as information sheets that shared caregiving support information but not respite care contact information, news articles or general reports on respite care, were not included. When eligibility was unclear, the team discussed the service to determine if the result should be included.

Step 4: Data Collection

Once screened, each eligible respite care organization's website was saved and reviewed to extract information on the service eligibility criteria, service features, geographic availability, targeted demographics, costs, and language of the respite care service [5]. Similar variables have been identified and used in previous research [3,27,38,39]. To foster a consistent approach, the data collection was done independently by 1 researcher. If any discrepancies arose, issues were discussed and resolved with the research team.

Step 5: Conducting Expert Consultations

Preliminary search strategy findings with a current list of services were sent to a group of 5 stakeholders (experts) comprising community members involved in respite care coordination and research. For review and feedback, experts were asked to verify our list of respite care services. They were also invited to direct us to any other respite care services in Quebec and identify any other essential feature required to describe the respite care services [39]. Stakeholders and identified organizations were also asked to provide feedback on the final paper and results.

Step 6: Data Analyses

Qualitative deductive content analysis was used to descriptively analyze and interpret the data using a predetermined coding framework consisting of the following categories: service features, length of services, setting, care provider, region, costs, language, eligibility criteria, and user profile [40]. A geographical map of the services by region was created using graphic design software.

A framework defining "access" to health care was also identified post hoc as part of our iterative data analyses for further analyzing the data related to "accessibility" [41]. Norris and Aiken [41] conceptualized access to health care as characterized by (1) the family's amenability to receive services (ie, the client's readiness and knowledge of service and contextual factors), (2) the services' availability (including location and hours of operation), (3) the eligibility of the client to access such services (including costs), and (4) the compatibility between the service and individual needs. This framework helped contextualize and structure our analysis of the findings, whereby each predetermined coding category was matched to 1 of the 4 components of health care accessibility.

Results

Overview

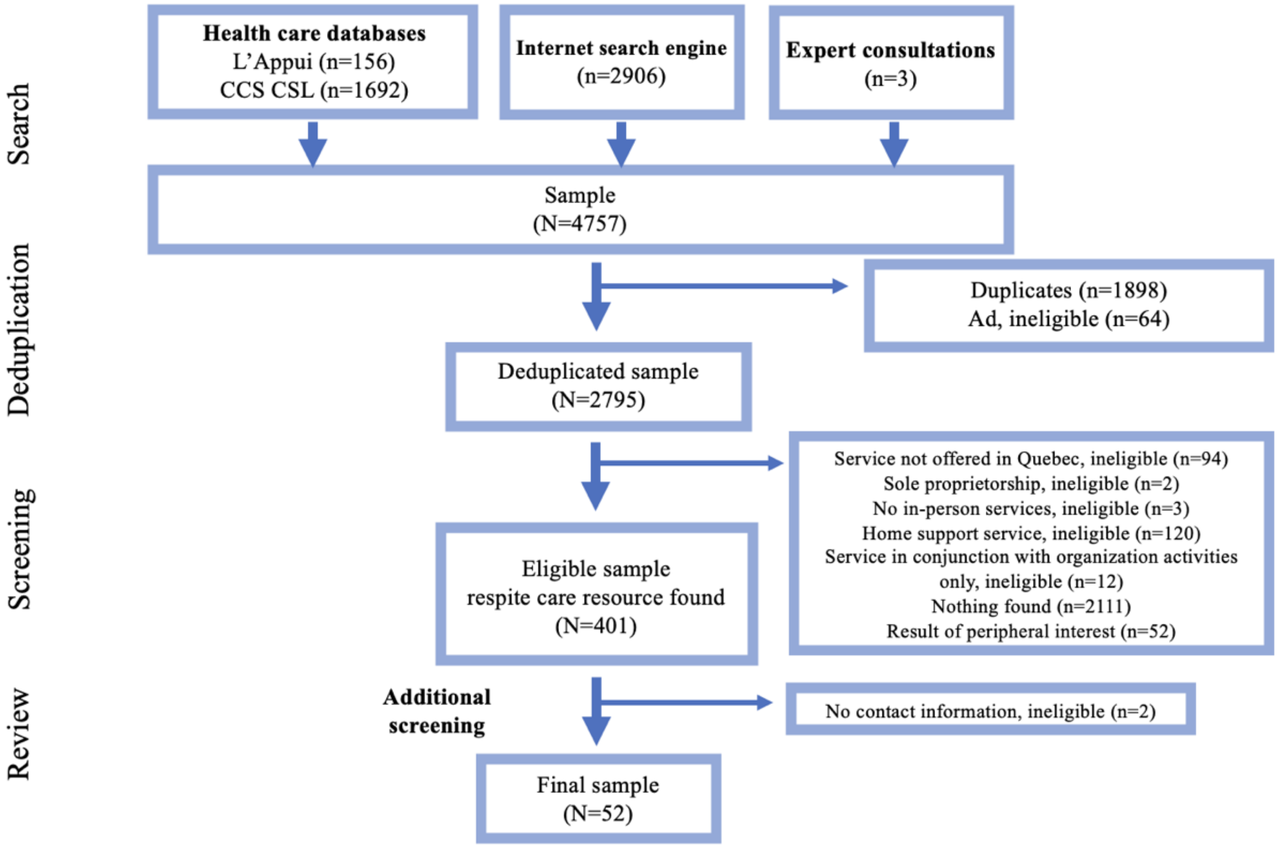
We used descriptions of the services along with specific service features, according to Norris and Aiken's [41] framework of personal access to health care, to determine the overall accessibility of the respite care services identified—amenability, availability, eligibility, and compatibility.

Amenability

A total of 100 searches were conducted, including 41 on the Canadian Cancer Society Community Services Locator, 18 on the L'Appui Resource Directory, and 41 on Google (including monthly search alerts) producing a total of 4757 search results. Of these results, 401 results corresponded to respite care services, 52 of which were included in our analyses as they offered in-home respite care targeted to individuals with palliative care needs. The remainder of services were offered in a designated location (eg, a hospice or care home) and targeted to other key populations (eg, children with chronic disabilities). The most common reasons for exclusion were that respite care services were offered outside the province of Quebec (n=94), that home support services did not mention respite (n=120), and overwhelmingly, that no services specific to the concept of respite care were found on the website (n=2111). A total of 2 services were ultimately excluded due to providing no contact information. In some cases, these identified websites corresponded to an unrelated database, caregiving resource, news article, miscellaneous service, or obituary. Figure 1 summarizes the results obtained through data collection and screening.

Google was the most successful database for the identification of relevant respite care services. In fact, 40 eligible services (40/52, 76%) were discovered through Google, 26 of which (26/40, 65%) were exclusive to this search engine and were not found in the Canadian Cancer Society Community Services Locator or L'Appui databases. The Canadian Cancer Society Community Services Locator enabled the identification of 23 eligible services (8 exclusively), while the L'Appui Resource Directory identified 7 eligible services (1 exclusively). The expert consultations uncovered 3 services, 1 of which is currently in development, as well as others already identified through the other search strategies. An overview of each respite care service's characteristics is explored in the following sections and summarized in Multimedia Appendix 1.

Figure 1. Flowchart of respite care data collection strategy, adapted from Moher et al's model [42]. CCS CCL: Canadian Cancer Society Community Services Locator..



Description of the Variety of Respite Care Services Offerings

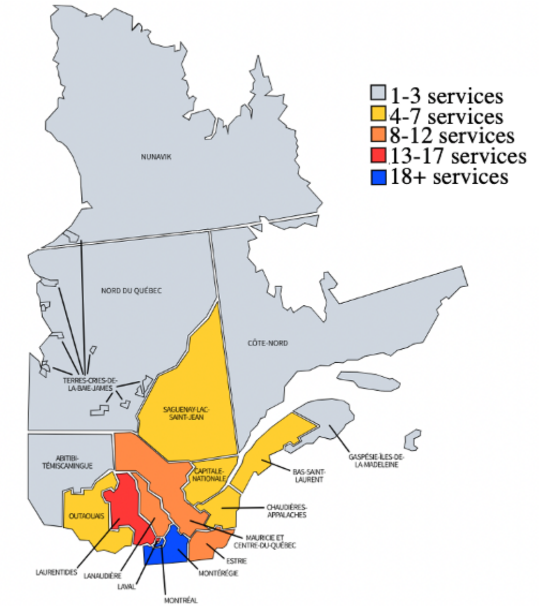
The specific respite care offerings were characterized by a variety of activities and types of care for both the caregiver and the care recipient. All of these activities occurred in the context of a respite care visit, that is, this visit consisted of another person coming to the home to provide care for the care recipient so that the informal caregiver could leave the premises if they so desired.

The most common respite care activities offered were accompaniment (36/52, 69%), assistance with daily activities (29/52, 56%), personal care (19/52, 36%), and specialized care (17/52, 33%). In many cases, the organizations offered several types of specialized care, like palliative and cancer care. A total of 7 (14%) organizations specifically mentioned that they provided symptom and pain management as part of their respite care services. A total of 2 (4%) organizations listed restricted activities that they could not offer during the respite period (ie, medication administration and hygiene care). All organizations focused on assisting the care recipient. A total of 9 (17%) organizations also included some type of support for informal caregivers while on respite; for example, 1 organization had a rest lounge available for caregivers that the caregivers could visit while the respite care provider went to the care recipient's home.

Availability, Including Flexibility

Respite care services were found primarily across Eastern Quebec, as can be observed in Figure 2. Only 1 service was identified in the regions of Abitibi-Témiscamingue, Nord-du-Québec, Nunavik and Terres-Cries-de-la-Baie-James. The greatest concentration of services was found in Greater Montreal, a densely populated metropolitan area comprised of the health regions of Montreal and Laval, as well as parts of Lanaudière, Laurentides, and Montérégie [43].

Figure 2. Locations of respite care services across Quebec health regions. The map was adapted from Qualifications Quebec and the Ministry of Health and Social Services [44,45]. Some services are offered in more than 1 region.



Agencies valued service flexibility. Many organizations emphasized individualized care for the unique situation of the family and explicitly specified that both planned and unplanned (emergency or on call) services were available (10/52, 19%). Some services had a designated telephone line for questions and service requests, available at all times (3/52, 6%). Furthermore, the majority of services report a 7-days-a-week (28/52, 54%), 24-hours-a-day (22/52, 42%) availability, for periods of a few hours (31/52, 60%), and at a frequency of once or twice a week (3/52, 6%). Some services explicitly advertised overnight respite services (9/52, 17%) and for lengths of over 24 hours (8/52, 15%). More flexibility with the number of hours and timing of the service was seen in some exceptional situations. A total of 4 (8%) organizations stated that overnight services were available for patients at the end of life. That said, it is unclear how quickly families can access respite care services identified in the sample due to delays between a request and service provision (14/52, 27%) due to requirements for initial consultations or waitlists.

Eligibility

The care recipient target population for the identified respite care services consisted of persons in palliative care, at the end of life, persons with specific diagnoses like cancer, older adults, and persons affected by a loss of autonomy. Caregivers and loved ones were also targeted by the services, with some services citing specific eligibility requirements such as being a care recipient at the end-of-life, in palliative care, with a cancer diagnosis, or residing in a specific region. However, many organizations did not disclose their eligibility criteria (24/52, 46%).

A total of 20 (38%) respite care services were free of cost for the users, while 27 (52%) had associated fees. Often, these fees were not defined or openly available on the organization's website (23/27, 85%), thus, requiring families to contact the respite care organization for more information. The disclosed fees ranged from CAD $15 (US $11.08) per day to CAD $32 (US $23.63) per hour, with the bottom range much lower than

Quebec's minimum hourly wage of CAD $15.25 (US $11.26) [46].

Compatibility

Of the 52 services identified, 29 (56%) were offered by organizations classified as nonprofits as per Quebec's Enterprise Register [47]. Respite care services often involved either volunteers (17/52, 33%); a team of multidisciplinary health professionals including patient care attendants and nurses (21/52, 40%); or a combination of volunteers and health care providers (4/52, 8%). Volunteer-provided services were most frequently free and accompaniment-based, whereas health care professional-provided services generally consisted of nursing-oriented care with associated fees. Nonetheless, staff, including volunteers, often had additional training for a specific clientele (23/52, 44%; eg, volunteers trained in end-of-life care). Agencies emphasized caregiver consistency and finding a good match between the caregiving dyad and staff.

A total of 29 (56%) organizations had a unilingual website (French or English) and 20 (38%) organizations had a bilingual website (French and English). The identified services' websites often did not specify which languages were available for the provision of care (18/52, 35%), although some organizations specified language—some services were available only in 1 language (French, 9/52, 17%); others were bilingual (English and French, 17/52, 33%); or in 3 or more languages (8/52, 15%). Additionally, the websites of these services were not always available in the languages offered.

Member-Checking Feedback From Organizations

An email was sent to respite organizations to confirm the findings of our research. A total of 15 (29%) organizations provided feedback on the results and validation for our project. Most frequently, organizations added additional information to what was provided on their website. For example, many organizations clarified the nature of activities performed during the respite period (5/15, 33%), the languages of services (6/15, 40%), or the availability and length of services (3/14, 21%). In some cases, the information gathered from the website was inaccurate and further clarified by the organization. For example, one organization provided fees that differed from that of their website.

Discussion

Overview

Respite care services should strive for high quality and safety. Norris and Aiken's [41] framework of personal access to health care was identified post hoc and seemed to match our themes nicely. We analyzed the results based on how these services fit into this framework of accessibility. We will use the following section to discuss the gaps affecting amenability, variety of types of services, limited availability of services, and eligibility and provider impacts, as well as the limitations, strengths of our research, and opportunities for future research.

Amenability: Gaps Affecting the Amenability of Respite Care Services

The need for advanced digital health literacy skills, incomplete information and language barriers are some of the key gaps affecting the amenability of respite care services that were identified as part of this environmental scan.

A significant time investment and high digital literacy skills were required to carefully create search strategies, sift through thousands of results, and retrieve a relatively small selection of respite care services relevant to palliative care families in Quebec. Even a sophisticated user may not have the mindset required to go through a tedious search process given the demanding nature of caregiving in the palliative care context. Caregivers or clinicians may not be familiar with internet search strategies or be in a position to dedicate time and energy to the search and identification process for respite care services. Thus, the intensive search and screening process constitutes an important accessibility barrier, needing to be addressed as part of best practice guidelines, and perhaps alleviated with the use of collaboratively developed digital tools (eg, chatbot) or care navigators [7,19,48,49].

Incomplete access to information was one of the most significant challenges encountered in this project. Many of the identified respite care organizations' websites did not share critical information on their services, such as the fees, eligibility criteria, or availability. In some cases, this missing information could be obtained by reaching out to the organization directly. However, many organizations did not respond to our request for feedback. Incomplete information on respite care services is a deterrent to access, often resulting in caregivers having unanswered questions and unclear expectations [50]. In other words, caregivers may find it difficult to gauge if the respite care service is relevant to their unique situation, if they are eligible and what procedure they should follow to access the service. Clinicians may also find it difficult to know what services are available in the community, where to link or refer their clients and what the request procedure looks like. This challenge may be accentuated when respite care organizations' websites are only available in 1 language, as was seen in our sample. With this in mind, respite care organizations may wish to make information about their services more widely available online and continue to incorporate clinician, caregiver, and care recipient feedback, so that their services can become more widely accessible, available, and family-centered [2,48].

Types of Services: Complex Variety of Respite Care Service Offerings

Respite care services take on many formats and should aim to address a variety of individualized needs [5,6,48,51,52]. Frequently cited priorities for end-of-life care at home include physical (eg, symptom management) and psychosocial care (eg, interpersonal connection), which nurses are often best equipped to provide [2,6,16,50,51,53,54]. Service offerings aimed at caregivers, like rest lounges or psychological care, may help to alleviate the caregiver burden in targeted ways so that they can be better equipped to cope and care for their loved one [9,52].

Our sample of 52 respite care services offers an array of respite care services and reflects the various priorities of families in a palliative stage of care. This data contradict the common criticism of respite care, that it is too often focused solely on caregiver needs and burdens while ignoring the care recipient's needs [2]. These findings also suggest that services have the potential to address a wide range of needs and provide caregivers with greater flexibility to choose how they want to spend their time while on respite [3]. However, the variety in respite care service descriptions may make it difficult for users and clinicians to compare and contrast options in their community, and perhaps select what they need. Systematic reporting of basic services across all service providers, such as an easy-to-search database that is regularly updated, is needed to determine the best types of service provision. Organizations should also troubleshoot how to deliver effective services within a low-cost model, in an effort to improve at-home respite care across Quebec regions.

Availability: Limited and Sparse Availability of Services

Rural and Indigenous communities are often faced with service provisions not meeting the needs and preferences of families, nor supporting death at home [20,52]. Our research identified a lack of in-person services in Western and Northern Quebec, areas representing approximately 2.2% of Québec's population (estimated population of 195,409 in 2022) and 2.5% of Quebec's deaths every year (1719 deaths in 2021) [43,55]. These findings accentuate the scarcity of resources described in the literature [56]. Therefore, to enable more caregiving dyads to benefit from adapted respite care, infrastructure, targeted funding, and service options need to be expanded, particularly in rural and Indigenous communities of Quebec. Inclusivity, community leadership, and family-centered approaches should take the forefront in these efforts [56].

Best practice guidelines for the provision of respite care stipulate that flexibility in service provision is a key criterion to ensure that the ever-changing needs of the caregiver and care recipient are being met, that a continuum of care is maintained, that the diversity of the clientele is respected and that caregiving dyads can make the most of the respite period [5,6,19,48]. In Quebec, the length of the 52 identified services' availability and frequency were diverse. Flexible services, such as those available 24 hours a day and 7 days a week, for a longer period of time (hours to days) or with "on-call" availability, may enable the caregiving dyad to engage in a greater selection of activities (eg, sleeping, running errands, and social interactions), as opposed to respite care services limited to a specific time of the day. The services' flexibility also potentially impacts how quickly caregivers can access respite care when an urgent or unplanned need arises, to ensure the care recipient is still being cared for. Given the results' significant range of availabilities, we can conclude that some services are as flexible as current guidelines suggest. These results point to a larger issue of gaps and barriers affecting the accessibility and usage of respite care services.

Eligibility: Eligibility Requirements Limiting Access to Respite Care Services

The respite care clientele is diverse [11]. Hence, eligibility requirements have the potential to restrict access to families most likely to use such home-based nursing services, such as users with less financial resources or those who speak minority languages [3,7,16,20]. Services without specific eligibility criteria or free of charge may be more appealing to a greater population of families in need of respite. The organizations specifically mentioning eligibility criteria may help to ensure the population of a given region has access to services in their community, or that the respite care services meet the needs of that specific population (ie, services tailored to people at the end-of-life). However, the respite care services that were most flexible, were also generally fee-based. Consequently, financial barriers may limit access to such services for families who need them most.

Compatibility: Provider Impact on the Compatibility of Respite Care Services

The therapeutic relationship between the caregiver, care recipient, and respite care provider is essential in achieving satisfaction with a respite care service and is tightly linked with caregiver well-being [5,7,8,19,57]. Several organizations highlighted caregiver consistency in their description of services, which may play an important role in the development of a collaborative and trusting relationship. Thus, these results may prompt organization leaders to consider diversifying multidisciplinary teams, provide further training and aim for greater care provider consistency in an effort to achieve high-quality respite care service provision.

As suggested within best practice guidelines for respite care, service providers must be equipped with the skills, training, and experience to provide safe and high-quality care [5,19,48,57]. Volunteers are great resources for respite care service provision but may be limited in the offerings they are allowed to provide [8,48,58]. This may explain why many identified volunteer-provided respite care services in our sample were oriented around accompaniment, a service that may be more personalized and adaptable to a client's unique psychosocial needs [59]. Volunteer limitations may also provide context for the restrictions in service provision, a potential deterrent for families, depending on their care requirements [5]. On the other hand, health care providers have the benefit of training and experience with structured, specialized interventions corresponding to the common requests of caregivers, the needs of the care recipient, and the specialized nature of palliative care in general [50,51,54,59]. Nurses, in particular, are heavily involved in clinical, coordination, and leadership positions associated with palliative care and home care services due to the holistic nature of their role and therapeutic relationship with families [60,61]. In our sample of services, health care professional-provided services were often centered on physical care, symptom management, and other nursing interventions. Collaborations between health care professionals and volunteers, as seen in the sample, potentially contribute to providing cost-effective and family-centered respite care, while overcoming challenges associated with limited health care resources [60]. Similarly, additional training, showcased by some agencies, may further clarify the roles and responsibilities of the care provider while enabling them to provide high-quality care specifically targeted to individuals with cancer, at the end-of-life or in palliative care, for example [48]. This centralized information about respite care providers may encourage involvement in local respite care organization activities, for example, by creating a network of respite care providers and collaborative training opportunities.

Limitations and Strengths

Limitations to this research include the availability of information on the internet, the use of specific languages (ie, only English and French), limited data collection (ie, restricting to 3 search databases or engines, and 100 results per return), and the impact of digital algorithms. This analysis represents only the information available on the internet and feedback from a limited number of organizations, which may slightly differ from actual respite care service features or currently available services. Many excluded services highlighted the provision of home care services without specifically mentioning a respite component. Therefore, relevant services that provide respite care without explicitly advertising these services may have been excluded. However, “respite care” is the term most commonly found in the literature and that caregivers are most likely to use when seeking a break from their dyadic informal caregiving roles [2,8]. Future research could examine subsets of this project’s ineligible services (ie, home care services and respite care services outside the home) in an effort to better understand the breadth of community health care services available to informal caregivers and care recipients.

Additionally, due to resource constraints, not every postal code could be searched in the L’Appui Resource Directory, and only the first 100 results for each search were screened. This cut-off point was chosen in other grey literature searches and justified by the amount of traffic received by results on the first page of Google compared to any additional pages [35,36,62]. Nonetheless, there is still the possibility that some less popular or poorly advertised respite care services may have been missed in the search process. Similarly, Google algorithms may have played a role in the display and order of search results despite taking precautions to disable such alterations. However, we believe our multimethod approach helps to overcome these limitations.

All things considered, the environmental scan methodology devised for this project was successful at identifying diverse at-home palliative respite care services across the province of Quebec and synthesizing service features [21,63]. Novel methodologies used in the project, such as combining search engines and internet-based community health databases, using postal codes to search for services, as well as seeking expert feedback via member-checking, may be useful for other researchers attempting to comprehensively map other types of services while reducing bias [64]. There is also a potential to further expand our search strategy by including other tools (eg, Google Maps and artificial intelligence chatbots), strategies we have attempted but ultimately abandoned due to the lack of existing methodologies and the current functioning of these tools not showcasing relevant results.

Opportunities for Future Research

Caregivers are often challenged by overwhelming amounts of information when seeking health care services on the internet, hence, a coordinated database is an important unmet caregiving need [6,7,19,53]. Therefore, concise and complete records of respite care services are warranted to (1) improve families’ knowledge of the services available in their community and how to access them, (2) to improve clinicians’ ability to share and refer clients to such services, and (3) to promote the expansion of existing services and development of complementary resources [49]. Best practice guidelines and digital databases should be updated, further developed, and validated by users and organizations, to reflect health care service search and identification challenges. For example, key filters like type of respite care provider, fees, service offerings, and eligibility criteria, could be included as part of a digital database. Moreover, the methodology and findings may be of interest to referring clinicians and policymakers responsible for planning future needs as Canada moves away from institutional care, toward holistic community care.

Conclusions

Comprehensively identifying available respite care services is essential for assessing the overall availability of respite services, as well as identifying potential barriers that individuals and clinicians face when seeking out these services [4,48]. The findings of this project emphasize that the identification, navigation, and access to such services likely remain challenging for individuals in need of respite and clinicians looking to refer their patients. These results stress the need for a centralized searchable database to render accessible information on respite care services available in communities across Québec. The proposed methodology, consisting of combining several data sources, may guide researchers in conducting other community health service environmental scans.

Acknowledgments

This project was partly funded with generous support from the Rossy Cancer Network’s Cancer Care Quality and Innovation Program (2020), the Ingram School of Nursing Student Summer Research Award 2022, Tsimicalis’ Fonds de Recherche du Québec—Santé (FRQS) Junior 1 Award, Lalonde-LeBlond’s Canadian Institutes of Health Research (CIHR) Master’s Scholarship (2023) and an operating grant from the McGill Nursing Collaborative for Education and Innovation in Patient-and-Family-Centered Care (Winter 2023). Castro and Lalonde-LeBlond are also supported by Ministère d’enseignement supérieur (MES; 2023) and Canadian Nurses Foundation scholars (2020, 2023). The authors would like to thank McGill University Research Librarian Francesca Frati for her feedback on the search strategy of this environmental scan.

Conflicts of Interest

Coauthor AJH is a nurse manager of one of the palliative home-care organizations that was also identified through the search.

Multimedia Appendix 1
List of 52 Quebec respite care services offered at home to families with palliative care needs identified via Google, in the Canadian Cancer Society Community Services Locator or the L'Appui Resource Directory.
[DOCX File , 42 KB - nursing_v7i1e53078_app1.docx]

References

1. Castro AR, Arnaert A, Moffatt K, Kildea J, Bitzas V, Tsimicalis A. "Informal caregiver" in nursing: an evolutionary concept analysis. ANS Adv Nurs Sci 2023;46(1):E29-E42. [doi: 10.1097/ANS.0000000000000439] [Medline: 36006014]
2. Evans D. Exploring the concept of respite. J Adv Nurs 2013;69(8):1905-1915. [doi: 10.1111/jan.12044] [Medline: 23157453]
3. Dunbrack J. Respite for family caregivers: an environmental scan of publicly-funded programs in Canada. Health Canada. 2003. URL: https://www.canada.ca/content/dam/hc-sc/migration/hc-sc/hcs-sss/alt_formats/hpb-dgps/pdf/pubs/2003-respite-releve/2003-respite-releve-eng.pdf [accessed 2024-03-21]
4. Smith CH, Graham CA, Herbert AR. Respite needs of families receiving palliative care. J Paediatr Child Health 2017;53(2):173-179. [doi: 10.1111/jpc.13324] [Medline: 27550644]
5. Whitmore KE. The concept of respite care. Nurs Forum 2017;52(3):180-187. [doi: 10.1111/nuf.12179] [Medline: 27438939]
6. Ingleton C, Payne S, Nolan M, Carey I. Respite in palliative care: a review and discussion of the literature. Palliat Med 2003;17(7):567-575. [doi: 10.1191/0269216303pm803ra] [Medline: 14594147]
7. Fenton D. A centralized internet-based resource center for primary caregivers of children with developmental disabilities. ProQuest. 2020. URL: https://tinyurl.com/nhc5jaj6 [accessed 2024-03-21]
8. Rao SR, Gupta M, Salins N. The concept of respite in palliative care: definitions and discussions. Curr Oncol Rep 2021;23(2):25. [doi: 10.1007/s11912-021-01015-z] [Medline: 33559761]
9. Gomes B, Calanzani N, Gysels M, Hall S, Higginson IJ. Heterogeneity and changes in preferences for dying at home: a systematic review. BMC Palliat Care 2013;12:7 [FREE Full text] [doi: 10.1186/1472-684X-12-7] [Medline: 23414145]
10. Canada's sky-high costs for end-of-life care need solutions. C.D. Howe Institute. 2021. URL: https://www.cdhowe.org/media-release/canadas-sky-high-costs-end-life-care-need-solutions [accessed 2024-03-21]
11. Respite care in Canada. Canadian Healthcare Association. 2012. URL: https://www.healthcarecan.ca/wp-content/themes/camyno/assets/document/PolicyDocs/2012/External/EN/RespiteCare_EN.pdf [accessed 2024-03-21]
12. Les personnes proches aidantes au Québec en 2018. Institut de la statistique du Québec. 2022. URL: https://statistique.quebec.ca/en/document/informal-caregiving-in-quebec-in-2018/publication/personnes-proches-aidantes-quebec-2018 [accessed 2024-03-21]
13. Guide to programs for people with disabilities, their families and caregivers. Office des personnes handicapées du Québec. 2017. URL: https://www.ophq.gouv.qc.ca/fileadmin/documents/GuideProgammes2017_Angl_Web.pdf [accessed 2024-03-21]
14. Crédit d'impôt pour répit à un aidant naturel (Ligne 462). Revenu Québec. 2021. URL: https://www.revenuquebec.ca/fr/citoyens/declaration-de-revenus/produire-votre-declaration-de-revenus/comment-remplir-votre-declaration/aide-par-ligne/451-a-480-remboursement-ou-solde-a-payer/ligne-462/point-21/ [accessed 2021-08-08]
15. Access to the internet in Canada, 2020. Statistics Canada. 2020. URL: https://www150.statcan.gc.ca/n1/daily-quotidien/210531/dq210531d-eng.htm [accessed 2021-05-31]
16. Cai J, Guerriere DN, Zhao H, Coyte PC. Socioeconomic differences in and predictors of home-based palliative care health service use in Ontario, Canada. Int J Environ Res Public Health 2017;14(7):802 [FREE Full text] [doi: 10.3390/ijerph14070802] [Medline: 28718797]
17. Wavrock D, Schellenberg G, Schimmele C. Internet-use typology of Canadians: online activities and digital skills. Statistics Canada. 2021. URL: https://www150.statcan.gc.ca/n1/pub/11f0019m/11f0019m2021008-eng.htm [accessed 2024-03-21]
18. Phillipson L, Jones SC, Magee C. A review of the factors associated with the non-use of respite services by carers of people with dementia: implications for policy and practice. Health Soc Care Community 2014;22(1):1-12 [FREE Full text] [doi: 10.1111/hsc.12036] [Medline: 23530738]
19. Doig JL, McLennan JD, Urichuk L. 'Jumping through hoops': parents' experiences with seeking respite care for children with special needs. Child Care Health Dev 2009;35(2):234-242. [doi: 10.1111/j.1365-2214.2008.00922.x] [Medline: 19228157]
20. Quinn K, Isenberg S, Downar J. Expensive endings: reining in the high cost of end-of-life care in Canada. SSRN. 2021. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4096093 [accessed 2024-03-21]
21. Rowel R, Moore ND, Nowrojee S, Memiah P, Bronner Y. The utility of the environmental scan for public health practice: lessons from an urban program to increase cancer screening. J Natl Med Assoc 2005;97(4):527-534. [Medline: 15868772]
22. Charlton P, Kean T, Liu RH, Nagel DA, Azar R, Doucet S, et al. Use of environmental scans in health services delivery research: a scoping review. BMJ Open 2021;11(11):e050284 [FREE Full text] [doi: 10.1136/bmjopen-2021-050284] [Medline: 34758992]

23. Charlton P, Doucet S, Azar R, Nagel DA, Boulos L, Luke A, et al. The use of the environmental scan in health services delivery research: a scoping review protocol. BMJ Open 2019;9(9):e029805 [FREE Full text] [doi: 10.1136/bmjopen-2019-029805] [Medline: 31494613]
24. Choo CW. Environmental scanning as information seeking and organizational learning. Inf Res 2001;7(1):29 [FREE Full text]
25. Hatch TF, Pearson TG. Using environmental scans in educational needs assessment. J Contin Educ Health Prof 1998;18(3):179-184. [doi: 10.1002/chp.1340180308]
26. Peters MDJ, Marnie C, Tricco AC, Pollock D, Munn Z, Alexander L, et al. Updated methodological guidance for the conduct of scoping reviews. JBI Evid Synth 2020;18(10):2119-2126 [FREE Full text] [doi: 10.11124/JBIES-20-00167] [Medline: 33038124]
27. Wurz A, Daeggelmann J, Albinati N, Kronlund L, Chamorro-Viña C, Culos-Reed SN. Physical activity programs for children diagnosed with cancer: an international environmental scan. Support Care Cancer 2019;27(4):1153-1162. [doi: 10.1007/s00520-019-04669-5] [Medline: 30726517]
28. Linguee. DeepL. URL: https://www.deepl.com/translator [accessed 2021-08-05]
29. Community services locator. Canadian Cancer Society. URL: https://csl.cancer.ca/en [accessed 2021-08-28]
30. Resource directory. L'Appui. URL: https://www.lappui.org/en/Find-resources/Resource-directory [accessed 2021-08-28]
31. Population and dwelling count highlight tables, 2016 census. Statistics Canada. 2017. URL: https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/hlt-fst/pd-pl/index-eng.cfm [accessed 2024-03-21]
32. Québec health regions. Ministère de la santé et des services sociaux. URL: https://www.msss.gouv.qc.ca/en/reseau/regions-sociosanitaires-du-quebec/ [accessed 2024-03-21]
33. Search engine market share Canada. Statcounter GlobalStats. URL: https://gs.statcounter.com/search-engine-market-share/all/canada [accessed 2021-08-23]
34. Monton O, Lambert S, Belzile E, Mohr-Elzeki D. An evaluation of the suitability, readability, quality, and usefulness of online resources for family caregivers of patients with cancer. Patient Educ Couns 2019;102(10):1892-1897. [doi: 10.1016/j.pec.2019.05.010] [Medline: 31151780]
35. Godin K, Stapleton J, Kirkpatrick SI, Hanning RM, Leatherdale ST. Applying systematic review search methods to the grey literature: a case study examining guidelines for school-based breakfast programs in Canada. Syst Rev 2015;4:138 [FREE Full text] [doi: 10.1186/s13643-015-0125-0] [Medline: 26494010]
36. Donnelly KZ, Thompson R. Medical versus surgical methods of early abortion: protocol for a systematic review and environmental scan of patient decision aids. BMJ Open 2015;5(7):e007966 [FREE Full text] [doi: 10.1136/bmjopen-2015-007966] [Medline: 26173718]
37. Dean B. We analyzed 4 million Google search results: here's what we learned about organic click through rate. BackLinko. 2023. URL: https://backlinko.com/google-ctr-stats [accessed 2024-03-21]
38. Fortin MMR, Brown C, Ball GDC, Chanoine JP, Langlois MF. Weight management in Canada: an environmental scan of health services for adults with obesity. BMC Health Serv Res 2014;14:69 [FREE Full text] [doi: 10.1186/1472-6963-14-69] [Medline: 24521300]
39. Légaré F, Politi MC, Drolet R, Desroches S, Stacey D, Bekker H, SDM-CPD Team. Training health professionals in shared decision-making: an international environmental scan. Patient Educ Couns 2012;88(2):159-169. [doi: 10.1016/j.pec.2012.01.002] [Medline: 22305195]
40. Elo S, Kyngäs H. The qualitative content analysis process. J Adv Nurs 2008;62(1):107-115. [doi: 10.1111/j.1365-2648.2007.04569.x] [Medline: 18352969]
41. Norris TL, Aiken M. Personal access to health care: a concept analysis. Public Health Nurs 2006;23(1):59-66. [doi: 10.1111/j.0737-1209.2006.230109.x] [Medline: 16460422]
42. Moher D, Liberati A, Tetzlaff J, Altman DG, PRISMA Group. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Med 2009 Jul 21;6(7):e1000097 [FREE Full text] [doi: 10.1371/journal.pmed.1000097] [Medline: 19621072]
43. Population estimates for administrative regions, administrative regions, Québec, July 1, 1986 to 2021. Institut de la statistique du Québec. URL: https://statistique.quebec.ca/en/produit/tableau/estimations-population-regions-administratives [accessed 2024-03-21]
44. Le Québec et ses régions. Qualifications Québec. URL: https://qualificationsquebec.com/le-quebec-et-ses-regions/ [accessed 2022-08-23]
45. Carte des régions sociosanitaires du Québec. Ministère de la Santé et des Services sociaux. 2020. URL: https://publications.msss.gouv.qc.ca/msss/document-001640/ [accessed 2022-12-14]
46. Minimum wage in Québec: $15.25 per hour. Commission des normes de l'équité, de la santé et de la sécurité du travail. 2023. URL: https://tinyurl.com/ms58ej2f [accessed 2024-03-21]
47. Search for a company in the register. Registraire des entreprises Québec. URL: https://www.registreentreprises.gouv.qc.ca/RQAnonymeGR/GR/GR03/GR03A2_19A_PIU_RechEnt_PC/PageRechSimple.aspx?T1.CodeService=S00436 [accessed 2024-03-21]

48. Edgar M, Uhl M. National respite guidelines, guiding principles for respite models and services. ARCH National Respite Network. 2011. URL: https://archrespite.org/wp-content/uploads/2022/04/NationalRespite_Guidelines_Final_October_2011_1MB.pdf [accessed 2024-03-21]
49. Castro AR, Brahim LO, Chen Q, Arnaert A, Quesnel-Vallée A, Moffatt K, et al. Information and communication technologies to support the provision of respite care services: scoping review. JMIR Nurs 2023;6:e44750 [FREE Full text] [doi: 10.2196/44750] [Medline: 37252760]
50. Skilbeck JK, Payne SA, Ingleton MC, Nolan M, Carey I, Hanson A. An exploration of family carers' experience of respite services in one specialist palliative care unit. Palliat Med 2005;19(8):610-618. [doi: 10.1191/0269216305pm1087oa] [Medline: 16450878]
51. Wolkowski A, Carr SM, Clarke CL. What does respite care mean for palliative care service users and carers? Messages from a conceptual mapping. Int J Palliat Nurs 2010;16(8):388-392. [doi: 10.12968/ijpn.2010.16.8.388] [Medline: 20852515]
52. Harding R, Higginson IJ. What is the best way to help caregivers in cancer and palliative care? A systematic literature review of interventions and their effectiveness. Palliat Med 2003;17(1):63-74. [doi: 10.1191/0269216303pm667oa] [Medline: 12597468]
53. Ventura AD, Burney S, Brooker J, Fletcher J, Ricciardelli L. Home-based palliative care: a systematic literature review of the self-reported unmet needs of patients and carers. Palliat Med 2014;28(5):391-402. [doi: 10.1177/0269216313511141] [Medline: 24292156]
54. Hagan TL, Xu J, Lopez RP, Bressler T. Nursing's role in leading palliative care: a call to action. Nurse Educ Today 2018;61:216-219 [FREE Full text] [doi: 10.1016/j.nedt.2017.11.037] [Medline: 29245101]
55. Births, deaths, natural increase and marriages, administrative regions, Québec, 1986-2021. Institut de la statistique du Québec. URL: https://tinyurl.com/2uy68zz9 [accessed 2024-03-21]
56. First Nations of Quebec and Labrador Health and Social Services. Exploring successful models of respite care for First Nations communities in Quebec. Digital BAnQ. 2007. URL: https://numerique.banq.qc.ca/patrimoine/details/52327/2491381?docref=F1x4MT8QpVGkW2AbZKZixA [accessed 2024-03-21]
57. Corrado AM. Receiving in-home respite when caring for a palliative family member at the end-of-life: family caregivers? experiences of the eShift model of care. Electronic Thesis and Dissertation Repository. URL: https://ir.lib.uwo.ca/cgi/viewcontent.cgi?article=8048&context=etd [accessed 2024-03-21]
58. Candy B, France R, Low J, Sampson L. Does involving volunteers in the provision of palliative care make a difference to patient and family wellbeing? A systematic review of quantitative and qualitative evidence. Int J Nurs Stud 2015;52(3):756-768 [FREE Full text] [doi: 10.1016/j.ijnurstu.2014.08.007] [Medline: 25205665]
59. Chinn PL. “Informal caregiver”. Advances in Nursing Science Blog. 2023. URL: https://ansjournalblog.com/2023/04/18/informal-caregiver/ [accessed 2024-03-21]
60. Sekse RJT, Hunskår I, Ellingsen S. The nurse's role in palliative care: a qualitative meta-synthesis. J Clin Nurs 2018;27(1-2):e21-e38. [doi: 10.1111/jocn.13912] [Medline: 28695651]
61. Schroeder K, Lorenz K. Nursing and the future of palliative care. Asia Pac J Oncol Nurs 2018;5(1):4-8 [FREE Full text] [doi: 10.4103/apjon.apjon_43_17] [Medline: 29379825]
62. The value of Google result positioning. Chitika. 2013. URL: https://research.chitika.com/wp-content/uploads/2022/02/chitikainsights-valueofgoogleresultspositioning.pdf [accessed 2024-03-21]
63. Graham P, Evitts T, Thomas-MacLean R. Environmental scans: how useful are they for primary care research? Can Fam Physician 2008;54(7):1022-1023 [FREE Full text] [Medline: 18625830]
64. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. Int J Soc Res Methodol 2005;8(1):19-32. [doi: 10.1080/1364557032000119616]

Edited by E Borycki; submitted 25.10.23; peer-reviewed by A Garcia Abejas, E Ray Chaudhuri; accepted 12.02.24; published 16.04.24.

Please cite as:
Castro A, Lalonde-LeBlond G, Freitas Z, Arnaert A, Bitzas V, Kildea J, Moffatt K, Phillips D, Wiseblatt L, Hall AJ, Després V, Tsimicalis A
In-Home Respite Care Services Available to Families With Palliative Care Needs in Quebec: Novel Digital Environmental Scan
JMIR Nursing 2024;7:e53078
URL: https://nursing.jmir.org/2024/1/e53078
doi:10.2196/53078
PMID:38625735

Original Paper

Embedding the Use of Patient Multimedia Educational Resources Into Cardiac Acute Care: Prospective Observational Study

Anastasia Hutchinson[1,2], BN, PhD; Damien Khaw[1], BA, PhD; Annika Malmstrom-Zinkel[2], BN(Hons), MN(Emerg); Natalie Winter[1,2], BN(Hons), PhD; Chantelle Dowling[2], BN, MPH; Mari Botti[1], BA, PhD; Joanne McDonall[1,2], BN(Hons), PhD

[1]Centre for Quality and Patient Safety Research—Epworth Partnership, Institute of Health Transformation, Faculty of Health, Deakin University, Melbourne, Australia

[2]School of Nursing and Midwifery, Faculty of Health, Deakin University, Geelong, Australia

Corresponding Author:
Anastasia Hutchinson, BN, PhD
Centre for Quality and Patient Safety Research—Epworth Partnership
Institute of Health Transformation, Faculty of Health
Deakin University
185-187 Hoddle St
Richmond
Melbourne, VIC 3121
Australia
Phone: 61 0437101349
Email: a.hutchinson@deakin.edu.au

Abstract

Background: Multimedia interventions may play an important role in improving patient care and reducing the time constraints of patient-clinician encounters. The “MyStay Cardiac” multimedia resource is an innovative program designed to be accessed by adult patients undergoing cardiac surgery.

Objective: The purpose of this study was to evaluate the uptake of the MyStay Cardiac both during and following the COVID-19 pandemic.

Methods: A prospective observational study design was used that involved the evaluation of program usage data available from the digital interface of the multimedia program. Data on usage patterns were analyzed for a 30-month period between August 2020 and January 2023. Usage patterns were compared during and following the lifting of COVID-19 pandemic restrictions. Uptake of the MyStay Cardiac was measured via the type and extent of user activity data captured by the web-based information system.

Results: Intensive care unit recovery information was the most accessed information, being viewed in approximately 7 of 10 usage sessions. Ward recovery (n=124/343, 36.2%), goal (n=114/343, 33.2%), and exercise (n=102/343, 29.7%) information were routinely accessed. Most sessions involved users exclusively viewing text-based information (n=210/343, 61.2%). However, in over one-third of sessions (n=132/342, 38.5%), users accessed video information. Most usage sessions occurred during the COVID-19 restriction phase of the study (August 2020-December 2021). Sessions in which video (*P*=.02, *phi*=0.124) and audio (*P*=.006, *phi*=0.161) media were accessed were significantly more likely to occur in the restriction phase compared to the postrestriction phase.

Conclusions: This study found that the use of digital multimedia resources to support patient education was well received and integrated into their practice by cardiac nurses working in acute care during the COVID-19 pandemic. There was a pattern for greater usage of the MyStay Cardiac during the COVID-19 pandemic when access to the health service for nonfrontline, essential workers was limited.

(JMIR Nursing 2024;7:e54317) doi:10.2196/54317

KEYWORDS

patient participation; digital technology; mHealth; mobile health; app; apps; digital health; smartphone; smartphones; multimedia; patient education; education; educational; educate; patient engagement; nursing; cardiac surgery; cardiology; cardiac; cardio;

CCU; cardiac care unit; CCC; complex cardiac care; coronary care nursing; nurse; nurse; COVID-19; SARS-COV-2; Coronavirus; severe acute respiratory syndrome; Coronavirus infections; novel Coronavirus

Introduction

In 2020, a total of 14,408 cardiothoracic operations were performed in 39 specialist cardiac surgery centers in Australia [1]. Open-heart surgery that involves sternotomy includes an intensive care unit (ICU) stay for 24-72 hours, followed by 5-7 days in a specialist cardiac ward for treatment optimization and recovery. Optimal recovery outcomes following major surgery require patients to be informed about and engaged in their care [2]. When patients are engaged in their own care, there is evidence to suggest that their recovery is both informed and safer [3,4]. The therapeutic relationship that develops between patients and nurses in acute care is the foundation for patient-centered care, which is required by the National Safety and Quality Health Service standards [5].

The journey of patients who underwent cardiac surgery through the hospital system begins prior to and on admission and is facilitated by a multidisciplinary team, including cardiac nurses, who educate patients about what can be expected during their ICU and cardiac ward admission. To aid and support patient recovery post cardiac surgery, administration of adequate analgesics to expedite participation in chest physiotherapy and early mobility [6-10] is a key recovery intervention facilitated by the multidisciplinary team [2,11]. Despite its importance, patient education can be time-consuming in acute care when the acuity of illness, an unfamiliar environment, and the effects of medications and treatment impact patients’ information recall [12].

Multimedia interventions may play an important role in improving patient comprehension and reducing the time constraints of patient-clinician encounters [13,14]. The use of multimedia interventions in patient care may help minimize time requirements that are usually needed for clinicians to provide patient education [12]. Several studies have shown that patients learn and retain information better when they are provided with both visual and verbal information presented together [15,16]. A major strength of using multimedia resources is the consistency of messaging and the fact that patients can access the resources at their convenience, which aids in the recall and retention of key information [14,17]. This is particularly important in the early stages of acute recovery when patients are busy with procedures and treatments that affect cognition. Having a resource for patients that is available when they have the opportunity, is easy to use, can be delivered when the patient is ready, and may help mitigate inequalities related to reading ability, viz, text-only patient education, are also important considerations [12,17].

It is important to evaluate the feasibility of nurses using digital multimedia to promote patient engagement and participation in care. Furthermore, with the increasing use of digital technology to promote patient participation in care [14,18,19], it is important to review the implementation of such technology in the postoperative setting [20]. The “MyStay Cardiac” multimedia program is an innovative program designed to be accessed by adult patients undergoing cardiac surgery. The program can be accessed by patients independently or with the assistance of nurses in the ICU, coronary care unit and cardiac ward to monitor their pain intensity score and mobility improvement while in hospital, recovering from cardiac surgery. The aim of the MyStay Cardiac program is to support the recovery of patients being admitted for cardiac surgery in the pre- and postoperative phases [17].

The MyStay Cardiac multimedia program was implemented at a private metropolitan hospital in Melbourne during the COVID-19 pandemic in July 2020. During 2020, with the escalating COVID-19 pandemic, the provision of nonmandatory staff education in hospitals was limited [21], and as such, a passive diffusion approach to implementation was used [22]. Evidence suggests that both patients and staff require structured education and support to implement such a program successfully [23]. It is therefore both important and interesting to gain an understanding of how successful the program has become without ongoing structured facilitation in the clinical practice setting [22].

The purpose of this study was to evaluate the uptake of a multimedia intervention, MyStay Cardiac, both during and following the COVID-19 pandemic. The specific aims of this study are provided in Textbox 1.

Textbox 1. Specific aims of this study.

- To explore the uptake and use of different modules and functionalities within the Cardiac MyStay multimedia program.
- To compare use of the MyStay Cardiac during periods of restricted access to hospitals due to the COVID-19 pandemic (August 2020-December 2021) to use once the COVID-19 restrictions were no longer in place (January 2022-January 2023).

Methods

Study Design

A prospective observational study design was used that involved the evaluation of program utilization data available from the digital interface for the multimedia program. Sampling was consecutive; all patients on the ward were offered the opportunity to use the MyStay app during their stay and to participate in this research. The inclusion criterion was as follows: patients on the cardiac ward who used the MyStay app. Patients who did not use the MyStay app were excluded from the study. Though not formally excluded on the basis of such characteristics, it is possible that adverse health events, language, or cognition issues may have precluded some patients from using the MyStay app and thus from participating in the study.

Study Site

The study was conducted at a large private health service in Victoria, Australia.

MyStay Cardiac Multimedia Resources

The MyStay Cardiac multimedia program combines text, audio, video, and 3D animations to deliver information to patients and their families to enhance their understanding of, and participation in, postoperative care, meeting recovery goals, and discharge planning [17]. The web-based platform allows patients to access MyStay both prior to and following their surgery. Content within the cardiac surgery app is organized into the following modules: (1) ICU stay, (2) ward stay, (3) exercise and rehabilitation, (4) pain management, (5) keeping you safe (preventing complications), and (6) preparing for discharge. The program can be accessed by patients independently or with the assistance of nurses in the ICU, coronary care unit, and cardiac ward to monitor their pain intensity score and mobility improvement whilst in hospital, recovering from cardiac surgery. During the study period, MyStay pain intensity scores were used for informational purposes only, that is, for patients' records and understanding, to encourage participation in their care, and not as a part of formal, clinical assessments of pain.

Implementation of the MyStay Cardiac at the Study Site

The MyStay Cardiac program was made available to cardiac nurses and allied health staff in July 2020, following a web-based education session. During this session, each module of the MyStay Cardiac was demonstrated to the cardiac nurse educators, cardiac ward nurses, and physiotherapy team. Hospital information technology administrators made the program accessible to the wide-screen, bedside computer terminals located in all patients' rooms. The clinicians were provided with a generic login and password so they could access the MyStay resources and familiarize themselves with the content. Clinicians were then encouraged to integrate the MyStay Cardiac resources into their interactions with patients undergoing cardiac surgery at the study site. Following this initial education session, further structured implementation by the research team was not possible in 2020-2021 due to state government restrictions on nonessential staff attending hospital sites during the COVID-19 pandemic in Melbourne, Australia [21]. There was no change to the physical infrastructure and availability of the app to patients either before or following COVID-19 restrictions. Further, in addition to using the bedside computers, patients could also access the app via their personal devices (eg, smartphones, tablets, and laptops).

To verify how the MyStay Cardiac resources were being used, 3 cardiac nurses (2 cardiac educators and 1 nurse manager) were interviewed in late 2021 and indicated high levels of satisfaction with the MyStay Cardiac resources, stating they were accessible, relevant to care delivery both before and after the cardiac survey, and a useful adjunction to the usual cardiac education they provided to patients during their admission. The cardiac nurse educators reported predominantly using the MyStay Cardiac resources in structured preoperative patient education sessions provided on the day prior to surgery. The availability of animations demonstrating what to expect during an ICU admission provides an alternative to an in-person ICU visit the day before surgery. As part of the standard routine of the cardiac wards, structured postoperative education sessions focusing on preparation for discharge, care, and recovery at home are provided regularly on Wednesdays.

Uptake and Usage of the MyStay Cardiac

Uptake of the MyStay Cardiac was measured via the type and extent of user activity data captured by the web-based information system: page visits; button clicks; audio starts and stops; and video starts and stops. Records were outputted into a spreadsheet. Specific data fields included: activity day of the week and date; activity duration; and activity location and type (Multimedia Appendix 1).

To aid the analysis of activity data, MyStay Cardiac usage records were partitioned into discrete usage sessions. A MyStay session was defined as an unbroken sequence of user activity, with gaps between activities not exceeding 15 minutes. The duration of an activity was calculated by the length of time between 2 consecutive activities. As no usage followed the final activity of each MyStay session, we substituted this value with the total mean activity duration for the corresponding MyStay session. Each session was categorized according to the combination of MyStay material accessed by users. Categories were as follows: (1) ICU stay information only (ICU and day 1 or 2); (2) ward stay information only (ward and day 3+); (3) exercise information only; (4) ICU and exercise information; (5) ward and exercise information; (6) ICU and ward information; and (7) all the above.

To evaluate the impact of the COVID-19 lockdowns that restricted access to health services by nonessential personnel, the following time periods were defined: restricted access to acute hospitals, August 2020-December 2021, and unrestricted access, January 2022-January 2023.

Data Analysis

Data summaries were performed using descriptive statistics. The normality of continuous variables was assessed via visual inspection of histograms: total items clicked; average activity duration; and total session length. Where continuous variables were non-normal, central tendency and spread were reported according to the median and IQR. Otherwise, means and SDs of continuous data were reported.

Strengths of association between categorical variables measuring app usage were evaluated using chi-square tests of Independence: ICU recovery material accessed; ward recovery material accessed; goals accessed; exercise material accessed; pain record accessed; video accessed; audio accessed; and access during patient education days (Wednesdays). Where contingency tables were 2×2, a continuity correction was applied to chi-square analyses. Between-group comparisons of continuous data were performed using Kruskal-Wallis H tests, with post hoc analyses performed using Mann-Whitney *U* tests. Data were summarized and analyzed in SPSS Statistics (version 29; IBM Corp).

Ethical Considerations

This paper reports on a specific component within a larger observational program of research on the MyStay multimedia app. Ethics and research governance approval for the larger study was given by the Human Research Ethics Committee of the participating university (#2020-053) and the Research Governance Unit of the hospital site, respectively. Participants engaged in the formal data collection methods within the larger study are required to give informed written consent to participate. However, the data collected as part of the protocols reported in this study were only anonymous application usage data, routinely collected by the technology platform as part of usual care. Consent to participate in these particular protocols was implied; the MyStay app indicates in its terms of service that users agree that de-identified, aggregated usage data may be used for the purposes of conducting health-related research.

Results

Principal Findings

Data on usage patterns of the MyStay Cardiac resources was analyzed for a 30-month period between August 2020 and January 2023.

Usage outcomes of MyStay Cardiac are reported for the 2 study phases in Table 1. ICU recovery information was the most accessed information, being viewed in approximately 7 in 10 usage sessions. Ward recovery (n=124/343, 36.2%), goal (n=114/343, 33.2%), and exercise (n=102/343, 29.7%) information were routinely accessed. However, access to the patient pain record was very infrequent (n=20/343, 5.8% of sessions). Most sessions involved users exclusively viewing text-based information (n=210/343, 61.2%). However, in over a third of sessions (n=132/342, 38.5%), users accessed video information. Further, over a third of sessions occurred were on patient education that was provided to patients on Wednesday during their acute care admission. The focus of these sessions was on recovery following surgery and rehabilitation following acute care discharge. This finding is in line with the report from the cardiac nurse educators that they predominantly used the MyStay Cardiac for pre- and postoperative education sessions.

Table 1. Usage of the MyStay Cardiac during COVID-19 restriction and post–COVID-19 restriction phases (August 2020-January 2023).

Use of MyStay Cardiac	COVID-19 restrictions		Total	*P* values
	Restriction phase[a]	Post-restriction phase[b]		
Number of usage sessions, n (%)	213 (62.1)	130 (37.9)	343 (100)	—[c]
Type of material accessed				
ICU[d] recovery, n (%)	141 (66.2)	96 (73.8)	237 (69.1)	.17[e,f]
Ward recovery, n (%)	81 (38)	43 (33.1)	124 (36.2)	.42[e,f]
Goals, n (%)	77 (36.2)	37 (28.5)	114 (33.2)	.18[e,f]
Exercise, n (%)	65 (30.5)	37 (28.5)	102 (29.7)	.78[e,f]
Pain record, n (%)	17 (8)	3 (2.3)	20 (5.8)	.05[e,f]
Accessed audio-visual material				
Video, n (%)	92 (43.2)	40 (30.8)	132 (38.5)	.03[e,f]
Audio, n (%)	21 (9.9)	2 (1.5)	23 (6.7)	.006[e,f]
Access day				
Patient education days (Wednesday), n (%)	81 (38)	45 (34.6)	126 (36.7)	.60[e,f]
Total items clicked, median (IQR)	13 (0.0-27.5)	9.5 (0.0-24.5)	12 (0.0-26.0)	.45[g]
Activity duration (seconds); median (IQR)	13 (2.5-23.5)	18 (6.5-29.5)	15 (4.0-26.0)	.11[g]
Total session length (minutes); median (IQR)	181 (0-586.5)	210 (0.0-810.0)	192 (0.0-706.0)	.67[g]

[a] Restriction phase August 2020-December 2021.

[b] Post-restriction phase January 2022-January 2023.

[c] Not applicable.

[d] ICU: intensive care unit.

[e] Chi-square test of independence.

[f] Continuity correction applied.

[g] Mann-Whitney *U* test.

Impact of COVID-19 Pandemic Restrictions on MyStay Cardiac Usage

Most usage sessions occurred during the COVID-19 restriction phase of the study (August 2020-December 2021). Sessions in which video (*P*=.02, *phi*=0.124) and audio (*P*=.006, *phi*=0.161) media were accessed were significantly more likely to occur in the restriction phase compared to the post-restriction phase. Information on ICU recovery was the most used module, with MyStay Cardiac being accessed by users in 237/343 (69.1%) usage sessions. This pattern of usage reflects the use of the MyStay Cardiac for preoperative education on the day of admission to the hospital. No significant associations were present between the study phase and whether system access occurred on patient education days or whether ICU recovery, ward recovery, goal, exercise, or pain record material was accessed during sessions. Furthermore, no significant differences in total items clicked, activity duration, and total session length between the restriction and postrestriction phases were found.

Usage Patterns

Associations and differences in usage outcomes between the 3 session types (rapid view, content exploration and in-depth look) are reported in Table 2. Chi-square tests of independence indicated statistically significant associations between patterns of MyStay use and the type of MyStay material accessed: ICU recovery (*P*<.001, Cramer V=0.373); ward recovery (*P*<.001, Cramer V=0.289); goals (*P*<.001, Cramer V=0.330); exercise (*P*<.001, Cramer V=0.531); audio content (*P*<.001, Cramer V=0.250); and pain records (*P*=.009, Cramer V=0.166). Examination of adjusted standardized residuals revealed that content exploration and in-depth look users were significantly more likely than rapid view users to access ICU recovery, ward recovery, and goal information ($z_{res} \geq 2.0$). In-depth users were significantly more likely than rapid view and content exploration users to access exercise, audio, and pain recording content ($z_{res} \geq 2.0$). No statistically significant association was found between patterns of MyStay use and use of the applications during the inpatient education sessions provided prior to hospital discharge.

Table 2. Usage of the MyStay Cardiac by session type: rapid views, content exploration, and in-depth looks.

	Session type		
	Rapid view	Content exploration	In-depth look
Number of usage sessions, n (%)	154 (44.9)	102 (29.7)	87 (25.4)
Type of material accessed			
Home page only, n (%)	40 (26)	0 (0)	0 (0)
ICU[a] recovery, n (%)	77 (50)	87 (85.3)[b]	73 (83.9)[b]
Ward recovery, n (%)	32 (20.8)	49 (48)[b]	43 (49.4)[b]
Goals, n (%)	25 (16.2)	45 (44.1)[b]	44 (50.6)[b]
Exercise, n (%)	9 (5.8)	36 (35.3)	57 (65.5)[b]
Audio content, n (%)	1 (0.6)	8 (7.8)	14 (16.1)[b]
Pain record, n (%)	3 (1.9)	7 (6.9)	10 (11.5)[b]
Access day			
Patient education days (Wednesday), n (%)	53 (34.4)	38 (37.3)	35 (40.2)
Total items clicked, median (IQR)	5 (1.9-8.1)	20 (6.1-33.9)[c]	44 (7.0-81.0)[c]
Activity duration (seconds); median (IQR)	6.5 (0.5-12.5)	23.5 (11.5-35.5)[c]	22 (10.0-34.0)[c]
Total session length (minutes); median (IQR)	33 (6.1-59.9)	524.5 (233.3-815.8)[c]	896 (399.0-1393.0)[c]

[a] ICU: intensive care unit.

[b] Standardised residuals of Chi-square test of Independence indicate statistically significant contribution of cell ($z_{res} \geq 2.0$).

[c] Post-hoc Mann-Whitney *U* test, *P*<.001.

There was a significant effect of the patterns of MyStay use on the total number of items clicked (*H*=185.58, *P*<.001, η^2=0.53), mean activity duration (*H*=78.072, *P*<.001, η^2=0.22), and total session length (*H*=241.861, *P*<.001, η^2=0.70). Post-hoc Mann-Whitney *U* tests revealed that content exploration and in-depth sessions involved significantly more total items clicked, and significantly higher mean activity and total session durations (all *P* values<.001).

Figures 1-3 describe the total usage sessions per month, the mean number of website clicks per month, and total clicks per month, respectively. Elective surgeries restarted following COVID-19 restrictions in July 2021 and corresponded with a spike in MyStay Cardiac usage (Figure 1). Figures 2 and 3 demonstrated that the most frequently accessed resources were information about the patients’ ICU stay, followed by information about their recovery on the ward and a recommended exercise program.

Figure 1. MyStay Cardiac—total number of usage sessions per month. Dotted lines denote the 95% CI around the mean.

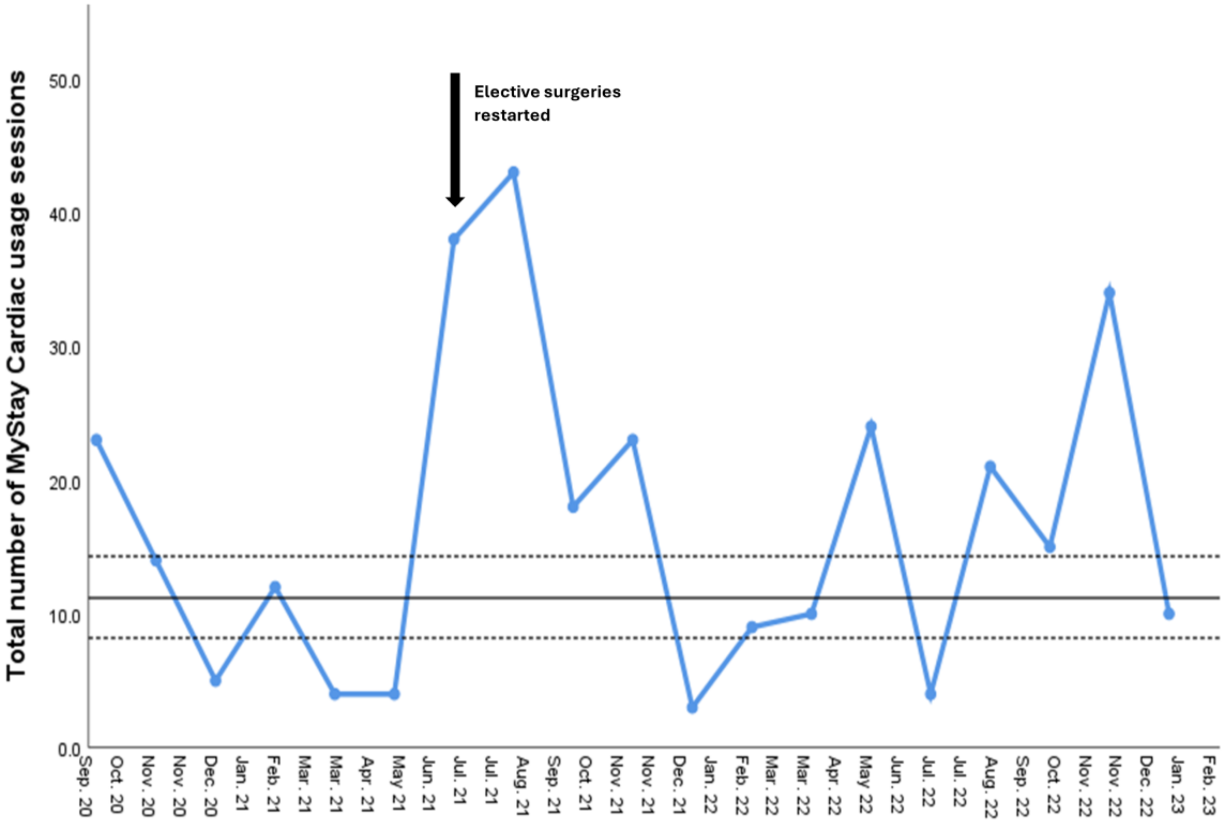


Figure 2. MyStay Cardiac—mean number of clicks within usage sessions per month. ICU: intensive care unit.

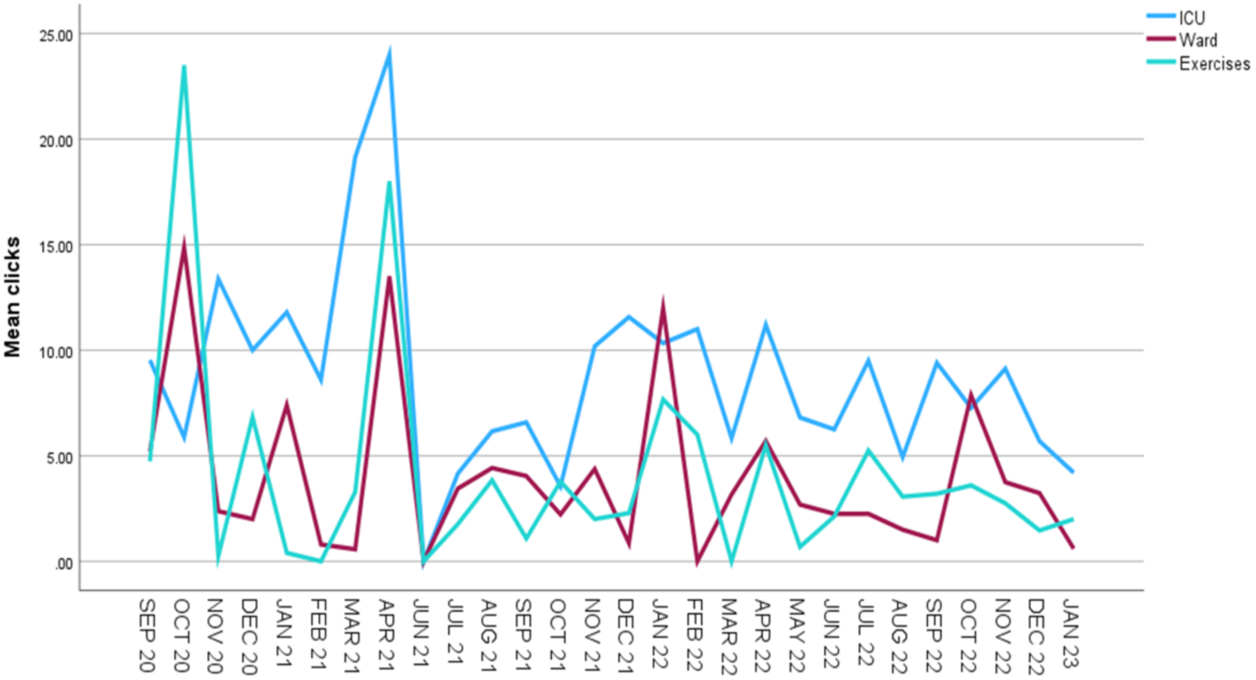
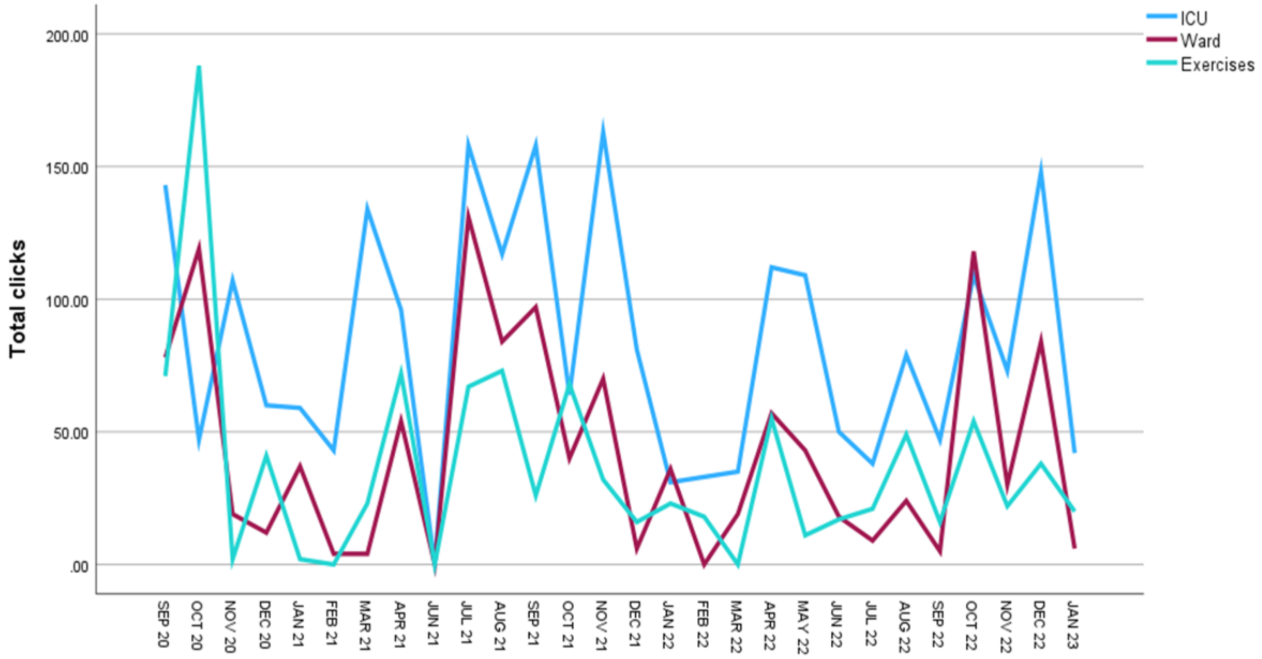


Figure 3. MyStay Cardiac—total website clicks per month. ICU: intensive care unit.



Discussion

Background

This study found that the use of digital multimedia resources to support patient education was well received and integrated into their practice by cardiac nurse educators working in acute care during the COVID-19 pandemic. Usage patterns fluctuated, reflecting variations in the number of elective cardiac surgery cases being treated at the study site over time. Data suggested a pattern of greater usage of the MyStay Cardiac during the COVID-19 pandemic when access to the health service for nonfrontline, essential workers was limited. Following the lifting of these restrictions, use of the MyStay Cardiac resources has been steady, reflecting ongoing use by the cardiac team for pre- and postoperative education. We acknowledge the possibility that the widespread diffusion of communications technologies during the COVID-19 pandemic may have increased patients' capacity to interact with health technologies in the post–COVID-19 era [24]. Despite this, observed trends for decreased use of the MyStay Cardiac in the final year of the follow-up period may reflect that clinicians were able to provide more in-person education to patients following the lifting of COVID-19 restrictions or that the novelty of using a new digital multimedia resource had decreased with time. This finding highlights the need for ongoing updates of educational materials and new approaches to engaging staff to use these resources in their practice to sustain staff interest over the longer term.

The finding that approximately a third of access sessions involved users reviewing the website content more extensively and a quarter of sessions involved the in-depth use of the website suggested that use of the multimedia resources was acceptable to consumers. This finding is in line with recent research using digital multimedia and animation with adults undergoing chemotherapy treatment [25]. In this study, the most popular resources were the animation providing advice about "COVID-19 and Oncology care," a general orientation to cancer care, and a video about receiving chemotherapy treatment.

The data on resource usage patterns and the length of time spent reviewing different sections of the program indicated that the cardiac nurses using the resource for patient education focused on information provision in relation to the patients' ICU and ward stay, rather than focusing on engaging patients to participate in their care. Review of patient recovery goals and recommended exercises only accounted for approximately a third of resource usage, while accessing information about pain management and the patient pain record accounted for 6%-10% of usage.

The lack of focus on promoting patient participation in their recovery goals may highlight some of the disadvantages of using a passive diffusion approach to implementation [22]. Cardiac nurses integrated the MyStay resources into their own workflow efficiently but did not use the digital materials to promote patient engagement in line with the initial design of the app. Rather, their focus was on the effective communication of information rather than the promotion of patient participation [26]. These findings highlight that to achieve all the potential benefits of using the MyStay Cardiac resources in clinical care, further implementation needs to be supported by a structured approach to upskilling nurses working in acute care through the use of coaching and rapport-building communication techniques that promote greater patient participation in their care [27]. Developing nurses' communication skills in partnering with consumers is particularly relevant with the increasing focus on developing comprehensive care plans that focus on achieving patient goals rather than clinician goals of care during an acute care admission [5].

The COVID-19 pandemic has accelerated the adoption of digital technology in health care settings [28]. A systematic review of literature published in 2020 (reflecting the height of pandemic-related health care activity worldwide) found 124 studies reporting the adoption of digital technology. Most studies reported digital technology use for diagnosis (n=64, 52.4%), surveillance (n=46, 37.1%), or prevention (n=37, 30.6%). Nine percent (n=11) of the included studies used digital technology to promote patient engagement in care [29]. During the pandemic, health service providers developed web-based platforms to facilitate patient engagement in a range of administrative tasks and access telehealth appointments [30]. However, the authors found that it was common for the level of sophistication of these websites and apps to insufficiently support patients in completing administrative tasks independently.

The use of electronic communication and digital communication technologies during COVID-19 was rapidly accepted by consumers from a diverse range of backgrounds, providing evidence that digital technology use in health care has been accelerated by the COVID-19 pandemic [31-33]. Cadel et al [31] conducted a scoping review of patient engagement activities used during the COVID-19 pandemic and found most activities focused on clinical interactions such as telehealth consultations, family visits, and community outreach using digital technology, and that most patients (>90%) were highly satisfied with their experiences of telehealth. Zeng et al [32] surveyed health care consumers in the United States on the use of electronic communication for health care before and during the COVID-19 pandemic and reported that the odds of technology use substantially increased during the COVID-19 pandemic (adjusted odds ratio 1.99, 95% CI 1.18-3.35). Individuals in the highest-income group were more likely to use technology than those in the lowest-income group. Despite this, individuals with lower educational attainment had similar growth in the use of electronic communication during the pandemic to those with postgraduate education.

Strengths and Limitations

The strength of this study is that it provides long-term follow-up data demonstrating the acceptability and durability of implementing the use of digital multimedia resources to support patient education and participation in the acute care context. Considering its unusual “diffusion” approach to implementation, this research has provided baseline data of particular relevance to future investigations in the uptake of multimedia education resources and to assess future enhancements such as multilingual functions to reduce health inequalities in the accessibility of such resources. Study limitations are that only group level data on usage patterns was available for analysis from the study site, meaning that it was not possible to evaluate individual patient factors that may influence engagement and uptake of the My Stay Cardiac resources. Further research will focus on evaluating patient factors that influence engagement and further development and evaluation of the MyStay Cardiac using a co-design approach involving both the multidisciplinary clinical team and consumers. Future research would also benefit from randomized controlled studies to demonstrate the efficacy and effectiveness of the platform, and such studies are planned.

Conclusions

The use of digital multimedia resources to support the education of patients undergoing cardiac surgery appeared to be well received by cardiac nurses and successfully integrated into usual practice during the COVID-19 pandemic. The acceptability of the MyStay Cardiac multimedia program to acute care nurses was demonstrated by sustained usage to support the provision of patient education over a 30-month follow-up period.

Acknowledgments

This study was supported by philanthropic funding from the Baker Foundation and the Epworth Medical Foundation.

Authors' Contributions

AH provided oversight of the project, data collection and analysis, and development of the draft manuscript; DK conducted the data analysis and contributed to drafting the manuscript; AMZ and CD were involved in data collection and drafting of the manuscript; NW, MB, and JMD contributed to the development of the MyStay Cardiac multimedia app, designed the study protocol, and reviewed and finalized the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
List of variables.
[DOCX File , 24 KB - nursing_v7i1e54317_app1.docx]

References

1. Shardey G, Tran L, Williams-Spence J, Solman N, McLaren J, Marrow N, et al. The Australian and New Zealand Society of Cardiac and Thoracic Surgeons' Cardiac Surgery Database Program Annual Report 2020. Australia: Monash University, Department of Epidemiology and Preventive Medicine; 2020.
2. Tobiano G, Marshall A, Bucknall T, Chaboyer W. Patient participation in nursing care on medical wards: an integrative review. Int J Nurs Stud 2015 Jun;52(6):1107-1120. [doi: 10.1016/j.ijnurstu.2015.02.010] [Medline: 25769475]

3. Bombard Y, Baker GR, Orlando E, Fancott C, Bhatia P, Casalino S, et al. Engaging patients to improve quality of care: a systematic review. Implement Sci 2018 Jul 26;13(1):98 [FREE Full text] [doi: 10.1186/s13012-018-0784-z] [Medline: 30045735]
4. Shahmoradi L, Rezaei N, Rezayi S, Zolfaghari M, Manafi B. Educational approaches for patients with heart surgery: a systematic review of main features and effects. BMC Cardiovasc Disord 2022 Jun 27;22(1):292 [FREE Full text] [doi: 10.1186/s12872-022-02728-0] [Medline: 35761186]
5. NSQHS Standards - Partnering with consumers standard. Australian Commission for Quality and Safety in HealthCare ACQSHC (2023). 2023. URL: https://www.safetyandquality.gov.au/standards/nsqhs-standards/partnering-consumers-standard [accessed 2024-05-28]
6. Chen B, Xie G, Lin Y, Chen L, Lin Z, You X, et al. A systematic review and meta-analysis of the effects of early mobilization therapy in patients after cardiac surgery. Medicine (Baltimore) 2021 Apr 16;100(15):e25314 [FREE Full text] [doi: 10.1097/MD.0000000000025314] [Medline: 33847630]
7. Mungovan S, Singh P, Gass G, Smart N, Hirschhorn A. Effect of physical activity in the first five days after cardiac surgery. J Rehabil Med 2017 Jan 19;49(1):71-77 [FREE Full text] [doi: 10.2340/16501977-2165] [Medline: 28101566]
8. Gray E, Smith C, Bunton R, Skinner M. Perceptions and experiences of engaging in physical activity following coronary artery bypass graft surgery. Physiother Theory Pract 2022 Nov;38(13):2841-2855. [doi: 10.1080/09593985.2021.1989733] [Medline: 34666600]
9. Kanejima Y, Shimogai T, Kitamura M, Ishihara K, Izawa KP. Effect of early mobilization on physical function in patients after cardiac surgery: a systematic review and meta-analysis. Int J Environ Res Public Health 2020 Sep 28;17(19):7091 [FREE Full text] [doi: 10.3390/ijerph17197091] [Medline: 32998202]
10. Takahashi T, Kumamaru M, Jenkins S, Saitoh M, Morisawa T, Matsuda H. In-patient step count predicts re-hospitalization after cardiac surgery. J Cardiol 2015 Oct;66(4):286-291 [FREE Full text] [doi: 10.1016/j.jjcc.2015.01.006] [Medline: 25728798]
11. McDonall J, Heynsbergh N, Oxley S, Botti M, Hutchinson A. Opportunities for patients to engage in postoperative recovery following cardiac surgery: a systematic narrative review. Patient Education and Counseling 2020 Oct;103(10):2095-2106. [doi: 10.1016/j.pec.2020.04.004] [Medline: 32381287]
12. Gesualdo F, Daverio M, Palazzani L, Dimitriou D, Diez-Domingo J, Fons-Martinez J, et al. Digital tools in the informed consent process: a systematic review. BMC Med Ethics 2021 Feb 27;22(1):18 [FREE Full text] [doi: 10.1186/s12910-021-00585-8] [Medline: 33639926]
13. Nehme J, El-Khani U, Chow A, Hakky S, Ahmed AR, Purkayastha S. The use of multimedia consent programs for surgical procedures: a systematic review. Surg Innov 2013 Feb;20(1):13-23. [doi: 10.1177/1553350612446352] [Medline: 22589017]
14. Sim V, Galbraith K. Effectiveness of multimedia interventions in the provision of patient education on anticoagulation therapy: a review. Patient Educ Couns 2020 Oct;103(10):2009-2017. [doi: 10.1016/j.pec.2020.05.003] [Medline: 32532633]
15. Farrell EH, Whistance RN, Phillips K, Morgan B, Savage K, Lewis V, et al. Systematic review and meta-analysis of audio-visual information aids for informed consent for invasive healthcare procedures in clinical practice. Patient Educ Couns 2014 Jan;94(1):20-32. [doi: 10.1016/j.pec.2013.08.019] [Medline: 24041712]
16. Hung S, Huang K, Yu W. An empirical study of the effectiveness of multimedia disclosure of informed consent: A technology mediated learning perspective. Inform Manage 2011 May;48(4-5):135-144. [doi: 10.1016/j.im.2011.03.002]
17. McDonall J, Hutchinson AF, Heynesbergh N, Redley B, de Steiger R, Khaw D, et al. MyStay—development of nurse-facilitated condition-specific multimedia resources to facilitate patient participation in postoperative care. Patient Exp J 2022;9(3):114-125. [doi: 10.35680/2372-0247.1631]
18. McDonall J, Hutchinson AF, Redley B, Livingston PM, Botti M. Usability and feasibility of multimedia interventions for engaging patients in their care in the context of acute recovery: a narrative review. Health Expect 2019 Dec;22(6):1187-1198 [FREE Full text] [doi: 10.1111/hex.12957] [Medline: 31778023]
19. Shaygan M, Yazdani Z, Valibeygi A. The effect of online multimedia psychoeducational interventions on the resilience and perceived stress of hospitalized patients with COVID-19: a pilot cluster randomized parallel-controlled trial. BMC Psychiatry 2021 Feb 11;21(1):93 [FREE Full text] [doi: 10.1186/s12888-021-03085-6] [Medline: 33573631]
20. Kaushik A, Patel S, Dubey K. Digital cardiovascular care in COVID-19 pandemic: a potential alternative? J Card Surg 2020 Dec;35(12):3545-3550 [FREE Full text] [doi: 10.1111/jocs.15094] [Medline: 33040399]
21. Pandemic Order Register—hospitals and care facilities orders. URL: https://www.health.vic.gov.au/covid-19/pandemic-order-register [accessed 2023-11-28]
22. Nilsen P. Making sense of implementation theories, models and frameworks. Implement Sci 2015 Apr 21;10(10):53 [FREE Full text] [doi: 10.1186/s13012-015-0242-0] [Medline: 25895742]
23. Kvæl LAH, Bergland A. The practice environment's influence on patient participation in intermediate healthcare services—the perspectives of patients, relatives and healthcare professionals. BMC Health Serv Res 2021 Feb 25;21(1):180 [FREE Full text] [doi: 10.1186/s12913-021-06175-z] [Medline: 33632241]
24. Liu L, Miguel-Cruz A. Technology adoption and diffusion in healthcare at onset of COVID-19 and beyond. Healthc Manage Forum 2022 May;35(3):161-167 [FREE Full text] [doi: 10.1177/08404704211058842] [Medline: 35240038]

25. Turkdogan S, Schnitman G, Wang T, Gotlieb R, How J, Gotlieb WH. Development of a digital patient education tool for patients with cancer during the COVID-19 pandemic. JMIR Cancer 2021 Jun 21;7(2):e23637 [FREE Full text] [doi: 10.2196/23637] [Medline: 34101611]
26. Hickmann E, Richter P, Schlieter H. All together now—patient engagement, patient empowerment, and associated terms in personal healthcare. BMC Health Serv Res 2022 Sep 02;22(1):1116 [FREE Full text] [doi: 10.1186/s12913-022-08501-5] [Medline: 36056354]
27. D'Agostino TA, Atkinson TM, Latella LE, Rogers M, Morrissey D, DeRosa AP, et al. Promoting patient participation in healthcare interactions through communication skills training: a systematic review. Patient Educ Couns 2017 Jul;100(7):1247-1257 [FREE Full text] [doi: 10.1016/j.pec.2017.02.016] [Medline: 28238421]
28. Peek N, Sujan M, Scott P. Digital health and care in pandemic times: impact of COVID-19. BMJ Health Care Inform 2020 Jun;27(1):e100166 [FREE Full text] [doi: 10.1136/bmjhci-2020-100166] [Medline: 32565418]
29. Lee A. COVID-19 and the advancement of digital physical therapist practice and telehealth. Phys Ther 2020 Jul 19;100(7):1054-1057 [FREE Full text] [doi: 10.1093/ptj/pzaa079] [Medline: 32343836]
30. Meyer MA. COVID-19 pandemic accelerates need to improve online patient engagement practices to enhance patient experience. J Patient Exp 2020 Oct;7(5):657-664 [FREE Full text] [doi: 10.1177/2374373520959486] [Medline: 33294595]
31. Cadel L, Marcinow M, Sandercock J, Dowedoff P, Guilcher SJT, Maybee A, et al. A scoping review of patient engagement activities during COVID-19: more consultation, less partnership. PLoS One 2021;16(9):e0257880 [FREE Full text] [doi: 10.1371/journal.pone.0257880] [Medline: 34587175]
32. Zeng B, Rivadeneira NA, Wen A, Sarkar U, Khoong EC. The impact of the COVID-19 pandemic on internet use and the use of digital health tools: secondary analysis of the 2020 Health Information National Trends Survey. J Med Internet Res 2022 Sep 19;24(9):e35828 [FREE Full text] [doi: 10.2196/35828] [Medline: 36041005]
33. Krukowski RA, Ross KM. Measuring weight with electronic scales in clinical and research settings during the Coronavirus disease 2019 pandemic. Obesity (Silver Spring) 2020;28(7):1182-1183 [FREE Full text] [doi: 10.1002/oby.22851] [Medline: 32339394]

Abbreviations

ICU: intensive care unit

Edited by E Borycki; submitted 06.11.23; peer-reviewed by K Malale, C Baxter; comments to author 07.02.24; revised version received 07.03.24; accepted 17.04.24; published 18.07.24.

Please cite as:
Hutchinson A, Khaw D, Malmstrom-Zinkel A, Winter N, Dowling C, Botti M, McDonall J
Embedding the Use of Patient Multimedia Educational Resources Into Cardiac Acute Care: Prospective Observational Study
JMIR Nursing 2024;7:e54317
URL: https://nursing.jmir.org/2024/1/e54317
doi:10.2196/54317
PMID:39024556

Original Paper

Health Care Workers' Expectations of the Mercury Advance SMARTcare Solution to Prevent Pressure Injuries: Individual and Focus Group Interview Study

Joeri Slob[1], MSc; Thijs van Houwelingen[2], PhD; Helianthe S M Kort[2,3], PhD

[1]Nursing Sciences, program in Clinical Health Sciences, University Medical Center Utrecht, Utrecht University, Utrecht, Netherlands

[2]Research Group Technology for Healthcare Innovations, Research Centre for Healthy and Sustainable Living, University of Applied Sciences Utrecht, Utrecht, Netherlands

[3]Building Healthy Environments for Future Users Group, Department of the Built Environment, Eindhoven University of Technology, Eindhoven, Netherlands

Corresponding Author:
Thijs van Houwelingen, PhD
Research Group Technology for Healthcare Innovations
Research Centre for Healthy and Sustainable Living
University of Applied Sciences Utrecht
Heidelberglaan 7
Utrecht, 3584 CS
Netherlands
Phone: 31 641097762
Email: thijs.vanhouwelingen@hu.nl

Abstract

Background: The transformation in global demography and the shortage of health care workers require innovation and efficiency in the field of health care. Digital technology can help improve the efficiency of health care. The Mercury Advance SMARTcare solution is an example of digital technology. The system is connected to a hybrid mattress and is able to detect patient movement, based on which the air pump either starts automatically or sends a notification to the app. Barriers to the adoption of the system are unknown, and it is unclear if the solution will be able to support health care workers in their work.

Objective: This study aims to gain insight into health care workers' expectations of factors that could either hamper or support the adoption of the Mercury Advance SMARTcare unit connected to a Mercury Advance mattress to help prevent patients from developing pressure injuries in hospitals and long-term care facilities.

Methods: We conducted a generic qualitative study from February to December 2022. Interviews were conducted, and a focus group was established using an interview guide of health care workers from both the United Kingdom and the Netherlands. Thematic analysis was performed by 2 independent researchers.

Results: A total of 14 participants took part in the study: 6 (43%) participants joined the focus group, and 8 (57%) participants took part in the individual interviews. We identified 13 factors based on four themes: (1) factors specifically related to SMARTresponse, (2) vision on innovation, (3) match with health care activities, and (4) materials and resources involved. *Signaling function*, *SMARTresponse as prevention*, *patient category*, *representatives*, and *implementation strategy* were identified as facilitators. *Perception of patient repositioning*, *accessibility to pressure injury aids*, and *connectivity* were identified as barriers.

Conclusions: Several conditions must be met to enhance the adoption of the Mercury Advance SMARTcare solution, including the engagement of representatives during training and a reliable wireless network. The identified factors can be used to facilitate the implementation process.

(JMIR Nursing 2024;7:e47992) doi:10.2196/47992

KEYWORDS

digital technology; pressure injury; health care professionals; mobile phone; health care workers

Introduction

Background

In recent years, the world's population has increased rapidly. In 1950, there were 2.5 billion people on our planet. In 2019, this number had increased to 7.7 billion [1]. Since the 1900s, the global average life expectancy has more than doubled and currently stands at >70 years [2]. Together with the global shortage of health care workers, in particular, nurses and midwives, this results in challenges for patient care [3]. One of the 5 most common injuries experienced by patients is a pressure injury. In 2016, the overall number of patients developing pressure injuries was estimated to be 2.5 million worldwide [4]. Patients with pressure injuries have higher 30-day readmission rates [4], and damage due to pressure injuries can result in complications such as amputation, septic infection, impaired health-related quality of life, and premature death [5]. Along with the global increase in life expectancy, innovation and efficiency in the current health care practices are necessary to preserve the quality of care for patients who are at risk of developing pressure injuries.

Current ways to prevent or treat pressure injuries usually include pressure-relieving devices, wound care, and patient repositioning [6]. For pressure-relieving devices, there are beds, mattresses, and mattress toppers. A subdivide is made between reactive static surfaces (constructed using foam, fiber, air cells, or water bags) that apply constant pressure to the skin and active (alternating pressure) surfaces that regularly redistribute the pressure underneath the body. However, according to a recent Cochrane systematic review [6], there is low-certainty evidence that the alternating pressure of active air surfaces reduces the risk of developing new pressure injuries compared to foam surfaces alone. A combination of reactive static surfaces and active surfaces is called a hybrid mattress, which usually consists of foam and air cells and can be connected to a control unit that is used to power the alternating air function.

The hybrid mattresses provided by Direct Healthcare Group (DHG) were clinically effective in a multisite evaluation study [7] conducted in 8 hospitals in the United Kingdom. DHG recently developed a control unit called Mercury Advance SMARTcare [8]. This unit is used to power the alternating air function on their alternating pressure (active) air surfaces (Mercury Advance mattress). The control unit can be connected to an app that can automatically turn on the alternating air function after a detected period of patient nonmovement. The app can also notify the health care professional of the detected patient's nonmovement; therefore, the health care professional can turn on the alternating air function remotely. This app (using digital technology) could potentially be an effective intervention for optimizing efficiency in the prevention and treatment of pressure injuries. However, digital technology is not always as useful as intended.

Prior Work

Digital technology has been studied comprehensively, and according to a barrier analysis published by Mathijssen et al [9], there is a mismatch between the available digital technology and the adoption of digital technology. In this analysis, a scoping review and a survey were conducted, and the barriers and facilitators were classified according to the capability, opportunity, motivation, and behavior (COM-B) model by Michie et al [10]. Most barriers in the analysis were found in the opportunity domain (eg, technical issues). Health care workers reported that digital technology should provide support in delivering health care instead of replacing it. The accessibility and reliability of digital technology were identified as facilitators in the adoption of digital technology. The privacy and security of patient data, training of health care workers, and practical support regarding digital technology were also marked as facilitators [9].

Barriers and facilitators regarding the adoption of digital technology in health care practices have been identified. It is currently unclear whether the Mercury Advance SMARTcare solution can support health care workers in their daily practices. DHG's hybrid mattress (Mercury Advance) has proven to be clinically efficient in hospital settings [7]. However, the expectations of health care workers will determine whether the Mercury Advance SMARTcare solution is suitable for adoption before clinical effectiveness can be investigated. The Mercury Advance SMARTcare unit is currently being tested at several sites in the United Kingdom, and the effectiveness of the app thus far is unknown. To reveal preconceptions, a study with an explorative design is suitable. Consequently, a generic qualitative study to investigate the expectations of health care workers of the Mercury Advance SMARTcare solution connected to the Mercury Advance mattress is necessary.

Objective of This Study

The objective of this study is to gain insight into health care workers' expectations of factors that could hamper or support the adoption of the Mercury Advance SMARTcare unit connected to a Mercury Advance mattress to prevent patients from developing pressure injuries in hospitals and long-term care facilities. The results can be used to improve the implementation process of the Mercury Advance SMARTcare solution and help identify potential knowledge gaps.

Methods

Study Design

A generic qualitative study with health care workers was conducted between February and December 2022 using in-depth individual interviews and a focus group. The focus group provided interaction between the participants, which is especially suitable for explorative research [11]. Individual interviews may reveal sensitive concepts, which may be left undiscussed in focus groups. In addition, the results of the individual in-depth interviews confirmed the findings of the focus group and contributed to method triangulation [12].

Setting

Sampling Technique

A purposive sampling technique was adopted for the recruitment of health care workers in both the United Kingdom and the Netherlands. The objective was to gain insight into health care workers' expectations of the Mercury Advance SMARTcare unit connected to the Mercury Advance mattress. More information about the Mercury Advance SMARTcare solution can be found on the developer's web page [8].

Eligibility

Most of the time, initial contact with study sites was maintained by a DHG product specialist. A team manager of the potential participants had initial contact by email consistently throughout the study. The eligibility criteria were adopted to ensure that participants were able to provide meaningful insights regarding the subject of this study. The required inclusion criteria for the participants were being a registered nurse, physiotherapist, or occupational therapist; working with patients directly; dealing with pressure injury prevention or treatment; and being able to read, write, and speak English or Dutch. When a participant agreed to participate, they would receive a participant information sheet, and an interview with them would be scheduled. Besides the purposive sampling technique, a snowballing selection strategy was used, signifying that the researcher asked the participants included if they knew the potential participants who met the abovementioned eligibility criteria.

Domain

The occupational sites of the participants included general hospital wards, psychiatric wards, and a rehabilitation center located in the Netherlands and the United Kingdom. The study population can be considered homogeneous, with health care workers working on preventing and managing pressure injuries. To achieve data saturation in a study, according to Holloway and Wheeler [13], a sample size of 6 to 8 participants is considered sufficient in a homogeneous sample. That is why we included a total of 14 participants. Of these 14 participants, 6 (43%) were scheduled for the focus group interview and the remaining 8 (57%) were scheduled for the individual interviews.

Data Collection

Qualitative data were collected using a focus group and in-depth individual interviews, which were recorded and transcribed verbatim. Sessions were held face-to-face at a location picked by the participants or via Microsoft Teams (version 1.4.00.22472; Microsoft Corp). Audio recordings were the main source of data. An interview guide for the focus group and the individual interviews was put together beforehand to facilitate a semistructured approach.

To make the participants feel comfortable, the interview started with the following question: "On a scale from 0-10, how important is pressure injury prevention for patients in general?" This question aimed to encourage the participants to narrate their views on patient care and to remember the importance of their work. Subsequently, our interview guide included the following topics, which were discussed using open-ended questions: (1) pressure injury equipment and current procedures (eg, "What is your experience with the pressure ulcer prevention tools that are currently in use in your department?"), (2) technology in health care, (3) SMARTresponse app video, (4) expectations of the SMARTresponse app, and (5) training regarding the SMARTresponse app (eg, "In your opinion, what is required in order to use the SMARTresponse application?"). Our interview guide topics were based on the barriers and the facilitators as described by Mathijssen et al [9]. During the interview, the participants were shown a short video (3 min) of the Mercury Advance SMARTcare solution to ensure that they could vividly imagine the application in their work environment. In the video, a trainer explained the use of the Dyna-Form SMARTresponse control unit and its connectivity to an Apple iPad. The activation of the automatic and manual functions was demonstrated on the iPad, using an app, including how it was applied to the control unit.

The interview guide was pilot-tested with 2 occupational therapists and 2 nursing science students at Utrecht University. A pilot interview was performed in English to improve its feasibility, as the interviewer was not a native English speaker. This gave the novice researcher (JS) the opportunity to get comfortable with the interview guide and to test the amount of content-specific information included in the interview guide. All individual interviews were carried out by JS. The focus group was facilitated by JS and moderated by a second researcher (TvH), who has experience in qualitative research. During the individual interviews and the focus group meeting, observational notes were made to gather nonverbal aspects regarding the data collection and to enhance the credibility of the findings [13].

Data Analysis

The data were analyzed by 2 independent researchers (JS and TvH) and was based on thematic analysis, as described by Braun and Clarke [14]. Considering the data analysis, an inductive (data-driven) approach was chosen. Data collection and analysis were performed simultaneously to contribute to the constant comparison approach [12]. The audio recordings were transcribed verbatim by JS, and these transcriptions were checked for inconsistencies by TvH. To support the data analysis, ATLAS.ti software (version 22; ATLAS.ti Scientific Software Development GmbH) was used. Entire transcripts were read and reread to get familiar with the data. The initial coding was done by JS and carried out inductively. Codes were discussed with TvH, and a code list was put together. Subthemes were generated to collate all codes from the code list. During this process, a mind mapping approach was used to get familiar with the structure of the data. All codes were run to determine whether they were associated with multiple subthemes. The 2 researchers discussed overarching candidate themes, subthemes, and related codes. During this process, insights were gathered, and the interview guide was adjusted accordingly. Factors emerged from the data, which were summarized by JS, who added illustrative quotes. Next, these factors were confirmed by TvH. Factors were divided into barriers and facilitators according to the objective of the study.

For further involvement in the underlying process of the data analysis, expert validation of preliminary findings was performed by a tissue viability nurse specializing in wound care and management. The findings were acknowledged and presented to the participants for a member check to enhance the credibility and validity of the study [13].

Ethical Considerations

This study was conducted in accordance with the General Data Protection Regulation [15] and the Declaration of Helsinki [16]. All participants provided informed consent before the study. The participants of the study were not subjected to procedures, actions, or behavioral rules. The expectations of health care workers were the primary study parameters, which fall outside the scope of medical or scientific research. According to the Central Committee on Research Involving Human Subjects, this study does not apply to the Medical-Scientific Research with People Act and was therefore not reviewed by a Medical Research Ethics Committee [17]. In addition to the interview, participants' characteristics were recorded to describe the study population. Participant identification codes were generated to ensure the participants' anonymity. Transcribed interviews, signed consent forms, participant identification codes, and study metadata were all stored on the university's research drive (HU University of Applied Sciences) [18], which is designed for the handling and storage of research data. This cloud service acquired the International Organization for Standardization 27001 certification and, therefore, legally adheres to the General Data Protection Regulation [15].

Results

Demographics

A total of 18 participants agreed to participate in the study, however, 4 (22%) were not able to schedule an interview with the researchers or attend the focus group meeting. Of the 14 participants included in the study, 6 (43%) attended the focus group and 8 (57%) participated in the individual interviews. One (7%) interview was carried out with a participant working in the United Kingdom; the remaining interviews and the focus group meeting were held with participants working in the Netherlands. The duration of the individual interviews was 32 to 67 minutes, with a mean interview time of 51 (SD 11) minutes. The duration of the focus group meeting was 96 minutes. The characteristics of the participants are presented in Table 1.

Table 1. Demographic characteristics of the participants (N=14).

Participant ID	Age (y), range[a]	Data collection method	Duration (min)	Occupation	Work experience (y)	Highest educational level
P1	30-39	Interview	32	Tissue viability nurse	14	HPE[b] nursing
P2	30-39	Focus group	96	Nurse	12	SVE[c] nursing
P3	60-69	Focus group	96	Physiotherapist	40	HPE physiotherapy
P4	60-69	Focus group	96	Nurse	36	SVE nursing
P5	30-39	Focus group	96	Nurse	14	SVE nursing
P6	50-59	Focus group	96	Nurse	35	SVE nursing
P7	50-59	Focus group	96	Nurse	32	SVE nursing
P8	40-49	Interview	67	Tissue viability nurse	25	SVE nursing
P9	20-29	Interview	56	Nurse	5	HPE nursing
P10	20-29	Interview	50	Nurse	1	HPE nursing
P11	30-39	Interview	63	Nurse	7	HPE nursing
P12	20-29	Interview	47	Nurse	3	HPE nursing
P13	20-29	Interview	49	Tissue viability nurse	8	HPE nursing
P14	40-49	Interview	45	Tissue viability nurse	27	SVE nursing

[a] Age is presented as a range to ensure participants' anonymity.

[b] HPE: higher professional education.

[c] SVE: secondary vocational education.

Overview

In total, 13 factors were identified that could hamper or support the adoption of the Mercury Advance SMARTcare solution. These 13 factors were included in the 22 subthemes as identified during the first phases of the qualitative analysis. The 22 subthemes were collated into four overarching themes: (1) *factors specifically related to SMARTresponse,* (2) *vision on innovation,* (3) *match with health care activities, and* (4) *materials and resources involved.* An overview of the themes, subthemes, and related factors is presented in Multimedia Appendix 1. During the final phases of the qualitative analysis, the 13 factors were divided into barriers or facilitators. To ensure that data saturation was achieved in the analysis of the study, 2 individual interviews were conducted after the division into barriers and facilitators. Analysis of these last interviews did not provide further insights into the barriers or facilitators overview. Using illustrative quotes, the Multimedia Appendix 2 shows how the factors can hamper (barriers) or support (facilitators) the adoption of the Mercury Advance SMARTcare solution.

Factors Specifically Related to SMARTresponse

The factors specifically related to SMARTresponse included three subthemes: (1) SMARTresponse, (2) training, and (3) supplier. Six facilitators were identified within these subthemes (reference to *Q* in the text refer to specific quotes in Multimedia Appendix 2). The Mercury Advance SMARTcare solution may have a signaling function (Q1-Q3) or a preventing function before pressure injuries occur (Q4-Q6). The adoption of the app is conditional upon the patient category (Q13-Q16). Patient involvement may help gain insight into patient movement, but, as a result, evaluation of adherence to the app is necessary (Q11 and Q12). Real-life practice with the app and available representatives with knowledge of the app are facilitators for both training and implementation of the system (Q23-Q30).

Four barriers were identified. The system will most likely not be suitable for a psychiatric ward (Q7 and Q8). The lights on the pump unit were a point of interest, especially at night (Q20-Q22). Although participants said that the supplier is required to manage the training (Q32), maintaining contact with the ward by the supplier was said to be undesirable (Q31). Finally, this app would require a lot of effort and persistence in the beginning, and the added value of it was discussed (Q17-Q19).

Vision on Innovation

The vision of the health care workers on innovation included six subthemes: (1) vision on pressure injuries, (2) adoption of innovation, (3) vision on technology, (4) pressure injury impact and present performance, (5) reflection on self, and (6) remote health care. Three facilitators were identified within these subthemes. The app could serve as a preventive aid (Q42 and Q43), and it could support the health care workers by acting as a signaling function (Q33 and Q34). The nature of the introduction of the system may help encourage the health care workers to use it (Q38-Q40).

Two barriers were identified. The app does not appear to be suitable for patient involvement in the neurological patient category (Q41). Participants' perception of patient repositioning changes whenever a pressure injury unit is adopted. Patient repositioning is less prioritized or even considered redundant (Q35-Q37 and Q44-Q46).

Match With Health Care Activities

The match with health care activities included six subthemes: (1) patient factors, (2) nurses' tasks, (3) patient repositioning, (4) patients' comfort, (5) mattress change, and (6) hygiene. A total of 4 facilitators were identified within these subthemes. The app can be useful whenever the patient's movement is unknown (Q47). Patient involvement results in control (Q48 and Q49). Cutoff values can determine the adoption of the app (Q52-Q54). The app can save a lot of time and effort (Q56 and Q57).

Five barriers were identified. A psychiatric ward may not be a suitable environment for the app (Q51 and Q52). Unlike the last facilitator described in the previous paragraph, the app requires new tasks as well (Q55). The frequency of patient repositioning is not clear, resulting in a debate among colleagues, especially when mattresses are used (Q58 and Q59). A mattress change is often performed during the work shift and does not require much effort for the health care workers (Q62 and Q63). Finally, some participants described that a hybrid mattress feels hard (Q60).

Materials and Resources Involved

The materials and resources involved included seven subthemes:(1) pressure injury equipment, (2) organization, (3) dynamic support surfaces, (4) performance appliances, (5) financials, (6) devices, and (7) time. Three facilitators were identified. In most organizations, representatives with specific areas of interest are present, which could help support the implementation of the system (Q66-Q68). In some centers, devices compatible with the app were readily available (Q73 and Q74). Patients experienced a dynamic mattress to be less comfortable than a hybrid mattress, resulting in supportive opinions about the Mercury Advance SMARTcare solution (Q69 and Q70).

Four barriers were identified. Some participants said that a dynamic mattress with configurable settings felt more comfortable than a hybrid mattress (Q64). The performance of appliances, such as the wireless network, needs to function sufficiently for the app to run properly (Q71 and Q72). At times, there was no access to devices compatible with the app. Participants described the adoption of a personal smartphone as undesirable, which can be considered a barrier (Q75 and Q76). Finally, the adoption of the system requires effort and time, which are not always available (Q77 and Q78).

Discussion

Principal Findings

This study found 13 factors that could hamper or support the adoption of the Mercury Advance SMARTcare solution. Factors from four overarching themes were included: (1) factors specifically related to SMARTresponse, (2) vision on innovation, (3) match with health care activities, and (4) materials and resources involved. Factors were often identified as either a facilitator or a barrier, but occasionally a factor was identified as both. This was the case with the following factors: *patient involvement*, *implementation engagement*, *time consuming*, *accessibility to devices compatible for the app*, and *comfort*. *Signaling function*, *SMARTresponse as prevention*, *patient category*, *representatives*, and *implementation strategy* were identified as facilitators. *Perception toward patient repositioning*, *accessibility to pressure injury aids*, and *connectivity* were identified as barriers.

This explorative study identified several factors that seem to influence the adoption of the Dyna-Form SMARTresponse app, according to the expectations of health care workers. The Mercury Advance SMARTcare solution could help support health care workers in their daily practices as a preventive aid with certain conditions in mind.

Patient involvement may serve as a facilitator, which was unknown according to the brochure for the Mercury Advance SMARTcare solution [8]. Therefore, patients need to be involved in the training aspect of the system whenever this is possible.

Before the implementation of the system is commenced, preliminary conditions apply. A guideline specifying the patient category or facility for which the system is suitable is needed. Health care workers are required to have and be able to operate a smartphone or tablet; otherwise, the app cannot be operated. Finally, the wireless network must function properly to make the app run smoothly and, as a result, reduce the risk of health care workers feeling agitated about the performance of the app.

Whenever the system is adopted in health care settings, training the health care workers is an important aspect of enhancing the success rate. Representatives from a specific area of interest need to engage more in training to ultimately support other health care workers and to act as an early adopter. Practical training in which the health care workers can experiment with the Mercury Advance SMARTcare solution could enhance the proportion in which the health care workers will adopt the system.

Although this study has identified barriers and facilitators that can hamper or support the adoption of the Mercury Advance SMARTcare solution, a knowledge gap still remains regarding health care workers who work in home care nursing, as these workers were not included in the study population. Therefore, more research on health care workers working in home care nursing is necessary to acknowledge the findings of this study. Subsequently, an implementation project is recommended for the promotion of the app in health care facilities and to determine its effectiveness regarding pressure injury prevention.

Comparison to Prior Work

During the analyses, similarities were observed between the subthemes and the diffusion of innovation theory [19]. This theory describes five categories of adopters in the context of technological adoption: (1) technology enthusiasts, (2) visionaries, (3) pragmatists, (4) conservatives, and (5) skeptics. The theme *vision on innovation* demonstrates the participants' preconceptions of digital technology and their views on the adoption of the SMARTresponse app. A division was observed among the participants, with some being obvious skeptics and others appearing to be visionaries or technology enthusiasts. In addition, the diffusion process among colleagues, as explained by the participants, clearly emerged from the data. Most participants reported that enthusiastic colleagues or representatives play a crucial role in the adoption process of a new product, practice, or idea.

Several studies have investigated the adoption of sensors to detect patient movement and increase adherence to patient repositioning protocols [20-23]. All studies reported that adherence to turning protocols increased whenever a sensor was adopted in intensive care units. According to the study by Yap et al [23], participants expressed satisfaction with the monitoring system and recommended improvements to support the adoption and use of technology. Our study included participants working at hospitals, psychiatric wards, and a rehabilitation center, which are considerably different from an intensive care unit. Moreover, the patient sensors that were adopted in the previous studies [20-23] are not comparable with the Mercury Advance SMARTcare solution, which uses a control unit to detect patient movement. However, qualitative outcome measures from a previous study [23] are in line with the findings of this study, and quantitative measures from previous studies [20-23] suggest that health care workers' awareness of a patient's movement or nonmovement increases when sensors are adopted.

Strengths and Limitations

An important strength of this study was the inclusion of 4 tissue viability nurses and 1 physiotherapist instead of nurses only. All these health care workers worked with pressure injury aids and cared for patients with pressure injuries on a regular basis. That is how it was possible to identify an extensive scope of perspectives from health care workers with different opinions regarding pressure injury prevention and treatment. An additional factor was identified during the analysis of the 12th transcript, with data saturation not being confirmed at first. For that reason, 2 more individual interviews were conducted to confirm data saturation and identify themes and factors regarding the first 12 transcripts. Furthermore, preliminary findings were presented repeatedly in a research group with experienced researchers, which enhanced the confirmability of the findings [13].

This study also has limitations. The initial interview with participant 1 had a duration of 32 minutes, which is relatively short compared to the other interviews. However, the subthemes identified in the first interview were also present in the other interviews. Although the occupational sites are considered heterogeneous, home care nursing was not incorporated as a study population site. Therefore, the perspectives of health care workers who work in home care are not incorporated in this study, despite them being an interest group according to the National Pressure Injury Advisory Panel [24]. Furthermore, in focus groups, participants may not contribute equally, leaving opinions and views on a specific topic undiscovered. When conducting focus groups in addition to individual interviews, different concepts might have been identified compared to individual interviews alone. However, we believe that conducting individual interviews felt inaccurate in this exploratory study because participant interactions would not have been revealed. Finally, the data collection for this study was conducted by a novice researcher (JS) with limited experience in qualitative research. To overcome this limitation, a second researcher with noticeable experience in qualitative research checked the first transcripts of the recorded interviews to confirm content validity.

Conclusions

This study explored the expectations of factors that could hamper or support the adoption of the Mercury Advance SMARTcare unit connected to a Mercury Advance mattress to prevent patients from developing pressure injuries in hospitals and long-term care facilities. The system is developed to support health care workers in their daily practices, especially as a preventive aid and due to its signaling function. However, several conditions need to be met to enhance the adoption of the system, such as guidelines concerning adherence to patient repositioning, the engagement of representatives in training, and a reliable wireless network. The factors identified in this study can be used to facilitate the implementation process and adoption of the Mercury Advance SMARTcare solution and to help provide quality care to patients who are at risk of developing pressure injuries.

Acknowledgments

The authors would like to thank Remco Mexsenaar, Product Specialist of Direct Healthcare Group, for the initial contact with centers to support the recruitment of participants, and Dr Hetty Ockhuijsen for her assistance in designing and constructing the study protocol.

Data Availability

The data sets generated during and analyzed during this study are not publicly available since the participants of this study did not provide written consent for their data to be shared publicly.

Authors' Contributions

JS contributed to conceptualization, writing the original draft, data curation, formal analysis, investigation, methodology, project administration, and visualization. TvH contributed to conceptualization, reviewing and editing the manuscript, data curation, formal analysis, investigation, methodology, project administration, and supervision. HSMK contributed to conceptualization, methodology, reviewing and editing the manuscript, and supervision.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Themes (bold), subthemes (underlined), and related factors (italics) regarding the Dyna-Form SMARTresponse app. Some factors were related to multiple themes or subthemes.

[PNG File , 182 KB - nursing_v7i1e47992_app1.png]

Multimedia Appendix 2

Barriers and facilitators regarding the Dyna-Form SMARTresponse app.

[DOCX File , 28 KB - nursing_v7i1e47992_app2.docx]

References

1. Ritchie H, Roser M. Age structure. Our World in Data. 2019. URL: https://ourworldindata.org/age-structure [accessed 2023-02-18]
2. Dattani S, Rodés-Guirao L, Ritchie H, Ortiz-Ospina E, Roser M. Life expectancy. Our World in Data. 2023. URL: https://ourworldindata.org/life-expectancy#article-citation [accessed 2023-02-18]
3. Nursing and midwifery. World Health Organization. 2022 Mar 18. URL: https://www.who.int/news-room/fact-sheets/detail/nursing-and-midwifery [accessed 2023-02-18]
4. Pressure injury fact sheet. National Pressure Injury Advisory Panel. URL: https://npiap.com/store/ViewProduct.aspx?id=14427618 [accessed 2023-02-18]
5. Redelings MD, Lee NE, Sorvillo F. Pressure ulcers: more lethal than we thought? Adv Skin Wound Care 2005 Sep;18(7):367-372 [FREE Full text] [doi: 10.1097/00129334-200509000-00010] [Medline: 16160463]
6. McInnes E, Jammali-Blasi A, Bell-Syer SE, Leung V. Support surfaces for treating pressure ulcers. Cochrane Database Syst Rev 2018 Oct 11;10(10):CD009490 [FREE Full text] [doi: 10.1002/14651858.CD009490.pub2] [Medline: 30307602]
7. Fletcher J, Tite M, Clark M. Real - world evidence from a large - scale multisite evaluation of a hybrid mattress. Wounds UK 2016;12(3):54-61.
8. Mercury advance SMARTcare. Direct Healthcare Group. URL: https://www.directhealthcaregroup.com/products/mercury-advance-smartcare/ [accessed 2024-02-28]
9. Mathijssen E, de Lange W, Bleijenberg N, van Houwelingen T, Jaarsma T, Trappenburg J, et al. Factors that influence the use of eHealth in home care: scoping review and cross-sectional survey. J Med Internet Res 2023 Mar 09;25:e41768 [FREE Full text] [doi: 10.2196/41768] [Medline: 36892935]
10. Michie S, Richardson M, Johnston M, Abraham C, Francis J, Hardeman W, et al. The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions. Ann Behav Med 2013 Aug;46(1):81-95 [FREE Full text] [doi: 10.1007/s12160-013-9486-6] [Medline: 23512568]

11. Cyr J. The pitfalls and promise of focus groups as a data collection method. Sociol Method Res 2015 Feb 05;45(2):231-259. [doi: 10.1177/0049124115570065]
12. Boeije HR. Analysis in Qualitative Research. Thousand Oaks, CA: SAGE Publications; 2009.
13. Holloway I, Wheeler S. Qualitative Research in Nursing and Healthcare 3rd Edition. Hoboken, NJ: John Wiley & Sons; 2009.
14. Braun V, Clarke V. Is thematic analysis used well in health psychology? a critical review of published research, with recommendations for quality practice and reporting. Health Psychol Rev 2023 Dec;17(4):695-718 [FREE Full text] [doi: 10.1080/17437199.2022.2161594] [Medline: 36656762]
15. Data protection in the EU. European Commission. URL: https://commission.europa.eu/law/law-topic/data-protection/data-protection-eu_en [accessed 2023-02-18]
16. WMA declaration of Helsinki – ethical principles for medical research involving human subjects. World Medical Association. 2022 Sep 6. URL: https://www.wma.net/policies-post/wma-declaration-of-helsinki-ethical-principles-for-medical-research-involving-human-subjects/ [accessed 2023-02-18]
17. Your research: is it subject to the WMO or not? Central Committee on Research Involving Human Subjects. URL: https://english.ccmo.nl/investigators/legal-framework-for-medical-scientific-research/your-research-is-it-subject-to-the-wmo-or-not [accessed 2023-02-18]
18. Onderzoeksdata opslaan/delen met research drive. Digitale Hu. 2020 Jun 25. URL: https://husite.nl/digitalehu/onderzoeksdata-opslaan-en-delen-met-research-drive/ [accessed 2023-02-18]
19. Dearing JW, Cox JG. Diffusion of innovations theory, principles, and practice. Health Aff (Millwood) 2018 Feb;37(2):183-190. [doi: 10.1377/hlthaff.2017.1104] [Medline: 29401011]
20. Pickham D, Berte N, Pihulic M, Valdez A, Mayer B, Desai M. Effect of a wearable patient sensor on care delivery for preventing pressure injuries in acutely ill adults: a pragmatic randomized clinical trial (LS-HAPI study). Int J Nurs Stud 2018 Apr;80:12-19 [FREE Full text] [doi: 10.1016/j.ijnurstu.2017.12.012] [Medline: 29331656]
21. Renganathan BS, Nagaiyan S, Preejith SP, Gopal S, Mitra S, Sivaprakasam M. Effectiveness of a continuous patient position monitoring system in improving hospital turn protocol compliance in an ICU: a multiphase multisite study in India. J Intensive Care Soc 2019 Nov;20(4):309-315 [FREE Full text] [doi: 10.1177/1751143718804682] [Medline: 31695735]
22. Schutt SC, Tarver C, Pezzani M. Pilot study: assessing the effect of continual position monitoring technology on compliance with patient turning protocols. Nurs Open 2018 Jan;5(1):21-28 [FREE Full text] [doi: 10.1002/nop2.105] [Medline: 29344391]
23. Yap TL, Kennerly SM, Ly K. Pressure injury prevention: outcomes and challenges to use of resident monitoring technology in a nursing home. J Wound Ostomy Continence Nurs 2019 May;46(3):207-213 [FREE Full text] [doi: 10.1097/WON.0000000000000523] [Medline: 31083063]
24. Pressure injury prevention points. National Pressure Injury Advisory Panel. URL: https://npiap.com/page/PreventionPoints [accessed 2023-02-18]

Abbreviations

COM-B: capability, opportunity, motivation, and behavior
DHG: Direct Healthcare Group

Edited by E Borycki; submitted 07.04.23; peer-reviewed by R Eckhoff, Y Chen; comments to author 17.02.24; revised version received 04.03.24; accepted 04.03.24; published 18.04.24.

Please cite as:
Slob J, van Houwelingen T, Kort HSM
Health Care Workers' Expectations of the Mercury Advance SMARTcare Solution to Prevent Pressure Injuries: Individual and Focus Group Interview Study
JMIR Nursing 2024;7:e47992
URL: https://nursing.jmir.org/2024/1/e47992
doi:10.2196/47992
PMID:38635323

Unobtrusive Nighttime Movement Monitoring to Support Nursing Home Continence Care: Algorithm Development and Validation Study

Hannelore Strauven[1], PhD; Chunzhuo Wang[1], PhD; Hans Hallez[2], Prof Dr; Vero Vanden Abeele[3], Prof Dr; Bart Vanrumste[1], Prof Dr

[1]e-Media Research Lab/STADIUS, Department of Electrical Engineering, KU Leuven, Andreas Vesaliusstraat 13, Leuven, Belgium
[2]Research Group M-Group/DistriNet, Department of Computer Science, KU Leuven, Brugge, Belgium
[3]e-Media Research Lab/Human-Computer Interaction, Department of Computer Science, KU Leuven, Leuven, Belgium

Corresponding Author:
Hannelore Strauven, PhD
e-Media Research Lab/STADIUS, Department of Electrical Engineering, KU Leuven, Andreas Vesaliusstraat 13, Leuven, Belgium

Abstract

Background: The rising prevalence of urinary incontinence (UI) among older adults, particularly those living in nursing homes (NHs), underscores the need for innovative continence care solutions. The implementation of an unobtrusive sensor system may support nighttime monitoring of NH residents' movements and, more specifically, the agitation possibly associated with voiding events.

Objective: This study aims to explore the application of an unobtrusive sensor system to monitor nighttime movement, integrated into a care bed with accelerometer sensors connected to a pressure-redistributing care mattress.

Methods: A total of 6 participants followed a 7-step protocol. The obtained dataset was segmented into 20-second windows with a 50% overlap. Each window was labeled with 1 of the 4 chosen activity classes: in bed, agitation, turn, and out of bed. A total of 1416 features were selected and analyzed with an XGBoost algorithm. At last, the model was validated using leave one subject out cross-validation (LOSOCV).

Results: The trained model attained a trustworthy overall F_1-score of 79.56% for all classes and, more specifically, an F_1-score of 79.67% for the class "Agitation."

Conclusions: The results from this study provide promising insights in unobtrusive nighttime movement monitoring. The study underscores the potential to enhance the quality of care for NH residents through a machine learning model based on data from accelerometers connected to a viscoelastic care mattress, thereby driving progress in the field of continence care and artificial intelligence–supported health care for older adults.

(JMIR Nursing 2024;7:e58094) doi:10.2196/58094

KEYWORDS

nursing home; agitation; incontinence; accelerometer; unobtrusive; enuresis; sensor technology

Introduction

Background

With the increase in life expectancy, there is a corresponding rise in the prevalence of urinary incontinence (UI), a common health problem among older adults [1]. Studies have indicated that UI affects over 50% of older adults residing in nursing homes (NHs) [2-4]. Current care practices for managing UI in NHs involve incontinence wear (ie, disposable absorbent products), with or without scheduled toilet visits (voiding) [5]. Unfortunately, these practices often lead to redundant checks and delayed interventions, thereby triggering undesirable consequences, such as disturbed sleep patterns [6]. Despite its significant impact for residents' health and overall quality of life, along with the increased burden it places on care personnel and noteworthy financial implications, UI remains underdiagnosed and its management underreported [7].

In a recent scoping review conducted by Omotunde and Wagg [8], authors found encouraging outcomes regarding technology-driven continence care with a majority of solutions incorporating sensor technology integrated into body-worn disposable absorbent products (colloquially referred to as "smart diapers"). These smart diapers offer feedback regarding saturation levels and are capable of identifying instances of leakage [9]. Complementary software apps are used to collate these data and generate insightful information and reminders intended for care personnel.

The introduction of technology-based continence care within NHs, facilitated by the use of smart diapers, holds the potential to monitor voiding processes and allows for timely product changes [10]. By embracing such advancements, NHs could potentially improve the quality of care delivered to residents with UI.

The technology, however, comes with significant expenses, with an initial installation and training cost up to US $3300, combined with an additional charge of up to US $3.50 per diaper for the incontinence wear [11]. Consequently, smart diapers are mainly used for a short period of time (ie, 3 days) to establish a personalized continence care plan of the resident [10,12]. Furthermore, the use of smart diapers is intrinsically linked to the use of continence wear, limiting the ability to monitor UI patterns exclusively during periods when these absorbent products are worn. This contrasts with the research findings of Ostaszkiewicz et al [13], which emphasized the urgent need for independent resources, for example, technology, to inform decision-making regarding continence wear.

Moreover, previous research [14] underlined the significance of developing technology solutions that exhibit sensitivity toward issues of intimacy, stigma, and taboo inherent in continence care to preserve the NH residents' dignity and overall quality of life. In light of this perspective, the design of a monitoring system for NHs should prioritize unobtrusiveness, discreteness, and compatibility with appropriate care equipment.

Prior research has explored monitoring nighttime movement and identifying sleep-related disorders or sleep stages via the use of unobtrusive sensor systems equipped with accelerometer or pressure sensors, connected to beds [15-18]. However, only a limited number of researchers have directed the focus of nighttime movement monitoring with accelerometer sensors connected to the bed toward the exploration of detecting nighttime movement to support NH continence care. These few studies [19-21] are listed in Table 1 and are further detailed in the section *Prior Work*.

Table . Overview of unobtrusive accelerometer sensor systems evaluated to monitor nighttime agitation with a relation to continence care, summarizing the number of participants (p) and location of the study setup, the sensor position on the mattress, and the algorithm deployed for data analysis.

Authors and study	Study setup	Sensor position (mattress)	Algorithm
Gong et al [19]	12 p at home	Top and bottom + wristbands	Cole's actigraphy [22] and STFT[a] [23]
T'Jonck et al [20]	4 p at home	Top	CNN[b]
T'Jonck et al [21]	1 p in lab	Bottom	FFT[c] and CNN

[a] STFT: short-time Fourier transform.

[b] CNN: convolutional neural network.

[c] FFT: fast Fourier transform.

Prior Work

Gong et al [19] monitored nighttime movement and incontinence in patients with Alzheimer disease. Their study encompassed 12 participants in a home environment. Wetness events were monitored via the wireless bed-wetting alarm system DryBuddy [24]. The system used two triaxial accelerometer sensors, positioned on the upper and lower sides of the mattress. They applied Cole's actigraphy algorithm [22] on the sensor data to estimate wake and sleep periods. Two additional accelerometer sensors [25] were strapped to both wrists of participants to monitor hand movements. For the nighttime sleep agitation assessment, they calculated a short-time Fourier transform [23], based on a combined dataset from the bed sensors data and wrists' nodes data, to indicate agitation.

The authors established that almost half (49%) of the sleep agitation events occurred before a voiding event, supporting the observation that a need to void can trigger agitation. However, authors did not provide evaluation metrics for the used algorithm, nor differentiated multiple nighttime activities.

In another study, T'Jonck et al [20] deployed a smartphone-integrated triaxial accelerometer, which was placed in 4 different positions on the mattress. Their study encompassed 4 participants within a home setting, using a convolutional neural network (CNN) approach for nighttime activity tracking (ie, none, sit down, lay down, sit up, and stand up). When including all sensor positions in the model, an accuracy (ie, the ratio of correct predictions to the total number of predictions [26]) of 92% was reached. Unfortunately, authors did not further elaborate on these different positions.

In a subsequent study of T'Jonck et al [21], the smartphone was substituted with an triaxial accelerometer sensor, positioned on the bottom surface of the mattress. This evaluation was conducted with one participant within a laboratory environment, and activity tracking (ie, none, in bed, out of bed, changing position, and agitation) was accomplished via a fast Fourier transform (FFT) model in addition to a CNN-based model. For the model that combines FFT and CNN, an accuracy of 88.96% was achieved, showing the applicability of unobtrusive monitoring of nighttime movement via accelerometer sensors.

Both studies yield outcomes that suggest promise for the detection of agitation and, hence, monitoring nighttime movement. However, Gong et al's [19] system design involved the use of nodes strapped on the participants' wrists, which could be perceived as obtrusive. Furthermore, their study did not include classification metrics to evaluate the used algorithm, hindering a meaningful comparison with alternative system designs.

Conversely, T'Jonck et al [20,21] prioritize an unobtrusive system design in their research, incorporating thorough evaluation metrics for their developed algorithms. Consequently, in their subsequent study, they substitute the smartphone app with a mattress-attached sensor. However, this modified setup is only validated using data from a single participant.

Both studies were conducted in a home environment or explicitly specified the use of a standard bed and mattress, without considering the pressure-redistributing features of care mattresses for care beds. Such a care mattress is composed of a temperature-sensitive cell structure that softens by the heat from an individual's body and molds around the body to distribute pressure efficiently [27]. This means that the individual's weight can spread over a much wider area compared with a conventional mattress. Such a care mattress is frequently used in NHs, as it reduces the risk of pressure ulcers and, thus, is recommended for use among individuals at high risk of developing pressure ulcers [28-30].

Goal of This Study

In this study, we extend the investigation of unobtrusive monitoring with accelerometer sensors positioned on the bottom surface of a pressure-redistributing care mattress. This exploration aims to monitor nighttime movement and detect large body movements, a symptom of nocturnal agitation [31], simulated by 6 adult participants in an experimental setup. Notably, our approach incorporates a care bed with a viscoelastic mattress as used in NH settings, for the purpose of tracking 4 activities: in bed, turn, agitation, and out of bed. Through this methodology, we endeavor to enhance the understanding of the potential of using artificial intelligence tools in advancing the field of NH continence care.

Methods

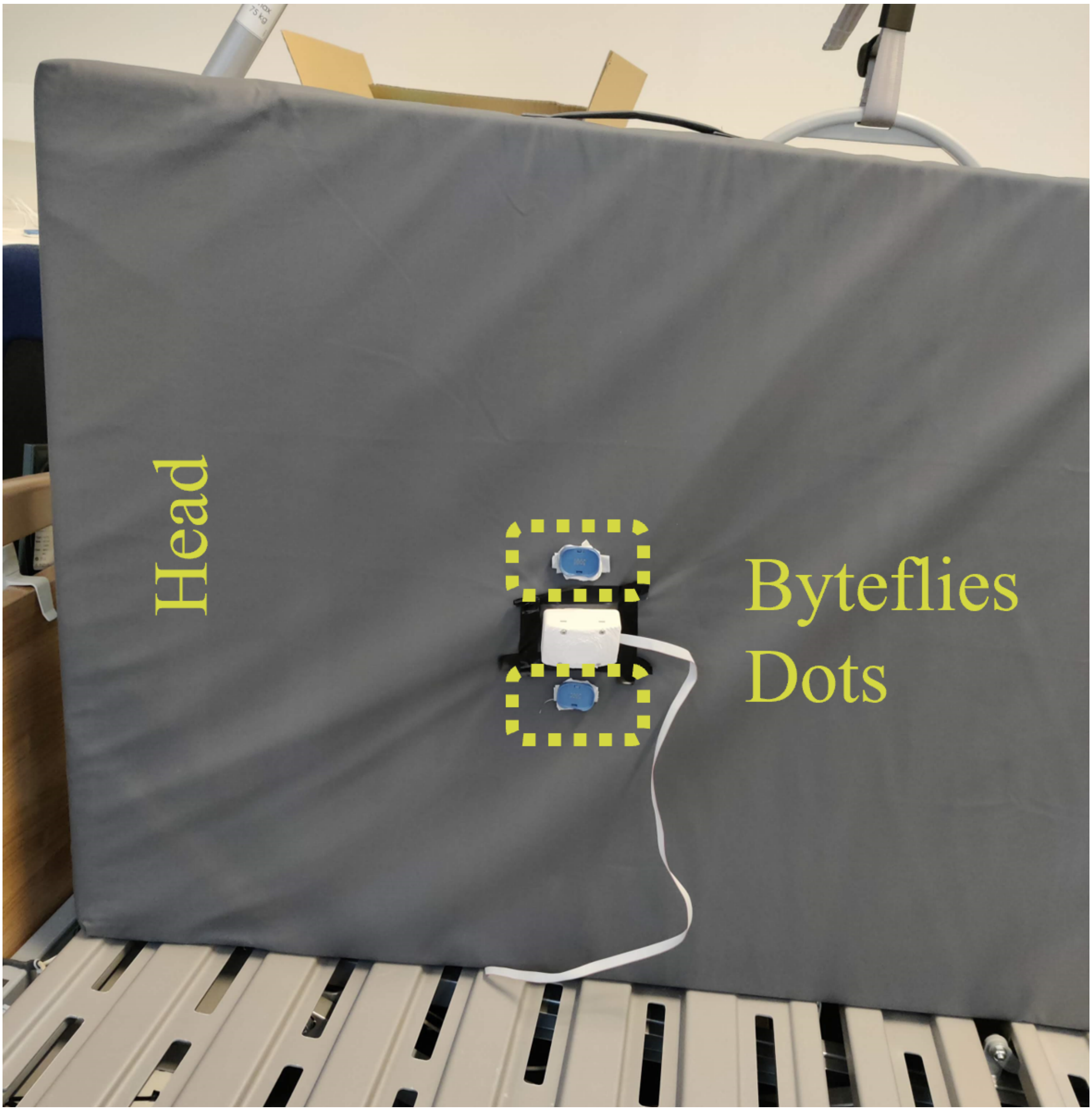
Movement Monitoring System

The movement of the participants was monitored using the Byteflies Kit [32], a medically certified motion monitoring device, with sensor dots. A single sensor dot can record triaxial accelerometer and triaxial gyroscope signals, sampled at 100 Hz. Sensor dots can last 24 hours and are charged via a docking station.

In this measurement, the researchers opted to attach two sensor dots to the bottom side of the mattress on an NH care bed (Figure 1) on the left and right side. The placement of the dots on the mattress aligned with the positioning in a previous study [33]. If a participant lay down on the care bed, the sensor dots were located beneath their back.

The pressure-redistributing care mattress is a Tempur-Med viscoelastic mattress with a width of 14 cm, as commonly used in NHs to reduce pressure ulcers [27].

Figure 1. Photograph of the movement monitoring system attached to the bottom side of the mattress on a nursing home care bed. The position of the two Byteflies sensor dots is circled by a dotted line, with dot 1 positioned on top and dot 2 on the bottom.



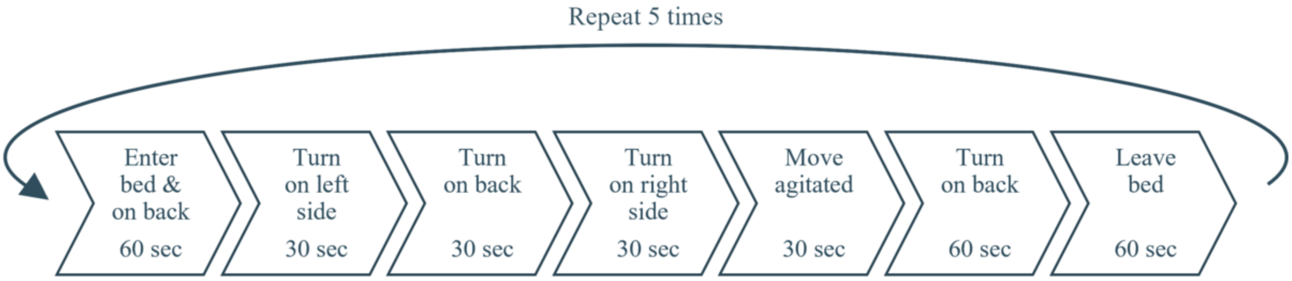
Recruitment

The data acquisition was carried out during the COVID-19 pandemic, from October 2020 until December 2020. NH residents are a frail population and were greatly affected by the adverse health effects of the pandemic. Therefore, we recruited university colleagues who were allowed to travel to campus. Ethical approval to conduct the research was obtained from the KU Leuven Social and Societal Ethics Committee with protocol number G-2020 - 2214. Safety measures as mandated by the national government were applied at all times. Inclusion criteria for participants were individuals 18 years or older, living in Belgium, and being able to participate independently, understanding the purpose and involvement and providing consent. In total, 6 colleagues volunteered their time with a mean age of 29 (SD=4) years, a mean height of 177 (SD=9) cm, and a mean weight of 74 (SD=20) kg. Among the participants, 2 were female, and 4 were male.

Measurement Protocol

The participants were instructed to follow a 7-step protocol outlined in Figure 2 to simulate nighttime movement, including (nocturnal) agitation. To start with step 1, the participants entered the care bed on their back, lying down for 60 seconds. Subsequently, for step 2, they turned onto their left side and waited for 30 seconds. This sequence continued with step 3, involving a return to their back and a 30-second wait, followed by step 4, requiring a turn to their right side with another 30-second interval. In step 5, participants engaged in large body movements for 30 seconds, with the execution left to the participants' interpretation, because the authors could not find a standardized definition or duration for nocturnal agitation in older adults correlated to incontinence. Step 5 was succeeded by step 6, involving lying on their back for 60 seconds. Finally, step 7 required participants to leave the bed for 60 seconds before repeating the entire protocol. Each participant completed the protocol 5 times. A Garmin Venue SQ smartwatch [34] guided the participants through the protocol, providing vibration notifications to prompt transitions between steps.

Figure 2. Illustration of the measurement protocol followed by the participants to monitor their movement.



Data Collection and Analysis

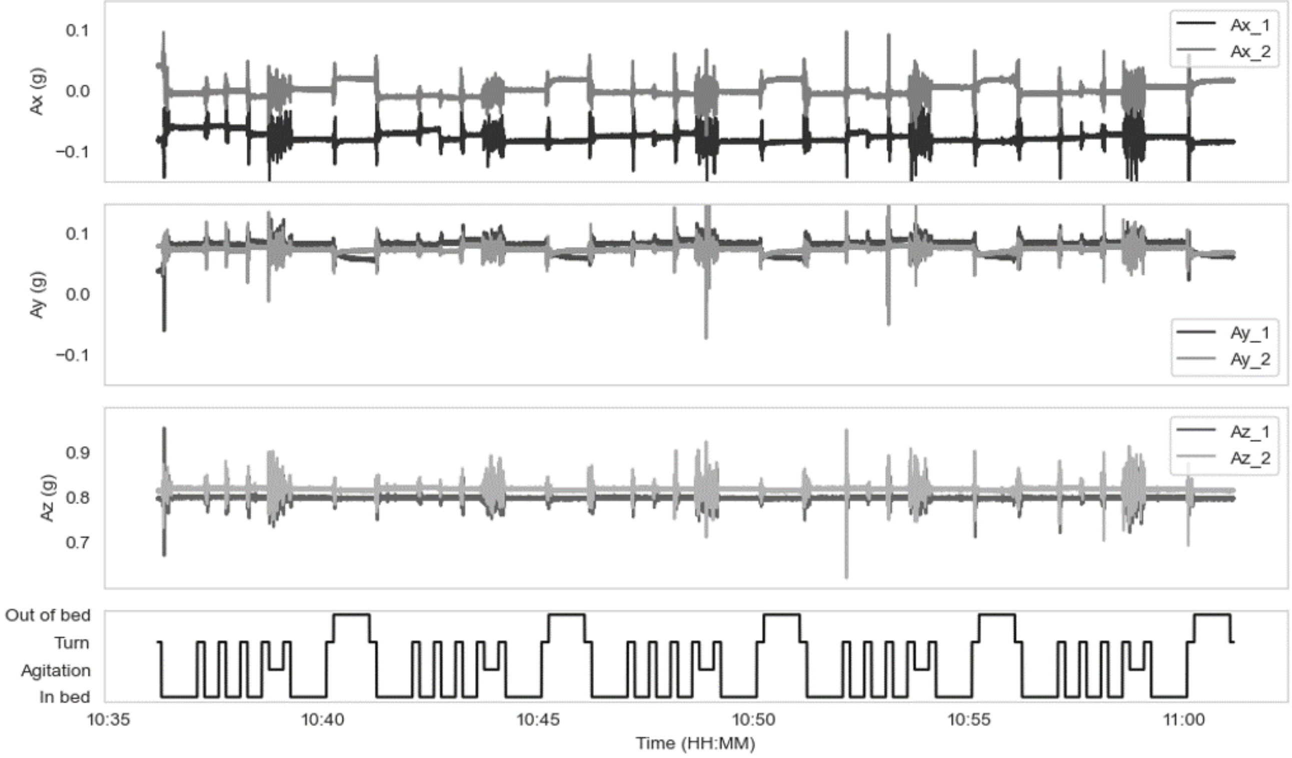
First, relevant settings and hyperparameters to start the data analysis and training process were tuned on the basis of the obtained results. After an exploration to identify the optimal settings, the following configurations were selected.

Signal Preprocessing and Annotation

Figure 3 displays the unfiltered triaxial accelerometer data gathered from the 2 Byteflies dots for participant 2. These data were annotated based on the protocol's time interval. In this preprocessing, the data were also scaled to the unit variance and band-pass filtered. Starting from the filter settings initially outlined by Razjouyan et al [35] and further fine-tuned for our dataset, a fourth-order Butterworth filter was applied with cutoff frequencies at 2 Hz and 10 Hz. At last, the data were categorized into 4 activity classes that are relevant for monitoring with regard to NH (continence) care management:

1. In bed: The bed is occupied, and the participant lies either on their back (steps 1, 3, and 6), left side (step 2), or right side (step 4). For NH residents, activity within this class is considered regular nighttime behavior.
2. Agitation: The bed is occupied, and the participant acts agitated by moving their arms and legs (step 5). For NH residents who need continence care, this agitated movement can be triggered by a voiding event.
3. Turn: The bed is occupied, and the participant transitions from the current step in the protocol to the following step (eg, from turning on the left side in step 2 to turning on the back in step 3). On each occasion in the measurement protocol, the last 5 seconds of the current step and the first 5 seconds of the following step are categorized as a turn. For NH residents, turning is considered to be an effective way of preventing pressure ulcers [36].
4. Out of bed (unoccupied): The bed is unoccupied, as the participant left the bed. This is regular daytime behavior for NH residents.

Figure 3. The unfiltered triaxial acceleration (Ax, Ay, and Az) in gravity (g) in time of two Byteflies dots for participant 2 for a complete measurement protocol. Beneath this sensor data, the signal is categorized into 4 activity classes.



Sliding Window

A sliding window was applied on the dataset and the selected window size was 20 seconds with 50% overlapping for a sampling frequency of 100 Hz. If there were multiple classes present within one window, the window was annotated as the majority class.

Feature Extraction and Selection

To extract features from the segmented time series dataset, the Time Series Feature Extraction Library Python package was selected [37]. Time Series Feature Extraction Library is an automated process of feature extraction, designed to accelerate the time consuming and complex exploratory analysis of multidimensional time series. The library computes over 60 different parameters across temporal, statistical, and spectral domains. Out of the computed set of 4668 features, a refined subset of 1416 features was derived after eliminating correlated and zero-variance features. Subsequently, this selected subset was scaled to unit variance.

Machine Learning Algorithm

On the basis of the selected features and obtained results in the training process, the scalable end-to-end tree extreme gradient boosting system, XGBoost, was used to train the model for the classification task at hand [38]. It is an open-source Python package that implements gradient boosting and tree learning paralleling, effective in applications with limited data and in human activity recognition, including older adults [38-41]. The hyperparameters of the XGBoost algorithm were optimally adapted to obtain a robust and accurate model. SHAP (Shapley additive explanations) TreeExplainer was used as the explanation method for the model's output, providing fast local explanations with guaranteed consistency [42].

Model Training and Evaluation

To evaluate the model, leave one subject out cross-validation (LOSOCV) was used. This statistical technique divides the original dataset into a training and validation set, alternating between them in successive rounds and ensuring each data point undergoes validation [43]. Gholamiangonabadi et al [44] demonstrated that LOSOCV serves as a rigid criterion for evaluation models of times series accelerometer data in human activity recognition.

In this study, the process involved 6 iterations and, for each iteration, data from 1 out of the 6 participants was left out as the validation set to train the XGBoost classification model.

Ethical Considerations

Ethical approval to conduct the research was obtained from the KU Leuven Social and Societal Ethics Committee with protocol number G-2020‐2214. All participants were invited to participate voluntarily and received verbal and written information about the study in advance. Each participant signed an informed consent form and was assigned a unique identifier for data processing. The first author kept the names and unique identifiers separately from the obtained study data.

Results

Algorithm Performance

Upon acquisition of data from all participants, the data were processed to assess the effectiveness of the XGBoost model for the task at hand. The validation outcomes are represented in Tables 2 and 3, with the results for the total dataset from two

Byteflies dots at the top and the results split per Byteflies dot at the bottom. In total, the dataset encompasses 898 windows, of which 481 windows (53.56%) were attributed to the class “In bed,” 60 windows (6.68%) to “Agitation,” 207 windows (23.05%) to “Turn,” and 150 windows (16.70%) to “Out of bed.” Because the number of windows per class is not proportional, the dataset can be considered imbalanced.

Table . Overview of the distribution of windows (n and %) per class for the total dataset from two Byteflies dots and the classification metrics precision, recall, and F_1-score (%) per class for the leave one subject out cross-validation of the XGBoost model.

	In bed	Agitation	Turn	Out of bed
Windows, n (%)	481 (53.6)	60 (6.7)	207 (23)	150 (16.7)
Precision (%)	84.32	77.78	69.67	78.95
Recall (%)	86.07	81.67	71.01	70
F_1-score (%)	85.19	79.67	70.33	74.24

Table . Overview of the classification metrics precision, recall, and F1-score (%) per Byteflies dot (d1 and d2) for the leave one subject out cross-validation of the XGBoost model.

	In bed		Agitation		Turn		Out of bed	
	d1	d2	d1	d2	d1	d2	d1	d2
Precision (%)	81.75	77.99	84.13	68.06	71.83	59.46	77.97	80.70
Recall (%)	85.65	85.45	88.33	81.67	73.56	52.88	61.74	61.74
F_1-score (%)	83.65	81.55	86.18	74.24	72.68	55.98	68.91	69.96

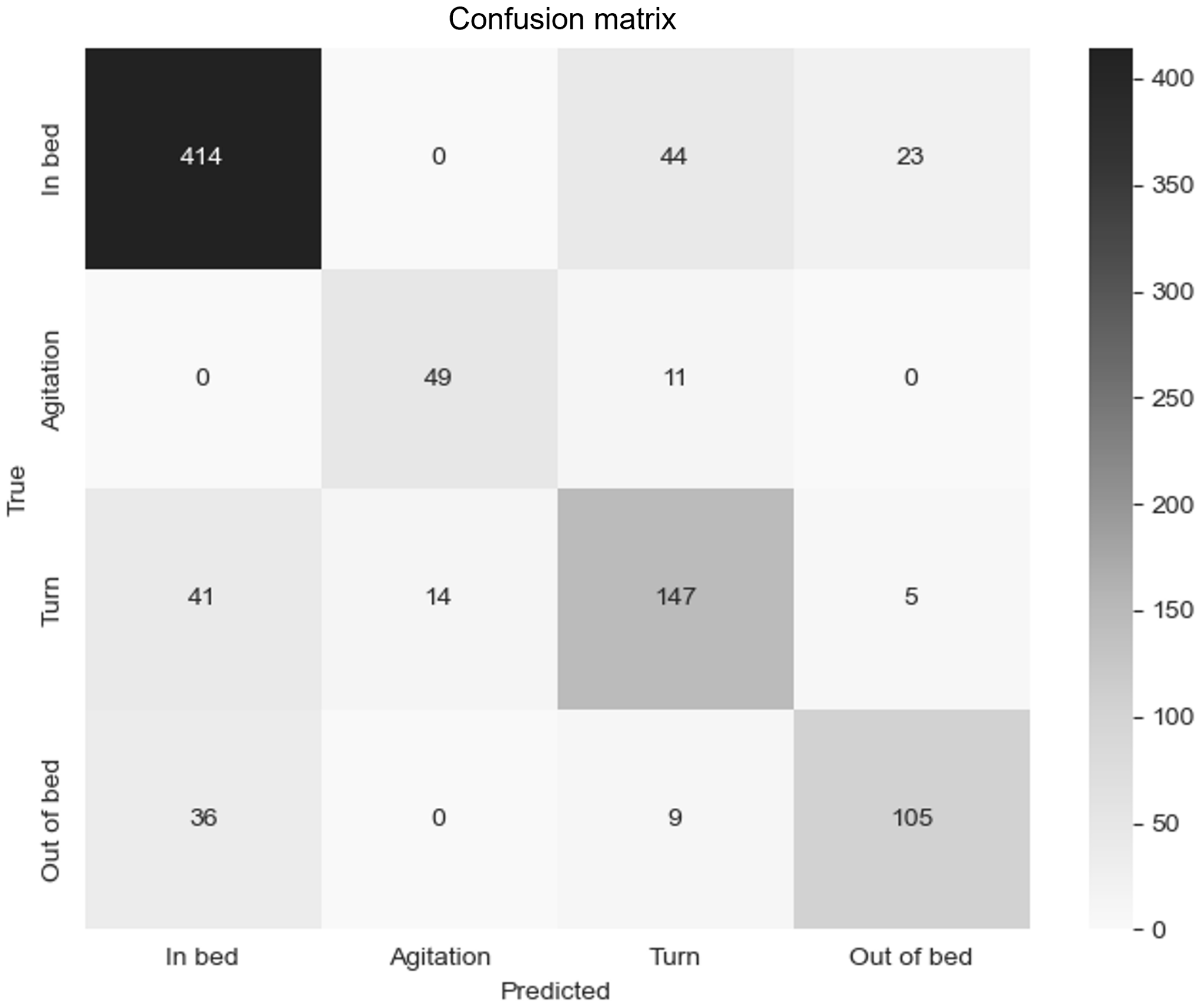
The classification metrics (ie, precision, recall, and F_1-score) listed in Tables 2 and 3 provide a performance assessment of the deployed algorithm. The confusion matrix depicted in Figure 4 illustrates the distribution of the number of windows predicted per class for the total cross-validation dataset from two Byteflies dots. Precision is the measure to tell how many correct positive predictions the model made [26]. It is calculated as the ratio of true positive predictions to the total positive predictions (true and false positive). The class “In bed” attained the highest precision (84.32%) and the model interpreted a few of the windows from the classes “Turn” (41) and “Out of bed” (36) as “In bed.” These are called false positives. The precision for “Agitation” was 77.78% as the model predicted some windows from the class “Turn” as “Agitation” too.

Recall is another classification metric to measure the ratio of correct positive predictions to all actual positives [26]. The recall for the class “In bed” scored the highest (86.07%), and the misclassified windows were predicted as “Turn” (44) or “Out of bed” (23) (false negatives). Also for the “Agitation” class, it was observed that 11 of the incorrectly predicted windows were labeled as “Turn.” Conversely, the incorrect predictions for “Turn” also had a majority of 41 windows in “In bed.” For the class “Out of bed,” the most incorrectly predicted windows were observed in “In bed” (36).

At last, the F_1-score is the harmonic mean or weighted average of precision and recall for a classification problem and especially useful with an imbalanced dataset [26]. The class “In bed” attained the highest overall F_1-score (85.19%) and “Turn” manifested the lowest F_1-score (70.33%).

The results split per Byteflies dot in Table 2, revealed an overall better outcome for dot 1, compared with dot 2, especially for the classes “Agitation” and “Turn.” When combining the data from two dots, the results for the classes “In Bed” and “Out of bed,” improved. In contrast, the results for “Agitation” and “Turn” were higher for dot 1 than combined with the lower result of dot 2.

Figure 4. The confusion matrix of the leave one subject out cross-validation of the XGBoost model, containing data from 2 Byteflies dots, visualizing the number of windows predicted per class.

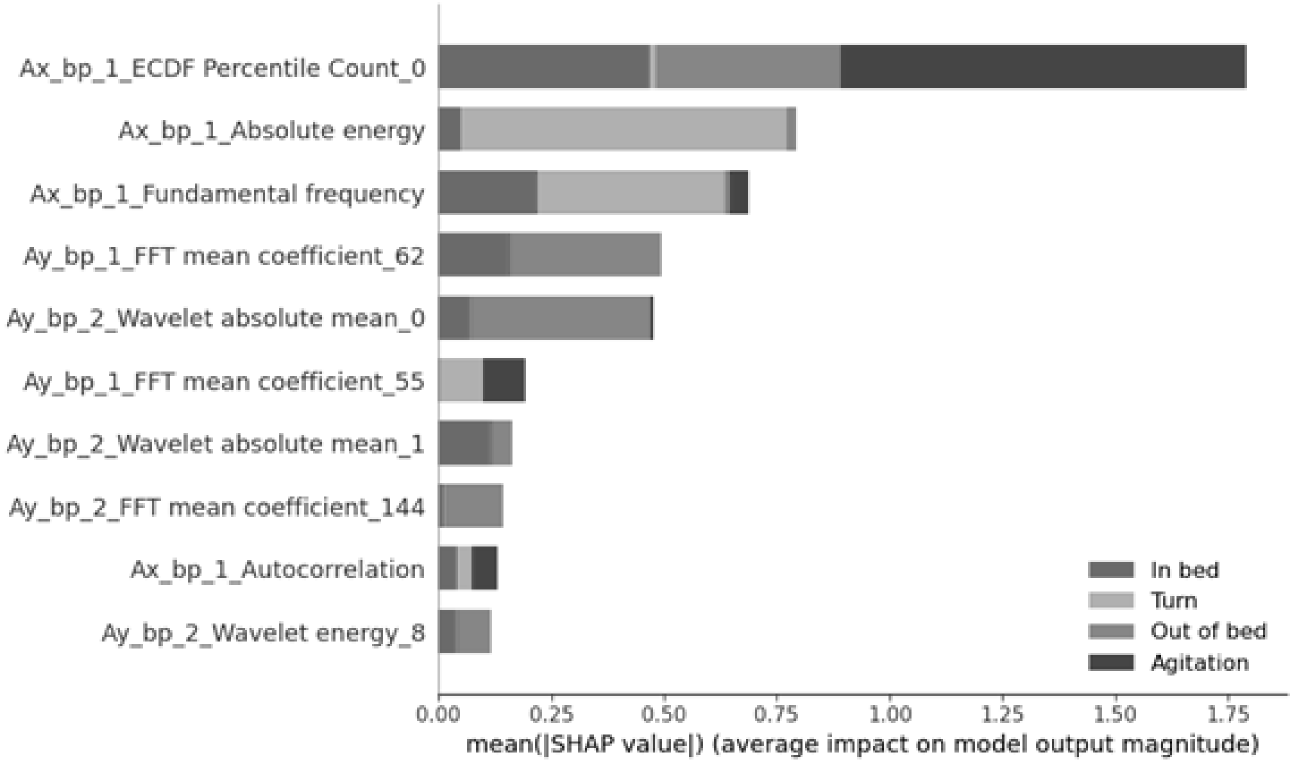


High-Impact Features

Figure 5 illustrates the mean absolute SHAP value per class for the top 10 features with the highest impact on the model predictions. SHAP values use a game-theoretic approach to quantify the contribution of each feature to the machine learning model's outcome [45]. These values assign an importance value to each feature, reflecting how much it influences the final prediction. To specifically elaborate on the tree-based XGBoost model at hand, the TreeExplainer explanation method is used. The name of the feature provides information on the data used to compute the feature: the axis (Ax, Ay, or Az), the applied filter (band-pass), and the sensor dot (1 or 2).

Among the selected features, the "ECDF Percentile Count" computes the cumulative sum of samples falling below the percentile of the empirical cumulative distribution function (ECDF) [37].

Figure 5. The bar plot of the mean absolute Shapley additive explanations values per class for the top 10 features with the highest impact on the XGBoost model's output. The name of the feature provides information on the data used to compute the feature: the acceleration axis (Ax, Ay, or Az), the applied band-pass filter (bp), and the sensor dot (1 or 2). ECDF: Empirical Cumulative Distribution Function; FFT : Fast Fourier Transform.



The ECDF is a simple nonparametric estimator and is obtained by calculating the cumulative probability for each number of unique observations in the data sample less than or equal to a given unique observation x, divided by the total number of observations n (Equation 1) [46,47].

$$(1)\mathrm{ECDF}(x)=(\mathrm{numberofuniqueobservations}\leq xn)$$

Notably, the "ECDF Percentile Count_0" for data along the x-axis of sensor dot 1 computes the cumulative sum of samples falling below the 20th ECDF percentile and significantly impacts the model's output across the three classes "In bed," "Out of bed," and "Agitation." For the class "Turn," the feature "Absolute energy" for data of the x-axis of sensor dot 1, which computes the absolute energy of the signal, has the highest average impact [37]. In addition, 3 features in the plot involve FFT mean coefficients, capturing the mean value of each spectrogram frequency [37]. With a default setting of 256 bins and a sampling frequency of 100 Hz, the bin width is calculated with Equation 2 and is 0.39 Hz. This means that bin 55 corresponds to 21.48 Hz, bin 62 to 24.22 Hz, and bin 144 to 43.68 Hz. The frequency of bin 144 is the same as for bin 112, as only half of the bins are unique in the FFT spectrum of a signal [48].

$$(2)\mathrm{Binwidth}=\mathrm{SamplingfrequencyNumberofbins}=100\mathrm{Hz}256\mathrm{bins}=0.39\mathrm{Hz}$$

Another set of 3 features in the plot relates to continuous wavelet transform (CWT): "Wavelet absolute mean"' computes the CWT absolute mean value for each wavelet scale, while "Wavelet energy" quantifies the CWT energy for each wavelet scale [37]. Importantly, none of the selected features are computed based on z-axis data. Based on the positioning of the sensor dots, the z-axis was directed upwards, from the bottom to the top of the mattress [32].

Leave One Subject Out Cross-Validation

Table 4 presents the weighted F1-score and accuracy for the LOSOCV set per participant, along with the overall result. The accuracy, or the ratio of correct predictions to the total number of predictions [26], is chosen to be able to compare the results with prior work. However, the weighted F1-score is the more appropriate metric here for model validation due to the label imbalance of the dataset, as illustrated in Table 2 and Table 3. The model achieved an overall score of 79.56% for F1-score and 79.62% for accuracy. Participant-specific performance ranged from a minimum F1-score of 69.40% (participant 3) to a maximum of 87.72% (participant 4), and accuracy ranged from 69.33% (participant 3) to 88% (participant 4).

Table . Overview of the weighted F_1-score and accuracy (%) per participant (p) and in total for the leave one subject out cross-validation of the XGBoost model, containing data from two Byteflies dots.

	p1	p2	p3	p4	p5	p6	Total
F_1-score (%)	80.71	79.27	69.40	87.72	77.37	81.67	79.56
Accuracy (%)	80.54	79.33	69.33	88.00	78.00	82.55	79.62

Discussion

Principal Results

The study gained insights into using accelerometer sensors, an XGBoost model, and LOSOCV as an unobtrusive approach for monitoring nighttime movements to support NH continence care, using a viscoelastic care mattress in our setup, which effectively distributes an individual's weight over a broader surface area.

The confusion matrix indicated that the model correctly classified most windows. With an overall F_1-score of 79.56%, and more specifically 79.67% for the class "Agitation," the algorithm developed in this study has attained a high level of trustworthiness. The validation results for each participant revealed a variation in F_1-score of 18.32% among participants. Despite this variability, it is noteworthy that all participants' test outcomes achieved strong model performance. This was particularly remarkable given the considerable differences in weight and height among participants.

A notable observation is applied to the results for class "Turn," where 41 windows are misclassified as "In bed." This misclassification may be attributed to the selected window size of 20 seconds. This window size provided the best overall result during the exploration phase, but is considerably larger than the 10-second duration of a turn in the dataset. Given that the primary emphasis of the study was on the detection of agitation, this misclassification was not deemed as concerning. Another issue arose with the smaller number of misclassifications between "In bed" and "Out of bed." By removing the signal's direct current component with a band-pass filter, the difference between the 2 activities became less visible. Given the importance of being able to accurately determine whether the bed of an NH resident is occupied or not, the sensor system could be enhanced by incorporating additional components, such as a pressure sensor.

In our investigation of feature impact on the output model, the cumulative sum of samples falling below the 20th percentile of the ECDF has a high impact on 3 of the 4 classes: "In bed," "Out of bed," and "Agitation." Interestingly, none of the selected features are computed based on the z-axis data. This suggests that movement in the (inverse) direction from the bottom to the top of the mattress provides less informative input for our classification task.

Upon comparing the outcomes for the individual sensor dots with the combined result, it became evident that using more than one sensor only slightly improved the model's overall performance for 2 out of 4 classes. When learning more about the results per dot for "Agitation," it was observed that only 4 additional windows were misclassified for dot 2, compared with the result for dot 1. Since there was only a limited number of windows for this class, this is immediately notable in a performance assessment. Unfortunately, there was no clear explanation for this discrepancy in the classification.

In practical application, a nighttime movement monitoring system could support (continence) care in NHs by notifying care personnel based on the detected events. In the case of the detected event "In bed," no immediate action from care personnel is required. However, when the system detects "Agitation," care personnel should receive a notification, especially when multiple successive agitation events are identified. For incontinent residents, care personnel could then assess and, if necessary, change the incontinence material. To provide personalized support, the NH would have the flexibility to adjust the threshold for the number of detected events per resident. For the event "Turn," action from care personnel would only be necessary when it occurs infrequently, aimed at preventing decubitus. Here, the frequency could be tailored to each resident. Finally, when "Out of bed" is detected, care personnel should be notified that the resident has left the bed, allowing them to assist the resident back into bed without further complications.

Comparison With Prior Work

Gong et al [19] detected agitation using data from both bed sensors and wristbands for the algorithm, yet the paper lacks detailed precision insights or evaluation metrics for their model to compare with the results of this study.

T'Jonck et al [20,21] achieved a high accuracy (92% and 85%) using FFT and CNN models across various bed sensor setups and participants. Their studies, however, entailed fewer participants and did not use a viscoelastic care mattress.

Notably, the smartphone accelerometer placed on top of the mattress yielded higher accuracy than the bottom placement of the accelerometer sensor, indicating the latter as a more challenging position for movement measurement. Nonetheless, the bottom placement aligns more closely with the goal of developing an unobtrusive system. T'Jonck et al [20,21] also concluded that the accelerometer's position on the bed should not significantly impact the model's ability to classify the data. This is contradictory to our findings, where a difference in performance is recorded between the two Byteflies dots.

Limitations

The dataset of our study is limited, incorporating only 6 iterations (1 per participant). A larger sample size by including more participants in the study could potentially yield improved results.

Another limitation was the absence of NH residents or older adults among the participants. The simulation of large body movements was based on participants' own interpretation, which may not authentically mirror the nocturnal agitation experienced by older adults.

Finally, the study adhered to a protocol designed to simulate nighttime movement. It is essential to note that this simulation differs from real nighttime movement, where lying in a specific posture, turning, or experiencing agitation is not dictated by predefined time intervals and does not necessarily follow a sequential pattern.

Conclusions

This study presented the exploration of accelerometer-based unobtrusive monitoring of nighttime movements to support NH continence care. The XGBoost model combined with an

LOSOCV approach provided valuable insights into activity tracking. The model was able to successfully detect the specified activities with an overall F_1-score of 79.56%.

To gain deeper insights into the developed sensor system and to address its limitations, we recommend conducting a follow-up study in an NH setting. This will enhance the study's external validity by capturing real-world conditions. Incorporating NH residents and monitoring their nighttime behavior present new challenges, including limited bed mobility and the need for transfers.

Acknowledgments

The research was carried out within the imec.icon project DISCRETE that ran from October 1, 2018, to March 31, 2021, and joined forces of commercial partners Televic Healthcare, Corilus, Distrac Group, and the know-how of Zorg Kortrijk and WZC Sint-Bernardus, with the scientific expertise of researchers from van imec-KU Leuven-DISTRINET, imec-KU Leuven STADIUS, and KU Leuven-HCI. The project was funded by Flanders Innovation & Entrepreneurship. This research also acknowledges the project PROCON in the Erasmus+ 2021-2027 program of the European Commission funding (project ID 101185699). We used the generative AI tool ChatGPT by OpenAI [49] to optimize the paper's academic writing.

Conflicts of Interest

None declared.

References

1. Ageing and health. World Health Organization. 2022. URL: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health [accessed 2024-09-24]
2. Offermans MPW, Du Moulin M, Hamers JPH, Dassen T, Halfens RJG. Prevalence of urinary incontinence and associated risk factors in nursing home residents: a systematic review. Neurourol Urodyn 2009;28(4):288-294. [doi: 10.1002/nau.20668] [Medline: 19191259]
3. Jerez-Roig J, Santos MM, Souza DLB, Amaral F, Lima KC. Prevalence of urinary incontinence and associated factors in nursing home residents. Neurourol Urodyn 2016 Jan;35(1):102-107. [doi: 10.1002/nau.22675] [Medline: 25307780]
4. Higami Y, Yamakawa M, Kang Y, et al. Prevalence of incontinence among cognitively impaired older residents in long - term care facilities in East Asia: a cross - sectional study. Geriatr Gerontol Int 2019 May;19(5):444-450. [doi: 10.1111/ggi.13639] [Medline: 30811809]
5. Huion A, De Witte N, Everaert K, Halfens RJG, Schols J. Care dependency and management of urinary incontinence in nursing homes: a descriptive study. J Adv Nurs 2021 Apr;77(4):1731-1740. [doi: 10.1111/jan.14702] [Medline: 33277758]
6. O'Dell KK, Jacelon C, Morse AN. I'd rather just go on as I am'--pelvic floor care preferences of frail, elderly women in residential care. Urol Nurs 2008 Feb;28(1):36-47. [Medline: 18335696]
7. Hillary CJ, Slovak M, McCarthy A, Hashim H, Chapple CR. Recent developments in technology for the assessment and management of incontinence. J Med Eng Technol 2015 Oct 3;39(7):434-440. [doi: 10.3109/03091902.2015.1088088]
8. Omotunde M, Wagg A. Technological solutions for urinary continence care delivery for older adults: a scoping review. J Wound Ostomy Continence Nurs 2023;50(3):227-234. [doi: 10.1097/WON.0000000000000965] [Medline: 36856187]
9. Lin SH, Kajiyama K, Wu T. Smart diaper: how it works. Presented at: Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers; Sep 11-15, 2017; Maui, HI, USA p. 29-132. [doi: 10.1145/3123024.3123167]
10. Rajabali SN, Hunter KF, Asaana P, McCreary ML, Nazari S, Wagg AS. Effectiveness of a smart urinary continence care assessment system for nursing home residents: a quasi-experimental, sequential quantitative-qualitative methods trial. J Wound Ostomy Continence Nurs 2023;50(1):48-56. [doi: 10.1097/WON.0000000000000937] [Medline: 36640164]
11. De Wever N, Clarysse B. De perceptie van Belgische woonzorgcentra op slimme luiers [Master's Dissertation in Dutch]. : Universiteit Gent Faculteit Economie en Bedrijfskunde; 2021 URL: http://lib.ugent.be/catalog/rug01:003010197 [accessed 2024-12-10]
12. Cho JH, Choi JY, Kim NH, et al. A smart diaper system using bluetooth and smartphones to automatically detect urination and volume of voiding: prospective observational pilot study in an acute care hospital. J Med Internet Res 2021 Jul 30;23(7):e29979. [doi: 10.2196/29979] [Medline: 34328427]
13. Ostaszkiewicz J, Tomlinson E, Hutchinson AM. "Dignity": a central construct in nursing home staff understandings of quality continence care. J Clin Nurs 2018 Jun;27(11-12):2425-2437. [doi: 10.1111/jocn.14293] [Medline: 29396885]
14. Strauven H, Spiel K, D'Haeseleer I, Hallez H, Vanrumste B, Vanden Abeele V. From promoting dignity to installing distrust: understanding the role of continence care technology in nursing homes. Presented at: Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society; Oct 25-29, 2020; Tallinn, Estonia p. 1-11. [doi: 10.1145/3419249.3420104]

15. Lokavee S, Tantrakul V, Pengjiam J, Kerdcharoen T. A sleep monitoring system using force sensor and an accelerometer sensor for screening sleep apnea. Presented at: 2021 13th International Conference on Knowledge and Smart Technology (KST); Jan 21-24, 2021; Bangsaen, Chonburi, Thailand p. 208-213. [doi: 10.1109/KST51265.2021.9415835]
16. Nam Y, Kim Y, Lee J. Sleep monitoring based on a tri-axial accelerometer and a pressure sensor. Sensors (Basel) 2016 May 23;16(5):750. [doi: 10.3390/s16050750] [Medline: 27223290]
17. Yi R, Enayati M, Keller JM, Popescu M, Skubic M. Non-invasive in-home sleep stage classification using a ballistocardiography bed sensor. Presented at: 2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI); May 19-22, 2019; Chicago, IL, USA p. 1-4. [doi: 10.1109/BHI.2019.8834535] [Medline: 31849551]
18. Laurino M, Arcarisi L, Carbonaro N, Gemignani A, Menicucci D, Tognetti A. A smart bed for non-obtrusive sleep analysis in real world context. IEEE Access 2020;8(8):45664-45673. [doi: 10.1109/ACCESS.2020.2976194]
19. Gong J, Rose KM, Emi IA, et al. Home wireless sensing system for monitoring nighttime agitation and incontinence in patients with alzheimer's disease. Presented at: Proceedings of the Conference on Wireless Health; Oct 14-16, 2015; Bethesda Maryland. [doi: 10.1145/2811780.2822324]
20. T'Jonck K, Kancharla CR, Hallez H, Boydens J. Accelerometer based activity tracking to support elderly care in nursing homes. Presented at: 2020 XXIX International Scientific Conference Electronics (ET); Sep 16-18, 2020; Sozopol, Bulgaria p. 1-4. [doi: 10.1109/ET50336.2020.9238180]
21. T'jonck K, Kancharla CR, Vankeirsbilck J, Hallez H, Boydens J, Pang B. Real-time activity tracking using tinyml to support elderly care. Presented at: 2021 XXX International Scientific Conference Electronics (ET); Sep 15-17, 2021; Sozopol, Bulgaria p. 1-6. [doi: 10.1109/ET52713.2021.9579991]
22. Cole RJ, Kripke DF, Gruen W, Mullaney DJ, Gillin JC. Automatic sleep/wake identification from wrist activity. Sleep 1992 Oct;15(5):461-469. [doi: 10.1093/sleep/15.5.461] [Medline: 1455130]
23. Hanson MA, Powell HC, Frysinger RC, et al. Teager energy assessment of tremor severity in clinical application of wearable inertial sensors. Presented at: 2007 IEEE/NIH Life Science Systems and Applications Workshop; Nov 8-9, 2007; Bethesda, MD, USA p. 136-139. [doi: 10.1109/LSSA.2007.4400903]
24. Drybuddy. URL: https://drybuddy.com/ [accessed 2024-09-24]
25. Barth AT, Hanson MA, Powell Jr. HC, Lach J. TEMPO 3.1: a body area sensor network platform for continuous movement assessment. Presented at: 2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks; Jun 3-5, 2009; Berkeley, CA, USA p. 71-76. [doi: 10.1109/BSN.2009.39]
26. Grandini M, Bagli E, Visani G. Metrics for multi-class classification: an overview. arXiv. Preprint posted online on Aug 13, 2020. [doi: 10.48550/arXiv.2008.05756]
27. Marino J. Tempur-Med: choosing the correct pressure area care system. Br J Nurs 2001;10(20):1364-1367. [doi: 10.12968/bjon.2001.10.20.9356] [Medline: 11873231]
28. Bai DL, Liu TW, Chou HL, Hsu YL. Relationship between a pressure redistributing foam mattress and pressure injuries: an observational prospective cohort study. PLoS One 2020;15(11):e0241276. [doi: 10.1371/journal.pone.0241276] [Medline: 33166300]
29. Cullum N, McInnes E, Bell-Syer SEM, Legood R. Support surfaces for pressure ulcer prevention. Cochrane Database Syst Rev 2004(3):CD001735. [doi: 10.1002/14651858.CD001735.pub2] [Medline: 15266452]
30. Defloor T. The effect of position and mattress on interface pressure. Appl Nurs Res 2000 Feb;13(1):2-11. [doi: 10.1016/s0897-1897(00)80013-0] [Medline: 10701278]
31. Lopez R, Micoulaud-Franchi JA, Peter-Derex L, Dauvilliers Y. Nocturnal agitation: from sleep state dissociation to sleep-related dissociative state. Rev Neurol (Paris) 2023 Oct;179(7):675-686. [doi: 10.1016/j.neurol.2023.07.003] [Medline: 37625976]
32. Byteflies. URL: https://byteflies.com/ [accessed 2024-09-24]
33. Strauven H, D'Haeseleer I, T'Jonck K, et al. Towards an ambient support system for continence management in nursing homes: an exploratory study. Presented at: 13th International Conference on Health Informatics; Feb 24-26, 2020; Valletta, Malta p. 438-446. [doi: 10.5220/0008963404380446]
34. Garmin Venu® Sq. Garmin. URL: https://www.garmin.com/en-US/p/707174 [accessed 2024-09-24]
35. Razjouyan J, Lee H, Parthasarathy S, Mohler J, Sharafkhaneh A, Najafi B. Improving sleep quality assessment using wearable sensors by including information from postural/sleep position changes and body acceleration: a comparison of chest-worn sensors, wrist actigraphy, and polysomnography. J Clin Sleep Med 2017 Nov 15;13(11):1301-1310. [doi: 10.5664/jcsm.6802] [Medline: 28992827]
36. Defloor T, De Bacquer D, Grypdonck MHF. The effect of various combinations of turning and pressure reducing devices on the incidence of pressure ulcers. Int J Nurs Stud 2005 Jan;42(1):37-46. [doi: 10.1016/j.ijnurstu.2004.05.013] [Medline: 15582638]
37. Barandas M, Folgado D, Fernandes L, et al. TSFEL: Time Series Feature Extraction Library. SoftwareX 2020 Jan;11(11):100456. [doi: 10.1016/j.softx.2020.100456]
38. Chen T, Guestrin C. XGBoost: a scalable tree boosting system. Presented at: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining; Aug 13-17, 2016; San Francisco, CA, USA p. 785-794. [doi: 10.1145/2939672.2939785]

39. Ambati LS, El-Gayar O. Human activity recognition: a comparison of machine learning approaches. J Midwest Assoc Inf Syst 2021(1):49-60. [doi: 10.17705/3jmwa.000065]
40. Wu Y, Qi S, Hu F, Ma S, Mao W, Li W. Recognizing activities of the elderly using wearable sensors: a comparison of ensemble algorithms based on boosting. Sensor Review 2019 Nov 18;39(6):743-751. [doi: 10.1108/SR-11-2018-0309]
41. Cahoolessur DK, Rajkumarsingh B. Fall detection system using XGBoost and IoT. R&D Journal 2020. [doi: 10.17159/2309-8988/2020/v36a2]
42. Lundberg SM, Erion G, Chen H, et al. From local explanations to global understanding with explainable AI for trees. Nat Mach Intell 2020 Jan;2(1):56-67. [doi: 10.1038/s42256-019-0138-9] [Medline: 32607472]
43. Refaeilzadeh P, Tang L, Liu H. Cross-validation. In: Liu L, Özsu MT, editors. Encyclopedia of Database Systems: Springer; 2009:532-538. [doi: 10.1007/978-0-387-39940-9_565]
44. Gholamiangonabadi D, Kiselov N, Grolinger K. Deep neural networks for human activity recognition with wearable sensors: leave-one-subject-out cross-validation for model selection. IEEE Access 2020;8:133982-133994. [doi: 10.1109/ACCESS.2020.3010715]
45. Lundberg SM, Lee SI. A unified approach to interpreting model predictions. In: Guyon I, Luxburg UV, Bengio S, et al, editors. Advances in Neural Information Processing Systems: Curran Associates, Inc; 2017.
46. Castro R. Lecture 1-introduction and the empirical CDF. Rui Castro. 2013. URL: https://www.win.tue.nl/~rmcastro/AppStat2013/files/lecture1.pdf [accessed 2024-09-24]
47. Brownlee J. How to use an empirical distribution function in Python. Machine Learning Mastery. 2020. URL: https://machinelearningmastery.com/empirical-distribution-function-in-python [accessed 2024-09-24]
48. Schneider P, Xhafa F. Data stream processing: models and methods. In: Anomaly Detection and Complex Event Processing over IoT Data Streams: Elsevier; 2022:29-47. [doi: 10.1016/B978-0-12-823818-9.00012-2]
49. ChatGPT. URL: https://openai.com/chatgpt [accessed 2023-09-24]

Abbreviations

CNN: convolutional neural network
CWT: continuous wavelet transform
ECDF: empirical cumulative distribution function
FFT: fast Fourier transform
LOSOCV: leave one subject out cross-validation
NH: nursing home
SHAP: Shapley additive explanations
UI: urinary incontinence

Edited by E Borycki; submitted 06.03.24; peer-reviewed by A Wagg, S Mao; revised version received 09.09.24; accepted 23.09.24; published 24.12.24.

Please cite as:
Strauven H, Wang C, Hallez H, Vanden Abeele V, Vanrumste B
Unobtrusive Nighttime Movement Monitoring to Support Nursing Home Continence Care: Algorithm Development and Validation Study
JMIR Nursing 2024;7:e58094
URL: https://nursing.jmir.org/2024/1/e58094
doi:10.2196/58094

Assessing Visitor Expectations of AI Nursing Robots in Hospital Settings: Cross-Sectional Study Using the Kano Model

Aimei Kang[1*], MEng; XiuLi Wu[2*], BSc, RN

[1]Department of Nursing, Wuhan Asia Heart Hospital Affiliated to Wuhan University of Science and Technology, Wuhan, China

[2]Institute of Nursing Research, School of Medicine, Wuhan University of Science and Technology, Wuhan, China

[*]all authors contributed equally

Corresponding Author:
Aimei Kang, MEng
Department of Nursing, Wuhan Asia Heart Hospital Affiliated to Wuhan University of Science and Technology, , Wuhan, , China

Abstract

Background: Globally, the rates at which the aging population and the prevalence of chronic diseases are increasing are substantial. With declining birth rates and a growing percentage of older individuals, the demand for nursing staff is steadily rising. However, the shortage of nursing personnel has been a long-standing issue. In recent years, numerous researchers have advocated for the implementation of nursing robots as a substitute for traditional human labor.

Objective: This study analyzes hospital visitors' attitudes and priorities regarding the functional areas of artificial intelligence (AI) nursing robots based on the Kano model. Building on this analysis, recommendations are provided for the functional optimization of AI nursing robots, aiming to facilitate their adoption in the nursing field.

Methods: Using a random sampling method, 457 hospital visitors were surveyed between December 2023 and March 2024 to compare the differences in demand for AI nursing robot functionalities among the visitors.

Results: A comparative analysis of the Kano attribute quadrant diagrams showed that visitors seeking hospitalization prioritized functional aspects that enhance medical activities. In contrast, visitors attending outpatient examinations focused more on functional points that assist in medical treatment. Additionally, visitors whose purpose was companionship and care emphasized functional aspects that offer psychological and life support to patients.

Conclusions: AI nursing robots serve various functional areas and cater to diverse audience groups. In the future, it is essential to thoroughly consider users' functional needs and implement targeted functional developments to maximize the effectiveness of AI nursing robots.

(JMIR Nursing 2024;7:e59442) doi:10.2196/59442

KEYWORDS

nursing robot; artificial intelligence; Kano model; demand survey; nursing; care robots; nursing management

Introduction

With the gradual increase in the number of older and chronically ill individuals worldwide, the shortage of human nursing resources has emerged as a significant global issue [1]. This shortage not only compromises the quality of care services but also poses challenges to the efficiency and sustainability of the overall medical system [2,3]. Integrating artificial intelligence (AI) and mobile medicine into clinical practice is becoming more prevalent to address the current inadequate amount of nursing personnel. For instance, Wu et al [4] demonstrated that AI-based personalized interventions can enhance the self-management of patients with type 2 diabetes in primary care settings, thereby improving behavioral effectiveness. Additionally, Turkish scholars have used AI to develop predictive models that assist physicians in the prediagnosis and differential diagnosis of children's mental illnesses in clinical practices [5]. Among the various intelligent technologies, AI nursing robots have garnered significant attention from the nursing community. These robots are intelligent devices that combine AI algorithms with robotics technology to deliver nursing services and support [6]. Over the past decade, AI nursing robots have rapidly advanced within the medical field, showing substantial potential to enhance nursing services and alleviate the burden on nursing staff [7]. In nursing practices, robots have taken over specific labor-intensive tasks traditionally performed by human nurses, proving them to be practical auxiliary tools in various medical scenarios [8]. For example, during the COVID-19 pandemic, scholars such as Yang et al [9] suggested that AI nursing robots can serve as a tool to reduce the risk of virus transmission and mitigate the impact on frontline health care practitioners. In addition to the benefits that a socially assistive robot can provide to individuals with cognitive impairment [10], there exists a multifunctional robot known as Pepper. This versatile robot can be applied in various sectors, including industry, entertainment, and patient care, offering innovative solutions and enhancing experiences across diverse fields. Its primary functions involve engaging individuals with specific diseases in therapeutic activities, assisting them in completing tasks that enhance their physical functions, and offering emotional support to patients [11].

People’s attitudes and opinions toward new products and technologies are influenced by specific contexts, such as families and schools. Research groups can be diverse, including nurses, nursing managers, and medical students. For instance, a recent survey indicated that caregivers prefer robots to perform simple, highly repetitive tasks [12]. Conversely, medical students hold differing perspectives, believing that nursing robots are incapable of providing patient companionship and that they can only function as assistants to medical staff [13]. Notably, while most researchers agree that patients and their families are the primary beneficiaries of AI nursing robots, there is a scarcity of studies addressing their functional needs regarding these robots. Consequently, this study is grounded in the Kano theoretical model and analyzes hospital visits, offering insights for the development of medical care robots that are safe, efficient, and aligned with clinical requirements.

The Kano model, proposed by Japanese scholar Noriaki Kano in the 1980s, serves to classify user needs and expectations, enabling designers to prioritize the development of product features and functions more effectively [14]. Currently, demand surveys based on the Kano model are widely used in the medical field, proving to be an effective tool for assessing both patient and worker satisfaction [15,16]. Specifically, the Kano model categorizes functional attitude attributes into six distinct types: attractive attributes, one-dimensional attributes, must-be attributes, indifferent attributes, reverse attributes, and questionable results [15]. Table 1 summarizes the characteristics of each attribute. When applying the Kano model for product analysis, the general priority ranking of functional requirements is as follows: must-be attributes>one-dimensional attributes>attractive attributes>indifferent attributes [17]. In product development, it is advisable to prioritize functions that possess must-be, one-dimensional, or attractive attributes. Indifferent attributes may be appropriately discarded after carefully considering factors such as market demand, user feedback, resource constraints, and the competitive environment [18].

Table . Characteristic table of Kano attributes.

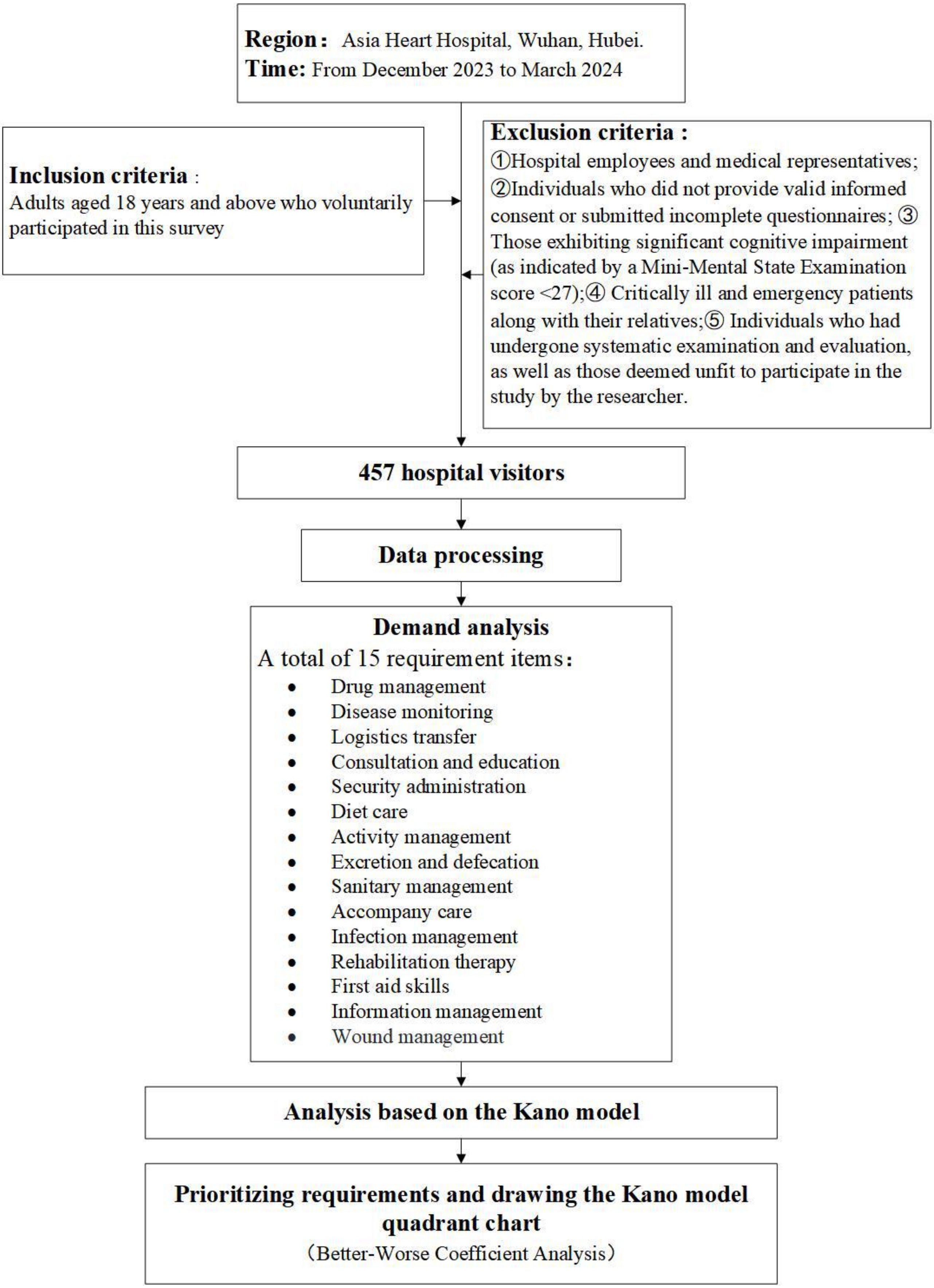
Attribute name	Attribute characteristics
Attractive attribute	If the function exceeds the user’s expectations, the function is highly perfect, and user satisfaction and acceptance will increase significantly. Without the function, user satisfaction and acceptance will not decrease significantly.
One-dimensional attribute	The presence of a particular function enhances satisfaction and acceptance, while its absence leads to a decrease in satisfaction and acceptance.
Must-be attribute	The presence of a specific function does not directly enhance satisfaction and acceptance, but its absence results in a decline in satisfaction and acceptance.
Indifferent attribute	The presence or absence of a specific function does not impact satisfaction and acceptance.
Reverse attribute	Without a particular function, satisfaction would be higher.
Questionable result	The user does not understand a question or answer it correctly.

Methods

Study Design

This study employed a cross-sectional survey design to assess the needs of the respondents. Subsequently, the data was analyzed using the Kano model to evaluate demand attributes and importance coefficients. Figure 1 displays the research flowchart.

Figure 1. Research flowchart.



Inclusion criteria : Adults aged 18 years and above who voluntarily participated in this survey

Exclusion criteria : ①Hospital employees and medical representatives; ②Individuals who did not provide valid informed consent or submitted incomplete questionnaires; ③ Those exhibiting significant cognitive impairment (as indicated by a Mini-Mental State Examination score <27);④ Critically ill and emergency patients along with their relatives;⑤ Individuals who had undergone systematic examination and evaluation, as well as those deemed unfit to participate in the study by the researcher.

Participants

A random sampling method was employed to select visitors from the Wuhan Asia Heart Hospital as the primary subjects of this study, irrespective of their region or age. The minimum required number of questionnaires was determined using formula 1.

$$(1) N=Z2\sigma 2d2$$

In this formula, σ represents the SD of the population, typically set at 0.5, while *d* refers to the CI of 50%. Given that the Kano model is employed to assess users' opinions regarding a particular function, which is inherently subjective, we opted for a wider CI of 90%. Consequently, the confidence level statistic *Z* was determined to be 1.64, and the calculated sample size was a minimum of 68 cases. To mitigate the risk of bias in the study, after thorough discussions among the researchers and considering the hospital's foot traffic, it was decided to increase the number of questionnaires distributed to 500. This adjustment aimed to balance the limitations of sample size, time, and resources, thereby facilitating the attainment of reliable research results.

The inclusion criteria for study participants were adults aged 18 years and older who voluntarily participated in this survey. The exclusion criteria included hospital employees and medical representatives, individuals who did not provide valid informed consent or whose questionnaires were incomplete, those with significant cognitive impairment (indicated by a Mini-Mental State Examination score<27), critically ill and emergency patients along with their relatives, individuals who had undergone systematic examination and evaluation, and those deemed by the researcher to be unfit for participation in the study.

Survey Tools

The survey tool consisted of a questionnaire we designed, primarily divided into two sections: a general information survey and a Kano survey scale. The general information questionnaire aimed to gather essential demographic data, including sex, marital status, age, education level, prior exposure to AI nursing robots, acceptance of AI nursing robots for nursing services, and the reasons for visiting the hospital. The second section features the Kano survey scale, which assessed the desired functional requirements of AI nursing robots. Through an integrated analysis of the potential for robots to perform nursing tasks in clinical settings, we delineated 15 nursing fields using card induction classification (see Textbox 1). Consequently, the Kano survey scale was constructed, comprising the 15 items. Each item consisted of two questions—one framed positively and the other negatively—to evaluate hospitalized patients' attitudes and preferences regarding the functionalities of AI nursing robots. Each question encompassed five dimensions: very much liked, taken for granted, indifferent, reluctantly accepted, and very disliked. The attributes of each factor were then classified based on the survey results.

Textbox 1. Classification of nursing fields and a summary of the functional points.

1. Drug management

- Intravenous dispensing and transport
- Drug distribution

2. Disease monitoring

- Determination of vital signs
- Warning of critical condition
- Access monitoring

3. Logistics transfer

- Patient transfer and goods consignment

4. Consultation and education

- Outpatient guidance, consultation, and registration
- Explanation of nursing measures
- Guidance on disease knowledge and health behavior promotion

5. Security administration

- Prevention of falls, bed falls, and other accidental injuries
- Danger warning and disaster prevention

6. Diet care

- Dining guidance and supervision
- Nutritional status monitoring and diet planning
- Nursing measures related to gastric tube maintenance

7. Activity management

- Positioning and assisted ambulation
- Activity training

8. Excretion and defecation

- Handling of excreta, cleansing, and documentation
- Toilet assistance

9. Sanitary management

- Personal hygiene and cleaning
- Bed linen and clothing maintenance and replacement

10. Accompany care

- Interpersonal interaction
- Social skills training

11. Infection management

- Ward cleaning, disinfection, and sterilization
- Biological sampling
- Microbial identification and antimicrobial efficacy evaluation

12. Rehabilitation therapy

- The restoration of physical function and exercise
- Perceived training

- Daily functional training and treatment

13. First aid skills

- Cardiopulmonary resuscitation
- Oxygen absorption and sputum absorption

14. Information management

- Collection and storage of hospital admission personnel information
- Information retrieval

15. Wound management

- Replacing wound dressings, alleviating pain, and protecting the wound

We employed a Cronbach α coefficient to assess the reliability of the questionnaire and conducted a factor analysis to evaluate its validity. Given that the Kano questionnaire includes both forward and reverse questions for each item, the reliability and validity analyses were performed separately for these two types of questions. The results indicated that the Cronbach α coefficient for the forward questions was 0.952, while the Cronbach α for the reverse questions was 0.958, demonstrating high reliability for the scale. The Kaiser-Meyer-Olkin values for the forward and reverse questions were 0.945 and 0.954, respectively. Additionally, the results of Bartlett's test of sphericity revealed a significance level of $P<.001$, suggesting that the validity and reliability of the questionnaire are both acceptable.

Data Collection and Analysis

From December 2023 to March 2024, we conducted random sampling at the outpatient department of the Wuhan Asia Heart Hospital in Hubei, China, selecting a total of 510 hospital visitors, of whom 482 agreed to participate in our study. After identifying the survey subjects, we employed face-to-face surveys to collect data, with each questionnaire taking between 10 to 30 minutes to complete. Subsequently, two nursing graduate students used Excel 2019 (Microsoft Corporation) to verify and correct the data. Upon obtaining the original dataset, we calculated the Better value and Worse value for each functional area using IBM SPSS 26.0 (IBM Corp). Finally, we employed Prism 10 (GraphPad Software) to create the Kano demand quadrant diagram, using the Better value as the ordinate and the absolute value of Worse as the abscissa, thereby incorporating each function point for a more intuitive classification display. In the Kano demand quadrant chart, the attributes that fall into the first quadrant are one-dimensional attributes, those in the second quadrant are attractive attributes, those in the third quadrant are indifferent attributes, and those in the fourth quadrant are must-be attributes.

Ethical Considerations

Approval for this study was granted by the Ethics Committee at Wuhan University of Science and Technology (No. 2024 - 096). The research was carried out in alignment with the guidelines established in the Declaration of Helsinki and its later revisions, along with other relevant ethical standards. Before participating, all individuals gave informed consent, the questionnaires were filled out anonymously, and we complied with the principles of voluntary withdrawal and the avoidance of harm. Participants in this study did not receive any form of compensation for their involvement.

Results

Basic Information Statistics Table of Survey Objects

The hospitals surveyed were primarily located in Wuhan, Hubei. A total of 482 questionnaires were distributed, of which 24 were deemed disqualified and subsequently removed, resulting in a final collection of 457 questionnaires. The effective recovery rate for the questionnaires was 94.8% (457/482). Male participants constituted 48.4% (221/457) of the survey, while female participants represented 51.6% (236/457). Among the participants, 10 were younger than 18 years old, 37 were between 18 and 25 years old, 85 were aged between 26 and 30 years, 60 participants were between 31 and 40 years old, and 100 participants were between 41 and 50 years old. Additionally, 154 participants were aged between 51 and 60 years, and the remaining 21 participants were older than 60 years old. Further details are provided in Table 2.

Table . Basic information statistics table.

Categories	Participants (n=457), n (%)
Sex	
Male	221 (48.4)
Female	236 (51.6)
Marital status	
Married	201 (44)
Unmarried	256 (56)
Age (years)	
18-20	10 (2.2)
20-25	27 (5.9)
26 - 30	85 (18.6)
31 - 40	60 (13.1)
41 - 50	100 (21.9)
51 - 60	154 (33.7)
>60	21 (4.6)
Educational background	
Primary school and below	30 (6.6)
Junior middle school	120 (26.3)
High school/technical secondary school	184 (40.3)
Undergraduate/junior college	92 (20.1)
Master’s degree or above	31 (6.8)
Have you used intelligent nursing robots before?	
Yes	229 (50.1)
No	228 (49.9)
Whether to accept the AI[a] nursing robot to provide nursing services	
Yes	313 (68.5)
No	103 (22.5)
Uncertainty	41 (9)
Reason for hospital visit	
Hospitalization	154 (33.7)
Outpatient examination	159 (34.8)
Accompany care	144 (31.5)

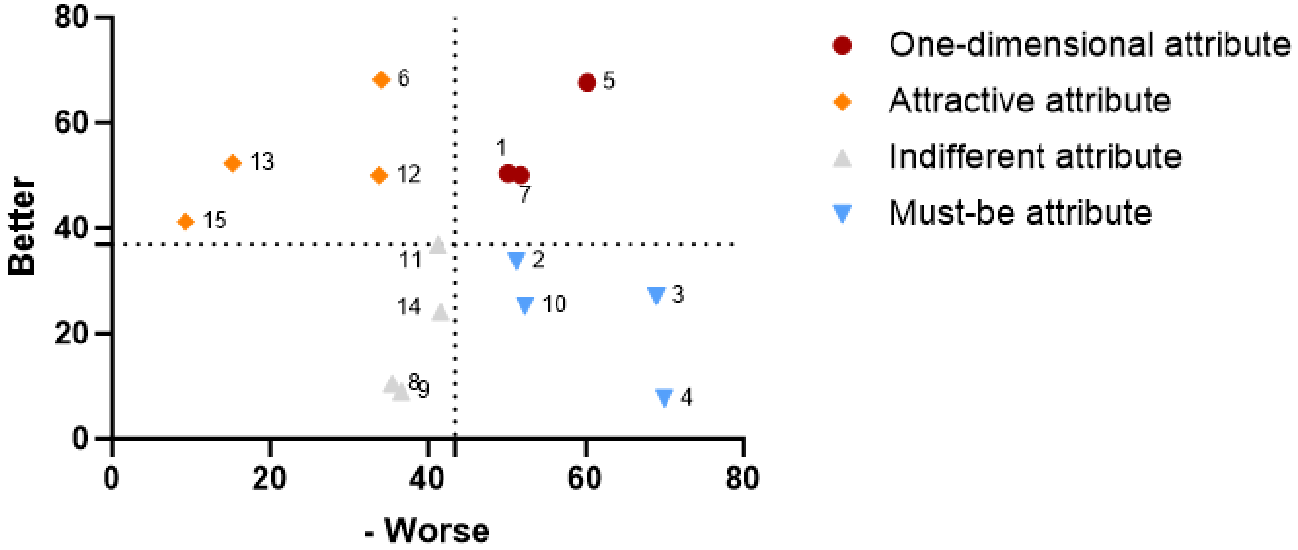
[a] AI: artificial intelligence.

Requirements Result Analysis

Classification of Functional Demand Attributes of AI Nursing Robots

According to the overall personnel Kano demand quadrant diagram, a total of four items were classified within the must-be attribute quadrant, three items fell into the one-dimensional attribute quadrant, four items were categorized in the attractive attribute quadrant, and the remaining four items were placed in the indifferent attribute quadrant (Figure 2). This indicates that hospital visitors in this survey prioritized the functional needs of AI nursing robots in the following order: disease monitoring, accompany care, logistics transfer, and consultation and education>drug management, activity management, and security administration>dietcare, rehabilitation therapy, first aid skills, and wound management>infection management, information management, excretion and defection, and sanitary management. This result suggests that if AI nursing robots can effectively provide functions such as condition monitoring, companion care, logistics transfer, and consultation and education, along with support in areas like medication management, safety management, activity management, rehabilitation physiotherapy, nutritional care, and first aid skills, user satisfaction and recognition will likely increase. In contrast, hospital visitors appear to be less concerned about functions such as infection management and excretion care, possibly due to the personal privacy implications associated with these tasks. Therefore, when designing and implementing nursing robots in the future, it is crucial to focus on how to protect user privacy.

Figure 2. Overall personnel demand quadrant chart for artificial intelligence nursing robot functions.



Hospital Visitors‘ Functional Demand Preferences for AI Nursing Robots Based on Reason for Attending the Hospital

In the general information questionnaire, the survey participants were categorized into three groups based on their primary reason for visiting the hospital. Among these, 154 individuals sought hospitalization, 159 individuals attended outpatient examinations, and 144 individuals came for companionship and care. To determine whether the purpose of the hospital visit influenced the wanted functional requirements of nursing robots, we constructed Kano quadrant diagrams illustrating the functional requirements of AI nursing robots for hospital visitors for three distinct purposes, as depicted in Figures 3-5. Figure 3 indicated that the priority of functional requirements for AI nursing robots aimed at hospitalized patients was as follows: infection management, consultation and education, and disease monitoring>security administration, information management, activity management, drug management, and logistics transfer>wound care, diet care, and rehabilitation physiotherapy. The least prioritized functions included first aid skills, life care, companionship care, and excretion care. For visitors seeking outpatient examinations, the prioritized functions of AI nursing robots were logistics transfer, infection management, information management, and consultation and education, followed by security administration and accompanying care, and then drug management, diet care, first aid skills, and wound care. Rehabilitation physiotherapy, excretion care, activity management, sanitary management, and condition monitoring were of lesser priority (Figure 4). Conversely, visitors whose purpose was to provide companionship and care prioritized these functions for AI nursing robots in the following order: drug management, excretion and defecation, logistics transfer, sanitary management, companion care, and consultation and education>activity management, rehabilitation physiotherapy, disease monitoring, diet care, and safety education>first aid skills and infection management>information management and wound management (Figure 5).

Figure 3. Demand quadrant chart for artificial intelligence nursing robot functions among visitors seeking hospitalization.

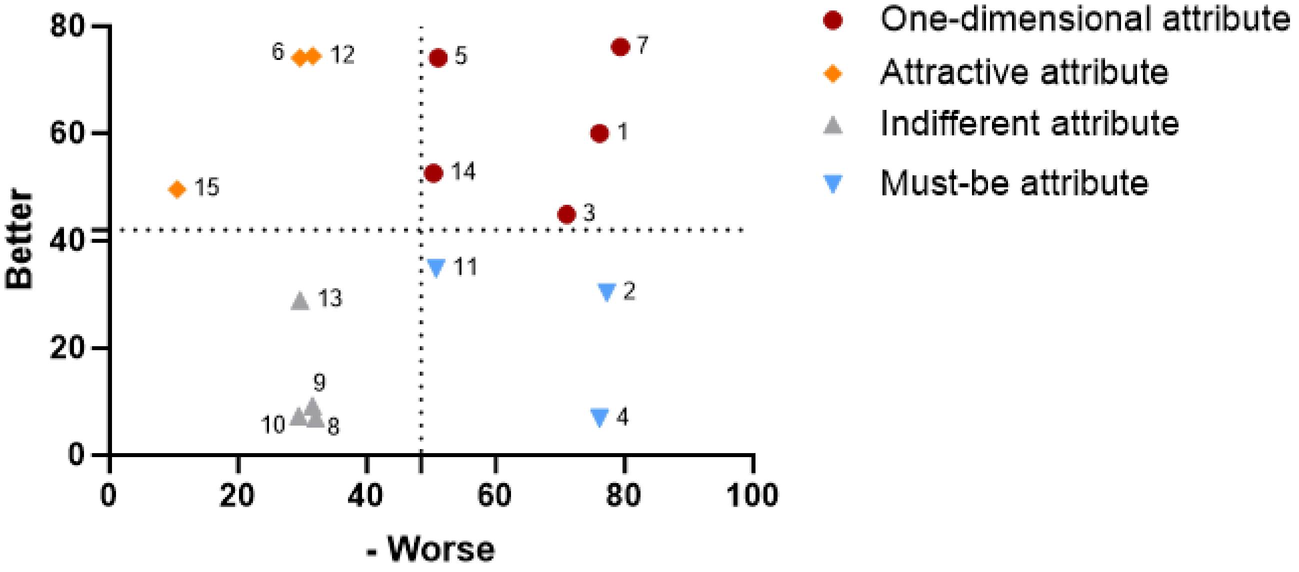


Figure 4. Demand quadrant chart for artificial intelligence nursing robot functions among visitors seeking outpatient examination.

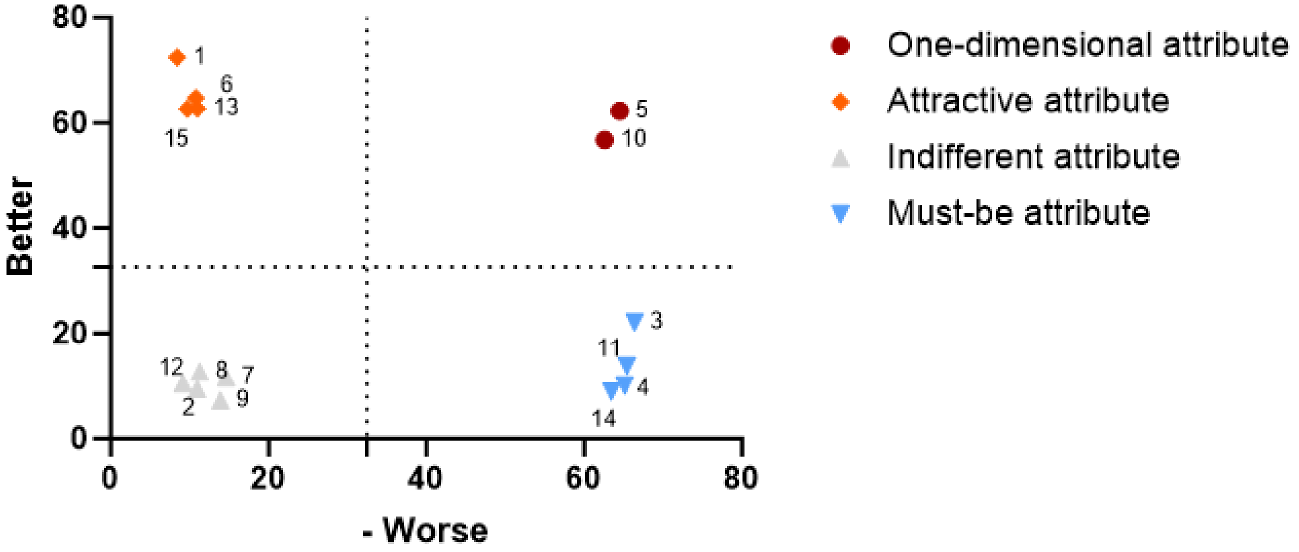
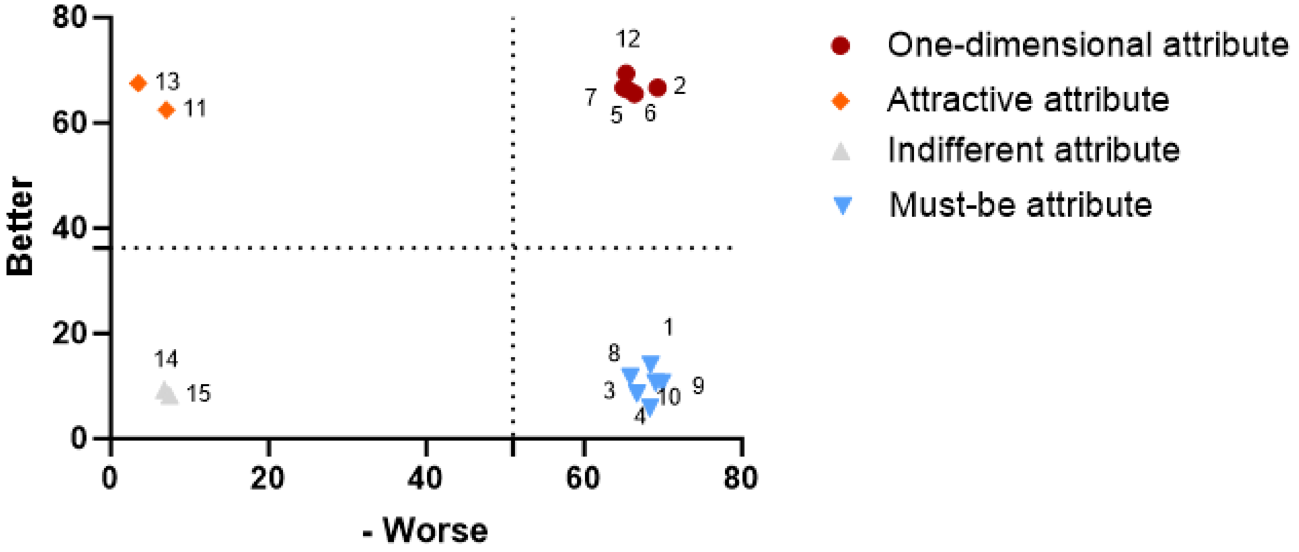


Figure 5. Demand quadrant chart for artificial intelligence nursing robot functions among visitors for accompany care.



Discussion

Summary

This article thoroughly examines hospital visitors' current use of AI nursing robots and their preferred specific functional requirements. Given the rapid advancements in AI and mobile medical technologies, it is essential to gain a comprehensive understanding of the preferences and needs of hospital visitors regarding these robots. Such insights will provide a solid foundation for future policy development and the implementation of advanced technologies, thereby facilitating the progressive enhancement of intelligent nursing practices in China. Through this research, we aim to assist nurses in fully leveraging the potential of AI in clinical settings, promoting the seamless integration and efficient transformation of technology within clinical applications.

Positive Acceptance Attitude

Overall, respondents had a positive attitude toward the clinical application of AI nursing robots. In this study, 50.1% (229/457) of hospital visitors reported having used AI nursing robots, while 68.5% (313/457) expressed a strong interest in and willingness to explore the clinical applications of these robots. This indicates that hospital visitors possess a certain level of awareness regarding the potential value and advantages of AI nursing robots and are open to the integration of this emerging technology into clinical care, which aligns with the perspectives of nursing leaders on robotics [19]. However, some respondents also voiced concerns related to nursing robots, including issues of privacy exposure and operational safety, and this concern is corroborated by the findings of Wong et al [20]. Recently, social robots using AI technology have made advancements in memory training, medication guidance, and emotional communication services, with some of their functionalities becoming integrated into people's daily lives [21]. However, reports indicate these robots are not yet equipped to deliver such complex services reliably [22]. To mitigate the potential risks that robots may pose to patients and their families, actively promoting the intelligent nursing processes within Chinese medical institutions is essential. Additionally, there is a need for the gradual enhancement of relevant legislation, the standardization of industry standards for the production of service robots, and the strengthening of institutional support and policy guarantees. Ultimately, these measures will foster the overall development of China's intelligent care industry.

Different Purposes Affect the Choice of Hospital Visitors' Preferred Functional Requirements for AI Nursing Robots

By examining the overall demand survey results, we can conclude that participants exhibit distinct differences in their functional attribute requirements for AI nursing robots based on their reasons for visiting the hospital. Individuals seeking hospitalization are generally more receptive to AI nursing robots that enhance their medical care, such as condition monitoring, consultation and education, medication management, safety oversight, and rehabilitation physiotherapy. In contrast, those attending outpatient examinations tend to prioritize AI nursing robots that assist with medical treatment logistics, information management, and companion care, showing less interest in rehabilitation, physiotherapy, activity management, and life care functionalities. Furthermore, individuals seeking companionship care emphasize the companionship functions of AI nursing robots, expressing a desire for these robots to offer psychological support and assistance in daily activities, including necessary help with excretion and other daily living tasks. In light of the findings from this Kano survey, we recommend that designers and developers undertake targeted functional developments tailored to medical institutions' specific functional scenarios when creating nursing service robots [12]. Furthermore, when medical institutions implement and deploy AI nursing robots, they should carefully consider the specific application scenarios and tasks, ensuring the effective use of various functional areas. For instance, in hospital outpatient departments, service robots equipped with guidance and consultation capabilities should be prioritized. In care wards, those with condition monitoring functions should take precedence. In rehabilitation wards, robots designed for rehabilitation physiotherapy should be prioritized, and particularly in home or community settings, robots with companion care functionalities should be deployed.

Currently, the application of AI nursing robots is primarily focused on areas such as logistics and transportation [23], infection wards [24], and rehabilitation [25], where they have demonstrated promising results. Considering the functional needs expressed by survey respondents regarding AI nursing robots, it is crucial to emphasize the expansion and enhancement of these robots' functional capabilities in the future. Specifically, there should be a focus on the development of features related to consultation, education, and companion care. This approach will better address the needs of patients in hospitals and ultimately enhance the clinical application value of AI nursing robots.

Limitations

This study has several limitations. First, the research subjects were confined to the Wuhan Asia Heart Hospital, and the potential influence of factors such as hospital grade, region, education level, salary level, and medical insurance on the experimental results, as well as the ethical issues associated with the use of robots, were not examined. Second, while the purpose for attending the hospital may be more varied and diverse in practice, this study only included three primary purposes. Finally, this study primarily focuses on AI nursing robots; future research should also consider other intelligent products.

Conclusion

As a product needs analysis tool, the Kano model can be used to identify and classify the impact of various needs on user acceptance and satisfaction [26]. This study examined multiple perspectives from hospital visitors, including inpatients, outpatients, and individuals accompanying patients, and it investigated the differences in the prioritization of hospital visitors' needs for AI nursing robots based on these differing visitation purposes. We identified that people have a positive attitude toward the use of AI nursing robots and that the preferred functional requirements of AI nursing robots differ depending on their reason for going to the hospital. This provides valuable insights for robot developers and guidance for hospitals and individuals. Notably, the development of new functionalities for nursing robots encompasses multiple disciplines, including health care, engineering, and human-computer interaction. We anticipate future interdisciplinary collaboration to explore practical solutions to the challenges faced by AI-assisted nursing, thereby accelerating the advancement of this field. The transformation of these solutions into practical functions within actual products and apps will foster the development and application of nursing robot technology, driving innovation and progress in the medical sector.

Acknowledgments

First, we would like to thank Wuhan Asian Heart Hospital for providing the investigation platform for this study. Second, I would like to thank the staff who provided technical support for this study, Ms Ding Jingjing and Ms Liao Wenyu. Finally, we sincerely thank the reviewers and editors for their hard work and valuable comments. It is your professional guidance that makes our research more rigorous and perfect. Your dedication and professionalism not only improve the quality of the paper but also point the way for our future academic research. Once again, I would like to express my most sincere thanks and high respect to you!

Data Availability

The datasets generated or analyzed during this study are not publicly available due to privacy protection but are available from the corresponding author upon reasonable request.

Authors' Contributions

Concept and design: AK, XW
Data collection and analysis: XW
Drafting of the article: AK, XW
Critical revision of the article for important intellectual content: AK, XW
Study supervision: AK, XW

Conflicts of Interest

None declared.

References

1. Wu X, Kang A. Demand forecasting of nurse talents in China based on the Gray GM (1,1) Model: model development study. Asian Pac Isl Nurs J 2024 Aug 14;8:e59484. [doi: 10.2196/59484] [Medline: 39141916]
2. Boniol M, McCarthy C, Lawani D, Guillot G, McIsaac M, Diallo K. Inequal distribution of nursing personnel: a subnational analysis of the distribution of nurses across 58 countries. Hum Resour Health 2022 Mar 5;20(1):22. [doi: 10.1186/s12960-022-00720-5] [Medline: 35248061]
3. Zhang WQ, Tang W, Hu FH, et al. Impact of the National Nursing Development Plan on nursing human resources in China: an interrupted time series analysis for 1978-2021. Int J Nurs Stud 2023 Dec;148:104612. [doi: 10.1016/j.ijnurstu.2023.104612] [Medline: 37839307]
4. Wu Y, Min H, Li M, et al. Effect of artificial intelligence-based health education accurately linking system (AI-HEALS) for type 2 diabetes self-management: protocol for a mixed-methods study. BMC Public Health 2023 Jul 11;23(1):1325. [doi: 10.1186/s12889-023-16066-z] [Medline: 37434126]
5. Ucuz İ, Özcan Ö, Mete B, Arı A, Tetik B, Yıldırım K. Evaluation of inflammatory markers in childhood-onset psychiatric disorders by using artificial intelligence architectures. Anad Psik Derg 2020;21(3):301-309. [doi: 10.5455/apd.56153]
6. Ergin E, Karaarslan D, Şahan S, Çınar Yücel Ş. Artificial intelligence and robot nurses: from nurse managers' perspective: a descriptive cross-sectional study. J Nurs Manag 2022 Nov;30(8):3853-3862. [doi: 10.1111/jonm.13646] [Medline: 35474366]
7. Seibert K, Domhoff D, Bruch D, et al. Application scenarios for artificial intelligence in nursing care: rapid review. J Med Internet Res 2021 Nov 29;23(11):e26522. [doi: 10.2196/26522] [Medline: 34847057]
8. Ohneberg C, Stöbich N, Warmbein A, et al. Assistive robotic systems in nursing care: a scoping review. BMC Nurs 2023 Mar 18;22(1):72. [doi: 10.1186/s12912-023-01230-y] [Medline: 36934280]
9. Yang G, Lv H, Zhang Z, et al. Keep healthcare workers safe: application of teleoperated robot in isolation ward for COVID-19 prevention and control. Chin J Mech Eng 2020 Dec;33(1):1-4. [doi: 10.1186/s10033-020-00464-0]
10. Fan J, Mion LC, Beuscher L, Ullal A, Newhouse PA, Sarkar N. SAR-Connect: a socially assistive robotic system to support activity and social engagement of older adults. IEEE Trans Robot 2022 Apr;38(2):1250-1269. [doi: 10.1109/tro.2021.3092162] [Medline: 36204285]

11. Miyagawa M, Yasuhara Y, Tanioka T, et al. The optimization of humanoid robot’s dialog in improving communication between humanoid robot and older adults. ICA 2019;10(3):118-127. [doi: 10.4236/ica.2019.103008]
12. Gu Y, Shi T, Guo S. Requirements survey of clinical nurses on nursing robot application scenario based on Kano model. J Nurs 2023;38(11):53-58. [doi: 10.3870/j.issn.1001-4152.2023.11.053]
13. Łukasik S, Tobis S, Kropińska S, Suwalska A. Role of assistive robots in the care of older people: survey study among medical and nursing students. J Med Internet Res 2020 Aug 12;22(8):e18003. [doi: 10.2196/18003] [Medline: 32784187]
14. Wang Z, Tang X, Li L, et al. Spiritual care needs and their attributes among Chinese inpatients with advanced breast cancer based on the Kano model: a descriptive cross-sectional study. BMC Palliat Care 2024 Feb 22;23(1):50. [doi: 10.1186/s12904-024-01377-8] [Medline: 38388378]
15. Mao J, Xie L, Zhao Q, et al. Demand analysis of an intelligent medication administration system for older adults with chronic diseases based on the Kano model. Int J Nurs Sci 2022 Jan;9(1):63-70. [doi: 10.1016/j.ijnss.2021.12.012] [Medline: 35079606]
16. Chen MC, Hsu CL, Lee LH. Service quality and customer satisfaction in pharmaceutical logistics: an analysis based on Kano model and importance-satisfaction model. Int J Environ Res Public Health 2019 Oct 24;16(21):4091. [doi: 10.3390/ijerph16214091] [Medline: 31652926]
17. Kermanshachi S, Nipa TJ, Nadiri H. Service quality assessment and enhancement using Kano model. PLoS ONE 2022;17(2):e0264423. [doi: 10.1371/journal.pone.0264423] [Medline: 35213604]
18. Zhou Z, Wang L, Dong Y. Research on innovative design of community mutual aid elderly care service platform based on Kano model. Heliyon 2023 May;9(5):e15546. [doi: 10.1016/j.heliyon.2023.e15546] [Medline: 37131443]
19. Lee JY, Song YA, Jung JY, et al. Nurses’ needs for care robots in integrated nursing care services. J Adv Nurs 2018 May 13. [doi: 10.1111/jan.13711] [Medline: 29754395]
20. Wong KLY, Hung L, Wong J, et al. Adoption of artificial intelligence-enabled robots in long-term care homes by health care providers: scoping review. JMIR Aging 2024 Aug 27;7:e55257. [doi: 10.2196/55257] [Medline: 39190455]
21. Kim JW, Choi YL, Jeong SH, Han J. A care robot with ethical sensing system for older adults at home. Sensors (Basel) 2022 Oct 3;22(19):7515. [doi: 10.3390/s22197515] [Medline: 36236614]
22. Körtner T. Ethical challenges in the use of social service robots for elderly people. Z Gerontol Geriatr 2016 Jun;49(4):303-307. [doi: 10.1007/s00391-016-1066-5] [Medline: 27220734]
23. Di Lallo A, Murphy R, Krieger A, Zhu J, Taylor RH, Su H. Medical robots for infectious diseases: lessons and challenges from the COVID-19 pandemic. IEEE Robot Automat Mag 2021;28(1):18-27. [doi: 10.1109/MRA.2020.3045671]
24. Qassim HM, Wan Hasan WZ. A review on upper limb rehabilitation robots. Appl Sci (Basel) 2020;10(19):6976. [doi: 10.3390/app10196976]
25. Sharma M, Savage C, Nair M, Larsson I, Svedberg P, Nygren JM. Artificial intelligence applications in health care practice: scoping review. J Med Internet Res 2022 Oct 5;24(10):e40238. [doi: 10.2196/40238] [Medline: 36197712]
26. Wang X, Tang P, Jiang Y, et al. The application value of kano model in quality of healthcare: a scoping review. medRxiv. Preprint posted online on Mar 30, 2024. [doi: 10.1101/2024.03.30.24305047]

Abbreviations

AI: artificial intelligence

Edited by E Borycki, K Cato; submitted 12.04.24; peer-reviewed by S Minshall, Y Wu; revised version received 08.10.24; accepted 11.10.24; published 27.11.24.

Please cite as:
Kang A, Wu X
Assessing Visitor Expectations of AI Nursing Robots in Hospital Settings: Cross-Sectional Study Using the Kano Model
JMIR Nursing 2024;7:e59442
URL: https://nursing.jmir.org/2024/1/e59442
doi:10.2196/59442

Viewpoint

The Cooperation Between Nurses and a New Digital Colleague “AI-Driven Lifestyle Monitoring” in Long-Term Care for Older Adults: Viewpoint

Sjors Groeneveld[1,2,3], MSc; Gaya Bin Noon[4], BSc; Marjolein E M den Ouden[1,5], PhD; Harmieke van Os-Medendorp[6,7], PhD; J E W C van Gemert-Pijnen[8], PhD; Rudolf M Verdaasdonk[3], PhD; Plinio Pelegrini Morita[4,9,10,11,12], PhD

[1]Research Group Technology, Health & Care, Saxion University of Applied Sciences, Enschede, Netherlands
[2]Research Group Smart Health, Saxion University of Applied Sciences, Enschede, Netherlands
[3]TechMed Center, Health Technology Implementation, University of Twente, Enschede, Netherlands
[4]School of Public Health Sciences, University of Waterloo, Waterloo, ON, Canada
[5]Research Group Care and Technology, Regional Community College of Twente, Hengelo, Netherlands
[6]Domain Health, Sports, and Welfare, Inholland University of Applied Sciences, Amsterdam, Netherlands
[7]Spaarne Gasthuis Academy, Hoofddorp, Netherlands
[8]Centre for eHealth and Wellbeing Research, Section of Psychology, Health and Technology, University of Twente, Enschede, Netherlands
[9]Research Institute for Aging, University of Waterloo, Waterloo, ON, Canada
[10]Department of Systems Design Engineering, University of Waterloo, Waterloo, ON, Canada
[11]Centre for Digital Therapeutics, Techna Institute, University Health Network, Toronto, ON, Canada
[12]Institute of Health Policy, Management, and Evaluation, Dalla Lana School of Public Health, University of Toronto, Toronto, ON, Canada

Corresponding Author:
Sjors Groeneveld, MSc
Research Group Technology, Health & Care
Saxion University of Applied Sciences
Postbox 70.000
Enschede, 7500 KB
Netherlands
Phone: 31 88 019 8888
Email: s.w.m.groeneveld@saxion.nl

Abstract

Technology has a major impact on the way nurses work. Data-driven technologies, such as artificial intelligence (AI), have particularly strong potential to support nurses in their work. However, their use also introduces ambiguities. An example of such a technology is AI-driven lifestyle monitoring in long-term care for older adults, based on data collected from ambient sensors in an older adult’s home. Designing and implementing this technology in such an intimate setting requires collaboration with nurses experienced in long-term and older adult care. This viewpoint paper emphasizes the need to incorporate nurses and the nursing perspective into every stage of designing, using, and implementing AI-driven lifestyle monitoring in long-term care settings. It is argued that the technology will not replace nurses, but rather act as a new digital colleague, complementing the humane qualities of nurses and seamlessly integrating into nursing workflows. Several advantages of such a collaboration between nurses and technology are highlighted, as are potential risks such as decreased patient empowerment, depersonalization, lack of transparency, and loss of human contact. Finally, practical suggestions are offered to move forward with integrating the digital colleague.

(JMIR Nursing 2024;7:e56474) doi:10.2196/56474

KEYWORDS

artificial intelligence; data; algorithm; nurse; nurses; health care professional; health care professionals; health professional; health professionals; health technology; digital health; smart home; smart homes; health monitoring; health promotion; aging in place; assisted living; ambient assisted living; aging; gerontology; geriatric; geriatrics; older adults; independent living; machine learning

Introduction

The growing preference of older adults to age in place requires technologies that can help them to do so. One potential technology is artificial intelligence (AI)–driven lifestyle monitoring, based on data collected from ambient sensors in an older adult's home. However, designing and implementing this technology in such an intimate setting requires collaboration with nurses experienced in long-term and older adult care. This viewpoint paper emphasizes the need to incorporate nurses and the nursing perspective at every stage of designing, using, and implementing AI-driven lifestyle monitoring in long-term care settings. The goal of this collaboration for nurses would be to gain a tool that does not replace them in their role but rather acts as a sort of coworker providing care support and data insights, seamlessly integrating into nursing workflows. Let us welcome this new digital colleague.

While definitions of AI differ, a simple one would be "computers mimicking human behavior" [1]. In the simplest terms, AI is computers learning to interpret large amounts of data and come to conclusions based on that interpretation. AI is essentially a system that gets smarter the more information it is given and uses that knowledge to provide solutions or create products. AI works by taking a large quantity of heterogeneous data, finding patterns in it, and using those learning elements to make more accurate predictions [1]. While AI may appear to be a fairly new technological advancement, its roots actually date back to the 1950s, with its trajectory experiencing various periods of growth and decline over time [2]. In recent years, however, attention toward AI has grown significantly. In particular, so-called generative AI (for example ChatGPT [3], which can "create" outputs such as texts and photos) has received a lot of attention and opened new possibilities [4].

However, the impact of AI is far greater than text and photo generation. AI has been dubbed a general-purpose technology; a game-changer that affects many parts of our lives and industries [5]. Other examples of such breakthrough technologies are the steam engine, electricity, and computers [6]. AI can do many things, from helping doctors diagnose diseases to streamlining business processes. However, as we use AI more and more and increase our reliance on it, we need to make sure we apply it responsibly and intelligently. The growing attention toward AI is also reflected in national and international reports describing AI strategies, with more than 25 countries having developed such a strategy, though views toward AI vary widely around the world [7]. While national AI policies strongly differ from each other, there is generally a lot of attention paid to AI expertise and data policies, whereas attention toward human-computer cooperation has been mostly lacking. In recent years, legislation around AI has received more consideration, with several AI-specific acts and legal frameworks developed around the world [8], focusing on topics such as responsible, validated, and fair data exchange. For instance, the use of AI in the European Union will be regulated by the European Union AI Act [9].

The use of AI leads to a need to consider some broader societal implications including potential downsides. In particular, the prospect of increasing our reliance on automation raises concerns about loss of compassion and humanity in interactions with the subjects of data [10-12]. Indeed, overreliance on algorithms risks increasing bias by a range of societal factors such as age, gender, ethnicity, ability, and socioeconomic status [12-14]. Furthermore, there are privacy concerns: given that AI potentially involves novel uses of sensitive data, there is a need to ensure that this data (and by extension, its subjects) are still protected [15-17].

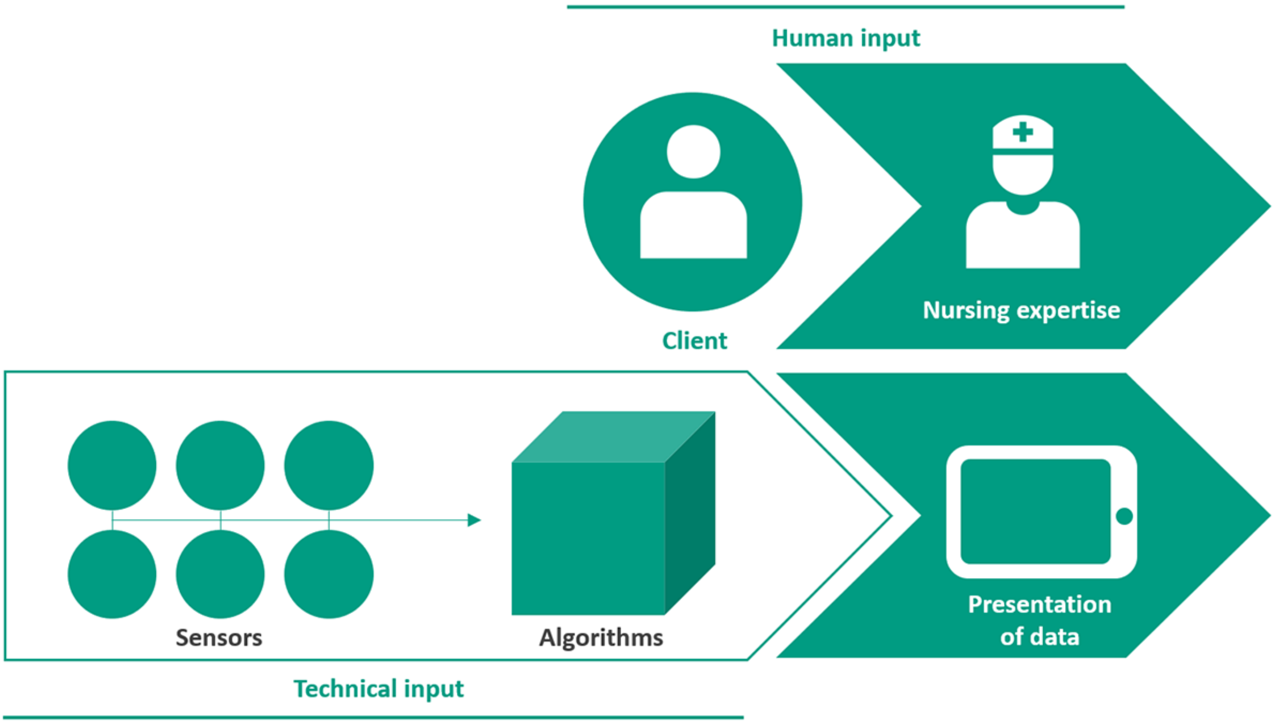
AI in Nursing

The added value of AI in health care is evident in various aspects, including the enhancement of health care research equity and versatility, the streamlining of workflows in health care practice, and the personalization of learning within health care education [18]. However, while there is extensive available literature on how AI changes health care in general, the influence on nursing in long-term care is less commonly discussed [19,20]. Especially in more clinical settings, the use of AI is further developed and already being used; for instance, for breast cancer detection in screening mammography [21]. From previous research, the reception of the prospect of a more AI-involved future for nursing has been mixed, with concerns having been expressed regarding the complexity of AI and how its use may affect human interaction and professional autonomy [20,22,23]. This has been especially well-studied among nursing students, who can reasonably expect to see more AI used during their careers [23,24]. Given the relative newness of this area, the precise impact of AI on the nursing field in long-term care is still up in the air. The potential impact includes opportunities for in-home assessment of patients, offering greater time savings and convenience for both patients and health care professionals such as nurses [15,25-28]. This aspect of time savings could also be helpful given the shortage of nurses [29] as the use of technology could potentially reduce the nursing workload [30]. Furthermore, the general provision of more evidence-based, personalized care based on algorithmically derived health information [19,31] can help to overcome intuitively based decisions. The advantage of automation is the ability to take away some of the repetitive drudgery of background work, such as gathering information and administration, as this is handled by the algorithm. Rather, professionals can spend more time on directly action-oriented tasks [31].

AI-Driven Lifestyle Monitoring System

This paper will focus on the use of AI-driven lifestyle monitoring systems such as those often implemented in smart living environments and smart homes [32]. These systems can be used in long-term care, where over time people might struggle to maintain the basic abilities necessary to keep living well. AI-driven lifestyle monitoring systems are used to obtain insights into a person's behavior. Examples of such are their daily routine, habits, and activity patterns [25,33,34]. These insights can be used to assist nurses in providing personalized care and support older adults to age in place [15,33,35]. AI-driven lifestyle monitoring systems (Figure 1) work by getting input from ambient and environmental sensors in the home of a person. These can be various types of sensors, such as those for infrared motion, contact, light, temperature, and humidity [36], as well as sensors for physiologic parameters such as heart rate, blood oxygen saturation, and respiratory rate [37]. These sensors monitor the home and the person living there continuously. The combination of the output of those sensors is used by an algorithm to identify patterns and learn what a common lifestyle pattern is for this specific person. While this continuous monitoring takes place, deviations from the common pattern can also be detected [38]. Examples of such deviations include a noticeable decrease in movement, more frequent use of the toilet, or a more restless sleep pattern [36]. The system will then give some form of output (eg, reports or alerts to care providers) by presenting the findings to the user [39]. These findings could potentially support nurses in clinical decision-making, although it is important to include the perspective of nurses when designing these systems, to make the output meaningful for practice [19,40] (Textbox 1).

Figure 1. Visualization of the cooperation between nurses and the new digital colleague: artificial intelligence–driven lifestyle monitoring systems.



Textbox 1. The use of artificial intelligence–driven lifestyle monitoring in practice.

Case

Emma Smith, a 53-year-old nurse, is deeply committed to the residents she cares for. She works at a long-term care facility for people with early-stage dementia. Recently, artificial intelligence–driven lifestyle monitoring has been introduced in her department. The residents are monitored using various sensors. Emma finds this both convenient and a bit nerve-wracking. She wonders, “Can I truly rely on the system? What if it misses something?” She also feels slightly uneasy about the sensors taking over a part of her job. However, she appreciates that these tools provide her with a better understanding of the residents’ situations. Every morning, she opens the overview that is generated by the system and sees in one glance if the system has identified any deviations in the metrics of the residents she cares for. Additionally, if there is an incident like a fall, the system immediately sends an alert. “It took me some time to incorporate this in my daily workflow, but now it is part of my routine.”

This technology is of interest due to its potential impact on several trends in nursing that are expected to receive increased attention in coming years: personalized care, aging in place, and positive health. Regarding the first, greater use of AI-driven lifestyle monitoring facilitates understanding of patient health, which in turn can be used to optimize their care plan [12,34]. Furthermore, AI-driven lifestyle monitoring can provide better oversight for patients living at home, meaning they can potentially remain in their preferred living environments longer [27,41], which is desired by many older adults [42]. Last, positive health revolves around the ability to not focus on the signs, symptoms, and restrictions of disease, but rather to focus on what is possible for the person [43]. AI has the potential to enhance positive health by providing predictive care for older adults [12], thus helping them to maintain or even improve their health.

The potential implications for nurses with the growing integration of AI-driven lifestyle monitoring need attention. Nurses are the largest group of health care professionals worldwide [44], and as such they play a crucial role in the provision of health care. Although it is not commonly expected that AI will replace nurses [10,45], and indeed this is a discussion of complementing nurses rather than replacing them, it is suggested that the dynamics between health care professionals and their patients might be altered by the adoption of AI [46]. For instance, by using AI systems, health care professionals can save time on administrative tasks, thus enhancing efficiency and allowing them to devote more time to establishing trust-based relationships with their patients [20]. Moreover, AI is expected to influence other dimensions of job design such as autonomy, skills, and job demands [20,45]. For example, if AI-driven lifestyle monitoring provides patients with increased information about their health, nurses play a crucial role in guiding and explaining the outcomes to patients, acting as a sort of advisor. As a result, the skills required for health care professionals to effectively interact with both AI systems and increasingly informed patients are undergoing significant changes [20].

Complementarity Between Nurses and AI-Driven Lifestyle Monitoring

We argue that the qualities of nurses and AI-driven lifestyle monitoring systems in long-term care complement each other, leading to increased value when combined. Nurses excel in the relationship domain, offering emotional support, empathy, and compassion, and working toward the benefit of other humans [13,24], also known as the humane element of nursing and recognized as part of fundamental care [47]. They are good at considering contextual variables to get a holistic view of a patient, are compassionate, and can make genuine connections with the persons for whom they provide care [13]. However, there are limitations to human capabilities. Nurses cannot be present or observe patients around the clock, making it challenging to maintain an objective and comprehensive understanding of a patient's condition.

On the other hand, AI-driven technologies are particularly skilled at handling tasks that involve analyzing large amounts of data and require substantial computational power [24,36]. AI-driven lifestyle monitoring is capable of identifying long-term behavioral patterns and synthesizing these with data collected from various scenarios. Furthermore, this type of technology can provide continuous monitoring around the clock, even between nursing visits [15,28]. However, AI-driven lifestyle monitoring does lack certain health care–relevant abilities such as dealing with unpredictable situations, considering contextual nuances [36], and the human element of caregiving [16]; skills that are second nature to nurses.

If we were to make use of the qualities of nurses on the one hand and AI-driven lifestyle monitoring systems on the other, we would be able to have the "best of both worlds." In this situation, we could enrich the nursing caregiving process by adding additional insights from lifestyle monitoring technology and using nursing expertise and patient experience to improve the technology's practical applications [39] (Figure 1). Next to the human input of the nurse and patient in the care process, a new stream of technical input is provided, formed by the sensors and algorithms of the AI-driven lifestyle monitoring, leading to a visually-presented output [19,28,40] which could provide decision support for nurses [19,40]. For example, sensors could detect disrupted sleep patterns, bathroom use, or changes in how a person moves and walks [27]. If nurses could enrich these findings with nursing expertise and integrate them into clinical knowledge and experience, this would greatly influence the care given. When the output of the sensors is combined with nursing expertise, there is greater potential for care that is better tailored to the current situation and where less time is consumed by gathering information and administration, leaving more time for human contact between the nurse and patient. The AI-driven technical input could be seen as a new digital colleague for the nurse, an idea previously mentioned by Swan [22]. This digital colleague provides deeper insights into the needed care of the older adult and could potentially enhance nurses' ability to offer more compassionate [13], personalized [12,13,19], and evidence-based [19] care.

Challenges of the New Digital Colleague

Although we show that cooperation between nurses and AI-driven lifestyle monitoring has promise, it also raises several valid concerns among nurses that should be discussed and considered. First among these is the possibility of decreased patient empowerment and depersonalization, as an overreliance on algorithms could neglect the individual circumstances, preferences, and abilities of the patient [11,12]. In such a situation, actions that are in actuality against the patient's interest may be justified by the person doing them because they were recommended by the algorithm, as opposed to any normative evaluation by a nurse [11]. At this point, questions of transparency come to mind, as well as the chance of turning care into part of a "black box society," wherein decisions are made or recommendations are given automatically with limited recourse [17,24]. A lack of algorithmic transparency (ie, poor clarity in how the AI came to the recommendations that it presents) makes it difficult to interrogate those recommendations and decide whether to accept them.

This, in turn, raises a more philosophical, ethical, and methodological concern regarding the use of AI in nursing: given that humanity and human contact have traditionally been seen as a crucial part of the role, there are concerns of this being lost if too much of the care process is based in machines and algorithms [31]. Nurses spend a lot of time interacting directly with patients, often on a personal level. Thus, they are better equipped than most health care professionals to build relationships with those patients and more holistically observe their well-being, meaning they can more easily catch issues that might be missed in clinical assessment [12,31]. As such, it has been argued that overreliance on technology could lead to the dehumanization of patients and overall poorer care [11,12]. Last, on a practical, implementation level, not all nurses currently possess the competence or comfort of working with AI-based systems [24,48,49]. As such, expanded use of AI could lead to more work for nurses, who are often already overextended in their responsibilities [49]. These issues are often exacerbated by poor usability design of the AI interfaces, which may make use of the AI unintuitive and difficult to navigate [10,50].

How to Collaborate With Our New Digital Colleague

We propose that greater involvement of nurses in the actual design, use, and implementation of AI—in a way, shaping their digital colleague—offers a way to mitigate some of the risks.

For example, the nurse's understanding of patient behaviors and circumstances could act as a sort of counterbalance to the depersonalization of the algorithm [31]. This can be used during the delivery of care, and nurses should certainly be encouraged to not always take the output of the algorithm at face value. However, only having this quality assessment happen at that end point, where nurses have many other tasks and priorities to manage, is not reasonable; far more benefits could be realized by appreciating the role of nurses as knowledge-holders during the algorithm and interface design [1,32,36]. To optimize meaningful health-related features and functionality, it will be necessary to integrate clinical nursing knowledge in the design of the AI. For example, to train AI-driven lifestyle monitoring to identify the early signs of urinary tract infections [27], clinical knowledge provided by nurses should be merged with data from sensors [36]. In short, nurses should be involved in the design process of AI technology [51], also referred to as "nurse-in-the-loop" [27].

Based on their knowledge, nurses may act as advocates for their patients, thereby supporting patient empowerment. Furthermore, with a greater understanding of the AI systems and how the algorithm comes to certain conclusions, nurses are afforded more transparency that they may then pass on to their patients [45]. In practical terms, this would enable them to understand the argumentation of how AI-driven lifestyle monitoring comes to certain conclusions, and thereby could act more critically toward faults or biases. In other words, the much-feared black box society is easier to avoid with a workforce of experienced, knowledgeable nurses who can "shine a light" into that black box [12]. To do this, it is essential to determine the specific competencies required to work with AI-based lifestyle monitoring systems [22,24] and to discuss the responsibilities of individual nurses who work with AI-driven lifestyle monitoring. Nurses should be continuously educated based on these needed competencies [19].

Conclusion

AI is not, and cannot be, a replacement for nurses. We argue that instead of replacing nurses, AI-driven lifestyle monitoring in long-term care should be seen as a new digital colleague that provides data-based insights to support nursing care. The complementarity of the humane quality of nurses on one side and the AI technology on the other side could lead to more compassionate, personalized, and evidence-based long-term care and can support older adults to age in place. The humane qualities of nurses are enriched by the insights from AI, and vice versa.

This collaboration does come with concerns such as the potential of decreased patient empowerment, depersonalization, and a lack of transparency due to an overreliance on data insights. Furthermore, humanity and human contact could be at stake as the role of AI technology grows. However, these concerns may be addressed with greater nurse involvement. From a practical point of view, to work with AI-driven lifestyle monitoring, specific competencies are required for nurses and the technology should be co-designed in such a way that it fits within nursing workflows. It is therefore crucial to identify the needed competencies to work with AI technology and to gain insight into the needs and wishes of nurses to ensure the design fits within nursing workflows.

Recommendations

We recommend that long-term care nurses be involved in the actual design, use, and implementation of AI-driven lifestyle monitoring, thus shaping their new digital colleague. This way, nurses can advocate for patient empowerment, add to the transparency of the AI systems, and design the technology to fit within nursing workflows. Furthermore, we recommend prioritizing the development of educational programs to educate our current and future generation nurses to appreciate the potential of AI and be able to collaborate with their new digital colleague.

Lessons Learned in This Paper

First, AI-driven lifestyle monitoring in long-term care can be seen as a new digital colleague, complementing the qualities of human nurses.

Second, increased use of AI-driven lifestyle monitoring in long-term care comes with some potential risks such as decreased patient empowerment, depersonalization, lack of transparency, and loss of human contact.

Third, the involvement of long-term care nurses in the design, use, and implementation of AI-driven lifestyle monitoring systems could mitigate these challenges.

Finally, AI-driven lifestyle monitoring promises to be a valuable type of AI in long-term care and could potentially enhance long-term care nurses' ability to offer more compassionate, personalized, and evidence-based care.

Acknowledgments

This paper is part of a project (023.017.064) of the research program, Doctoral Grant for Teachers, which is (partly) financed by NWO (the Dutch Research Council).

Conflicts of Interest

None declared.

References

1. Shang Z. A concept analysis on the use of artificial intelligence in nursing. Cureus 2021;13(5):e14857 [FREE Full text] [doi: 10.7759/cureus.14857] [Medline: 34113496]
2. Boden MA. Artificial Intelligence: A Very Short Introduction. Walton Street, Oxford: Oxford University Press; 2018.
3. How can i help you today? ChatGPT. URL: https://chat.openai.com/ [accessed 2024-04-23]
4. Dwivedi YK, Kshetri N, Hughes L, Slade EL, Jeyaraj A, Kar AK, et al. Opinion paper: "So what if ChatGPT wrote it?" multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. Int J Inf Manag 2023;71:102642 [FREE Full text] [doi: 10.1016/j.ijinfomgt.2023.102642]
5. Brynjolfsson E, Mcafee A. Artificial intelligence, for real. Harv Bus Rev 2017;1:1-31 [FREE Full text] [doi: 10.1162/99608f92.92fe150c]
6. Opgave AI—de nieuwe systeemtechnologie in beeld [Assignment AI—a closer look at the new system technology]. Wetenschappelijke Raad voor het Regeringsbeleid [Scientific Council for Government Policy]. 2021. URL: https://www.wrr.nl/binaries/wrr/documenten/rapporten/2021/11/11/opgave-ai-de-nieuwe-systeemtechnologie/Opgave+AI+in+beeld.pdf [accessed 2024-04-23]
7. Mols B. Internationaal AI-beleid. domme data, slimme computers en wijze mensen [International AI policy: dumb data, smart computers, and wise people]. Wetenschappelijke Raad voor het Regeringsbeleid: Den Haag [Scientific Council for Government Policy]. 2019. URL: https://www.wrr.nl/publicaties/working-papers/2019/06/12/internationaal-ai-beleid [accessed 2024-04-23]
8. Floridi L. The European legislation on AI: a brief analysis of its philosophical approach. Philos Technol 2021;34(2):215-222 [FREE Full text] [doi: 10.1007/s13347-021-00460-9] [Medline: 34104628]
9. EU AI Act: first regulation on artificial intelligence. Topics European Commission. 2023. URL: https://www.europarl.europa.eu/news/en/headlines/society/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence [accessed 2024-04-23]
10. Buchanan C, Howitt ML, Wilson R, Booth RG, Risling T, Bamford M. Predicted influences of artificial intelligence on the domains of nursing: scoping review. JMIR Nurs 2020;3(1):e23939 [FREE Full text] [doi: 10.2196/23939] [Medline: 34406963]
11. Rubeis G. Adiaphorisation and the digital nursing gaze: liquid surveillance in long-term care. Nurs Philos 2023;24(1):e12388 [FREE Full text] [doi: 10.1111/nup.12388] [Medline: 35355391]
12. Rubeis G. The disruptive power of artificial intelligence. ethical aspects of gerontechnology in elderly care. Arch Gerontol Geriatr 2020;91:104186. [doi: 10.1016/j.archger.2020.104186] [Medline: 32688106]
13. Israni ST, Verghese A. Humanizing artificial intelligence. JAMA 2019;321(1):29-30. [doi: 10.1001/jama.2018.19398] [Medline: 30535297]
14. Walker R, Dillard-Wright J, Iradukunda F. Algorithmic bias in artificial intelligence is a problem-and the root issue is power. Nurs Outlook 2023;71(5):102023 [FREE Full text] [doi: 10.1016/j.outlook.2023.102023] [Medline: 37579574]
15. Majumder S, Aghayi E, Noferesti M, Memarzadeh-Tehran H, Mondal T, Pang Z, et al. Smart homes for elderly healthcare-recent advances and research challenges. Sens (Basel) 2017;17(11):2496 [FREE Full text] [doi: 10.3390/s17112496] [Medline: 29088123]
16. Stokes F, Palmer A. Artificial intelligence and robotics in nursing: ethics of caring as a guide to dividing tasks between AI and humans. Nurs Philos 2020;21(4):e12306. [doi: 10.1111/nup.12306] [Medline: 32609420]
17. Kennedy MR, Huxtable R, Birchley G, Ives J, Craddock I. "A question of trust" and "a leap of faith"-study participants' perspectives on consent, privacy, and trust in smart home research: qualitative study. JMIR Mhealth Uhealth 2021;9(11):e25227 [FREE Full text] [doi: 10.2196/25227] [Medline: 34842551]
18. Sallam M. ChatGPT utility in healthcare education, research, and practice: systematic review on the promising perspectives and valid concerns. Healthcare (Basel) 2023;11(6):887 [FREE Full text] [doi: 10.3390/healthcare11060887] [Medline: 36981544]
19. Ronquillo CE, Peltonen LM, Pruinelli L, Chu CH, Bakken S, Beduschi A, et al. Artificial intelligence in nursing: priorities and opportunities from an international invitational think-tank of the nursing and artificial intelligence leadership collaborative. J Adv Nurs 2021;77(9):3707-3717 [FREE Full text] [doi: 10.1111/jan.14855] [Medline: 34003504]
20. Tursunbayeva A, Renkema M. Artificial intelligence in health-care: implications for the job design of healthcare professionals. Asia Pac J Hum Resour 2023;61(4):845-887 [FREE Full text] [doi: 10.1111/jan.14855]
21. Dembrower K, Crippa A, Colón E, Eklund M, Strand F, ScreenTrustCAD Trial Consortium. Artificial intelligence for breast cancer detection in screening mammography in Sweden: a prospective, population-based, paired-reader, non-inferiority study. Lancet Digit Health 2023;5(10):e703-e711 [FREE Full text] [doi: 10.1016/S2589-7500(23)00153-X] [Medline: 37690911]
22. Swan BA. Assessing the knowledge and attitudes of registered nurses about artificial intelligence in nursing and health care. Nurs Econ 2021;39(3):139 [FREE Full text]
23. Lukić A, Kudelić N, Antičević V, Lazić-Mosler E, Glunčić V, Hren D, et al. First-year nursing students' attitudes towards artificial intelligence: cross-sectional multi-center study. Nurse Educ Pract 2023;71:103735. [doi: 10.1016/j.nepr.2023.103735] [Medline: 37541081]

24. Taneri GU. Artificial intelligence and higher education: towards customized teaching and learning, and skills for an AI world of work. research and occasional paper series: CSHE. 6.2020. Center for Studies in Higher Education. 2020. URL: https://eric.ed.gov/?id=ED606654 [accessed 2024-04-23]
25. Naccarelli R, Casaccia S, Revel GM. The problem of monitoring activities of older people in multi-resident scenarios: an innovative and non-invasive measurement system based on wearables and PIR sensors. Sens (Basel) 2022;22(9):3472 [FREE Full text] [doi: 10.3390/s22093472] [Medline: 35591160]
26. Bian C, Ye B, Mihailidis A. The development and concurrent validity of a multi-sensor-based frailty toolkit for in-home frailty assessment. Sens (Basel) 2022;22(9):3532 [FREE Full text] [doi: 10.3390/s22093532] [Medline: 35591222]
27. Fritz R, Wuestney K, Dermody G, Cook DJ. Nurse-in-the-loop smart home detection of health events associated with diagnosed chronic conditions: a case-event series. Int J Nurs Stud Adv 2022;4:100081 [FREE Full text] [doi: 10.1016/j.ijnsa.2022.100081] [Medline: 35642184]
28. Coelho C, Coelho D, Wolf M. An IoT smart home architecture for long-term care of people with special needs. : IEEE; 2015 Presented at: 2015 IEEE 2nd World Forum on Internet of Things (WF-IoT); December 14-16, 2015; Milan, Italy URL: https://ieeexplore.ieee.org/document/7389126/ [doi: 10.1109/wf-iot.2015.7389126]
29. Peters M. Time to solve persistent, pernicious and widespread nursing workforce shortages. Int Nurs Rev 2023;70(2):247-253 [FREE Full text] [doi: 10.1111/inr.12837] [Medline: 37000668]
30. Mohammadnejad F, Freeman S, Klassen-Ross T, Hemingway D, Banner D. Impacts of technology use on the workload of registered nurses: a scoping review. J Rehabil Assist Technol Eng 2023;10:20556683231180189 [FREE Full text] [doi: 10.1177/20556683231180189] [Medline: 37342268]
31. Rubeis G. Guardians of humanity? the challenges of nursing practice in the digital age. Nurs Philos 2021;22(2):e12331 [FREE Full text] [doi: 10.1111/nup.12331] [Medline: 32996687]
32. Dermody G, Fritz R. A conceptual framework for clinicians working with artificial intelligence and health-assistive smart homes. Nurs Inq 2019;26(1):e12267. [doi: 10.1111/nin.12267] [Medline: 30417510]
33. Cook DJ, Schmitter-Edgecombe M, Jonsson L, Morant AV. Technology-enabled assessment of functional health. IEEE Rev Biomed Eng 2019;12:319-332. [doi: 10.1109/RBME.2018.2851500] [Medline: 29994684]
34. Wrede C, Braakman-Jansen A, van Gemert-Pijnen L. Requirements for unobtrusive monitoring to support home-based dementia care: qualitative study among formal and informal caregivers. JMIR Aging 2021;4(2):e26875 [FREE Full text] [doi: 10.2196/26875] [Medline: 33843596]
35. Rantz M, Popejoy LL, Galambos C, Phillips LJ, Lane KR, Marek KD, et al. The continued success of registered nurse care coordination in a state evaluation of aging in place in senior housing. Nurs Outlook 2014;62(4):237-246. [doi: 10.1016/j.outlook.2014.02.005] [Medline: 24731918]
36. Fritz RL, Dermody G. A nurse-driven method for developing artificial intelligence in "smart" homes for aging-in-place. Nurs Outlook 2019;67(2):140-153. [doi: 10.1016/j.outlook.2018.11.004] [Medline: 30551883]
37. Krizea M, Gialelis J, Protopsaltis G, Mountzouris C, Theodorou G. Empowering people with a user-friendly wearable platform for unobtrusive monitoring of vital physiological parameters. Sens (Basel) 2022;22(14):5226 [FREE Full text] [doi: 10.3390/s22145226] [Medline: 35890907]
38. Dawadi PN, Cook DJ, Schmitter-Edgecombe M, Parsey C. Automated assessment of cognitive health using smart home technologies. Technol Health Care 2013;21(4):323-343. [doi: 10.3233/THC-130734] [Medline: 23949177]
39. Le T, Reeder B, Chung J, Thompson H, Demiris G. Design of smart home sensor visualizations for older adults. Technol Health Care 2014;22(4):657-666. [doi: 10.3233/THC-140839] [Medline: 25267608]
40. Liao PH, Hsu PT, Chu W, Chu WC. Applying artificial intelligence technology to support decision-making in nursing: a case study in Taiwan. Health Informatics J 2015;21(2):137-148 [FREE Full text] [doi: 10.1177/1460458213509806] [Medline: 26021669]
41. Noon GB, Hanjahanja-Phiri T, Dave H, Fadrique L, Teague J, Morita PP. Exploring the role of active assisted living in the continuum of care for older adults: thematic analysis. JMIR Aging 2023;6:e40606 [FREE Full text] [doi: 10.2196/40606] [Medline: 37213201]
42. Kivimäki T, Stolt M, Charalambous A, Suhonen R. Safety of older people at home: an integrative literature review. Int J Older People Nurs 2020;15(1):e12285. [doi: 10.1111/opn.12285] [Medline: 31746103]
43. Seligman MEP. Positive health. Appl Psychol 2008;57(s1):3-18 [FREE Full text] [doi: 10.1111/j.1464-0597.2008.00351.x]
44. Boniol M, Kunjumen T, Nair TS, Siyam A, Campbell J, Diallo K. The global health workforce stock and distribution in 2020 and 2030: a threat to equity and 'universal' health coverage? BMJ Glob Health 2022;7(6):e009316 [FREE Full text] [doi: 10.1136/bmjgh-2022-009316] [Medline: 35760437]
45. Robert N. How artificial intelligence is changing nursing. Nurs Manage 2019;50(9):30-39 [FREE Full text] [doi: 10.1097/01.NUMA.0000578988.56622.21] [Medline: 31425440]
46. Rimmer A. Technology will improve doctors' relationships with patients, says Topol review. BMJ 2019;364:l661. [doi: 10.1136/bmj.l661] [Medline: 30745296]
47. Feo R, Conroy T, Jangland E, Athlin Å, Brovall M, Parr J, et al. Towards a standardised definition for fundamental care: a modified delphi study. J Clin Nurs 2018;27(11-12):2285-2299. [doi: 10.1111/jocn.14247] [Medline: 29278437]

48. Tolsgaard MG, Boscardin CK, Park YS, Cuddy MM, Sebok-Syer SS. The role of data science and machine learning in health professions education: practical applications, theoretical contributions, and epistemic beliefs. Adv Health Sci Educ Theory Pract 2020;25(5):1057-1086. [doi: 10.1007/s10459-020-10009-8] [Medline: 33141345]
49. Collins S, Yen PY, Phillips A, Kennedy MK. Nursing informatics competency assessment for the nurse leader: the delphi study. J Nurs Adm 2017;47(4):212-218. [doi: 10.1097/NNA.0000000000000467] [Medline: 28333789]
50. Yuan MJ, Finley GM, Long J, Mills C, Johnson RK. Evaluation of user interface and workflow design of a bedside nursing clinical decision support system. Interact J Med Res 2013;2(1):e4 [FREE Full text] [doi: 10.2196/ijmr.2402] [Medline: 23612350]
51. Groeneveld SWM, den Ouden MEM, van Gemert-Pijnen JEWC, Verdaasdonk RM, van Os-Medendorp H. Underestimated factors regarding the use of technology in daily practice of long-term care: qualitative study among health care professionals. JMIR Nurs 2023;6:e41032 [FREE Full text] [doi: 10.2196/41032] [Medline: 37494092]

Abbreviations

AI: artificial intelligence

Edited by E Borycki; submitted 17.01.24; peer-reviewed by C Makridis, K Esquivel; comments to author 17.03.24; revised version received 27.03.24; accepted 03.04.24; published 23.05.24.

Please cite as:
Groeneveld S, Bin Noon G, den Ouden MEM, van Os-Medendorp H, van Gemert-Pijnen JEWC, Verdaasdonk RM, Morita PP
The Cooperation Between Nurses and a New Digital Colleague “AI-Driven Lifestyle Monitoring” in Long-Term Care for Older Adults: Viewpoint
JMIR Nursing 2024;7:e56474
URL: https://nursing.jmir.org/2024/1/e56474
doi:10.2196/56474
PMID:38781012

Review

Using AI-Based Technologies to Help Nurses Detect Behavioral Disorders: Narrative Literature Review

Sofia Fernandes[1,2,3], MScN; Armin von Gunten[4], MPhil, MD; Henk Verloo[1,4], PhD

[1]School of Health Sciences, University of Applied Sciences and Arts Western Switzerland (HES-SO), Sion, Switzerland
[2]Les Maisons de la Providence Nursing Home, Le Châble, Switzerland
[3]Faculty of Biology and Medicine, Institute of Higher Education and Research in Healthcare, University of Lausanne, Lausanne, Switzerland
[4]Service of Old Age Psychiatry, Lausanne University Hospital and University of Lausanne, Lausanne, Switzerland

Corresponding Author:
Sofia Fernandes, MScN
School of Health Sciences
University of Applied Sciences and Arts Western Switzerland (HES-SO)
Chemin de l'Agasse 5
Sion, 1950
Switzerland
Phone: 41 00415860861
Email: sofia.fernandes@hevs.ch

Abstract

Background: The behavioral and psychological symptoms of dementia (BPSD) are common among people with dementia and have multiple negative consequences. Artificial intelligence–based technologies (AITs) have the potential to help nurses in the early prodromal detection of BPSD. Despite significant recent interest in the topic and the increasing number of available appropriate devices, little information is available on using AITs to help nurses striving to detect BPSD early.

Objective: The aim of this study is to identify the number and characteristics of existing publications on introducing AITs to support nursing interventions to detect and manage BPSD early.

Methods: A literature review of publications in the PubMed database referring to AITs and dementia was conducted in September 2023. A detailed analysis sought to identify the characteristics of these publications. The results were reported using a narrative approach.

Results: A total of 25 publications from 14 countries were identified, with most describing prospective observational studies. We identified three categories of publications on using AITs and they are (1) predicting behaviors and the stages and progression of dementia, (2) screening and assessing clinical symptoms, and (3) managing dementia and BPSD. Most of the publications referred to managing dementia and BPSD.

Conclusions: Despite growing interest, most AITs currently in use are designed to support psychosocial approaches to treating and caring for existing clinical signs of BPSD. AITs thus remain undertested and underused for the early and real-time detection of BPSD. They could, nevertheless, provide nurses with accurate, reliable systems for assessing, monitoring, planning, and supporting safe therapeutic interventions.

(JMIR Nursing 2024;7:e54496) doi:10.2196/54496

KEYWORDS

artificial intelligence; behavioral and psychological symptoms of dementia; neuropsychiatric symptoms; early detection; management; narrative literature review

Introduction

Demographic aging is a worldwide phenomenon, with significant growth in the number of older adults expected in the coming decades [1]. The number of people aged 80 years or older is expected to reach 426 million by 2050, with a high prevalence of dementia and other mental health disorders [2]. According to the World Health Organization, more than 55 million people worldwide endure dementia, and around 10 million new cases are diagnosed yearly [3]. More than 90% of them are affected by 1 or more of the behavioral and psychological symptoms of dementia (BPSD) and 80%-90%

live in nursing homes. The BPSD, also known as neuropsychiatric symptoms related to dementia, is characterized by changes in behavior, perception, thought content, and mood [4]. The most common symptoms are apathy, aberrant motor behaviors, mood disturbances, aggression, anxiety, irritability, and sleep disorders [4]. The BPSD has a negative impact on the quality of life, accelerating functional decline and leading to earlier mortality [5,6]. The BPSD can be the source of social isolation, abuse, and burdens for informal caregivers [7,8]. For health care professionals, including nurses, managing BPSD can lead to work overload, stress, burnout, reduced quality of care, and the risks of patient abuse [9-11]. Finally, BPSD can increase health care system costs through more consultations, hospitalizations, and the prescription of more psychotropic drugs and mood stabilizers [12].

The etiopathogenesis of the BPSD is complex. Although dementia is a prerequisite for the onset of its behavioral and psychological symptoms, it is not the sole determinant. The BPSD can result from a convergence of factors, including neurological alterations, somatic problems, psychological factors, environmental conditions, and individual patient characteristics [13]. Moreover, the frequency, intensity, and types of symptoms vary considerably from 1 person to another. Thus, effectively managing the BPSD requires a structured approach that identifies and acts on various trigger factors [4,13-15]. The literature suggests different models or approaches, but all agree on three distinct steps which are (1) assessing manifestations of the BPSD that the patients present with, (2) formulating a hypothesis to help understand them, and (3) designing 1 or more interventions targeting their trigger factors [4,13-15]. Interventions can be psychosocial, pharmacological, or a combination of both [4,13-15]. Traditionally, detecting symptoms, monitoring their evolution, and evaluating treatment efficacy are based on nursing observations documented using assessment scales (Neuropsychiatric Inventory and Cohen-Mansfield Agitation Inventory) or solely using written notes in the patient's medical record [15,16]. However, this process may prove ineffective for the early detection of the signs of BPSD, and nurses may perceive it as a potential factor in work overload [12]. Indeed, the first 2 steps require the investment of health care professionals, informal caregivers, and other individuals, and the third is more complex due to the variability and multifactorial nature of the BPSD. The BPSD challenges nurses daily, often triggering crises that are extremely complex to manage. Responding effectively and efficiently to these clinical issues requires more intensive observation and specialized care, with a greater emphasis on the prodromal detection of warning signs. However, due to an aging workforce and difficult working conditions (eg, high levels of stress and burnout, job dissatisfaction, and low levels of retention), the health care sector is facing a shortage of nursing staff [17]. The International Council of Nurses estimates a need for 13 million extra nurses to fill the worldwide shortages in the profession [18]. This shows the limitations of current human resources–based strategies, with the corollary need to explore innovative and sustainable solutions.

In recent decades, new information technologies have been adopted by every area of health care [19]. The first information technologies to be integrated into health care were electronic medical and health records, clinical information systems, and health information exchanges. More recently, other technologies have emerged, such as clinical decision support systems, mobile health apps, telehealth, telemedicine, robotics, wireless medical devices, and virtual reality [19-21]. Technological development in the health care sector, including nursing, is currently focused on artificial intelligence (AI) [19]. In the field of health care, AI usually refers to software capable of interpreting clinical data, learning from it, and helping clinical decision-making [19,22]. Combined with critical thinking and human judgment, AI has the potential to improve nurses' clinical reasoning by increasing the speed and accuracy of assessment, anticipation, synthesis, and knowledge generation [23]. From 1985 to date, the PubMed database lists 1086 publications on AI in nursing. There has been a significant growth in the number of these publications since 2020, reinforcing the nursing sciences' aims of developing and adapting nursing practices in line with sociodemographic changes and health care system, and medical and technical progress. [24]. Promoting the development, adoption and effective use of AI-based technologies (AITs) in health care has been identified as a key strategy to address the challenges related to both the complexity of managing the BPSD and limited resources [19,25-28]. Despite significant recent interest in the topic and the increasing number of technical devices on the market, little information is available on introducing AITs to help nurses attempting to detect BPSD as early as possible. This narrative review aims to identify and summarize the characteristics of existing publications concerning the use of AITs to support nurses in the early identification and management of BPSD.

Methods

Search Strategy

This narrative review was conducted following the Toronto and Remington guidelines [29]. The research question used to guide it was as follows:

> *What are the available publications on the use of artificial-intelligence-based technologies in neuropsychiatric symptoms related to dementia?*

We consulted the PubMed database in September 2023 using the descriptors and keywords "artificial intelligence," "behavioural and psychological symptoms of dementia," and "neuropsychiatric symptoms" (Multimedia Appendix 1).

Eligibility Criteria

Publications addressing the concept of dementia were included because the literature often links the concepts of dementia and the BPSD. The inclusion and exclusion criteria are presented in Textbox 1.

A total of 30 publications were identified and included after their titles and abstracts were reviewed. Following a thorough examination of their full texts, 5 publications were excluded because they focused on mental health issues unrelated to dementia or BPSD. In total, 25 publications were included.

Textbox 1. Inclusion and exclusion criteria.

Inclusion criteria

- Mental health disorder
  - Dementia
  - Behavioral and psychological symptoms of dementia
- Health care setting
  - No restrictions
- Artificial intelligence–based technology type
  - No restrictions
- Artificial intelligence–based technology use
  - No restrictions
- Publication type
  - No restrictions
- Publication date
  - No restrictions
- Language
  - No restrictions

Exclusion criteria

- Mental health disorder
  - Other mental health disorders

Data Extraction and Synthesis

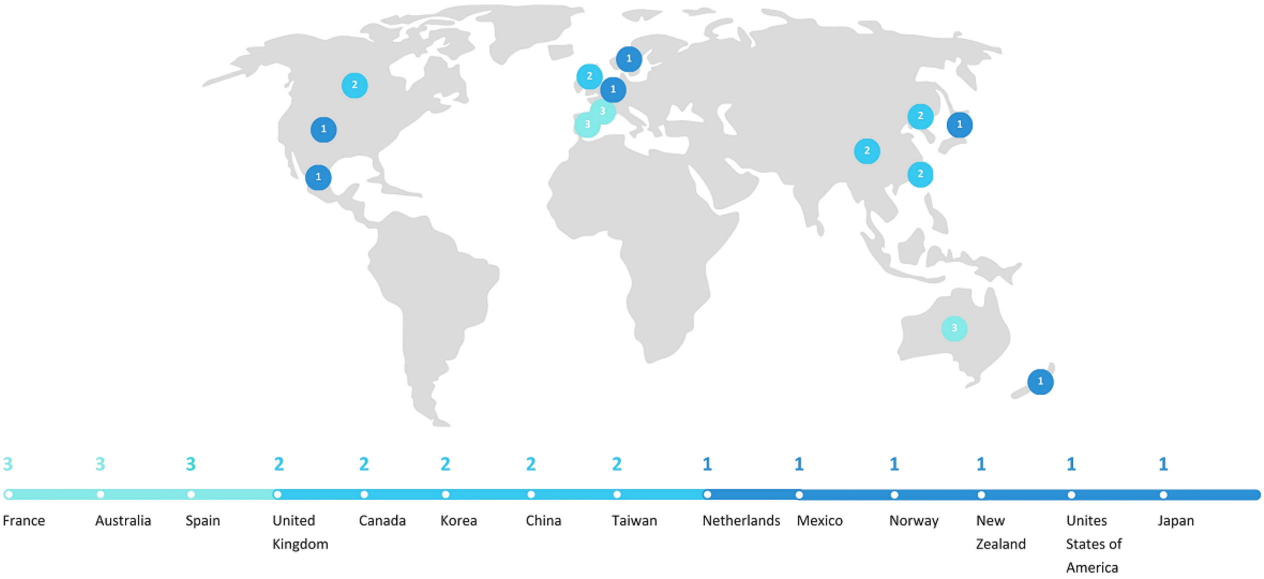
Information extracted from the publications retained for analysis included study design, country, journal title and category, mental health disorder addressed, type, subtype, use of the AITs, and health care setting. The type, subtype, and use of each AIT were identified via a basic qualitative content analysis, based on the authors’ stated aims and objectives (information found in the introduction and methods sections of the papers retained). In the context of mental health care, the type of AIT used was categorized according to the groups proposed by Jin et al [30], which are, machine learning, natural language processing, and digital health. Once this information was extracted, keywords were chosen to categorize the AIT’s use, with keywords determined based on the verbs used in each paper’s objectives (eg, measure, evaluate, screen, manage, and predict). The results are reported using a narrative approach.

Results

Study Characteristics

Publications from 14 countries were identified, with publication dates ranging from 2006 to 2023 (Figure 1). A total of 8 publications addressed acute care settings [31-38], 6 looked at nursing homes [39-44], and 3 examined community care [45-47]. The majority described prospective observational studies published in journals covering geriatrics and psychogeriatrics [31,33,34,36,46-48] (Multimedia Appendix 2) [31-55].

Figure 1. Number of publications per country.



Uses of AITs

A total of 12 publications reported using machine learning–type AITs, including the facial expression recognition and predictive modeling subtypes [31,34-38,43,46,47,49,50,55], 11 publications explored digital health–type AITs, including the wearable technologies and robotic subtypes [32,39-42,44,45,51-54], and 2 publications examined natural language processing–type AITs [33,48] (Figure 2).

We identified three categories of publications depending on the AIT's use and they are (1) predicting behavior and the stage and progression of dementia, (2) screening and assessing clinical symptoms, and (3) managing dementia and the BPSD (Figure 3).

A total of 4 publications reported on the use of machine learning technology to predict dementia behavior and the stage and progression of dementia [34,36-38]. Three publications referred to the use of natural language processing for screening and assessing clinical symptoms [35,48,49] and 1 reported on the use of machine learning [50]. One publication described the use of wearable technologies [40], and 1 combined this type of AIT with machine learning [46]. Finally, 10 publications reported on the use of robotics as a psychosocial approach to managing dementia and BPSD [32,39,41,42,44,45,51-54] (Table 1).

One publication reported on the use of AITs to predict the stage and progression of dementia [31], 1 described the detection and measurement of dementia's clinical symptoms [48], and 6 examined dementia management [39,41,44,51-53]. As for the BPSD, 5 publications reported using AITs to predict behavior [33,36,37,46,47], 3 described the detection and assessment of clinical symptoms [35,40,49], and 5 looked at managing behavior [32,42-44,55] (Figure 4). In the context of the BPSD, behavior management refers to interventions carried out to identify and act on trigger factors.

Figure 2. Number of publications by type of artificial intelligence–based technology.

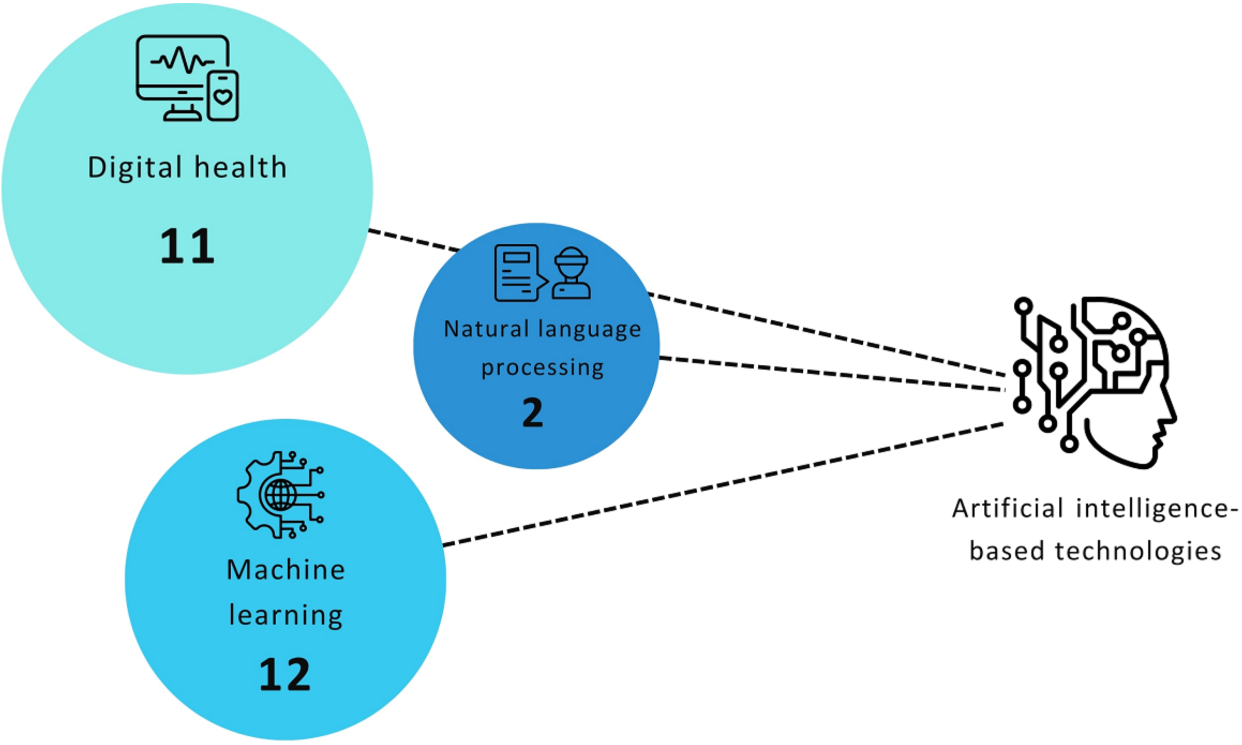


Figure 3. Number of publications by artificial intelligence–based technology use.

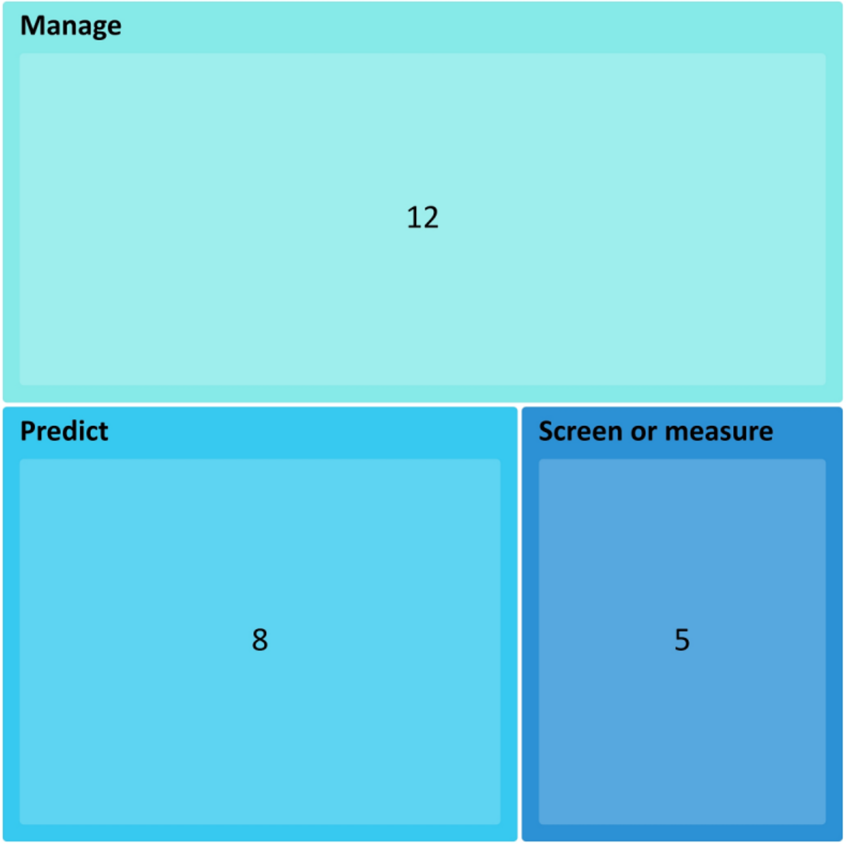


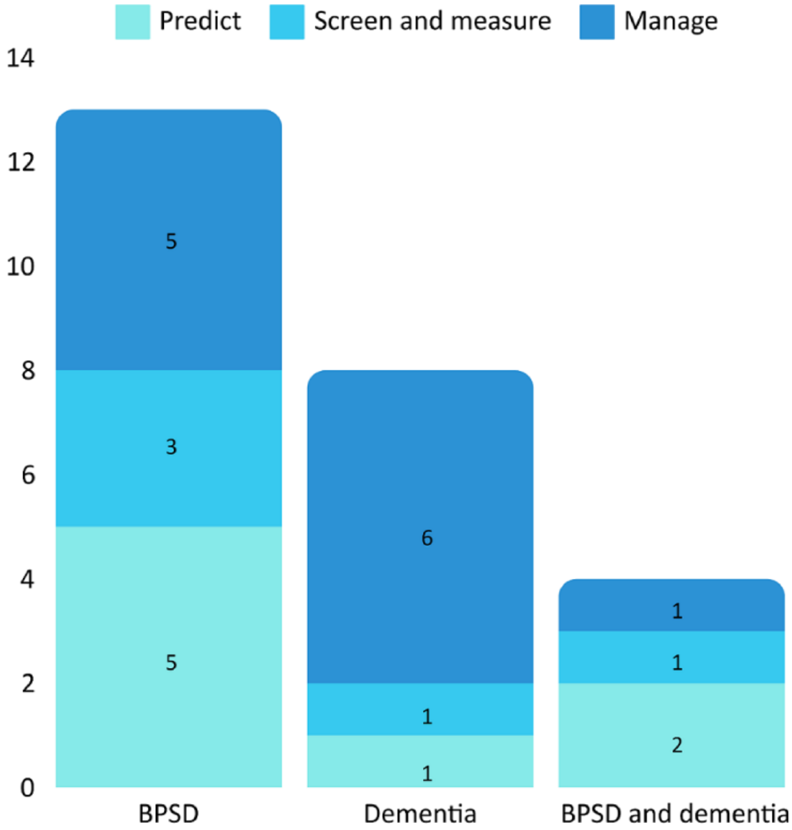
Table 1. Publications by type of AIT[a] and use.

Reference	AIT types			AITs subtype	AITs use		
	Machine learning	Natural language processing	Digital health		Predict	Screen and measure	Manage
Al-Harrasi et al [48]		✓		N/A[b]		✓	
Byeon [31]	✓			Predictive modeling	✓		
Chen et al [39]			✓	Robotics			✓
Chen et al [47]	✓			Facial expression recognition	✓		
Cho et al [46]	✓			Predictive modeling	✓		
Demange et al [32]			✓	Robotics			✓
Eikelboom et al [33]		✓		N/A	✓		
Favela et al [40]			✓	Wearable technology		✓	
Filan and Llewellyn-Jones [51]			✓	Robotics			✓
Gill et al [34]	✓			N/A	✓		
Hsieh et al [41]			✓	Robotics			✓
Jøranson et al [44]			✓	Robotics			✓
König et al [49]	✓			N/A		✓	
König et al [35]	✓			N/A		✓	
Leng et al [52]			✓	Robotics			✓
Liang et al [45]			✓	Robotics			✓
Mallo et al [36]	✓			N/A	✓		
Mar et al [38]	✓			N/A	✓		
Mar et al [37]	✓			N/A	✓		
Moyle et al [42]			✓	Robotics			✓
Pu et al [53]			✓	Robotics			✓
Russo et al [55]	✓			N/A			✓
Shah et al [50]	✓			N/A		✓	
Tadokoro et al [43]	✓			Facial expression recognition			✓
Yu et al [54]			✓	Robotics			✓

[a] AIT: artificial intelligence–based technology.

[b] N/A: not applicable.

Figure 4. Number of publications by artificial intelligence–based technology use and mental health issues. BPSD: behavioral and psychological symptoms of dementia.



Discussion

Principal Results

Despite the growing interest in AITs, most of those currently used take a psychosocial approach to treating and caring for patients with BPSD by using the clinical signs that are already present. AI remains largely unexplored in terms of its potential for the early, real-time detection of BPSD. Yet, in different health care settings and contexts, AITs could provide nurses with accurate and reliable systems for assessing, monitoring, planning, and supporting safe therapeutic interventions [27,56]. Based on our findings, it appears that the use of AITs has been explored more in acute care than in long-term care settings, which include community care and nursing homes. However, the prevalence of BPSD seems to be higher in the context of long-term care, particularly in nursing homes where 80%-90% of residents exhibit at least 1 of the BPSD and institutional resources tend to be more limited [57].

As mentioned above, BPSD has traditionally been assessed and monitored by health care professionals' observations of patients' behaviors [15,16]. However, this process may have limited success in the early detection of warning signs of the BPSD, and health care professionals perceive it to be another task or factor leading to work overload [11]. Therefore, it seems appropriate to anticipate symptom escalation and optimize staff and financial resources. Multimodal sensors for capturing physiological parameters, activity trackers, and facial expression recognition are all promising AITs that make the process of managing the BPSD more efficient and personalized [40,58-61]. By mining information from such devices, nurses could detect early warning signs of BPSD and their trigger factors. By combining this information with their clinical knowledge and experience, nurses could be equipped with a clinical decision-making support system enabling them to guide and personalize their therapeutic interventions [56,62-64].

Although nurses agree about the potential usefulness of AITs, most do not fully understand AI's underlying principles, and they are concerned about the potential consequences of its use in clinical practice [65-68]. Other obstacles pertaining to AITs include the unknown cost-benefits of their use in health care settings, the current lack of use and data management protocols in those settings, and the lack of information technology capacity there to support them [69,70]. The published papers identified in this review reinforced these points as the involvement of nurses in designing studies and the use of AITs was low. However, in interdisciplinary contexts, nurses have key roles to play in the conception and design of AIT devices, verifying their effectiveness and adapting their use.

Strengths and Limitations

The characteristics of the publications retained in this narrative review revealed the countries and contexts where AITs have been integrated into settings dealing with the BPSD and have been investigated. It also demonstrated the types of technologies available and their intended purposes, as well as the clinical contexts in which they are deployed. These results, while not exhaustive, provide a preliminary overview of this emerging topic and identify AITs' potential benefits for clinical practice and pathways for future research. This narrative review has some limitations, nevertheless. The absence of an assessment of the quality and validity of the selected publications may bias the quality of their reported outcomes. Furthermore, including publications that address dementia could lead to confusion regarding this narrative review's focus. Although the concepts of dementia and BPSD are frequently interrelated in the specialized literature, including the concept of dementia could lead readers to misunderstand the scope of the results presented.

Conclusions

AI has the potential to transform nursing practice, particularly in support of the diagnosis and management of BPSD, which are currently among the major challenges in caring for older adults with dementia. However, our literature review found little experimental evidence, data, or understanding of how these types of technologies could be applied advantageously to the early detection of BPSD by nurses. Furthermore, although these are preliminary findings, the results of this review showed that research on this topic has only been done in relatively few countries, despite the impact of the BPSD being a global phenomenon. Based on this fact and the review's limitations, we would recommend that a more comprehensive examination be performed, such as a scoping review, to meticulously explore the research conducted on AITs for the early detection of BPSD. It also seems important that future experimental research investigates the effectiveness, feasibility, and acceptability of using devices based on AITs for the prodromal detection of BPSD. Specific research in long-term care settings seems to be particularly lacking. Nurses are intimately involved in creating a vision of contemporary professional nursing practice and then applying that practice. Therefore, it seems appropriate that they should be involved in strengthening collaboration with information technology engineers and programmers. Nurses' perceptions and experiences of using AITs to detect BPSD should also be explored, using a qualitative approach, as should how the data provided by these types of technologies contribute to nurses' clinical reasoning and decision-making processes.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Search query.
[DOCX File , 31 KB - nursing_v7i1e54496_app1.docx]

Multimedia Appendix 2
Description of the selected publications.
[DOCX File , 25 KB - nursing_v7i1e54496_app2.docx]

References

1. Vieillissement et santé. World Health Organization. 2022. URL: https://www.who.int/fr/news-room/fact-sheets/detail/ageing-and-health [accessed 2023-09-06]
2. von Gunten A. Psychiatrie de la personne âgée en Suisse. Swiss Arch Neurol Psychiatr Psychother 2017;168(02):33-40 [FREE Full text] [doi: 10.4414/sanp.2017.00450]
3. Démence. Organisation mondiale de la santé [World Health Organization]. 2023. URL: https://www.who.int/fr/news-room/fact-sheets/detail/dementia [accessed 2023-09-06]
4. Kales HC, Lyketsos CG, Miller EM, Ballard C. Management of behavioral and psychological symptoms in people with Alzheimer's disease: an international Delphi consensus. Int Psychogeriatr 2019;31(1):83-90. [doi: 10.1017/S1041610218000534] [Medline: 30068400]
5. Bränsvik V, Granvik E, Minthon L, Nordström P, Nägga K. Mortality in patients with behavioural and psychological symptoms of dementia: a registry-based study. Aging Ment Health 2021;25(6):1101-1109 [FREE Full text] [doi: 10.1080/13607863.2020.1727848] [Medline: 32067466]
6. Cepoiu-Martin M, Tam-Tham H, Patten S, Maxwell CJ, Hogan DB. Predictors of long-term care placement in persons with dementia: a systematic review and meta-analysis. Int J Geriatr Psychiatry 2016;31(11):1151-1171. [doi: 10.1002/gps.4449] [Medline: 27045271]
7. Feast A, Orrell M, Charlesworth G, Melunsky N, Poland F, Moniz-Cook E. Behavioural and psychological symptoms in dementia and the challenges for family carers: systematic review. Br J Psychiatry 2016;208(5):429-434 [FREE Full text] [doi: 10.1192/bjp.bp.114.153684] [Medline: 26989095]
8. Pinyopornpanish K, Soontornpun A, Wongpakaran T, Wongpakaran N, Tanprawate S, Pinyopornpanish K, et al. Impact of behavioral and psychological symptoms of Alzheimer's disease on caregiver outcomes. Sci Rep 2022;12(1):14138 [FREE Full text] [doi: 10.1038/s41598-022-18470-8] [Medline: 35986203]
9. Kang Y, Hur Y. Nurses' experience of nursing workload-related issues during caring patients with dementia: a qualitative meta-synthesis. Int J Environ Res Public Health 2021;18(19):10448 [FREE Full text] [doi: 10.3390/ijerph181910448] [Medline: 34639748]

10. Ostaszkiewicz J, Lakhan P, O'Connell B, Hawkins M. Ongoing challenges responding to behavioural and psychological symptoms of dementia. Int Nurs Rev 2015;62(4):506-516. [doi: 10.1111/inr.12180] [Medline: 25711925]
11. Steele C, Berry K, Brown LJE. Healthcare professionals' experiences of using a biopsychosocial approach to understand behavioural and psychological symptoms of dementia: a qualitative interview study. Int J Older People Nurs 2022;17(2):e12427. [doi: 10.1111/opn.12427] [Medline: 34561970]
12. Butler M, Gaugler JE, Talley KMC, Abdi HI, Desai PJ, Duval S, et al. Care interventions for people living with dementia and their caregivers. Comparative Effectiveness Review No. 231. Agency for Healthcare Research and Quality. Rockville, MD URL: https://effectivehealthcare.ahrq.gov/sites/default/files/pdf/cer-231-dementia-interventions-final_0.pdf [accessed 2024-05-08]
13. Dementia: Assessment, Management and Support for People Living with Dementia and Their Carers. London: National Institute for Health and Care Excellence; 2018.
14. Ma H, Lu X, Zhou A, Wang F, Zuo X, Zhan M, et al. Clinical practice guidelines for the management of behavioral and psychological symptoms of dementia: a systematic review with AGREE II. Front Neurol 2022;13:799723 [FREE Full text] [doi: 10.3389/fneur.2022.799723] [Medline: 35693007]
15. Tible OP, Riese F, Savaskan E, von Gunten A. Best practice in the management of behavioural and psychological symptoms of dementia. Ther Adv Neurol Disord 2017;10(8):297-309 [FREE Full text] [doi: 10.1177/1756285617712979] [Medline: 28781611]
16. Bessey LJ, Walaszek A. Management of behavioral and psychological symptoms of dementia. Curr Psychiatry Rep 2019;21(8):66. [doi: 10.1007/s11920-019-1049-5] [Medline: 31264056]
17. Drennan VM, Ross F. Global nurse shortages-the facts, the impact and action for change. Br Med Bull 2019;130(1):25-37 [FREE Full text] [doi: 10.1093/bmb/ldz014] [Medline: 31086957]
18. ICN policy brief—the global nursing shortage and nurse retention. International Council of Nurses. 2021. URL: https://www.icn.ch/node/1297 [accessed 2023-09-06]
19. Raymond L, Castonguay A, Doyon O, Paré G. Nurse practitioners' involvement and experience with AI-based health technologies: a systematic review. Appl Nurs Res 2022;66:151604. [doi: 10.1016/j.apnr.2022.151604] [Medline: 35840270]
20. Golinelli D, Boetto E, Carullo G, Nuzzolese AG, Landini MP, Fantini MP. Adoption of digital technologies in health care during the COVID-19 pandemic: systematic review of early scientific literature. J Med Internet Res 2020;22(11):e22280 [FREE Full text] [doi: 10.2196/22280] [Medline: 33079693]
21. Lu L, Zhang J, Xie Y, Gao F, Xu S, Wu X, et al. Wearable health devices in health care: narrative systematic review. JMIR Mhealth Uhealth 2020;8(11):e18907 [FREE Full text] [doi: 10.2196/18907] [Medline: 33164904]
22. Douthit BJ, Hu X, Richesson RL, Kim H, Cary MP. How artificial intelligence is transforming the future of nursing. Am J Nurs 2020;15(9):100-102 [FREE Full text]
23. Artificial intelligence, critical thinking, and the nursing process. HIMSS. 2019. URL: https://www.himss.org/resources/artificial-intelligence-critical-thinking-and-nursing-process [accessed 2023-09-06]
24. Pepin J, Ducharme F, Kérouac S. La Pensée Infirmière, 4e édition. Montréal: Chenelière éducation; 2017.
25. Boyne JJ, Ski CF, Fitzsimons D, Amin H, Hill L, Thompson DR. The changing role of patients, and nursing and medical professionals as a result of digitalization of health and heart failure care. J Nurs Manag 2022;30(8):3847-3852 [FREE Full text] [doi: 10.1111/jonm.13888] [Medline: 36329647]
26. The Topol review: preparing the healthcare workforce to deliver the digital future. NHS Health Education England. 2019. URL: https://topol.hee.nhs.uk [accessed 2023-09-06]
27. Stavropoulos TG, Papastergiou A, Mpaltadoros L, Nikolopoulos S, Kompatsiaris I. IoT wearable sensors and devices in elderly care: a literature review. Sensors (Basel) 2020;20(10):2826 [FREE Full text] [doi: 10.3390/s20102826] [Medline: 32429331]
28. Global Strategy on Digital Health 2020-2025. Geneva: World Health Organization; 2021.
29. Toronto CE, Remington R. A Step-by-Step Guide to Conducting an Integrative Review. Cham: Springer International Publishing; 2020.
30. Jin KW, Li Q, Xie Y, Xiao G. Artificial intelligence in mental healthcare: an overview and future perspectives. Br J Radiol 2023;96(1150):20230213 [FREE Full text] [doi: 10.1259/bjr.20230213] [Medline: 37698582]
31. Byeon H. Predicting the severity of Parkinson's disease dementia by assessing the neuropsychiatric symptoms with an SVM regression model. Int J Environ Res Public Health 2021;18(5):2551 [FREE Full text] [doi: 10.3390/ijerph18052551] [Medline: 33806474]
32. Demange M, Lenoir H, Pino M, Cantegreil-Kallen I, Rigaud AS, Cristancho-Lacroix V. Improving well-being in patients with major neurodegenerative disorders: differential efficacy of brief social robot-based intervention for 3 neuropsychiatric profiles. Clin Interv Aging 2018;13:1303-1311 [FREE Full text] [doi: 10.2147/CIA.S152561] [Medline: 30057445]
33. Eikelboom WS, Singleton EH, van den Berg E, de Boer C, Coesmans M, Goudzwaard JA, et al. The reporting of neuropsychiatric symptoms in electronic health records of individuals with Alzheimer's disease: a natural language processing study. Alzheimers Res Ther 2023;15(1):94 [FREE Full text] [doi: 10.1186/s13195-023-01240-7] [Medline: 37173801]

34. Gill S, Mouches P, Hu S, Rajashekar D, MacMaster FP, Smith EE, et al. Using machine learning to predict dementia from neuropsychiatric symptom and neuroimaging data. J Alzheimers Dis 2020;75(1):277-288 [FREE Full text] [doi: 10.3233/jad-191169]
35. König A, Mallick E, Tröger J, Linz N, Zeghari R, Manera V, et al. Measuring neuropsychiatric symptoms in patients with early cognitive decline using speech analysis. Eur Psychiatry 2021;64(1):e64 [FREE Full text] [doi: 10.1192/j.eurpsy.2021.2236] [Medline: 34641989]
36. Mallo SC, Valladares-Rodriguez S, Facal D, Lojo-Seoane C, Fernández-Iglesias MJ, Pereiro AX. Neuropsychiatric symptoms as predictors of conversion from MCI to dementia: a machine learning approach. Int. Psychogeriatr 2019;32(3):381-392. [doi: 10.1017/s1041610219001030]
37. Mar J, Gorostiza A, Ibarrondo O, Cernuda C, Arrospide A, Iruin Á, et al. Validation of random forest machine learning models to predict dementia-related neuropsychiatric symptoms in real-world data. J Alzheimers Dis 2020;77(2):855-864 [FREE Full text] [doi: 10.3233/JAD-200345] [Medline: 32741825]
38. Mar J, Gorostiza A, Arrospide A, Larrañaga I, Alberdi A, Cernuda C, et al. Estimation of the epidemiology of dementia and associated neuropsychiatric symptoms by applying machine learning to real-world data. Rev Psiquiatr Salud Ment (Engl Ed) 2021 Mar 25;15(3):167-175. [doi: 10.1016/j.rpsm.2021.03.001] [Medline: 33774222]
39. Chen K, Lou VWQ, Tan KCK, Wai MY, Chan LL. Effects of a humanoid companion robot on dementia symptoms and caregiver distress for residents in long-term care. J Am Med Dir Assoc 2020;21(11):1724-1728.e3. [doi: 10.1016/j.jamda.2020.05.036] [Medline: 32713772]
40. Favela J, Cruz-Sandoval D, Morales-Tellez A, Lopez-Nava IH. Monitoring behavioral symptoms of dementia using activity trackers. J Biomed Inform 2020;109:103520 [FREE Full text] [doi: 10.1016/j.jbi.2020.103520] [Medline: 32783922]
41. Hsieh CJ, Li PS, Wang CH, Lin SL, Hsu TC, Tsai CMT. Socially assistive robots for people living with dementia in long-term facilities: a systematic review and meta-analysis of randomized controlled trials. Gerontology 2023;69(8):1027-1042 [FREE Full text] [doi: 10.1159/000529849] [Medline: 36871553]
42. Moyle W, Bramble M, Jones CJ, Murfield JE. "She had a smile on her face as wide as the great Australian bite": a qualitative examination of family perceptions of a therapeutic robot and a plush toy. Gerontologist 2019;59(1):177-185 [FREE Full text] [doi: 10.1093/geront/gnx180] [Medline: 29165558]
43. Tadokoro K, Yamashita T, Kawano S, Sato J, Omote Y, Takemoto M, et al. Immediate beneficial effect of makeup therapy on behavioral and psychological symptoms of dementia and facial appearance analyzed by artificial intelligence software. J Alzheimers Dis 2021;83(1):57-63. [doi: 10.3233/JAD-210284] [Medline: 34250937]
44. Jøranson N, Pedersen I, Rokstad AMM, Ihlebæk C. Effects on symptoms of agitation and depression in persons with dementia participating in robot-assisted activity: a cluster-randomized controlled trial. J Am Med Dir Assoc 2015;16(10):867-873. [doi: 10.1016/j.jamda.2015.05.002] [Medline: 26096582]
45. Liang A, Piroth I, Robinson H, MacDonald B, Fisher M, Nater UM, et al. A pilot randomized trial of a companion robot for people with dementia living in the community. J Am Med Dir Assoc 2017;18(10):871-878. [doi: 10.1016/j.jamda.2017.05.019] [Medline: 28668664]
46. Cho E, Kim S, Heo SJ, Shin J, Hwang S, Kwon E, et al. Machine learning-based predictive models for the occurrence of behavioral and psychological symptoms of dementia: model development and validation. Sci Rep 2023;13(1):8073 [FREE Full text] [doi: 10.1038/s41598-023-35194-5] [Medline: 37202454]
47. Chen LY, Tsai TH, Ho A, Li CH, Ke LJ, Peng LN, et al. Predicting neuropsychiatric symptoms of persons with dementia in a day care center using a facial expression recognition system. Aging (Albany NY) 2022;14(3):1280-1291 [FREE Full text] [doi: 10.18632/aging.203869] [Medline: 35113806]
48. Al-Harrasi AM, Iqbal E, Tsamakis K, Lasek J, Gadelrab R, Soysal P, et al. Motor signs in Alzheimer's disease and vascular dementia: detection through natural language processing, co-morbid features and relationship to adverse outcomes. Exp Gerontol 2021;146:111223. [doi: 10.1016/j.exger.2020.111223] [Medline: 33450346]
49. König A, Linz N, Zeghari R, Klinge X, Tröger J, Alexandersson J, et al. Detecting apathy in older adults with cognitive disorders using automatic speech analysis. J Alzheimers Dis 2019;69(4):1183-1193. [doi: 10.3233/JAD-181033] [Medline: 31127764]
50. Shah J, Rahman Siddiquee MM, Krell-Roesch J, Syrjanen JA, Kremers WK, Vassilaki M, et al. Neuropsychiatric symptoms and commonly used biomarkers of Alzheimer's disease: a literature review from a machine learning perspective. J Alzheimers Dis 2023;92(4):1131-1146. [doi: 10.3233/JAD-221261] [Medline: 36872783]
51. Filan SL, Llewellyn-Jones RH. Animal-assisted therapy for dementia: a review of the literature. Int Psychogeriatr 2006;18(4):597-611. [doi: 10.1017/S1041610206003322] [Medline: 16640796]
52. Leng M, Liu P, Zhang P, Hu M, Zhou H, Li G, et al. Pet robot intervention for people with dementia: a systematic review and meta-analysis of randomized controlled trials. Psychiatry Res 2019;271:516-525. [doi: 10.1016/j.psychres.2018.12.032] [Medline: 30553098]
53. Pu L, Coppieters MW, Byrnes J, Jones C, Smalbrugge M, Todorovic M, et al. Feasibility study protocol of the PainChek app to assess the efficacy of a social robot intervention for people with dementia. J Adv Nurs 2022;78(2):587-594. [doi: 10.1111/jan.15106] [Medline: 34825740]

54. Yu C, Sommerlad A, Sakure L, Livingston G. Socially assistive robots for people with dementia: systematic review and meta-analysis of feasibility, acceptability and the effect on cognition, neuropsychiatric symptoms and quality of life. Ageing Res Rev 2022;78:101633 [FREE Full text] [doi: 10.1016/j.arr.2022.101633] [Medline: 35462001]
55. Russo FA, Mallik A, Thomson Z, de Raadt St James A, Dupuis K, Cohen D. Developing a music-based digital therapeutic to help manage the neuropsychiatric symptoms of dementia. Front Digit Health 2023;5:1064115 [FREE Full text] [doi: 10.3389/fdgth.2023.1064115] [Medline: 36744277]
56. Pappadà A, Chattat R, Chirico I, Valente M, Ottoboni G. Assistive technologies in dementia care: an updated analysis of the literature. Front Psychol 2021;12:644587 [FREE Full text] [doi: 10.3389/fpsyg.2021.644587] [Medline: 33841281]
57. Cloak N, Al Khalili Y. Behavioral and psychological symptoms in dementia. In: StatPearls. Treasure Island, FL: StatPearls Publishing; 2022.
58. Goerss D, Hein A, Bader S, Halek M, Kernebeck S, Kutschke A, et al. Automated sensor-based detection of challenging behaviors in advanced stages of dementia in nursing homes. Alzheimers Dement 2020;16(4):672-680 [FREE Full text] [doi: 10.1016/j.jalz.2019.08.193] [Medline: 31668595]
59. Iaboni A, Spasojevic S, Newman K, Schindel Martin L, Wang A, Ye B, et al. Wearable multimodal sensors for the detection of behavioral and psychological symptoms of dementia using personalized machine learning models. Alzheimers Dement (Amst) 2022;14(1):e12305 [FREE Full text] [doi: 10.1002/dad2.12305] [Medline: 35496371]
60. Kyriakou K, Resch B, Sagl G, Petutschnig A, Werner C, Niederseer D, et al. Detecting moments of stress from measurements of wearable physiological sensors. Sensors (Basel) 2019;19(17):3805 [FREE Full text] [doi: 10.3390/s19173805] [Medline: 31484366]
61. Melander CA, Kikhia B, Olsson M, Wälivaara BM, Sävenstedt S. The impact of using measurements of electrodermal activity in the assessment of problematic behaviour in dementia. Dement Geriatr Cogn Dis Extra 2018;8(3):333-347 [FREE Full text] [doi: 10.1159/000493339] [Medline: 30386370]
62. Dada S, van der Walt C, May AA, Murray J. Intelligent assistive technology devices for persons with dementia: a scoping review. Assist Technol 2022:1-14. [doi: 10.1080/10400435.2021.1992540] [Medline: 34644248]
63. Husebo BS, Heintz HL, Berge LI, Owoyemi P, Rahman AT, Vahia IV. Sensing technology to monitor behavioral and psychological symptoms and to assess treatment response in people with dementia. a systematic review. Front Pharmacol 2019;10:1699 [FREE Full text] [doi: 10.3389/fphar.2019.01699] [Medline: 32116687]
64. Lai Kwan C, Mahdid Y, Motta Ochoa R, Lee K, Park M, Blain-Moraes S. Wearable technology for detecting significant moments in individuals with dementia. Biomed Res Int 2019;2019:6515813 [FREE Full text] [doi: 10.1155/2019/6515813] [Medline: 31662986]
65. Abuzaid MM, Elshami W, Fadden SM. Integration of artificial intelligence into nursing practice. Health Technol (Berl) 2022;12(6):1109-1115 [FREE Full text] [doi: 10.1007/s12553-022-00697-0] [Medline: 36117522]
66. Buchanan C, Howitt ML, Wilson R, Booth RG, Risling T, Bamford M. Predicted influences of artificial intelligence on nursing education: scoping review. JMIR Nurs 2021;4(1):e23933 [FREE Full text] [doi: 10.2196/23933] [Medline: 34345794]
67. Castagno S, Khalifa M. Perceptions of artificial intelligence among healthcare staff: a qualitative survey study. Front Artif Intell 2020;3:578983 [FREE Full text] [doi: 10.3389/frai.2020.578983] [Medline: 33733219]
68. Topaz M, Pruinelli L. Big data and nursing: implications for the future. Stud Health Technol Inform 2017;232:165-171. [Medline: 28106594]
69. Olaye IM, Seixas AA. The gap between AI and bedside: participatory workshop on the barriers to the integration, translation, and adoption of digital health care and AI startup technology into clinical practice. J Med Internet Res 2023;25:e32962 [FREE Full text] [doi: 10.2196/32962] [Medline: 37129947]
70. Tachkov K, Zemplenyi A, Kamusheva M, Dimitrova M, Siirtola P, Pontén J, et al. Barriers to use artificial intelligence methodologies in health technology assessment in Central and East European countries. Front Public Health 2022;10:921226 [FREE Full text] [doi: 10.3389/fpubh.2022.921226] [Medline: 35910914]

Abbreviations

AI: artificial intelligence
AIT: artificial intelligence–based technology
BPSD: behavioral and psychological symptoms of dementia

Edited by E Borycki, K Cato; submitted 12.11.23; peer-reviewed by A Hidki, L Nunes, A Haddadi Avval; comments to author 20.02.24; revised version received 15.04.24; accepted 26.04.24; published 28.05.24.

Please cite as:
Fernandes S, von Gunten A, Verloo H
Using AI-Based Technologies to Help Nurses Detect Behavioral Disorders: Narrative Literature Review
JMIR Nursing 2024;7:e54496
URL: https://nursing.jmir.org/2024/1/e54496
doi:10.2196/54496
PMID:38805252

Viewpoint

Navigating the Pedagogical Landscape: Exploring the Implications of AI and Chatbots in Nursing Education

Muthuvenkatachalam Srinivasan[1], MSc, PhD; Ambili Venugopal[1], MSc; Latha Venkatesan[2], MSc, MPhil, PhD; Rajesh Kumar[3], MSc, PhD

[1]College of Nursing, All India Institute of Medical Sciences, Mangalagiri, India
[2]College of Nursing, All India Institute of Medical Sciences, New Delhi, India
[3]College of Nursing, All India Institute of Medical Sciences, Rishikesh, India

Corresponding Author:
Muthuvenkatachalam Srinivasan, MSc, PhD
College of Nursing
All India Institute of Medical Sciences
Guntur Dt
Mangalagiri, 522503
India
Phone: 91 9410366146
Email: muthu.venky@gmail.com

Abstract

This viewpoint paper explores the pedagogical implications of artificial intelligence (AI) and AI-based chatbots such as ChatGPT in nursing education, examining their potential uses, benefits, challenges, and ethical considerations. AI and chatbots offer transformative opportunities for nursing education, such as personalized learning, simulation and practice, accessible learning, and improved efficiency. They have the potential to increase student engagement and motivation, enhance learning outcomes, and augment teacher support. However, the integration of these technologies also raises ethical considerations, such as privacy, confidentiality, and bias. The viewpoint paper provides a comprehensive overview of the current state of AI and chatbots in nursing education, offering insights into best practices and guidelines for their integration. By examining the impact of AI and ChatGPT on student learning, engagement, and teacher effectiveness and efficiency, this review aims to contribute to the ongoing discussion on the use of AI and chatbots in nursing education and provide recommendations for future research and development in the field.

(JMIR Nursing 2024;7:e52105) doi:10.2196/52105

KEYWORDS

AI; artificial intelligence; ChatGPT; chatbots; nursing education; education; chatbot; nursing; ethical; ethics; ethical consideration; accessible; learning; efficiency; student; student engagement; student learning

Introduction

Artificial intelligence (AI) and AI-based chatbots such as ChatGPT have become popular in many industries, including health care. AI refers to the use of computer algorithms and machine learning techniques to enable machines to perform tasks that traditionally require human intelligence, such as perception, reasoning, and decision-making. AI has numerous applications in health care, including in nursing education. AI uses computers and specially designed software to perform tasks and reasoning in different areas of health care, including screening, diagnosis, education, telecommunications, data security, finance, research, and the legal system [1,2]. However, in the present era, the scope of AI is limited to carrying out specific tasks and solutions to predefined problems [3].

A chatbot is a computer program designed to simulate conversation with human users through text or voice-based interactions. Chatbots use natural language processing and AI technologies to understand and respond to user queries and requests in a conversational manner [4]. ChatGPT is one such state-of-the-art language processing models that generates human-like responses to text prompts. It is trained on vast amounts of text data and uses machine learning algorithms to predict the likelihood of a particular sequence of words. OpenAI, a Microsoft Corp–backed start-up, recently unveiled GPT-4, a highly advanced version of ChatGPT. GPT-4's upgraded capabilities enable it to engage in dialogic conversations and provide more comprehensive answers, incorporating improved data, facts, and analytical insights. It predicts the next word in a given set of text based on patterns it learned from a massive amount of data during its training process. The AI processes user requests and responds based on available information. Likewise, AI is identical to machine learning and human learning and uses specially designed software and machine-based algorithms to complement human learning in education, learning, analysis, and other multifaceted medical and health care fields [5].

The scope of this viewpoint paper is to explore the pedagogical implications of AI and AI-powered chatbots in nursing education; it will examine the potential uses and benefits of AI and chatbots in nursing education and the challenges and ethical considerations that must be addressed when integrating these technologies into the classroom. By examining the impact of AI and chatbots on student learning, engagement, and teacher effectiveness and efficiency, this viewpoint paper aims to provide educators and researchers in nursing education with a deeper understanding of the potential benefits and challenges of integrating AI and chatbots into their teaching practice.

However, there are also challenges and ethical considerations that must be addressed. As such, it is crucial to examine the role of AI and chatbots in nursing education and explore its implications to prepare nursing students for the digital age. The objective of this viewpoint paper is to provide insights into navigating the pedagogical landscape of nursing education with AI and chatbots.

Understanding AI and Chatbots in Nursing Education

Chatbots have potential applications in health care education, research, and practice [6]. There is currently a surge in the development of desktop and mobile applications powered by AI and ChatGPT technology. Several chatbots have been created with specialized capabilities to perform specific tasks. These specialized chatbots are designed to excel in their specific area of expertise and are trained with data and algorithms that enable them to provide accurate and relevant responses to user queries related to their area of specialization.

In nursing education, AI and chatbots can potentially transform the learning experience for students and teachers alike. For example, ChatGPT can be used to summarize large amounts of text data such as research articles, clinical notes, and patient records, which could help nurses quickly identify key findings and insights from a large body of literature [7]. Chatbots help nursing students interact with AI-generated natural language prompts to better understand medical concepts. It has the potential to become a go-to assistant for nursing students who aspire to become more proficient in their field. Students can use chatbots to develop study schedules, create multifaceted questions and scenarios, and quiz themselves on topics they want to be prompted about. Recent developments have been made in this area, such as ChatGPT being integrated as a journal author for a publication titled, “Open Artificial Intelligence Platforms In Nursing Education: Tools For Academic Progress Or Abuse” [8]. AI can be used to analyze data and identify patterns to personalize learning material and provide student feedback. It can also be used to simulate patient scenarios and provide a safe and controlled environment for students to practice clinical skills. Chatbots using AI technology can also provide immediate responses to students’ questions and offer 24/7 support, enabling students to learn at their own pace and on their own schedule.

Additionally, AI can be used to improve the efficiency and effectiveness of administrative tasks such as scheduling, record-keeping, and grading. This can free up teachers’ time to focus on more meaningful student interactions, such as providing personalized feedback and support. The potential uses of AI and chatbots in nursing education are vast and varied, offering exciting opportunities for innovation and transformation in the field.

Benefits of AI and Chatbots in Nursing Education

Incorporating AI and chatbots in nursing education leads to a multitude of benefits, including personalized learning experiences achieved by analyzing data and identifying patterns. This tailoring of learning materials offers customized feedback based on each student’s needs, which, in turn, enhances engagement and motivation. AI-powered simulations provide a safe environment for practicing clinical skills, thus minimizing risks to real patients, while AI-driven chatbots, such as ChatGPT, offer continuous support and immediate responses to questions, thus promoting self-paced learning [9]. Furthermore, AI streamlines administrative tasks, such as grading and record-keeping, allowing educators to focus on meaningful student interactions. Real-time risk assessment and triage of patients are facilitated by machine learning–based systems such as Enlitic, which prioritize and direct cases to appropriate clinicians [10]. The influence of AI and chatbots on nursing education manifests in improved student learning and engagement. Interactional learning experiences, such as simulated patient scenarios and gamification, foster enhanced engagement and outcomes. Additionally, AI and chatbots improve access to resources by providing round-the-clock support, fostering a culture of continuous learning.

Pedagogical Implications of Integrating AI Into Nursing Education

The integration of AI and chatbots into nursing education brings forth several pedagogical implications, including increased engagement and motivation for students through personalized feedback, adaptation to individual learning styles, and prompt responses to queries. This enhanced learning experience improves students’ knowledge retention and problem-solving skills by offering real-time feedback, tailored assessments, and interactional simulations. Additionally, AI and chatbots augment teacher support by streamlining grading, feedback, and administrative tasks, allowing educators to concentrate on more meaningful interactions with their students. Finally, the development of clinical competencies and confidence is facilitated by simulating realistic patient scenarios coupled with immediate feedback, better preparing students for encounters with actual patients in the clinical setting.

Teaching Effectiveness and Efficiency

AI and chatbots can significantly enhance teaching effectiveness and efficiency in nursing education in various ways. These technologies enable more efficient grading and feedback, reducing the workload for educators and offering students immediate feedback for faster learning and better retention. An AI-powered writing assistant can check student papers for grammar, spelling errors, plagiarism, and readability, providing instant feedback and allowing teachers to focus on more in-depth evaluations. Moreover, AI and chatbots can facilitate personalized teaching by adapting to individual learning styles and identifying knowledge gaps, resulting in improved learning outcomes. Adaptive learning systems can assess students' strengths and weaknesses, tailoring teaching materials to their specific needs.

Furthermore, AI and chatbots can create realistic simulations for students to practice clinical skills and build confidence in their abilities. Virtual reality simulations can provide lifelike patient scenarios for practicing skills such as medication administration or vital sign monitoring. Additionally, these technologies can augment teacher support by identifying struggling students and offering targeted interventions to enhance their learning outcomes. Learning analytics tools can help educators track student progress and pinpoint areas requiring additional support.

Integrating AI Into Nursing Education for Clinical Excellence

The integration of AI into nursing education marks a transformative stride toward clinical excellence. As AI technologies become increasingly prevalent in health care, nurses are presented with new opportunities and challenges. This paradigm shift prompts a reevaluation of nursing education practices, emphasizing the need for a curriculum that incorporates AI competencies [11]. In a hospital setting, training on AI-assisted patient monitoring systems for nursing nurses may equip them to interpret AI-generated insights, enabling proactive interventions. For example, nurses using AI alerts to predict deteriorating patient conditions can respond swiftly, showcasing the interdependence of human expertise and AI assistance in ensuring patient safety. Nurse educators play a pivotal role in this transformation, guiding students to navigate AI applications within clinical settings. This holistic approach seeks to bridge the gap between traditional nursing practices and the advancements brought forth by AI, ultimately shaping a future where clinical excellence is synonymous with technological proficiency.

Limitations

Despite the significant benefits of incorporating AI and chatbots in nursing education, there are essential limitations to consider. One critical aspect is the lack of human interaction, as AI and chatbots cannot entirely replace the development of interpersonal skills and empathy in nursing students. Ethical considerations, such as privacy, confidentiality, and bias, must be thoroughly addressed to ensure the safe, effective, and ethical use of these technologies without harming patients or perpetuating inequalities.

The adoption of AI and chatbots in nursing education necessitates a significant financial investment. Institutions must allocate resources for acquiring advanced technologies, specialized software, and ongoing technical support. Moreover, the costs associated with staff training on these technologies should not be underestimated. This financial burden can be prohibitive for some institutions, potentially creating disparities in access to AI-enhanced education [12]. Another concern is the potential for error, as AI and chatbots are not infallible and may lead to incorrect diagnoses or treatment plans, requiring cautious use to avoid misdiagnoses in medical tests. By carefully considering and addressing these limitations, the integration of AI and chatbots into nursing education can be optimized for safety, effectiveness, and ethicality.

Ethical and Social Considerations

Although AI and chatbots offer numerous benefits to nursing education, they also bring about ethical and social concerns that must be considered [13]. Issues such as bias and discrimination, privacy and security, accountability and transparency, displacement of human labor, and dehumanization and depersonalization must be addressed [14]. For example, biased or incomplete data used to train AI systems could lead to skewed information on certain health conditions or patient populations. Biased or incomplete data used to train AI systems in nursing education may manifest in skewed information on specific health conditions or patient populations. For instance, let us consider an AI-driven module designed to teach nursing students about prevalent health issues in India. If the training data predominantly include information from urban health care settings, the AI system may unintentionally neglect health concerns prevalent in rural areas. In this scenario, the AI system, having learned from biased data, might emphasize urban-centric health challenges while overlooking issues specific to rural communities, such as unique infectious diseases or limited access to certain health care resources. As a result, nursing students exposed primarily to this skewed information may not be adequately prepared to address the diverse health needs of the entire population, leading to an unintentional bias in their education. To mitigate this, it is essential to ensure that the training data encompass a comprehensive representation of health care scenarios, including both urban and rural contexts. Thus, the AI system can offer a more balanced and inclusive educational experience, fostering a nuanced understanding of diverse health conditions prevalent across different regions of India.

In addition, sensitive data storage and processing raise privacy and security concerns, while the opaque nature of AI systems presents challenges for accountability and transparency. To address these considerations, it is vital to develop and use AI and chatbot systems ethically and responsibly. This includes ensuring data diversity and representativeness, implementing robust privacy and security measures, promoting transparency and accountability, and creating policies and regulations to tackle potential social and economic implications. Involving stakeholders, such as educators, students, and patient advocates, in the development and implementation of AI and chatbot systems is essential to align them with ethical and social values, fostering the best possible outcomes for nursing education [15].

Challenges and Opportunities

Integrating AI and chatbots into nursing education can present significant challenges and barriers for nursing educators. Technical expertise and resources, such as programming skills and access to specialized hardware and software, may be required to integrate these technologies into teaching and learning practices successfully. Additionally, some educators and students may resist change, and nursing programs may need additional training and support to encourage adoption. The cost of implementing AI and chatbots may be prohibitive, and programs must carefully consider the long-term sustainability of such investments. Data quality and availability may also be challenging, as AI and chatbots require large amounts of data to be effective.

Concerns related to data theft and cybersecurity are the major challenges, as these technologies are vulnerable to breaches and unauthorized access to confidential patient information. Adherence to laws and guidelines concerning information technology use and implementation of stringent security measures is crucial to address this issue [16]. Additionally, incorporating AI and chatbots requires technical support, infrastructure, and expertise, which may be challenging for institutions with limited resources or technical capabilities. Since AI models and platforms are often developed by professionals outside the nursing and medical fields, end users such as nurses and health care professionals may struggle to understand the technical aspects, potentially leading to errors or inaccurate findings [17].

Although laden with challenges, integrating AI and chatbots into nursing education, presents numerous opportunities and potential solutions. One key aspect is providing technical support and training to both educators and students, ensuring their comfort with these new technologies. Adopting a collaborative approach with other nursing programs and institutions can alleviate cost and sustainability issues, as resources, knowledge, and expertise can be shared among them. Moreover, forging partnerships with technology companies and industry experts can grant access to specialized hardware, software, and proficiency in AI and chatbots' implementation.

Another crucial factor is establishing clear data governance policies and protocols to tackle data quality and availability challenges while securing sensitive information. Developing ethical frameworks and guidelines can help address ethical and legal concerns, including data privacy, security, bias, discrimination, and accountability. By incorporating AI and chatbots into innovative pedagogical approaches, nursing education can create more personalized learning experiences for students, leading to improved health care delivery. By capitalizing on these opportunities and implementing potential solutions, nursing programs can successfully integrate AI and chatbots, reaping the numerous benefits and opportunities offered by these advanced technologies.

Best Practices for Integrating AI and Chatbots in Nursing Education

Integrating AI and chatbots in nursing education requires a strategic approach that considers the unique needs and goals of each institution. While some nursing programs have been slower in integrating AI and chatbots, others have successfully implemented these technologies to improve student learning outcomes and enhance teaching effectiveness. One such example is the use of virtual patient simulations, which use AI to create realistic patient scenarios for nursing students to practice their skills in a safe and controlled environment [18,19]. Another successful integration of AI in nursing education is the use of adaptive learning platforms, which use chatbots to provide personalized learning experiences for students based on their individual needs and learning styles. These platforms can help identify areas of weakness and provide targeted feedback to improve student learning outcomes. Additionally, some nursing programs have used AI-powered chatbots to provide 24/7 support to students, answering their questions and providing additional resources and support when needed. These examples demonstrate the potential benefits of integrating AI and chatbots in nursing education and outline best practices for other institutions looking to implement these technologies.

To ensure the effective and ethical integration of AI and chatbots in nursing education, a thoughtful approach and best practices are essential. It is crucial to define clear goals that align with the institution's mission and educational objectives, fostering targeted and effective use of AI and chatbots for improved student learning outcomes. Involving key stakeholders, such as nursing faculty, educational technologists, and student representatives, in the planning process guarantees their needs and concerns are considered.

Adequate training and support for faculty and students are crucial for the successful integration of AI and chatbots into the curriculum, ensuring their effective use in enhancing learning outcomes. Continual evaluation and refinement of AI and chatbots' implementation, based on data regarding their impact on student learning outcomes, enables institutions to make informed decisions about future adjustments.

As AI and chatbots transform nursing education, further research and development are needed to maximize their potential benefits. With increased integration, ethical considerations such as privacy, bias, and transparency must be tackled to ensure equitable use. For instance, AI algorithms could perpetuate health care biases if not properly designed and validated. Future research should explore ways to mitigate these biases, promoting social justice and equity in AI and chatbots' usage.

Another area for future research is the long-term impact of AI and chatbots on nursing education. While early studies suggest that these technologies can enhance student learning outcomes and teaching effectiveness [20], it is important to evaluate their long-term impact on the nursing profession. Future research can explore how integrating AI and chatbots in nursing education affects the nursing workforce and their ability to provide quality patient care.

Conclusion

The viewpoint paper discusses the various ways AI and chatbots can be used in nursing education, such as providing personalized learning experiences, facilitating clinical reasoning, and enhancing communication skills. Additionally, the review highlights the potential implications of these technologies on the nursing profession, including improving patient outcomes, advancing research, and promoting evidence-based practice. The impact of AI and chatbots on nursing education and the nursing profession as a whole can be significant. These technologies can provide nursing educators new tools to engage students and enhance their learning experiences. Moreover, they can help nurses improve their clinical practice and provide better patient care.

AI and chatbots have the potential to revolutionize nursing education and the nursing profession. Educators and researchers in nursing education should explore the potential of these technologies and incorporate them into their teaching practices. However, addressing the potential ethical implications of using AI in nursing education and practice is also important. Therefore, researchers and educators should collaborate to develop guidelines and best practices to ensure the responsible use of AI in nursing education and practice.

Conflicts of Interest

None declared.

References

1. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Future Healthc J 2019 Jun 13;6(2):94-98 [FREE Full text] [doi: 10.7861/futurehosp.6-2-94] [Medline: 31363513]
2. Mudgal SK, Agarwal R, Chaturvedi J, Gaur R, Ranjan N. Real-world application, challenges and implication of artificial intelligence in healthcare: an essay. Pan Afr Med J 2022;43:3 [FREE Full text] [doi: 10.11604/pamj.2022.43.3.33384] [Medline: 36284890]
3. Preparing for the future of artificial intelligence. Executive Office of the President of the United States. 2016. URL: https://obamawhitehouse.archives.gov/sites/default/files/whitehouse_files/microsites/ostp/NSTC/preparing_for_the_future_of_ai.pdf [accessed 2023-03-23]
4. What is Chatbot? IBM. URL: https://www.ibm.com/topics/chatbots [accessed 2023-03-23]
5. Francesca R. Artificial Intelligence: Potential Benefits and Ethical Considerations. Policy Department C: Citizens' Rights and Constitutional Affairs. URL: https://www.europarl.europa.eu/RegData/etudes/BRIE/2016/571380/IPOL_BRI(2016)571380_EN.pdf [accessed 2023-03-23]
6. Sallam M. ChatGPT utility in healthcare education, research, and practice: systematic review on the promising perspectives and valid concerns. Healthcare (Basel) 2023 Mar 19;11(6):887 [FREE Full text] [doi: 10.3390/healthcare11060887] [Medline: 36981544]
7. Moons P, Van Bulck L. ChatGPT: can artificial intelligence language models be of value for cardiovascular nurses and allied health professionals. Eur J Cardiovasc Nurs 2023 Oct 19;22(7):e55-e59 [FREE Full text] [doi: 10.1093/eurjcn/zvad022] [Medline: 36752788]
8. O'Connor S. Open artificial intelligence platforms in nursing education: tools for academic progress or abuse? Nurse Educ Pract 2023 Jan;66:103537. [doi: 10.1016/j.nepr.2022.103537] [Medline: 36549229]
9. Chang C, Hwang G, Gau M. Promoting students' learning achievement and self‐efficacy: a mobile chatbot approach for nursing training. Brit J Educational Tech 2021 Aug 22;53(1):171-188 [FREE Full text] [doi: 10.1111/bjet.13158]
10. Ng ZQP, Ling LYJ, Chew HSJ, Lau Y. The role of artificial intelligence in enhancing clinical nursing care: a scoping review. J Nurs Manag 2022 Nov 13;30(8):3654-3674. [doi: 10.1111/jonm.13425] [Medline: 34272911]
11. Akgun S, Greenhow C. Artificial intelligence in education: addressing ethical challenges in K-12 settings. AI Ethics 2022 Sep 22;2(3):431-440 [FREE Full text] [doi: 10.1007/s43681-021-00096-7] [Medline: 34790956]
12. Kabudi T, Pappas I, Olsen DH. AI-enabled adaptive learning systems: a systematic mapping of the literature. Comput Educ: Artif Intell 2021;2:100017. [doi: 10.1016/j.caeai.2021.100017]
13. Dilmegani C. Top 18 AI Use Cases in Healthcare Industry in 2024. AIMultiple. 2024. URL: https://research.aimultiple.com/healthcare-ai-use-cases/ [accessed 2023-03-24]
14. Zhang L, Tan J, Han D, Zhu H. From machine learning to deep learning: progress in machine intelligence for rational drug discovery. Drug Discov Today 2017 Nov;22(11):1680-1685 [FREE Full text] [doi: 10.1016/j.drudis.2017.08.010] [Medline: 28881183]
15. Okonkwo C. W. ; Ade-Ibijola, A. Evaluating the ethical implications of using chatbot systems in higher education.digiTAL2021,2021 2021:68 [FREE Full text]
16. Lebo C, Brown N. Integrating artificial intelligence (AI) simulations into undergraduate nursing education: an evolving AI patient. Nurs Educ Perspect 2022 Dec 23;45(1):55-56. [doi: 10.1097/01.nep.0000000000001081]

17. Kooli C. Chatbots in education and research: a critical examination of ethical implications and solutions. Sustainability 2023 Mar 23;15(7):5614 [FREE Full text] [doi: 10.3390/su15075614]
18. Sharkey A, Sharkey N. Granny and the robots: ethical issues in robot care for the elderly. Ethics Inf Technol 2010 Jul 3;14(1):27-40 [FREE Full text] [doi: 10.1007/s10676-010-9234-6]
19. Lee D, Yoon SN. Application of artificial intelligence-based technologies in the healthcare industry: opportunities and challenges. Int J Environ Res Public Health 2021 Jan 01;18(1):271 [FREE Full text] [doi: 10.3390/ijerph18010271] [Medline: 33401373]
20. Berry MCDC, de M Neto JM, de Souza MIDC, Figueredo CMDS, Reher V, Evans JL. Effectiveness of technology-enhanced learning to improve periodontics educational outcomes: a systematic review. J Dent Educ 2020 Jul 18;84(7):830-839. [doi: 10.1002/jdd.12179] [Medline: 32421234]

Abbreviations

AI: artificial intelligence

Edited by K Cato; submitted 23.08.23; peer-reviewed by L Zhu, NQK Le, M Gheisari, S Zhu; comments to author 09.11.23; revised version received 30.11.23; accepted 12.12.23; published 13.06.24.

Please cite as:
Srinivasan M, Venugopal A, Venkatesan L, Kumar R
Navigating the Pedagogical Landscape: Exploring the Implications of AI and Chatbots in Nursing Education
JMIR Nursing 2024;7:e52105
URL: https://nursing.jmir.org/2024/1/e52105
doi:10.2196/52105
PMID:38870516

Original Paper

A Scalable and Extensible Logical Data Model of Electronic Health Record Audit Logs for Temporal Data Mining (RNteract): Model Conceptualization and Formulation

Victoria L Tiase[1*], PhD; Katherine A Sward[1,2*], PhD; Julio C Facelli[1*], PhD

[1] Department of Biomedical Informatics, University of Utah, Salt Lake City, UT, United States

[2] College of Nursing, University of Utah, Salt Lake City, UT, United States

[*] all authors contributed equally

Corresponding Author:
Victoria L Tiase, PhD
Department of Biomedical Informatics
University of Utah
421 Wakara Way
Salt Lake City, UT, 84108
United States
Phone: 1 801 585 3945
Email: victoria.tiase@utah.edu

Abstract

Background: Increased workload, including workload related to electronic health record (EHR) documentation, is reported as a main contributor to nurse burnout and adversely affects patient safety and nurse satisfaction. Traditional methods for workload analysis are either administrative measures (such as the nurse-patient ratio) that do not represent actual nursing care or are subjective and limited to snapshots of care (eg, time-motion studies). Observing care and testing workflow changes in real time can be obstructive to clinical care. An examination of EHR interactions using EHR audit logs could provide a scalable, unobtrusive way to quantify the nursing workload, at least to the extent that nursing work is represented in EHR documentation. EHR audit logs are extremely complex; however, simple analytical methods cannot discover complex temporal patterns, requiring use of state-of-the-art temporal data-mining approaches. To effectively use these approaches, it is necessary to structure the raw audit logs into a consistent and scalable logical data model that can be consumed by machine learning (ML) algorithms.

Objective: We aimed to conceptualize a logical data model for nurse-EHR interactions that would support the future development of temporal ML models based on EHR audit log data.

Methods: We conducted a preliminary review of EHR audit logs to understand the types of nursing-specific data captured. Using concepts derived from the literature and our previous experience studying temporal patterns in biomedical data, we formulated a logical data model that can describe nurse-EHR interactions, the nurse-intrinsic and situational characteristics that may influence those interactions, and outcomes of relevance to the nursing workload in a scalable and extensible manner.

Results: We describe the data structure and concepts from EHR audit log data associated with nursing workload as a logical data model named RNteract. We conceptually demonstrate how using this logical data model could support temporal unsupervised ML and state-of-the-art artificial intelligence (AI) methods for predictive modeling.

Conclusions: The RNteract logical data model appears capable of supporting a variety of AI-based systems and should be generalizable to any type of EHR system or health care setting. Quantitatively identifying and analyzing temporal patterns of nurse-EHR interactions is foundational for developing interventions that support the nursing documentation workload and address nurse burnout.

(JMIR Nursing 2024;7:e55793) doi:10.2196/55793

KEYWORDS

burnout; professional; nursing; nurse; electronic health record; EHR; data modeling; data set; temporal machine learning; machine learning; ML; artificial intelligence; AI; algorithm; predictive model; predictive analytics; practical model

Introduction

Workload as a Contributor to Burnout

Nursing workload, representing the amount of time, physical, and cognitive effort needed to provide nursing care, is an ongoing concern in health care settings and can pose significant challenges for nurses [1]. Increasing cost pressures and the lingering effects of COVID-19 have resulted in nurses taking care of sicker patients than in the past [2]. Many health care facilities experience a shortage of qualified nursing staff, resulting from factors such as insufficient recruitment and retention efforts or high turnover rates due to burnout [2]. There is also a higher demand for nurses given the aging population so that supply no longer meets demand [2]. As more nurses continue to exit the workforce, the workload increases further for those who remain on the job [3].

Measuring Nursing Workload

Historically, the most commonly used measure of nursing workload is the nurse-patient ratio [4], referring to the number of patients assigned to a nurse during a specific shift or time frame [5]. These ratios play a role in determining the amount of direct patient care that each nurse must provide, which directly impacts workload and the quality of care nurses can deliver. Research on patient ratios provides evidence connecting nurse staffing to patient outcomes and more specifically to patient safety [4]. However, establishing a safe and effective nurse-patient ratio is an ongoing challenge for health care organizations and policy makers [6].

A major weakness to estimating nursing workload at this macro level is that this approach does not account for differences in patient illness or the amount of care needed by an individual patient, nor does it account for contextual and organizational characteristics that impact workload [3]. Additionally, recent studies found evidence that not all nurses, even within the same hospital unit, practice the same way; therefore, examining individual nurse practices becomes important in examining workload [4]. In addition to nurse-patient ratios, nursing workload has also been studied as a qualitative experience and estimated via time-motion studies, whereas the subjective and intrusive nature of these approaches suggests that more research is needed from a quantitative or mixed methods perspective [7,8].

Electronic Health Record Data as an Estimate of Workload

The health care industry has access to a massive amount of data that can be analyzed for trends, patterns, and insights [9]. Data regarding clinical care are encompassed within the electronic health record (EHR). Researchers have leveraged EHR interactions to track clinical work activities and associated workload for physicians, and EHR interactions or use patterns were used to predict physician departures and burnout [9-11]. Nursing clinical care and documentation are distinct from physician care; however, to date, nursing workload has not been similarly evaluated from EHR data. Although it is well-established that nursing work extends beyond what is recorded, we posit that EHR documentation could be a reasonable proxy for nursing workload.

As part of regulatory requirements, health care organizations must record and track EHR activity at the user level, including log-on attempts, what patient records are accessed, what documentation was entered, and the date and time of access [12]. These user-level metadata, stored as EHR audit logs, are an untapped resource that have potential to provide clinical insights [13]. Some nurse researchers have explored the suitability of EHR audit logs to understand the documentation burden [14]. However, these metadata are complex, change over time, and varied in how they are aggregated into higher-level measures [15]. To effectively use these data, it is necessary to structure the raw audit logs as part of a consistent and scalable logical data model that can be consumed by artificial intelligence (AI) algorithms.

Logical Data Models

A logical data model is a set of specifications that identifies the primary data concepts and relationships between them, serving as a blueprint or template on how information is organized for analysis [16]. Machine learning (ML) models typically organize data as vectors. In this context, a vector is a specific way to represent data as a matrix of values. In planning for ML, a logical data model can define the main categories of vectors that serve as model inputs or outputs, which can be implemented as a physical model consumable by any ML algorithm [16]. A logical data model is intentionally abstract, not constrained by either the data sources or the actual structure that will store the data [16]. Ultimately, the aspects of the logical data model will inform the physical implementation of the model [17].

Objective

We posit that gathering and modeling sufficient data that are reliable, reproducible, and generalizable, and that represent nursing contributions within the context of work activities and workload are achievable with data science–based research. We hypothesize that assessing the nursing workload requires objective measurement and a standardization of data elements that represent clinical activities and other nursing workload influences, which can be used as targets for modeling interventions at scale. This hypothesis is supported by the findings from a systematic review of studies using EHR audit logs to observe clinical activities [10]. Because EHR audit logs record all types of interactions with the health record, the logs may offer insights into how nurses interact with the EHR and the extent to which EHR interactions reflect workflow and workload. Our objective was to conceptualize a logical data model based on EHR audit log data as a first step toward analysis of nursing EHR documentation workflows. This is somewhat analogous to developing a conceptual framework before starting a traditional analysis.

Using concepts derived from our previous work in studying temporal biomedical data patterns [18,19], we formulated a data structure that can describe nurse-EHR interactions, nurse-intrinsic and situational characteristics, and nurse outcomes of interest in a scalable and extensible manner. We believe the selected features will allow for metadata aggregation into EHR use measures that can be used for a variety of nurse-centric outcomes. We then conceptually instantiated the model with an analysis plan for a quantitative study of the characteristics and expected outcomes associated with nurse-EHR interactions using AI and temporal ML methods. Although our purpose is to focus on the EHR audit log data, we also provide details on additional data sources that will be needed to instantiate the logical data model. We conceptualize how the model could be used to support data science methods based on AI and ML approaches. The physical implementation of the model will be described in subsequent work.

Methods

Study Design

To develop this proposed conceptual framework, we began with a search of the literature, and expanded upon previous work that examined the workload of physicians using EHR data and researched components of nursing workload that can be extracted from other (non-EHR) health system databases [20]. Two experienced nurses iteratively refined the concepts and interactions until consensus was achieved. We conducted a preliminary review of the audit log from a commercial EHR vendor (Epic) implemented at an academic medical center to confirm that the conceptualized model corresponded to generalizable structures for audit log data.

Ethical Considerations

Given that EHR audit log data are user-centric and not patient-centric, we protected user identity by deidentifying users and aggregating activity according to the generic user role "nurse." After consultation with the University of Utah Institutional Review Board, the protocol received an exemption determination.

EHR Audit Log Metadata

In our review of the EHR audit logs, we found that nursing interactions with the EHR extend beyond clinical data input. Within the EHR audit logs, we were able to distinguish between data review and data input, identify the particular section of the EHR accessed (eg, medication administration record, best-practice advisories, or notes), and determine the workflow activities such as navigation between records. We focused on data specific to nurse users. In their current form, these data lack a hierarchical data structure and do not contain a taxonomy related to specific user or task types.

Results

Data Model: Concepts

The data model, which we named RNteract, contains elements that describe the nurse tasks (NTask), nurse characteristics (NType), specific type of patient or *patient panel* (NPanel), and the resulting nurse-relevant outcomes (NOutcome). Each concept will be represented via a value set for physical implementation of the model. The value sets can be defined based on the purpose or goals of the analysis. As an example, the NTask value set can describe a general type of task (such as *medication tasks*) or can be more granular (eg, specific steps of medication administration) depending on the objectives of the model.

Model Structure: Vectors

This logical data model is intended to support temporal ML models. These approaches are grounded in the concept of vectors or numerical arrays. A vector is a mathematically based approach for expressing and organizing data in a predefined manner. Vectors in ML represent input data, including bias or weights. In the same way, output from an ML model can be represented as a vector. To perform a given ML task, the first step is to represent the input. For this logical data model, we provide a set of specifications and primary data structures with a focus on the NTask input.

Model Component: NTask

Our initial focus will be on defining the NTask element. For each nurse, ID=k, we define a vector <NTask(k, i)>, i=1 to N, as a vector of dimension N, where N is the number of time periods considered in the study. Any resolution (eg, day, hour, 30-minute intervals, each minute) can be used for the time periods. The individual nurse performing the task is represented by k and the i component of the vector corresponds to the time interval under study.

The value representing the specific task is taken from a value set that describes the nursing tasks considered in the model and can be as general or specific as desired. For instance, if a value set for tasks has been defined broadly such that 1=no EHR interaction, 2=read EHR data, and 3=input EHR data, if the nurse identified with ID 55 has been reading the EHR for the first time period, does nothing with the EHR for the next three periods, and then writes a note in the EHR for the fifth time period, the corresponding NTask vector will be (55, 2, 1, 1, 1, 3).

The NTask vector will allow the classification of activity patterns in EHR data for any finite number of nurses, for an arbitrary set of tasks, and for any finite time resolution. Instantiation of the model would result in a set of vectors that can then be classified with temporal ML methods to model nurse activity trajectories and other patterns of nurse-EHR interactions. Resulting nurse activity trajectories can be associated with quantitative descriptors of NType, NPanel, and NOutcome, which are defined in further detail below.

Additional Components

NType

NType describes the nurse user within the EHR audit log data. For each nurse with ID=k, the NType data element is a vector of dimension M in which the i component of the vector <NType (k, i)>, i=1 to M, is an integer, real, or categorical value defined by a value set that describes both intrinsic and situational characteristics of the nurse. The dimension of the vector, M, is defined by the number of characteristics we desire to model and to assign to a nurse.

Audit logs, by themselves, have only limited information about the nurse characteristics other than identification of individual users. From the EHR audit logs, we can determine the location of where the EHR interaction occurred (inferred from the computer location), and consequently can infer additional information based on the most common location of documentation and characteristics such as the environment the nurse primarily practices in (eg, medical/surgical environment or an intensive care unit). However, we will need to access data from other sources to incorporate other nurse characteristics. These data may be available from the EHR scheduling system or other auxiliary systems such as credentialing systems or human resources databases. Examples of a desired model value set using these additional data sources may be:

1. Nurse employment length, integer (eg, number of years in the job, workplace).

2. Nurse's highest professional accreditation, categorical variable (eg, licensed practical nurse, registered nurse [RN], nurse practitioner).

3. Average number of hours worked per week, integer, which is potentially derivable from the EHR audit log (eg, based on first and last EHR interactions in a 24-hour period).

4. Nurse primary assignment, categorical variable (eg, operating room [OR], intensive care, medical/surgical). This information can potentially be inferred from the EHR audit log based on the primary location of the computer used for documentation.

As an example, if a nurse with ID 55 has been in the organization for 5 years, is an RN, worked 48 hours per week, and is primarily assigned to the OR, the corresponding vector would be NType=(55, 5, RN, 3, OR).

NPanel

NPanel is a vector to describe the patient context for the tasks. The data element for the patient panel assigned to nurse with ID=k is a vector of dimension O in which the i element of <NPanel (k, i)>, i=1 to O, is an integer, real, or categorical value defined by a value set that describes the characteristics and the acuity of the patients in the panel. The dimension of the vector, O, is defined by the number of features used to describe the patient panel. For instance, this data element may accommodate the complexity level of the patients or the average length of stay of the patients. These data will not be available directly from EHR audit logs, but may be obtained from the admission, discharge, and transfer messages; a financial system; patient acuity; or other clinical sources. An example of a possible value set for a patient panel might be:

1. Admission from the emergency room; integer, number of patients admitted.

2. Admission from the OR; integer, number of patients admitted.

3. Discharged to home; integer, number of patients discharged.

4. Average length of stay; integer.

An example for this component is if nurse ID=55 has a panel of 12 patients with 1 admission from the OR, 2 discharges, and an average length of stay of 4, the corresponding vector would be NPanel=(55, 0, 1, 2, 4).

NOutcome

The NOutcome element for a nurse with ID=k is a vector of dimension P in which the i element of <NOutcome (k, i)>, i=1 to P, is an integer, real, or categorical value defined by a value set that describes long-term changes in the status of the nurse and P is the number of features included in the model to describe the nurse outcomes. This data element can accommodate events such as resignation, promotion, or salary increase. Other potential outcomes may include use of time off, patient safety events, and preventable harm. As with NType, these data may be available from the EHR or other ancillary systems. Examples of a value set may be:

1. Nurse salary increase; Boolean: YES, NO.

2. Nurse resignation; Boolean: YES, NO.

3. Nurse promotion; Boolean: YES, NO.

4. Nurse missed work; integer, number of days that the nurse missed work.

For example, if nurse ID=55 did not receive a salary increase, did not resign, was not promoted, but missed 6 days in the last month, the corresponding vector would be NOutcome=(55, NO, NO, NO, 6).

Such long-term outcomes will not be recorded in EHR audit logs and must be obtained from other data sources. However, audit logs may hint at intermediate outcomes and workflows, including workflows such as charting in a block of time (perhaps charting after the shift) versus charting throughout the shift. These intermediate outcomes may suggest hypotheses for further exploration, such as the extent to which charting in a block of time may reflect a high workload.

Extensibility/Generalizability

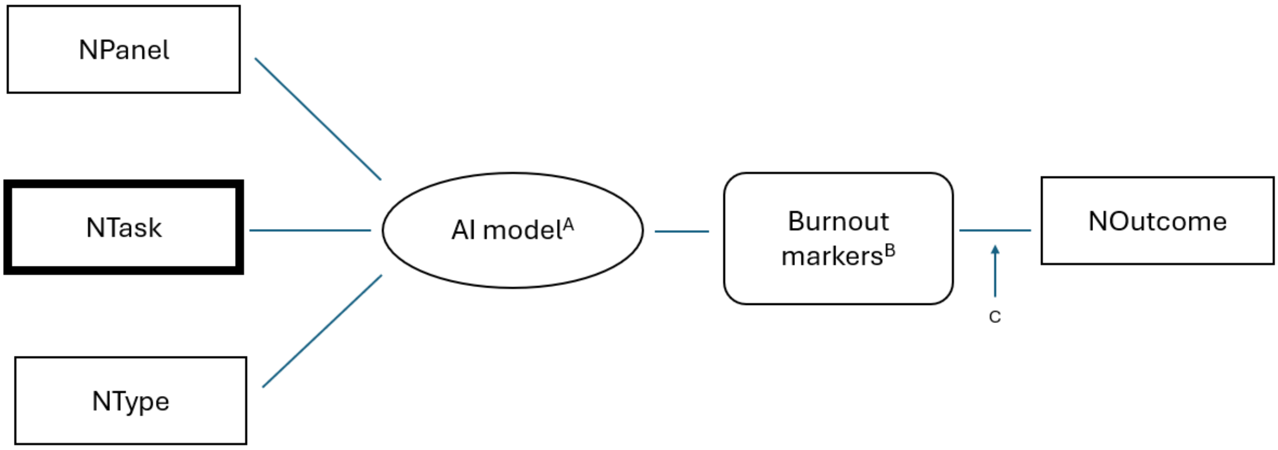
The definitions of NType, NPanel, and NOutcome are extensible and can accommodate any finite number of properties associated with any nurse. While we recognize that these properties may change over time, we chose to make NType, NPanel, and NOutcome independent of time because the variations in these categories are usually much slower than the variations of the time-dependent NTask vector. If necessary, categorical variables can be transformed into integers by defining a table transformation. This makes NType, NPanel, and NOutcome amenable to any ML approach that may be considered.

Conceptual Instantiation for AI and ML

Using temporal unsupervised classification [21-23], the <NTask (i, k)> nurse-EHR temporal interaction patterns can be classified through pattern recognition. The resulting archetypical activity patterns or clusters can be associated with any of the properties described in either NType, NPanel, or NOutcome, where the clusters can be described as enriched or depleted of any of the properties coded by these data elements. Using traditional statistics, the significance of the enrichments/depletions can be estimated.

Descriptive analysis of the NTask clusters can be used to gain insights from interaction patterns, which will allow for the development of predictive models for each cluster associated with the inputs for NTask, NType, and NPanel descriptors and outputs of interest described by NOutcome. As shown in Figure 1, this model allows for predictive modeling and is not constrained by the selection of AI method. This intersection of nurse types, patient panels, and tasks, aggregated over time and across patient encounters, can be analyzed using a range of state-of-the-art AI techniques for different purposes, revealing burnout markers such as charting, navigation, and searching patterns. Although we recognize that burnout is not entirely measurable from EHR interactions, we assumed a set of burnout markers with concrete measurements that can be obtained from the user-centric logs. The logical data model also allows for the inclusion of other contributors to burnout that can be incorporated prior to describing the outcome.

Figure 1. RNteract logical data model. A: Any state-of-the-art AI model can be accommodated; B: electronic health record–derived time patterns for charting, navigation, or searching; C: allows for the inclusion of other contributors to burnout. AI: artificial intelligence; NOutcome: nurse-relevant observations or outcomes; NPanel: patient panel being cared for; NTask: nurse tasks; NType: nurse characteristics.



Discussion

Clinical Implications

This paper describes the development of a scalable and extensible logical data model to represent interactions between nurses and EHR systems as recorded in EHR audit logs. We identified a general methodology for identifying concepts related to nursing workload and applied this methodology to EHR interactions as reflected in EHR audit logs.

AI-based systems have increasingly been incorporated into health care [24]. To date, research on AI in health care has largely neglected to consider real-world scenarios or real-world effect on outcomes [25]. Uses of AI in nursing span from virtual assistants to patient monitoring and predictive modeling [26]. AI can also contribute to nursing by helping to streamline workflows and analyze vast amounts of data for evidence-based recommendations, helping nurses make more informed decisions about patient care [26-28]. Nurses have had only limited engagement in workflow or workload modeling efforts, despite the potential for AI-based systems to contribute to advanced, effective, efficient care, such as through more effective ways to access and organize information from EHRs [25].

The metadata in audit logs can be complex and unstructured, making them difficult to interpret. Advanced analytics such as ML and data mining are necessary to identify patterns and insights in such complex data; however, to use these methods effectively, the data need to be structured in a way that it is consumable by AI and ML applications.

The logical data model presented herein provides a structured framework for organizing the vast amount of data generated in audit logs. This model can help in categorizing data elements and defining their relationships with a flow of logical reasoning, which is essential for understanding and using the data effectively. With a well-defined logical data model, it becomes easier to analyze audit log data by providing a clear representation of data flows and structures. We believe that this data model will provide a better understanding of nursing-related data elements and will assist others in using EHR audit log data to effectively model nursing workload or related outcomes of interest.

Prior to a physical implementation of the model (details will be described elsewhere), the non-EHR audit log data sources may require additional representation. However, as many of the other data sets have been described in the literature, our focus is to promote the broader use of EHR audit log data to understand the nursing workload [29,30].

Limitations

The data model was developed based on the literature and on the audit log of a single organization's EHR. The audit logs of other organizations using the same or different EHR systems may suggest additions or modifications to the model. Consultation with the nursing research community may lead to further refinements of the model; to this end, we envision subjecting the model to an open discussion in relevant research venues.

Conclusion

Using concepts derived from our previous experience in studying temporal biomedical data patterns, we formulated a data model that can be used to describe nurse-EHR interactions, intrinsic and situational characteristics of nurses and patient panels, and nurse outcomes of interest in a scalable and extensible manner. The definitions of NTask, NType, NPanel, and NOutcome are extensible and can accommodate any finite number of properties associated with a nurse. Through the use of the logical data model, we conceptualize how nurse-EHR interactions could be studied using temporal unsupervised ML as well as any state-of-the-art AI methods. Future work may include extensions or modifications of the model as we test its applicability to different organizations and different EHR systems.

Acknowledgments

The research reported in this publication was supported in part by the National Center for Advancing Translational Sciences of the National Institutes of Health (award UM1TR004409). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Authors' Contributions

All authors contributed to the conceptualization, model development, and writing of the manuscript.

Conflicts of Interest

None declared.

References

1. Ivziku D, Ferramosca FMP, Filomeno L, Gualandi R, De Maria M, Tartaglini D. Defining nursing workload predictors: a pilot study. J Nurs Manag 2022 Mar 12;30(2):473-481 [FREE Full text] [doi: 10.1111/jonm.13523] [Medline: 34825432]
2. Fleisher LA, Schreiber M, Cardo D, Srinivasan A. Health care safety during the pandemic and beyond - building a system that ensures resilience. N Engl J Med 2022 Feb 17;386(7):609-611. [doi: 10.1056/NEJMp2118285] [Medline: 35148040]
3. Carayon P, Gurses AP. Nursing workload and patient safety—a human factors engineering perspective. In: Hughes RG, editor. Patient Safety and Quality: An Evidence-Based Handbook for Nurses. Rockville, MD: Agency for Healthcare Research and Quality; 2008.
4. Aiken LH, Clarke SP, Sloane DM, Sochalski J, Silber JH. Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. JAMA 2002 Oct 23;288(16):1987-1993. [doi: 10.1001/jama.288.16.1987] [Medline: 12387650]
5. Driscoll A, Grant MJ, Carroll D, Dalton S, Deaton C, Jones I, et al. The effect of nurse-to-patient ratios on nurse-sensitive patient outcomes in acute specialist units: a systematic review and meta-analysis. Eur J Cardiovasc Nurs 2018 Jan 18;17(1):6-22 [FREE Full text] [doi: 10.1177/1474515117721561] [Medline: 28718658]
6. Aiken LH, Lasater KB, Sloane DM, Pogue CA, Fitzpatrick Rosenbaum KE, Muir KJ, US Clinician Wellbeing Study Consortium. Physician and nurse well-being and preferred interventions to address burnout in hospital practice: factors associated with turnover, outcomes, and patient safety. JAMA Health Forum 2023 Jul 07;4(7):e231809 [FREE Full text] [doi: 10.1001/jamahealthforum.2023.1809] [Medline: 37418269]
7. Doleman G, De Leo A, Bloxsome D. The impact of pandemics on healthcare providers' workloads: a scoping review. J Adv Nurs 2023 Dec 18;79(12):4434-4454. [doi: 10.1111/jan.15690] [Medline: 37203285]
8. Higgins L, Shovel J, Bilderback A, Lorenz HL, Martin SC, Rogers DJ, et al. Hospital nurses' work activity in a technology-rich environment: a triangulated quality improvement assessment. J Nurs Care Qual 2017;32(3):208-217. [doi: 10.1097/NCQ.0000000000000237] [Medline: 28541263]
9. Sinsky C, Rule A, Cohen G, Arndt BG, Shanafelt TD, Sharp CD, et al. Metrics for assessing physician activity using electronic health record log data. J Am Med Inform Assoc 2020 Apr 01;27(4):639-643 [FREE Full text] [doi: 10.1093/jamia/ocz223] [Medline: 32027360]
10. Rule A, Melnick E, Apathy N. Using event logs to observe interactions with electronic health records: an updated scoping review shows increasing use of vendor-derived measures. J Am Med Inform Assoc 2022 Dec 13;30(1):144-154 [FREE Full text] [doi: 10.1093/jamia/ocac177] [Medline: 36173361]
11. Rule A, Chiang MF, Hribar MR. Using electronic health record audit logs to study clinical activity: a systematic review of aims, measures, and methods. J Am Med Inform Assoc 2020 Mar 01;27(3):480-490 [FREE Full text] [doi: 10.1093/jamia/ocz196] [Medline: 31750912]
12. Understanding the HIPAA audit trail requirements: essentials for compliance. Auditboard. 2023. URL: https://www.auditboard.com/blog/hipaa-audit-trail-requirements [accessed 2023-09-05]
13. Rose C, Thombley R, Noshad M, Lu Y, Clancy HA, Schlessinger D, et al. Team is brain: leveraging EHR audit log data for new insights into acute care processes. J Am Med Inform Assoc 2022 Dec 13;30(1):8-15 [FREE Full text] [doi: 10.1093/jamia/ocac201] [Medline: 36303451]
14. Moy A, Hobensack M, Marshall K, Vawdrey DK, Kim EY, Cato KD, et al. Understanding the perceived role of electronic health records and workflow fragmentation on clinician documentation burden in emergency departments. J Am Med Inform Assoc 2023 Apr 19;30(5):797-808 [FREE Full text] [doi: 10.1093/jamia/ocad038] [Medline: 36905604]

15. Rule A, Kannampallil T, Hribar M, Dziorny AC, Thombley R, Apathy NC, et al. Guidance for reporting analyses of metadata on electronic health record use. J Am Med Inform Assoc 2024 Feb 16;31(3):784-789. [doi: 10.1093/jamia/ocad254] [Medline: 38123497]
16. McGilvray D. Executing Data Quality Projects: Ten Steps to Quality Data and Trusted Information. MIT Information Quality Industry Symposium. URL: http://mitiq.mit.edu/IQIS/Documents/CDOIQS_200977/Papers/01_02_T1D.pdf [accessed 2023-09-04]
17. Hughes R. Agile Data Warehousing for the Enterprise: A Guide for Solution Architects and Project Leaders. Waltham, MA: Morgan Kaufmann; 2015.
18. Mistry S, Gouripeddi R, Raman V, Facelli JC. Sequential data mining of infection patterns as predictors for onset of type 1 diabetes in genetically at-risk individuals. J Biomed Inform 2023 Jun;142:104385 [FREE Full text] [doi: 10.1016/j.jbi.2023.104385] [Medline: 37169058]
19. Mistry S, Gouripeddi R, Facelli JC. Prioritization of infectious epitopes for translational investigation in type 1 diabetes etiology. J Autoimmun 2023 Nov;140:103115. [doi: 10.1016/j.jaut.2023.103115] [Medline: 37774556]
20. Kannampallil T, Abraham J, Lou SS, Payne PRO. Conceptual considerations for using EHR-based activity logs to measure clinician burnout and its effects. J Am Med Inform Assoc 2021 Apr 23;28(5):1032-1037 [FREE Full text] [doi: 10.1093/jamia/ocaa305] [Medline: 33355360]
21. Zaki M. SPADE: An efficient algorithm for mining frequent sequences. Machine learning 2001;42(1):31-60. [doi: 10.1023/A:1007652502315]
22. Kour A. Sequential rule mining, methods, and techniques: a review. Int J Comput Intell Res 2017;13(7):1709-1715.
23. Lo D, Khoo S, Wong L. Non-redundant sequential rules—theory and algorithm. Inf Syst 2009 Jun;34(4-5):438-453. [doi: 10.1016/j.is.2009.01.002]
24. Lee D, Yoon SN. Application of artificial intelligence-based technologies in the healthcare industry: opportunities and challenges. Int J Environ Res Public Health 2021 Jan 01;18(1):271 [FREE Full text] [doi: 10.3390/ijerph18010271] [Medline: 33401373]
25. Pailaha AD. The impact and issues of artificial intelligence in nursing science and healthcare settings. SAGE Open Nurs 2023 Sep 08;9:23779608231196847 [FREE Full text] [doi: 10.1177/23779608231196847] [Medline: 37691725]
26. Yelne S, Chaudhary M, Dod K, Sayyad A, Sharma R. Harnessing the power of AI: a comprehensive review of its impact and challenges in nursing science and healthcare. Cureus 2023 Nov;15(11):e49252 [FREE Full text] [doi: 10.7759/cureus.49252] [Medline: 38143615]
27. Schwartz J, Moy A, Rossetti S, Elhadad N, Cato K. Clinician involvement in research on machine learning-based predictive clinical decision support for the hospital setting: a scoping review. J Am Med Inform Assoc 2021 Mar 01;28(3):653-663 [FREE Full text] [doi: 10.1093/jamia/ocaa296] [Medline: 33325504]
28. Korach ZT, Cato KD, Collins SA, Kang MJ, Knaplund C, Dykes PC, et al. Unsupervised machine learning of topics documented by nurses about hospitalized patients prior to a rapid-response event. Appl Clin Inform 2019 Oct 18;10(5):952-963 [FREE Full text] [doi: 10.1055/s-0039-3401814] [Medline: 31853936]
29. Effken JA, Brewer BB, Patil A, Lamb GS, Verran JA, Carley KM. Using computational modeling to transform nursing data into actionable information. J Biomed Inform 2003 Aug;36(4-5):351-361 [FREE Full text] [doi: 10.1016/j.jbi.2003.09.018] [Medline: 14643731]
30. Lindberg DS, Prosperi M, Bjarnadottir RI, Thomas J, Crane M, Chen Z, et al. Identification of important factors in an inpatient fall risk prediction model to improve the quality of care using EHR and electronic administrative data: a machine-learning approach. Int J Med Inform 2020 Nov;143:104272 [FREE Full text] [doi: 10.1016/j.ijmedinf.2020.104272] [Medline: 32980667]

Abbreviations

AI: artificial intelligence
EHR: electronic health record
ML: machine learning
NOutcome: nurse-relevant observations or outcomes
NPanel: patient panel being cared for
NTask: nurse tasks
NType: nurse characteristics
OR: operating room
RN: registered nurse

Edited by E Borycki, K Cato; submitted 28.12.23; peer-reviewed by L Carrasco-Ribelles, K Kochendorfer; comments to author 14.04.24; revised version received 02.06.24; accepted 02.06.24; published 24.06.24.

Please cite as:
Tiase VL, Sward KA, Facelli JC
A Scalable and Extensible Logical Data Model of Electronic Health Record Audit Logs for Temporal Data Mining (RNteract): Model Conceptualization and Formulation
JMIR Nursing 2024;7:e55793
URL: https://nursing.jmir.org/2024/1/e55793
doi:10.2196/55793
PMID:38913994

Review

Identifying Depression Through Machine Learning Analysis of Omics Data: Scoping Review

Brittany Taylor[1], AAS, BA, BS, MPhil; Mollie Hobensack[2], BSN, PhD; Stephanie Niño de Rivera[1], BS; Yihong Zhao[1], PhD; Ruth Masterson Creber[1], MSc, PhD; Kenrick Cato[3], PhD

[1]School of Nursing, Columbia University, New York, NY, United States

[2]Brookdale Department of Geriatrics and Palliative Care, Icahn School of Medicine, Mount Sinai Health System, New York, NY, United States

[3]School of Nursing, University of Pennsylvania, Philadelphia, PA, United States

Corresponding Author:
Brittany Taylor, AAS, BA, BS, MPhil
School of Nursing
Columbia University
560 W 168th St
New York, NY, 10032
United States
Phone: 1 2123424172
Email: bt2542@cumc.columbia.edu

Abstract

Background: Depression is one of the most common mental disorders that affects >300 million people worldwide. There is a shortage of providers trained in the provision of mental health care, and the nursing workforce is essential in filling this gap. The diagnosis of depression relies heavily on self-reported symptoms and clinical interviews, which are subject to implicit biases. The omics methods, including genomics, transcriptomics, epigenomics, and microbiomics, are novel methods for identifying the biological underpinnings of depression. Machine learning is used to analyze genomic data that includes large, heterogeneous, and multidimensional data sets.

Objective: This scoping review aims to review the existing literature on machine learning methods for omics data analysis to identify individuals with depression, with the goal of providing insight into alternative objective and driven insights into the diagnostic process for depression.

Methods: This scoping review was reported following the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) guidelines. Searches were conducted in 3 databases to identify relevant publications. A total of 3 independent researchers performed screening, and discrepancies were resolved by consensus. Critical appraisal was performed using the Joanna Briggs Institute Critical Appraisal Checklist for Analytical Cross-Sectional Studies.

Results: The screening process identified 15 relevant papers. The omics methods included genomics, transcriptomics, epigenomics, multiomics, and microbiomics, and machine learning methods included random forest, support vector machine, k-nearest neighbor, and artificial neural network.

Conclusions: The findings of this scoping review indicate that the omics methods had similar performance in identifying omics variants associated with depression. All machine learning methods performed well based on their performance metrics. When variants in omics data are associated with an increased risk of depression, the important next step is for clinicians, especially nurses, to assess individuals for symptoms of depression and provide a diagnosis and any necessary treatment.

(JMIR Nursing 2024;7:e54810) doi:10.2196/54810

KEYWORDS

machine learning; depression; omics; review; mental health; nurses

Introduction

Significance of Depression

Depression is one of the most common mood disorders, with a prevalence of approximately 20% in adults in the United States [1,2]. Among people with diagnosed depression, nearly half experience severe depression, and 40% experience moderate depression [1]. Between 2010 and 2018, the number of adults in the United States diagnosed with depression increased by 13%, and the associated health care costs also increased, including medical and pharmaceutical costs, workplace absenteeism, and suicide-related costs [3]. Despite a greater investment in mental health, approximately half of the people experiencing depression have been diagnosed and treated [4]. There have been limited improvements in the mental health care of depression during the past decade, primarily owing to the challenges in accurately diagnosing this complex illness [5]. Consequently, there is an urgent imperative to explore and establish more objective diagnostic approaches that can better identify individuals with depression and pave the way for more effective interventions and personalized treatment strategies.

Diagnostic Methods for Depression

The gold standard for depression diagnosis involves a structured psychiatric interview [2] that includes validated depression scales such as the Center for Epidemiologic Studies–Depression Scale, Hamilton Rating Scale for Depression-17, Montgomery-Asberg Depression Rating Scale, and the Beck Depression Inventory [6]. While these validated scales can be administered by a trained interviewer, a licensed mental health provider is required to make a formal diagnosis [2]. This method, while routinely used, is subjective to the clinician conducting the interview, leading to potential variations in diagnosis.

There are several other barriers to the diagnosis of depression, which include limited access to health care services and societal stigma toward mental health diagnoses. The *Diagnostic and Statistical Manual of Mental Disorders* defines depression as a heterogenous disorder that is diagnosed based on the core symptoms of depressed mood or anhedonia and at least 4 of the 9 other symptoms, including appetite changes, sleep changes, fatigue, difficulty in concentrating, feeling worthless, and suicidal ideation; depression is present if these symptoms last for at least 2 weeks [5]. Furthermore, the heterogeneity of symptoms in depression makes diagnosis difficult [7], and it is described differently across cultures [8]. In addition, there is social stigma and perceived conflict with normative social roles that prevent many patients from being honest about their thoughts and feelings [6].

Nursing Care for Depression

Second to social work, nursing is the largest profession in the mental health workforce [9]. In 2013, it was estimated that 4% of the total registered nursing workforce provided mental health care, and in 2015, the number was estimated by the National Nursing Workforce Survey to be 134,000 registered nurses [9]. Advanced practice registered nurses are a vital part of the mental health workforce, especially in rural areas where there are few licensed mental health professionals with prescribing capabilities [9].

Genomics of Depression

Owing to multilevel biases around diagnoses of depression, including implicit bias of providers, social desirability bias of patients, and bias introduced by data processing, alternative methods for an objective biologically informed diagnosis are being explored [10,11]. Currently, biomarkers, such as single nucleotide polymorphisms (SNPs), messenger RNA (mRNA), microRNA, proteins, and methylated DNA, are being sequenced and combined with scores on standardized depression instruments to evaluate whether they can improve the sensitivity and specificity of a depression diagnosis. Ideally, biomarker profiling would be performed on brain tissue, as it offers valuable insights into the underlying neurobiological mechanisms [6]. However, brain biopsies are dangerously invasive, so peripheral blood or saliva is often used as an alternative sample type [6]. Importantly, recent studies have shown a high correlation in gene expression and methylation patterns between blood and saliva samples and brain tissue, supporting the utility of peripheral samples as valuable surrogates for understanding the molecular mechanisms underlying depression [12-14]. Therefore, this study focuses on studies that use blood or saliva sample types for the diagnosis of depression.

The heritability of depression is estimated to be 40%, and many studies have been performed to identify genetic variants or SNPs that are associated with depression [15,16]. Genomic analysis can be performed through genome-wide association studies (GWASs). The 2 types of GWAS are classical and functional. Classical GWAS identifies SNPs that are associated with specific traits or diseases [15]. Functional GWAS determines how SNPs overlap with regulatory elements such as enhancers and promotors and predicts how these SNPs function [15]. A GWAS of samples in the Taiwan Biobank identified SNPs in 17 different genes that were significantly associated with depression [16]. Results from GWAS analyses suggest that depression is a polygenic disorder, meaning many SNPs can affect the hereditary influence [4]. SNPs identified through GWASs can be used to compute polygenic risk scores [4]. Polygenic risk scores combine the effects of genetic variants into an overall score that reflects an individual's propensity for a disease [17].

Transcriptomics of Depression

The transcriptome is all of the body's mRNA and contains coding instructions for protein synthesis [18,19]. Transcriptome analysis is useful for measuring gene expression. Recently developed sequencing techniques allow the expression levels of thousands of transcripts to be measured simultaneously [19]. Differentially expressed genes (DEGs) in patients with depression and healthy controls have been identified in both peripheral blood samples and brain tissues [18].

Epigenomics of Depression

Epigenetics leads to heritable changes in gene expression without affecting the underlying genetic sequences [20]. Studies have shown that epigenetics may be as influential as genetic variants in the development of depression [21]. Two types of epigenetic modifiers are DNA methylation (DNAm) and microRNA. DNAm occurs at sites in the genetic sequence where the nucleotides cytosine and guanine are bound together in clusters known as cytosine-phosphodiester bond-guanine (CpG) islands [21]. DNAm is responsive to environmental stimuli and can affect gene expression by inhibiting the transcription of affected genes [21]. MicroRNAs are small, noncoding RNAs up to 25 nucleotides in length [20]. Unlike mRNA, they are not translated into protein. Instead, they bind to mRNA to suppress protein translation, leading to decreased gene expression [20]. The effects of several microRNAs have been found to be upregulated or downregulated in individuals with depression [1].

In some studies, >1 sequencing method is used on the samples to produce different types of omics data. In the multiomics study by Bhak et al [6], blood samples were sequenced using Methyl-Seq to produce epigenomic data and RNA-Seq to produce transcriptomic data. Using these data, the authors were able to distinguish between people with depression who have attempted suicide, people with depression who have not attempted suicide, and healthy controls [6]. Combining >1 omics data type can improve prediction accuracy [6].

Microbiomics of Depression

The diversity of microbiota in the gut is influenced by genetics, development, and environment [22]. In the gut microbiome, the gut microbiota transmit signals to the brain through pathways associated with neural transmission and control of behaviors [22]. Depression has been associated with gut dysbiosis, an imbalance of the gut microbiota that is associated with adverse health outcomes [23,24]. Some strains of bacteria have been associated with depression in multiple studies, including *Eggerthella*, *Subdoligranulum*, *Coprococcus*, and *Ruminococcaceae* [25]. Furthermore, studies have found differences in metabolic pathways between individuals with depression and healthy controls [24].

Machine Learning Methods to Identify Individuals With Depression From Omics Data

Omics data are inherently complex and often too large for manual evaluation [26]. Machine learning, a form of artificial intelligence, is useful for detecting subtle patterns in large data sets, allowing it to predict multifactorial diseases [11,27]. By training algorithms on data, machine learning models identify patterns and make predictions that may be beyond human capabilities [28]. Machine learning algorithms can be supervised, where the algorithm learns from labeled training data to make predictions in unlabeled testing data, or unsupervised, where there is no labeling, and the algorithm categorizes the data into groups or finds complex patterns [29].

Machine learning models are being investigated to aid in the development of predictive algorithms to help understand how genetic variation can affect disease status [16]. A key aspect of machine learning is feature selection, which helps determine the importance of each feature and its contribution to the model's performance during training; in omics data, features can encompass various entities, such as SNPs, DEGs, or DNAm sites [6]. Machine learning can be useful for analyzing transcriptomic data because traditional statistical methods may not fully capture molecular interactions between genes [30].

Through machine learning, researchers can not only identify genes associated with a specific disease but also explore linear and nonlinear gene interactions [30]. While there is great potential in using machine learning to advance omics knowledge on depression, no prior studies have summarized the machine learning methods used to analyze omics data for depression. Therefore, this scoping review aims to provide an overview of the existing literature on using machine learning methods to analyze omics data to identify individuals with depression.

Methods

This scoping review was reported following the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) guidelines [31].

Search Strategies

Searches were conducted in 3 databases between November and December 2022: PubMed, CINAHL, and Scopus. The search strategy used terms representing machine learning; depression; and different types of omics, including genomics, transcriptomics, and epigenomics (Multimedia Appendix 1). Keywords were combined using Boolean operators.

Selection Criteria

After deduplication, 3 independent reviewers (BT, MH, and SN) conducted pairwise screening of titles and abstracts with specific inclusion and exclusion criteria using Covidence (Veritas Health Innovation) systematic review web software. This resulted in a set of papers for full-text review that were also reviewed pairwise, with disagreements resolved by consensus. Specific inclusion criteria consisted of studies published in peer-reviewed journals, English, and the past 5 years (ie, between January 1, 2017, and December 31, 2022). Publication dates were limited to the past 5 years because genetic sequencing is constantly evolving, and older studies may have used outdated methods [32]. Furthermore, all studies had to include (1) an omics method involving the sequencing of genetic material to identify depression and (2) an approach that used machine learning or deep learning to analyze the omics data. Papers were excluded if they focused on omics methods that did not involve sequencing of genetic material, such as metabolomics and lipidomics. In addition, review papers; deep learning studies of medical images; and studies focusing on other disorders, such as bipolar disorder, anxiety disorder, posttraumatic stress disorder, and schizophrenia, were excluded.

Any disagreements between screeners were discussed and resolved through consensus. After the initial screening, full texts of the remaining papers were reviewed. Reference lists were also screened to identify any additional papers meeting the inclusion criteria. Covidence software was used throughout the screening process. Data charting was completed for the eligible studies using Word (Microsoft Corp).

Data Extraction

Items extracted included author, year, study design, and sample size. Data extracted included the omics type, machine learning method, sample type, and depression screening instrument used. Charted data were synthesized by grouping studies according to their omics method (eg, genomics and transcriptomics).

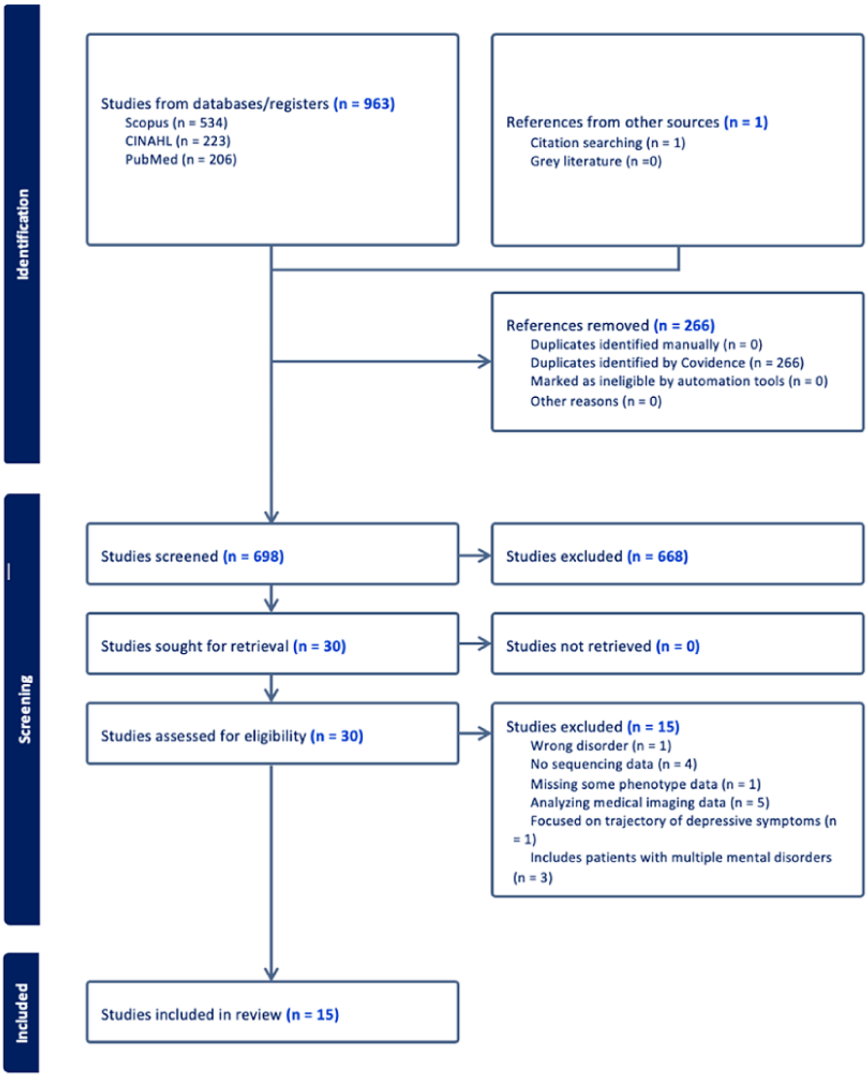
Critical appraisal was performed using the Joanna Briggs Institute Critical Appraisal Checklist for Analytical Cross-Sectional Studies [33]. This checklist was chosen because the genomic data in the studies included in this review were analyzed at a single point in time [34]. The checklist appraises inclusion criteria, measurement of exposure and outcomes, confounding, and statistical analysis. Questions are answered as yes, no, unclear, or not applicable [33].

Results

Search Summary

The initial database search yielded 964 papers; 266 (27.6%) papers were removed as duplicates. Of the 964 papers, the titles and abstracts of 698 (72.4%) papers were screened for eligibility. A priori exclusion criteria were applied throughout the title and abstract screening of the 698 papers, and 668 (95.7%) papers were excluded. Of the 698 papers, 30 (4.3%) met the criteria for full-text review and were assessed for eligibility, of which 15 (50%) were included in this scoping review. This screening process is visualized in a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram (Figure 1).

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



Summary of Study Characteristics

The included studies were published between 2017 and 2022. The studies were conducted in 8 countries: Germany (1/15, 7%), South Korea (1/15, 7%), Australia (1/15, 7%), China (1/15, 7%), Taiwan (1/15, 7%), Canada (2/15, 13%), United States (6/15, 40%), Japan (1/15, 7%), and India (1/15, 7%). All the studies were cross-sectional design studies. The studies addressed genomics (5/15, 33%), transcriptomics (5/15, 33%), epigenomics (3/15, 20%), multiomics (1/15, 7%), and microbiomics (1/15, 7%). Machine learning methods included random forest, support vector machine, k-nearest neighbor, artificial neural network, and deep learning. Study characteristics are further described in Table 1.

Table 1. Study characteristics.

Type of omics and study	Country	Sample size, n	Age range	Depression diagnosis	Screening instrument
Genomics					
Arabnejad et al [35], 2018	United States	922 (463 cases and 459 controls)	Not given	Screening	• Composite International Diagnostic Interview–Short Form • Structured Clinical Interview for DSM-IV[a] • Patient Health Questionnaire-9
Arloth et al [15], 2020	Germany	3514 (1476 cases and 2038 controls)	Not given	Not given	• Not given
Lin et al [16], 2021	Taiwan	9828 (2457 cases and 7371 controls)	Mean 51.2 (SD 10.4) years	Psychiatrist	• Patient Health Questionnaire
Sekaran and Sudha [26], 2019	United States	100 (66 cases and 34 controls)	Not given	Not given	• Not given
Takahashi et al [36], 2020	Japan	6733 (185 cases and 6548 controls)	Mean 60 (SD 11) years	Not given	• Center for Epidemiological Studies–Depression Scale
Transcriptomics					
Ciobanu et al [30], 2020	Australia	521 (27 cases and 494 controls)	70 to 90 years	Screening	• Geriatric Depression Scale • Patient Health Questionnaire • Neuropsychiatric Inventory
Le et al [37], 2020	United States	157 (78 cases and 79 controls)	Not given	Psychiatrist	• Montgomery-Asberg Depression Rating Scale
Parvandeh et al [38], 2020	United States	915 (463 cases and 452 controls)	Not given	Screening	• Composite International Diagnostic Interview–Short Form • Structured Clinical Interview for DSM-IV • Patient Health Questionnaire-9
Qi et al [18], 2021	Canada	2295 (1765 cases and 530 controls)	>18 years	Not given	• Not given
Verma and Shakya [19], 2022	India	59 (30 cases and 29 controls)	Not given	Not given	• Not given
Epigenomics					
Fan et al [27], 2021	China	391 (291 cases and 100 controls)	18 to 65 years	Psychiatrist	• Hamilton Rating Scale for Depression-17
Payne et al [39], 2020	United States	267 (54 cases and 213 controls)	Not given	Screening	• Edinburgh Postnatal Depression Scale
Qi et al [1], 2020	Canada	168 (140 cases and 28 controls)	Not given	Psychiatrist	• Montgomery-Asberg Depression Rating Scale
Microbiomics					
Stevens et al [24], 2021	United States	40 (20 cases and 20 controls)	Not given	Psychiatrist	• None
Multiomics					
Bhak et al [6], 2019	South Korea	182 (95 cases and 87 controls)	19 to 46 years	Psychiatrist	• Hamilton Rating Scale for Depression-17

[a] DSM-IV: Diagnostic and Statistical Manual of Mental Disorders (Fourth Edition).

Genomics

One study combined classical and functional GWASs and annotated SNPs based on their regulatory potential and combination with a functional unit (FU) [15]. This method is called a multivariate FU-wide association study (DeepWAS) [15]. A DeepWAS can identify SNPs associated with a disease (dSNPs) [15]. A DeepWAS successfully identified 61 dSNPs in 237 FUs that were associated with depression; 60 (25.3%) of these dSNPs were significant (Table 2) [15]. To validate these results, the dSNPs were compared to SNPs identified by other GWASs [15]. A total of 4 dSNPs overlapped with a large GWAS by the UK Biobank: the *LARP6-LRRC*49 gene, 2 intergenic regions near the *WNT2* and *ASZ1* genes, the *ATG9B* and *ABCB8* genes on chromosome 7, and a site near the *C1orf220* and *MIR4424* genes on chromosome 1 [15]. In addition, the DeepWAS identified an SNP on the transcription factor binding site of *MEF2C* on chromosome 8 as a regulator for depression [15]. The GWAS using data collected from 2 prefectures in Japan included 102 SNPs in the model with the highest prediction accuracy [36]. However, none of these variants were significant at the 5.0×10^{-8} level, and the top 11 variants only explained 0.0036% of the variance in the validation data set, which is a very small effect size [36].

Using data from the Taiwan Biobank, a novel SNP, rs192922209, located in the intron region of the *FBN1* gene on chromosome 15, was associated with depression [16]. In addition, a novel SNP was associated with depression in female individuals: rs114542799 in the intron region of the *ALDH1L1* gene on chromosome 3 [16]. Furthermore, this study identified 17 SNPs with potential roles as expression quantitative trait loci [16]. Arabnejad et al [35] used GWAS data to identify significant SNPs and their associated genes to test for pathways that overlap with depression. They identified the top 500 SNPs using different feature selection methods and compared the number of genes detected to the biological pathways [35]. Pathways that previous studies have associated with depression were reported: axon guidance pathway, neuronal system pathway, and pathways related to G protein–coupled receptors, which affect neurotransmitter signaling [35].

Sekaran and Sudha [26] aimed to identify genetic variants related to depression by using DNA microarrays. Sample participants were classified into 3 categories: patients with depression with lipopolysaccharide treatment, patients with depression without lipopolysaccharide treatment, and healthy controls [26]. A total of 27 genetic biomarkers associated with depression were identified; the biomarker *A_23_P109436*, was able to classify the data with the highest precision [26].

Table 2. Study findings.

Type of omics and study	Sample type	Key findings
Genomics		
Arabnejad et al [35], 2018	Blood	• Detected pathways associated with depression, including axon guidance, neuronal system, and G protein–coupled receptor signaling
Arloth et al [15], 2020	Not given	• Identified 61 dSNPs[a] in 237 FUs[b]; 60 of the dSNPs were significant • A total of 4 dSNPs were also found in a GWAS[c] by the UK Biobank • A SNP[d] on the MEF2C gene was identified as a regulator for depression
Lin et al [16], 2021	Blood	• This study identified a novel SNP on the FBN1 gene associated with depression • A novel SNP on the ALDH1L1 was associated with depression in female individuals • A total of 17 SNPs with potential roles as expression quantitative trait loci were pinpointed
Sekaran and Sudha [26], 2019	Not given	• Identified 27 genetic biomarkers associated with depression • A biomarker, A_23_P109436, classified the data with the highest precision
Takahashi et al [36], 2020	Blood	• The model with the highest prediction accuracy included 102 SNPs • None of these SNPs were significant at the 5.0×10–8 level
Transcriptomics		
Ciobanu et al [30], 2020	Blood	• Downregulation of the transferrin receptor gene is associated with depression
Le et al [37], 2020	Blood	• Identified 23 depression gene modules
Parvandeh et al [38], 2020	Blood	• The best performing model had a significant overlap of 959 genes with the initial 7616 genes (*P*<.001)
Qi et al [18], 2021	Brain and blood	• Analysis of brain mRNA[e] revealed 62 DEGs[f] used to distinguish cases from controls • Analysis of blood mRNA found 1376 DEGs
Verma and Shakya [19], 2022	Blood	• A total of 624 transcripts correlated with the classification of patients with depression who died by suicide, those who did not die by suicide, and healthy controls
Epigenomics		
Fan et al [27], 2021	Blood	• Identified 9 differentially methylated sites on the tryptophan hydroxylase-2 gene
Payne et al [39], 2020	Blood	• Found that DNAm[g] in the first trimester could accurately predict depression in the third trimester • Third-trimester DNAm predicted postpartum depression
Qi et al [1], 2020	Blood	• A total of 4 microRNAs differed significantly, but these differences were not significant
Microbiomics		
Stevens et al [24], 2021	Stool	• Found decreased amounts of Faecalibacterium, Ruminococcus, Lachnospiraceae, and Bacterioides species in the microbiomes of the individuals in the group with depressive symptoms
Multiomics		
Bhak et al [6], 2019	Blood	• Identified 48 DEGs and 810 differentially methylated sites that significantly correlated with depression scores

[a] dSNPs: single nucleotide polymorphisms associated with a disease.

[b] FU: functional unit.

[c] GWAS: genome-wide association study.

[d] SNP: single nucleotide polymorphism.

[e] mRNA: messenger RNA.

[f] DEG: differentially expressed gene.

[g] DNAm: DNA methylation.

Transcriptomics

Ciobanu et al [30] used transcriptomic data to identify a link between depression and the transferrin receptor gene on chromosome 3. When downregulated, this gene is associated with recurrent depression [30]. In the study by Verma and Shakya [19], differential gene expression was examined between patients with depression who died by suicide, those who did not die by suicide, and healthy controls. A total of 624 transcripts were found to be biologically and functionally related to classifying the 3 categories [19]. Most of these transcripts were associated with neurotransmitter receptors, postsynaptic signal transmission, synaptic depression, gamma-aminobutyric acid receptor activation, and glutamatergic synapse [19].

Using RNA sequence data, Parvandeh et al [38] aimed to classify patients with depression and healthy controls. They analyzed 7616 genes that are known to be associated with depression based on prior studies; these genes were compared to a repository of genes associated with mental disorders from the DisGeNET platform [38]. The best performing model had an overlap of 959 genes with the initial 7616 genes and $P<.001$, indicating significant overlap [38]. Using brain mRNA to discriminate between cases and controls, the best performing model identified 62 DEGs [18]. These genes were associated with upregulation of metalloaminopeptidase activity, downregulation of oxidoreductase activity, and upregulation of aminopeptidase activity [18]. Furthermore, this study used blood mRNA to identify 1376 DEGs associated with depression [18]. RNA-Seq Rdata was used to identify depression gene modules (DGMs), genes that are interconnected and coexpressed, and predict a clinical diagnosis of depression [37]. A total of 23 DGMs were identified; DGM-5 was most predictive of depression diagnosis and was significantly associated with depression severity [37].

Epigenomics

In the epigenetic study of postpartum depression by Payne et al [39], the authors used DNAm biomarker profiles on the *TTC9B* and *HP1BP3* genes to predict antenatal and postpartum depression [39]. A total of 4 separate cohorts were included in this study, and blood samples were drawn during different trimesters of pregnancy [39]. They found that DNAm biomarkers from samples collected during the first trimester could accurately predict depression in the third trimester [39]. In addition, biomarker profiles in third-trimester samples predicted depression in the postpartum period [39].

The DNAm study by Fan et al [27] focused on methylation of the tryptophan hydroxylase-2 gene, which functions in the production of serotonin. They identified 9 CpG sites on the tryptophan hydroxylase-2 gene that differ significantly between patients with depression and healthy controls [27]. In the microRNA study by Qi et al [1], 4 microRNAs were found to differ significantly between patients with depression and healthy controls. However, none of these microRNAs remained significant after Bonferroni correction [1].

Microbiomics

One study used genomic variants in the microbiome to distinguish between individuals with depression and healthy controls [24]. After examining exact amplicon sequence variants, biological sequences that have been inferred through shotgun sequencing, the authors found decreased abundances of *Faecalibacterium*, *Ruminococcus*, *Lachnospiraceae*, and *Bacterioides* species in the microbiomes of the individuals in the depression group compared to those in the healthy group [24]. Furthermore, they found that pathways involved in the degradation of the neurotransmitter gamma-aminobutyric acid and the fatty acid butyrate were more prominent in individuals with depression [24].

Multiomics

The multiomics study using blood transcriptome and methylome data identified DEGs and differentially methylated sites (DMSs) in individuals with depression and controls [6]. This study included 3 cohorts: 56 individuals with depression who attempted suicide, 39 individuals with depression who did not attempt suicide, and 87 healthy controls [6]. A total of 80 DMSs were identified between individuals with depression who did not attempt suicide, and 95 DMSs and 7 DEGs were identified between individuals with depression who attempted suicide and controls [6]. Between individuals with depression who did and did not attempt suicide, 69 DMSs were found [6]. In addition, 48 DEGs and 810 DMSs were significantly correlated with scores on the Hamilton Rating Scale for Depression-17 [6]. A functional enrichment test was conducted to investigate pathways associated with the model input features. A difference in enrichment was detected between depressed individuals who did not attempt suicide “and controls in the Hippo signaling pathway, which includes the Protein Kinase C gene on chromosome 2 and the Frizzled Class Receptor 7 gene on chromosome 1 [6]. In addition, protocadherin genes were enriched in depressed individuals who attempted suicide compared to controls [6].

Supervised Machine Learning

In an epigenomic study, linear discriminant analysis and support vector machine were used to predict depression in the first, second, or third trimester of pregnancy [39]. Linear discriminant analysis predicted depression in the third trimester with an accuracy >70% and an area under the curve (AUC) of 0.72 (Table 3); similarly, support vector machine predictions for the same trimester had an accuracy of 72% and AUC of 0.83 [39]. Support vector machine also successfully identified women with depression in the postpartum period with an AUC of 0.78; an AUC >0.5 indicates the model has some level of discriminatory ability and can adequately distinguish between cases and controls better than random chance [39].

Table 3. Machine learning methods and performance metrics.

Type of omics, study, and machine learning method	AUC[a]	Accuracy	Sensitivity	Specificity
Genomics				
Arabnejad et al [35], 2018[b]				
ReliefF	—[c]	—	—	—
Random forest	—	—	—	—
Lasso regression	—	—	—	—
Arloth et al [15], 2020				
DeepWAS[d] or DeepSEA[e]	0.59-0.66	—	—	—
Lin et al [16], 2021				
Random forest	0.82	—	0.76	0.76
Support vector machine	0.76	—	0.76	0.76
Decision tree	0.76	—	0.76	0.76
Logistic ridge regression	0.82	—	0.76	0.76
LogitBoost	0.82	—	0.76	0.76
Sekaran and Sudha [26], 2019				
Bayesian network	—	*0.96*[f]	—	—
Support vector machine	—	0.73	—	—
Random forest	—	0.91	—	—
Neural network	—	0.72	—	—
Linear discriminant analysis	—	0.70	—	—
Takahashi et al [36], 2020[g]				
Smooth-threshold multivariate genetic prediction	—	—	—	—
Genomics best linear unbiased prediction	—	—	—	—
Summary data–based best linear unbiased prediction	—	—	—	—
Bayes regression	—	—	—	—
Ridge regression	—	—	—	—
Transcriptomics				
Ciobanu et al [30], 2020				
Fuzzy forest	—	0.63	0.63	0.66
Le et al [37], 2020				
Tree-based pipeline optimization tool	—	*0.48-0.65*	—	—
Extreme gradient boost	—	0.49-0.59	—	—
Parvandeh et al [38], 2020				
Consensus nested cross-validation	—	*0.59*	—	—
Nested cross-validation	—	0.56	—	—
Private evaporative cooling	—	0.58	—	—
General Elastic net	—	0.51	—	—
Qi et al [18], 2021				
Extreme gradient boost	0.55-0.72	0.67-0.85	—	—
Logistic regression	*0.62-0.91*	—	—	—
Verma and Shakya [19], 2022				
Random forest	—	*0.39-0.61*	—	—

Type of omics, study, and machine learning method	AUC[a]	Accuracy	Sensitivity	Specificity
K-nearest neighbor	—	0.28-0.61	—	—
Epigenomics				
Fan et al [27], 2021				
Random forest	0.79-0.91	0.69-0.78	0.65-0.74	0.81-0.92
Support vector machine	0.57-0.86	0.50-0.85	0.41-0.83	0.49-0.88
Neural network	*0.78-0.99*	*0.75-0.97*	*0.78-0.98*	*0.49-0.95*
Payne et al [39], 2020				
Support vector machine	*0.77-0.84*	—	—	—
Linear discriminant analysis	0.72	—	—	—
Qi et al [1], 2020				
Clustering	0.49-0.97	—	—	—
Microbiomics				
Stevens et al [24], 2021				
Random forest	0.66-0.90	—	—	—
Multiomics				
Bhak et al [6], 2019				
Random forest	—	0.87-0.93	0.59-0.98	0.85-1

[a] AUC: area under the curve.

[b] Machine learning methods were evaluated based on the number of genes found in pathways implicated in mood disorders.

[c] Not reported.

[d] DeepWAS: multivariate functional unit–wide association study.

[e] DeepSEA: deep learning-based sequence analyzer.

[f] Italics represent the best performing models.

[g] The only performance metrics given were partial correlation coefficients.

The GWAS of the Taiwan Biobank used 5 machine learning algorithms to build creative models incorporating SNPs and demographic information: logistic ridge regression, support vector machine, decision tree, LogitBoost, and random forest [16]. Logistic ridge regression and LogitBoost had the best performance with an AUC >0.82 and sensitivity and specificity >0.76 [16]. In the GWAS study by Takahashi et al [36], the authors aimed to decrease overfitting by decreasing the number of null variants included in the model. They compared the performance of 6 different models: smooth-threshold multivariate genetic prediction, polygenic risk scores, genomic best linear unbiased prediction, summary data–based best linear unbiased prediction, a Bayesian hierarchical model for the analysis of complex traits, and ridge regression [36]. The smooth-threshold multivariate genetic prediction had the highest prediction accuracy with a partial correlation of 0.05 and P value of <.005; this model also successfully reduced overfitting [36]. The study by Sekaran and Sudha [26] used 5 different machine learning algorithms to identify genetic biomarkers: Bayesian network, support vector machine, random forest, back propagation neural network, and linear discriminant analysis. The accuracy of the Bayesian network and support vector machine was >90%; the accuracy of the other algorithms was <75% [26].

The transcriptomic study by Ciobanu et al [30] combined a random forest classifier model with Weighted Gene Coexpression Network Analysis into an algorithm called fuzzy forest that identified an association between depression and the transferrin receptor gene. The fuzzy forest classifier was able to reduce the dimensionality of the transcriptomic data and allow a predictive marker of depression to be identified with a smaller sample size [30]. In a transcriptomic study using brain tissue, extreme gradient boost (XGBoost) was chosen for its feature selection and reduction characteristics and ability to rank features by importance [18]. The AUC for the best performing model was 0.72 [18]. Furthermore, XGBoost was used in the transcriptomic study by Le et al [37], and its performance was compared to 2 tree-based pipeline optimization tools (TPOTs). XGBoost produced an accuracy of 0.59, and the standard TPOT produced a similar accuracy of 0.60 [37]. The TPOT combined with a feature set selector and the ability to slice the data into smaller subsets, produced the highest prediction accuracy of 0.68 [37].

In the multiomics study by Bhak et al [6], the authors used a random forest model and feature selection to analyze blood transcriptome and methylome data; this model correctly predicted the labels for suicide attempters and nonsuicide attempters with depression and controls. Scores on the Hamilton Rating Scale for Depression-17 were also correctly predicted by a linear regression model [6]. The microbiomic study by Stevens et al [24] used a random forest method to identify gut microbiome taxa and related metabolic pathways associated with depression. The R packages ALDEx2, DADA2, and PIME (R Foundation for Statistical Computing) analyzed the DNA sequences of the microbiota in stool samples to produce exact amplicon sequence variants, identify taxa associated with those variants using a Naive Bayes classifier, and filter the results into unique amplicon sequence variant sequences [24]. This approach differentiated between individuals with depression and healthy controls, and the results were supported by multivariate analyses with a P value of <.001 and effect size >0.5 [24]. Machine learning predicted metabolic pathways associated with the individuals in the depression and control groups with AUCs ranging from 0.66 to 0.9 [24].

Verma et al [19] used random forest and k-nearest neighbor methods to analyze transcriptomic data and classify patients as depressed and died by suicide, depressed and did not die by suicide, and healthy controls. K-nearest neighbor stores all cases and classifies new cases based on their similarity [19]. Using random forest, the test data were classified with an accuracy of 61.11%, and the training data were classified with an accuracy of 97.56%; with k-nearest neighbor, the accuracy was 61.11% for test data and 76.6% for training data [19].

The GWAS using the top 500 SNPs to identify biological pathways associated with depression compared the performance of random forest; least absolute shrinkage and selection operator; and ReliefF, a nearest neighbors feature selection algorithm [35]. ReliefF was the best performing algorithm, likely due to its ability to detect statistical interactions, and this method identified most genes associated with biological pathways related to depression [35]. Furthermore, ReliefF was used in a transcriptomic study and was combined with different cross-validation methods [38]. The private evaporative cooling and general elastic net algorithms had the highest accuracy on the training data, but consensus nested cross-validation had the highest accuracy on the validation data as well as low overfitting [38].

In the study of microRNAs by Qi et al [1], a regularized gradient boosted method was used to classify individuals with depression and healthy controls. The models were trained with cross-validation and 2500 iterations of parameter searches [1]. The models were then retrained using the best parameters [1]. The best model achieved an AUC of 0.93 [1]. When classifying cases as normal to mild or moderate to severe, the best model achieved an AUC of 0.76 [1].

Unsupervised Machine Learning

The study of microRNAs by Qi et al [1] used an unsupervised clustering approach to differentiate individuals with depression from healthy controls. A total of 500 iterations of a k-means clustering method were applied to the data set [1]. They obtained 2 clusters with similar sample sizes, both with an AUC >0.70 [1].

Deep Learning

The DeepWAS study by Arloth et al [15] used a deep learning method called deep learning-based sequence analyzer to predict the function of SNPs. Of >8 million SNPs analyzed; this method predicted 40,000 regulatory SNPs based on their affinity with an FU [15]. The AUCs ranged from 0.59 to 0.66 [15]. A regularized linear regression was used to determine which SNPs were associated with depression [15].

The DNAm study by Fan et al [27] used a support vector machine, random forest, and a neural network to predict depression based on methylation of the tryptophan hydroxylase-2 gene. The neural network had the best performance with an AUC of 0.988, sensitivity of 98.3%, specificity of 95%, accuracy of 97.4%, and positive predictive value of 98.3% [27]. In addition, they found that models combining clinical variables with tryptophan hydroxylase-2 methylation performed better than models based on clinical variables or methylation alone [27].

Critical Appraisal

The studies' strengths and weaknesses were identified using the Joanna Briggs Institute Critical Appraisal Checklist for Analytical Cross-Sectional Studies, as shown in Table 4. Of the 15 studies, only 2 (13%), Fan et al [27] and Qi et al [1], clearly defined the criteria for inclusion in the sample. However, in all 15 studies, the individuals and setting were described in detail. A total of 47% (7/15) of the studies classified participants as experiencing depression but did not report how depression was measured or diagnosed. This may be due to the authors using data from biobanks and not having access to specific data about the participants.

The authors did not identify possible confounding factors in 11 (73%) of the 15 studies. However, it is typical that confounding is addressed when processing variables and during feature engineering, but it may not always be described as it is such a regular process. Therefore, the questions addressing confounding factors were marked "not applicable." The study did not investigate the cause of depression or any associated diseases or disorders. Furthermore, those 11 studies did not present strategies to deal with confounding factors. The genomic outcomes were measured in a valid and reliable way in all the studies. The statistical analyses used seemed appropriate in all 15 studies.

Table 4. Joanna Briggs Institute Critical Appraisal Checklist for Analytical Cross-Sectional Studies.

Question	Arabnejad et al [35], 2018	Arloth et al [15], 2020	Bhak et al [6], 2019	Ciobanu et al [30], 2020	Fan et al 27], 2021	Le et al [37], 2020	Lin et al [16], 2021	Parvandeh et al [38], 2020	Payne et al [39], 2020	Qi et al [1], 2020	Qi et al [18], 2021	Sekaran and Sudha [26], 2019	Stevens et al [24], 2021	Takahashi et al [36], 2020	Verma and Shakya [19], 2022
Were the criteria for inclusion in the sample clearly defined?	Unclear	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	No
Were study individuals and setting described in detail?	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Was the exposure measured in a valid and reliable way?	Yes	Unclear	Yes	Yes	Yes	Unclear	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	No
Were objective, standard criteria used for measurement of the condition?	Yes	Unclear	Yes	Yes	Yes	Unclear	Yes	Unclear	Yes	Yes	No	No	Yes	Yes	No
Were confounding factors identified?	—[a]	—	—	—	Yes	—	Yes	—	—	—	Yes	—	Yes	—	—
Were strategies to deal with confounding factors stated?	—	—	—	—	Yes	—	Yes	—	—	—	Yes	—	Yes	—	—
Were the outcomes measured in a valid and reliable way?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Was appropriate statistical analysis used?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

[a] Not applicable.

Discussion

Principal Findings

Machine learning can enable researchers to identify specific features that impact depression, allowing providers to screen for these features in a clinical setting. In this scoping review, 15 studies published in the past 5 years reported on machine learning analysis of omics data to identify individuals with depression. Owing to the diversity of the data sources and methods, there was minimal overlap in comparable study results, indicating that this field is still in exploratory stages but will provide new avenues for future prediction of which patients are at risk of developing depression.

Future studies could help with diagnosing depression using genomic data in a more reliable way, helping to mitigate the potential biases of screening interviews. However, while the genomic studies identified many genetic variants associated with depression, the lack of overlap in study results indicates low reproducibility, which could be related to the low 40% heritability of depression. It may also be associated with the heterogeneity of depression symptoms, with different genetic variants correlating with different symptoms.

Genetic variants can be helpful in diagnosing depression, but they are not generally responsive to environmental stimuli. Most of the genomics studies in this review focused on identifying SNPs that differed between individuals with depression and healthy controls. One study focused on detecting pathways associated with depression, while another used gene probes as biomarkers [26,35]. With the varied outcomes, it was difficult to compare these 2 studies to the others and determine if the results were consistent.

Transcriptomics can identify transcripts associated with depression or genes that are differentially expressed in depression. Gene expression has some responsiveness to the environment, as does DNAm. Of the 5 transcriptomics studies, 1 (20%) used brain and blood samples, while the other 4 (80%) used only blood samples, so it was expected that the results may vary. One of the studies reported downregulation of a single gene; another study reported general dysregulation of a few 100 genes, and 1 study identified DEGs and upregulation or downregulation of related pathways [18,19,30]. Another study focused on DGMs, groups of genes that are coexpressed in individuals with depression [37]. The fifth transcriptomics study emphasized the machine learning models and reported how many genes were selected by each model [38]. It would be ideal for comparison if all the studies performed a transcriptome-wide analysis and reported upregulation or downregulation of each DEG identified.

The DNAm study of tryptophan hydroxylase-2 focused on the methylation of a single gene rather than an epigenome-wide approach, effectively limiting the results to that gene [27]. Similarly, the postpartum depression DNAm study focused on only 2 specific genes, making it impossible to compare the results of the 2 studies [39]. Epigenome-wide association studies would likely be more effective in identifying differentially expressed regions associated with depression and possibly replicating work across studies [40].

Microbiomics was an interesting approach, as it did not use blood or saliva samples to sequence genetic material from the human participant [24]. Analysis of microbiomics data obtained from stool samples found differences in the composition of gut microbiota between individuals with depression and healthy individuals [24]. Stevens et al [24] identified particular taxa that were more prominent or depleted in the 2 groups. Furthermore, they focused on identifying physiological pathways involving microbiota that were associated with depression [24]. The multiomics study identified many DEGs and DMSs related to depression [6]. This may be the most insightful method because of the volume of results. However, it might be challenging to determine which results are the most significant. In addition, in many studies, only 1 type of omics data is available, so the multiomics method is not feasible.

A total of 20% (3/15) of the studies focused on identifying biological pathways. The genomics pathways study used the top 500 genes determined through feature selection and found associations with pathways that regulate neurotransmitter signaling [35]. The transcriptomics study identified pathways related to neurotransmitter reception, postsynaptic signal transmission, synaptic depression, and receptor activation, while the multi-omics study identified the Hippo signaling pathway, which is involved in cell proliferation and affects antidepressant response [6,41]. The genomics and transcriptomics studies show relatively consistent results in finding associations with pathways affecting neurotransmitters. The multiomics study found a different type of pathway, which may reflect the heterogeneity of depression and could indicate that different mechanisms can lead to depression. Future omics studies could include pathways analysis to build upon the knowledge of which biological pathways are involved in depression.

All the machine learning methods performed well based on their individual performance metrics. However, supervised methods are preferred when attempting to identify biological features related to depression because of their interpretability. Of the 15 studies, 8 (53%) reported AUCs to indicate how well the machine learning models performed, while 5 (33%)only reported accuracy; 2 (13%) reported accuracy, sensitivity, and specificity; 1 (7%) reported partial correlation coefficients; and 1 (7%) only quantified the number of genes found in pathways related to mood disorders. A review of the literature found that the most common metric used to evaluate machine learning models was accuracy followed by sensitivity and specificity [42]. However, the use of AUC as a performance metric is increasing [42]. It was difficult to compare the performance of the machine learning models in this review due to the range of performance metrics; using a standardized metric could prove more useful when choosing a model and comparing results.

There are ethical considerations related to the prediction of depression, such as the possibility of increasing insurance premiums. The protection of patient privacy, confidentiality, and trust is central to using genomics data, especially given how sensitive the data are and how they could be used to predict the risk of future conditions. Moreover, if it becomes feasible to predict depression before an individual shows symptoms, providers will need to determine the appropriate timing for treatment. They could begin treating preemptively or wait for symptoms to manifest. Furthermore, the cost of analyzing omics data should be considered. Researchers should evaluate whether omics data have a higher predictive accuracy than formal psychiatric evaluation. If not, using omics data may not be the most cost-effective way to identify individuals with depression.

Limitations

Finally, this scoping review is not without limitations. First, many of the studies used data from biobanks, which did not provide detailed descriptions of the participants in the data sets. This makes it impossible to know the demographics and other sample characteristics. In addition, unknown sample characteristics make the generalizability of study results unclear. Moreover, some studies did not report how depression was screened or diagnosed among patients, so it is not known if validated screening measures or formal psychiatric diagnoses were used or only patient reports were used.

Future Work

In future research, it may be helpful to focus on machine learning methods that identify features rather than those that are more geared toward prediction. Identified features can include genetic variants, DEGs, or differentially methylated regions, which would provide more relevant information that could be used to identify depression. The long-term goal of this work is to be able to use these biomarkers for a more objective diagnosis of depression.

Nursing Implications

Nurses are in a unique position to provide mental health support to patients when they have received appropriate training and education in psychotherapy [43]. Nurses have been called the “gateway” for care because they are typically the first point of contact with the health system and are in a position to build therapeutic relationships with patients [44]. With their skills in establishing therapeutic relationships, building rapport, active listening, observing behaviors, and noticing the effects of medications, nurses serve an extremely important role in the health promotion of patients seeking mental health support [44].

In addition, machine learning–based prediction of depression will eventually become part of common nursing clinical workflow. Therefore, it is imperative that nurses bring their expertise to the creation, evaluation, and implementation of artificial intelligence approaches to depression prediction. Of note, none of the 15 studies had nurse researchers as members of their study team. Nursing involvement in the entire life cycle of artificial intelligence will positively impact the usability and usefulness of data tools in clinical practice.

Conclusions

This scoping review describes different types of omics data and machine learning methods used to analyze these data to predict and diagnose depression. The findings indicate that the omics methods had similar performance in identifying variants, differentially methylated sites, and differences in gene expression. All machine learning methods performed well based on the metrics provided. Further research is needed in omics methods to identify more variants and differential sites and gene expression. When variants in omics data indicate the possibility of depression, it is important for clinicians, especially nurses, to assess individuals for symptoms of depression and provide a formal diagnosis and treatment if appropriate.

Acknowledgments

This work was supported by the National Center for Advancing Translational Sciences (TL1TR001875 [BT]) and the National Institute of Neurological Disorders and Stroke (R01NS123639 [RMC]).

Conflicts of Interest

None declared.

Multimedia Appendix 1
Search strategy and keywords.
[DOCX File , 23 KB - nursing_v7i1e54810_app1.docx]

Multimedia Appendix 2
Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) checklist.
[DOCX File , 84 KB - nursing_v7i1e54810_app2.docx]

References

1. Qi B, Fiori LM, Turecki G, Trakadis YJ. Machine learning analysis of blood microrna data in major depression: a case-control study for biomarker discovery. Int J Neuropsychopharmacol 2020 Nov 26;23(8):505-510 [FREE Full text] [doi: 10.1093/ijnp/pyaa029] [Medline: 32365192]
2. Tomasik J, Han SY, Barton-Owen G, Mirea D, Martin-Key NA, Rustogi N, et al. A machine learning algorithm to differentiate bipolar disorder from major depressive disorder using an online mental health questionnaire and blood biomarker data. Transl Psychiatry 2021 Jan 12;11(1):41 [FREE Full text] [doi: 10.1038/s41398-020-01181-x] [Medline: 33436544]
3. Greenberg PE, Fournier AA, Sisitsky T, Simes M, Berman R, Koenigsberg SH, et al. The economic burden of adults with major depressive disorder in the United States (2010 and 2018). Pharmacoeconomics 2021 Jun 05;39(6):653-665 [FREE Full text] [doi: 10.1007/s40273-021-01019-4] [Medline: 33950419]
4. Di Y, Wang J, Liu X, Zhu T. Combining polygenic risk score and voice features to detect major depressive disorders. Front Genet 2021 Dec 20;12:761141 [FREE Full text] [doi: 10.3389/fgene.2021.761141] [Medline: 34987547]
5. Walther A, Cannistraci CV, Simons K, Durán C, Gerl MJ, Wehrli S, et al. Lipidomics in major depressive disorder. Front Psychiatry 2018 Oct 15;9:459 [FREE Full text] [doi: 10.3389/fpsyt.2018.00459] [Medline: 30374314]
6. Bhak Y, Jeong HO, Cho YS, Jeon S, Cho J, Gim J, et al. Depression and suicide risk prediction models using blood-derived multi-omics data. Transl Psychiatry 2019 Oct 17;9(1):262 [FREE Full text] [doi: 10.1038/s41398-019-0595-2] [Medline: 31624227]

7. Squarcina L, Villa FM, Nobile M, Grisan E, Brambilla P. Deep learning for the prediction of treatment response in depression. J Affect Disord 2021 Feb 15;281:618-622. [doi: 10.1016/j.jad.2020.11.104] [Medline: 33248809]
8. Kalibatseva Z, Leong FT. Cultural factors, depressive and somatic symptoms among Chinese American and European American college students. J Cross Cult Psychol 2018 Sep 29;49(10):1556-1572. [doi: 10.1177/0022022118803181]
9. Phoenix BJ, Hurd M, Chapman SA. Experience of psychiatric mental health nurse practitioners in public mental health. Nurs Adm Q 2016;40(3):212-224. [doi: 10.1097/NAQ.0000000000000171] [Medline: 27259125]
10. Chao YS, Lin KF, Wu CJ, Wu HC, Hsu HT, Tsao LC, et al. Simulation study to demonstrate biases created by diagnostic criteria of mental illnesses: major depressive episodes, dysthymia, and manic episodes. BMJ Open 2020 Nov 10;10(11):e037022 [FREE Full text] [doi: 10.1136/bmjopen-2020-037022] [Medline: 33172939]
11. Zhao S, Bao Z, Zhao X, Xu M, Li MD, Yang Z. Identification of diagnostic markers for major depressive disorder using machine learning methods. Front Neurosci 2021 Jun 18;15:645998 [FREE Full text] [doi: 10.3389/fnins.2021.645998] [Medline: 34220416]
12. Braun PR, Han S, Hing B, Nagahama Y, Gaul LN, Heinzman JT, et al. Genome-wide DNA methylation comparison between live human brain and peripheral tissues within individuals. Transl Psychiatry 2019 Jan 31;9(1):47 [FREE Full text] [doi: 10.1038/s41398-019-0376-y] [Medline: 30705257]
13. Ferguson LB, Roberts AJ, Mayfield RD, Messing RO. Blood and brain gene expression signatures of chronic intermittent ethanol consumption in mice. PLoS Comput Biol 2022 Feb 17;18(2):e1009800 [FREE Full text] [doi: 10.1371/journal.pcbi.1009800] [Medline: 35176017]
14. Nishitani S, Isozaki M, Yao A, Higashino Y, Yamauchi T, Kidoguchi M, et al. Cross-tissue correlations of genome-wide DNA methylation in Japanese live human brain and blood, saliva, and buccal epithelial tissues. Transl Psychiatry 2023 Feb 27;13(1):72 [FREE Full text] [doi: 10.1038/s41398-023-02370-0] [Medline: 36843037]
15. Arloth J, Eraslan G, Andlauer TF, Martins J, Iurato S, Kühnel B, et al. DeepWAS: multivariate genotype-phenotype associations by directly integrating regulatory information using deep learning. PLoS Comput Biol 2020 Feb 3;16(2):e1007616 [FREE Full text] [doi: 10.1371/journal.pcbi.1007616] [Medline: 32012148]
16. Lin E, Kuo PH, Lin WY, Liu YL, Yang AC, Tsai SJ. Prediction of probable major depressive disorder in the Taiwan biobank: an integrated machine learning and genome-wide analysis approach. J Pers Med 2021 Jun 24;11(7):597 [FREE Full text] [doi: 10.3390/jpm11070597] [Medline: 34202750]
17. Schultebraucks K, Choi KW, Galatzer-Levy IR, Bonanno GA. Discriminating heterogeneous trajectories of resilience and depression after major life stressors using polygenic scores. JAMA Psychiatry 2021 Jul 01;78(7):744-752 [FREE Full text] [doi: 10.1001/jamapsychiatry.2021.0228] [Medline: 33787853]
18. Qi B, Ramamurthy J, Bennani I, Trakadis YJ. Machine learning and bioinformatic analysis of brain and blood mRNA profiles in major depressive disorder: a case-control study. Am J Med Genet B Neuropsychiatr Genet 2021 Mar;186(2):101-112. [doi: 10.1002/ajmg.b.32839] [Medline: 33645908]
19. Verma P, Shakya M. Machine learning model for predicting major depressive disorder using RNA-Seq data: optimization of classification approach. Cogn Neurodyn 2022 Apr 22;16(2):443-453 [FREE Full text] [doi: 10.1007/s11571-021-09724-8] [Medline: 35401859]
20. Yao Q, Chen Y, Zhou X. The roles of microRNAs in epigenetic regulation. Curr Opin Chem Biol 2019 Aug;51:11-17. [doi: 10.1016/j.cbpa.2019.01.024] [Medline: 30825741]
21. Chen D, Meng L, Pei F, Zheng Y, Leng J. A review of DNA methylation in depression. J Clin Neurosci 2017 Sep;43:39-46. [doi: 10.1016/j.jocn.2017.05.022] [Medline: 28645747]
22. Limbana T, Khan F, Eskander N. Gut microbiome and depression: how microbes affect the way we think. Cureus 2020 Aug 23;12(8):e9966 [FREE Full text] [doi: 10.7759/cureus.9966] [Medline: 32983670]
23. Martinez JE, Kahana DD, Ghuman S, Wilson HP, Wilson J, Kim SC, et al. Unhealthy lifestyle and gut dysbiosis: a better understanding of the effects of poor diet and nicotine on the intestinal microbiome. Front Endocrinol (Lausanne) 2021;12:667066 [FREE Full text] [doi: 10.3389/fendo.2021.667066] [Medline: 34168615]
24. Stevens BR, Roesch L, Thiago P, Russell JT, Pepine CJ, Holbert RC, et al. Depression phenotype identified by using single nucleotide exact amplicon sequence variants of the human gut microbiome. Mol Psychiatry 2021 Aug 27;26(8):4277-4287. [doi: 10.1038/s41380-020-0652-5] [Medline: 31988436]
25. Radjabzadeh D, Bosch JA, Uitterlinden AG, Zwinderman AH, Ikram MA, van Meurs JBJ, et al. Gut microbiome-wide association study of depressive symptoms. Nat Commun 2022 Dec 06;13(1):7128 [FREE Full text] [doi: 10.1038/s41467-022-34502-3] [Medline: 36473852]
26. Sekaran K, Sudha M. Prediction of lipopolysaccharides simulation responsiveness on gene expression profiles of major depression disorder affected cases using machine learning. Int J Sci Technol Res 2019;8(11):21-24 [FREE Full text]
27. Fan R, Hua T, Shen T, Jiao Z, Yue Q, Chen B, et al. Identifying patients with major depressive disorder based on tryptophan hydroxylase-2 methylation using machine learning algorithms. Psychiatry Res 2021 Dec;306:114258. [doi: 10.1016/j.psychres.2021.114258] [Medline: 34749226]
28. Musolf AM, Holzinger ER, Malley JD, Bailey-Wilson JE. What makes a good prediction? Feature importance and beginning to open the black box of machine learning in genetics. Hum Genet 2022 Sep 04;141(9):1515-1528 [FREE Full text] [doi: 10.1007/s00439-021-02402-z] [Medline: 34862561]

29. Shatte AB, Hutchinson DM, Teague SJ. Machine learning in mental health: a scoping review of methods and applications. Psychol Med 2019 Jul;49(9):1426-1448. [doi: 10.1017/S0033291719000151] [Medline: 30744717]
30. Ciobanu LG, Sachdev PS, Trollor JN, Reppermund S, Thalamuthu A, Mather KA, et al. Downregulated transferrin receptor in the blood predicts recurrent MDD in the elderly cohort: a fuzzy forests approach. J Affect Disord 2020 Apr 15;267:42-48. [doi: 10.1016/j.jad.2020.02.001] [Medline: 32063571]
31. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Ann Intern Med 2018 Oct 02;169(7):467-473 [FREE Full text] [doi: 10.7326/M18-0850] [Medline: 30178033]
32. Koch L, Potenski C, Trenkmann M. Sequencing moves to the twenty-first century. Nature. 2021. URL: https://www.nature.com/articles/d42859-020-00100-w [accessed 2024-04-29]
33. Checklist for analytical cross sectional studies. The Joanna Briggs Institute. 2020. URL: http://joannabriggs.org/research/critical-appraisal-tools.html [accessed 2022-07-20]
34. Wang X, Cheng Z. Cross-sectional studies: strengths, weaknesses, and recommendations. Chest 2020 Jul;158(1S):S65-S71. [doi: 10.1016/j.chest.2020.03.012] [Medline: 32658654]
35. Arabnejad M, Dawkins BA, Bush WS, White BC, Harkness AR, McKinney BA. Transition-transversion encoding and genetic relationship metric in ReliefF feature selection improves pathway enrichment in GWAS. BioData Min 2018 Nov 3;11(1):23 [FREE Full text] [doi: 10.1186/s13040-018-0186-4] [Medline: 30410580]
36. Takahashi Y, Ueki M, Tamiya G, Ogishima S, Kinoshita K, Hozawa A, et al. Machine learning for effectively avoiding overfitting is a crucial strategy for the genetic prediction of polygenic psychiatric phenotypes. Transl Psychiatry 2020 Aug 17;10(1):294 [FREE Full text] [doi: 10.1038/s41398-020-00957-5] [Medline: 32826857]
37. Le TT, Fu W, Moore JH. Scaling tree-based automated machine learning to biomedical big data with a feature set selector. Bioinformatics 2020 Jan 01;36(1):250-256 [FREE Full text] [doi: 10.1093/bioinformatics/btz470] [Medline: 31165141]
38. Parvandeh S, Yeh HW, Paulus MP, McKinney BA. Consensus features nested cross-validation. Bioinformatics 2020 May 01;36(10):3093-3098 [FREE Full text] [doi: 10.1093/bioinformatics/btaa046] [Medline: 31985777]
39. Payne JL, Osborne LM, Cox O, Kelly J, Meilman S, Jones I, et al. DNA methylation biomarkers prospectively predict both antenatal and postpartum depression. Psychiatry Res 2020 Mar;285:112711 [FREE Full text] [doi: 10.1016/j.psychres.2019.112711] [Medline: 31843207]
40. Aberg KA, Dean B, Shabalin AA, Chan RF, Han LK, Zhao M, et al. Methylome-wide association findings for major depressive disorder overlap in blood and brain and replicate in independent brain samples. Mol Psychiatry 2020 Jun 21;25(6):1344-1354 [FREE Full text] [doi: 10.1038/s41380-018-0247-6] [Medline: 30242228]
41. Breitfeld J, Scholl C, Steffens M, Laje G, Stingl JC. Gene expression and proliferation biomarkers for antidepressant treatment resistance. Transl Psychiatry 2017 Mar 14;7(3):e1061 [FREE Full text] [doi: 10.1038/tp.2017.16] [Medline: 28291260]
42. Rjoob K, Bond R, Finlay D, McGilligan V, Leslie SJ, Rababah A, et al. Machine learning and the electrocardiogram over two decades: time series and meta-analysis of the algorithms, evaluation metrics and applications. Artif Intell Med 2022 Oct;132:102381. [doi: 10.1016/j.artmed.2022.102381] [Medline: 36207087]
43. da Silva Elias AD, Tavares CM, Muniz MP. The intersection between being a nurse and being a therapist in mental health. Rev Bras Enferm 2020;73(1):e20180134 [FREE Full text] [doi: 10.1590/0034-7167-2018-0134] [Medline: 32049227]
44. de Almeida JC, Barbosa CA, de Almeida LY, de Oliveira JL, de Souza J. Mental health actions and nurse's work. Rev Bras Enferm 2020;73 Suppl 1(suppl 1):e20190376 [FREE Full text] [doi: 10.1590/0034-7167-2019-0376] [Medline: 32667475]

Abbreviations

AUC: area under the curve
CpG: cytosine-phosphodiester bond-guanine
DeepWAS: functional unit–wide association study
DEG: differentially expressed gene
DGM: depression gene module
DMS: differentially methylated site
DNAm: DNA methylation
dSNP: single nucleotide polymorphisms associated with a disease
FU: functional unit
GWAS: genome-wide association study
mRNA: messenger RNA
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
SNP: single nucleotide polymorphism
TPOT: tree-based pipeline optimization tool

XGBoost: extreme gradient boost

Edited by E Borycki; submitted 22.11.23; peer-reviewed by Y Pan, J Chen; comments to author 23.02.24; revised version received 16.04.24; accepted 22.04.24; published 19.07.24.

Please cite as:
Taylor B, Hobensack M, Niño de Rivera S, Zhao Y, Masterson Creber R, Cato K
Identifying Depression Through Machine Learning Analysis of Omics Data: Scoping Review
JMIR Nursing 2024;7:e54810
URL: https://nursing.jmir.org/2024/1/e54810
doi:10.2196/54810
PMID:39028994

Original Paper

AI-Assisted Decision-Making in Long-Term Care: Qualitative Study on Prerequisites for Responsible Innovation

Dirk R M Lukkien[1,2], MSc; Nathalie E Stolwijk[1], MSc; Sima Ipakchian Askari[1,3], PhD; Bob M Hofstede[1,3], MSc; Henk Herman Nap[1,3], PhD; Wouter P C Boon[2], Prof Dr; Alexander Peine[4], Prof Dr; Ellen H M Moors[2], Prof Dr; Mirella M N Minkman[1,5], Prof Dr

[1]Vilans Centre of Expertise of Long Term Care, Utrecht, Netherlands
[2]Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, Netherlands
[3]Human Technology Interaction, Eindhoven University of Technology, Eindhoven, Netherlands
[4]Faculty of Humanities, Open University of The Netherlands, Heerlen, Netherlands
[5]TIAS School for Business and Society, Tilburg University, Tilburg, Netherlands

Corresponding Author:
Dirk R M Lukkien, MSc
Vilans Centre of Expertise of Long Term Care
Churchilllaan 11
Utrecht, 3505 RE
Netherlands
Phone: 31 612416513
Email: d.lukkien@vilans.nl

Abstract

Background: Although the use of artificial intelligence (AI)–based technologies, such as AI-based decision support systems (AI-DSSs), can help sustain and improve the quality and efficiency of care, their deployment creates ethical and social challenges. In recent years, a growing prevalence of high-level guidelines and frameworks for responsible AI innovation has been observed. However, few studies have specified the responsible embedding of AI-based technologies, such as AI-DSSs, in specific contexts, such as the nursing process in long-term care (LTC) for older adults.

Objective: Prerequisites for responsible AI-assisted decision-making in nursing practice were explored from the perspectives of nurses and other professional stakeholders in LTC.

Methods: Semistructured interviews were conducted with 24 care professionals in Dutch LTC, including nurses, care coordinators, data specialists, and care centralists. A total of 2 imaginary scenarios about AI-DSSs were developed beforehand and used to enable participants articulate their expectations regarding the opportunities and risks of AI-assisted decision-making. In addition, 6 high-level principles for responsible AI were used as probing themes to evoke further consideration of the risks associated with using AI-DSSs in LTC. Furthermore, the participants were asked to brainstorm possible strategies and actions in the design, implementation, and use of AI-DSSs to address or mitigate these risks. A thematic analysis was performed to identify the opportunities and risks of AI-assisted decision-making in nursing practice and the associated prerequisites for responsible innovation in this area.

Results: The stance of care professionals on the use of AI-DSSs is not a matter of purely positive or negative expectations but rather a nuanced interplay of positive and negative elements that lead to a weighed perception of the prerequisites for responsible AI-assisted decision-making. Both opportunities and risks were identified in relation to the early identification of care needs, guidance in devising care strategies, shared decision-making, and the workload of and work experience of caregivers. To optimally balance the opportunities and risks of AI-assisted decision-making, seven categories of prerequisites for responsible AI-assisted decision-making in nursing practice were identified: (1) regular deliberation on data collection; (2) a balanced proactive nature of AI-DSSs; (3) incremental advancements aligned with trust and experience; (4) customization for all user groups, including clients and caregivers; (5) measures to counteract bias and narrow perspectives; (6) human-centric learning loops; and (7) the routinization of using AI-DSSs.

Conclusions: The opportunities of AI-assisted decision-making in nursing practice could turn into drawbacks depending on the specific shaping of the design and deployment of AI-DSSs. Therefore, we recommend considering the responsible use of AI-DSSs as a balancing act. Moreover, considering the interrelatedness of the identified prerequisites, we call for various actors, including developers and users of AI-DSSs, to cohesively address the different factors important to the responsible embedding of AI-DSSs in practice.

(JMIR Nursing 2024;7:e55962) doi:10.2196/55962

KEYWORDS

decision support systems; ethics; long-term care; responsible innovation; stakeholder perspectives

Introduction

Background

For the long-term care (LTC) of older adults, technologies based on artificial intelligence (AI) are increasingly being developed and deployed to support the nursing process, from the assessment and diagnosis of care needs to the planning, implementation, and evaluation of care strategies addressing these needs [1-8]. For instance, AI-based decision support systems (AI-DSSs) can support specific aspects of the nursing process, such as monitoring the behavior and vital signs of clients with the aim of identifying frailty, assessing dementia-related problems and suitable interventions, and triaging health deterioration before eventually transferring clients to an emergency department or institutional care setting [1,9-13]. Throughout the nursing process, nurses, care coordinators, and other care professionals need to navigate a complex web of diagnostic and therapeutic uncertainties, client preferences and values, and cost considerations [14,15]. Against the backdrop of a growing gap between the number of qualified caregivers and the number of people in need of care, AI-assisted decision-making by caregivers could help sustain and improve the quality and efficiency of care.

AI-based technologies can, for explicit or implicit objectives, infer from the input they receive how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or web-based environments [16-18]. AI-DSSs refer to information systems that acquire relevant data about care needs or processes; present relevant data to users, such as nurses; and possibly translate raw data into actionable information, such as alerts, risk assessments, or recommendations about care strategies [15,19-21]. AI-based technologies such as AI-DSSs combine *preprogrammed, rule-based* algorithms and *data-driven, self-learning* algorithms rooted in machine learning. While initially rule focused, AI-DSSs are increasingly incorporating machine learning. This enables them to extract patterns and new insights from data sets that may be challenging for humans to analyze and improve their performance (eg, recommendations) based on the new data [2,15,21-23]. Therefore, the anticipated progress in AI-DSSs suggests their growing role in *proactively* supporting nurses and other stakeholders in decision-making regarding person-centered care strategies by harnessing relevant data.

Notwithstanding the potential of AI-DSSs and other AI-based technologies to support caregivers and other stakeholders in LTC, their deployment creates ethical and social challenges. The long-term gathering of data on the health and well-being of individuals, along with the pivotal role of algorithms in interpreting these data to arrive at care-related decisions, raises concerns. These concerns encompass the potential erosion of the privacy, autonomy, and self-determination of individuals; depersonalization of the caregiver-client relationship; and discrimination, problematization, and stigmatization of old age [4,21,24-27]. Owing to the impact that the use of AI-based technologies may have on the lives of older adults and the work of caregivers and the potential resistance that might emerge during implementation, implications need to be assessed and addressed at an early stage of their development.

In recent years, a growing prevalence of guidelines and frameworks to provide guidance on responsible AI innovation for diverse stakeholders, such as researchers, legislators, technology developers, and technology users, has been observed. Studies that have compared responsible AI frameworks emphasize a general consensus around high-level principles, such as transparency, justice, fairness, and nonmaleficence [28-30]. However, the current guidelines are generally highly abstract and leave much room for the interpretation of how these principles can be practically applied and contextualized to specific technologies, such as AI-DSSs, and specific settings, such as LTC [30,31]. Although scholars recognize the importance of a more context-specific conceptualization of these principles, multiple literature reviews have shown that only a few studies specify practical approaches to responsible AI innovation for specific application domains, which is particularly true for AI applications in LTC [5,7,32,33].

This Study

This study aimed to fill this knowledge gap by presenting the results of an interview study on prerequisites for responsible AI-assisted decision-making in nursing practice, with a specific focus on the LTC domain. In-depth interviews were conducted with Dutch nurses and professional stakeholders (ie, care coordinators, data specialists, and care centralists) with whom nurses closely collaborate. This holds particular relevance because these stakeholders have firsthand experience and practical insights into the nursing processes where AI-DSSs are anticipated to play an increasing role. Thereby, they can contribute significantly to understanding both the potential impact of AI-DSSs and the factors that need to be addressed for the responsible embedding of these technologies in practice. While various studies have offered conceptual expert analyses and synthesized relevant literature on factors important to the responsible embedding of AI-DSSs in health care (eg, the studies by Heyen and Salloch [22], Hindocha and Badea [34], and Skuban-Eiseler et al [35]), few have investigated (future) user perspectives on responsible AI-assisted decision-making [36]. This study first examined the perspectives of nurses and other professional stakeholders in LTC on the opportunities and risks of AI-assisted decision-making in nursing practice, thereby laying the groundwork for the second and main objective: exploring prerequisites for responsible innovation in this area.

The results can lead to recommendations for responsibly embedding AI-DSSs into nursing practice.

Methods

Overview

Semistructured interviews were conducted to explore the perspectives of nurses and other professional stakeholders in LTC regarding, first, the opportunities and risks of AI-assisted decision-making in nursing practice and, second, associated prerequisites for responsible innovation in this area. This approach enabled the researchers to delve deeply into specific areas of interest while also maintaining an open-ended format that encourages participants to share their perspectives freely. This was crucial to comprehending the rationale behind perceived opportunities and risks and, consequently, thoroughly exploring associated prerequisites for responsible innovation. The interviews were conducted as part of the Healthy Ageing Eco-system for People with Dementia (HAAL) project, which is part of the European Active and Assisted Living program (Active and Assisted Living Europe, 2021; project AAL-2020-7-229-CP). In HAAL, an international consortium consisting of care organizations, research institutes, and commercial firms from the Netherlands, Italy, Taiwan, and Denmark collaborates on the co-design, development, testing, and commercialization of an AI-DSS intended to provide actionable information to formal caregivers of frail older adults, particularly those with dementia, with the aim of reducing the caregiver workload and increasing the quality of care. The consortium acknowledges that innovators must anticipate, reflect on, and respond to the ethical and social implications of increasingly advanced AI-DSSs at an early stage of innovation. Therefore, in parallel with the iterative co-design, development, and field testing of a low-complexity AI-DSS, the empirical research presented in this paper was conducted to explore the prerequisites for responsible innovation in AI-DSSs.

As envisioning the potential impacts of using AI-DSSs can be challenging, we first used scenarios and then used principle-based probing themes as starting points to explore stakeholder perspectives on the potential impact of using AI-DSSs and prime interview participants toward reflecting on both opportunities and risks. A total of 2 distinct imaginary scenarios were developed as inputs for the interviews, outlining different roles of AI within AI-DSSs. The aim of the scenarios was to make abstract concepts such as AI and AI-DSSs more concrete, enabling interview participants to articulate their expectations and considerations regarding the opportunities and risks of AI-assisted decision-making in nursing practice more effectively [37-40]. The AI-DSS in the first scenario incorporates only descriptive analytical functions that examine data to uncover insights into past events or trends. This scenario was inspired by the AI-DSS developed in the HAAL project. The second scenario takes a more speculative and ambitious turn and involves a more advanced AI-DSS with descriptive, predictive, and prescriptive functions. Predictive functions analyze data to forecast future outcomes, and prescriptive functions analyze data to recommend specific actions or strategies to help achieve specific outcomes [41,42]. Thus, in comparison to the first scenario, the second scenario adopts a more proactive approach in supporting decision-making regarding person-centered care strategies.

In addition to the scenarios, specific principle-based probing themes were used to evoke thorough consideration of the risks of using AI-DSSs in LTC, along with possible strategies and actions to address or mitigate these risks in the design, implementation, and use of AI-DSSs. These probing themes were based on the six principles for responsible AI, as proposed by the World Health Organization (WHO) guidance on *Ethics and Governance of Artificial Intelligence for Health* [43]: (1) protecting human autonomy; (2) promoting human well-being and safety and the public interest; (3) ensuring transparency, explainability, and intelligibility; (4) fostering responsibility and accountability; (5) ensuring inclusiveness and equity; and (6) promoting AI that is responsive and sustainable. This particular guidance was selected because it represented one of the latest guidelines issued by an authoritative body in the health care domain. Moreover, it was explicitly designed as a starting point for context-specific discussions involving diverse stakeholders [43].

Participants

In total, 24 participants took part in this study. Recruitment took place through email inquiries to care organizations involved in the HAAL project and other LTC facilities in the Netherlands. The researchers aimed to achieve a varied composition of participants with different roles in the LTC for older adults and varying degrees of experience with technology, data, and AI. The inclusion of diverse professional perspectives offers insights into different facets of care where AI-DSSs might play an increasing role and contributes to a multifaceted understanding of prerequisites for responsible AI-assisted decision-making in nursing practice.

Participants were broadly categorized into 4 groups: nurses (13/24, 54%), care coordinators (6/24, 25%), data specialists (3/24, 12%), and care centralists (2/24, 8%). Nurses had various roles and education levels, ranging from executive district nurses to quality nurses with responsibilities in the care coordination of different clients. The group of care coordinators, including dementia case managers (2/6, 33%), geriatric care coordinators (2/6, 33%), and specialists in geriatric care (2/6, 33%), primarily coordinated and oversaw various aspects of care for frail older adults, including medical, social, and support services. Data specialists play a central role within their care organization in using data and developing tools, such as dashboards, to support decision-making by care teams. Finally, nursing care centralists are positioned within care centers in the Netherlands that respond to alarms (eg, from active and passive alarm instruments) and care-related questions, for instance, by calling in a caregiver on-site when needed.

Of the 24 participants, 16 (67%) held a formal role in advancing digitization within their care organizations. This might imply that these participants had already made or could relatively easily make explicit representations of the opportunities and risks of AI-assisted decision-making in LTC and prerequisites for responsible innovation in this area. More specifically, these participants consisted of 9 (69%) of the 13 participating nurses, 2 (33%) of the 6 participating care coordinators, all 3 (100%) data specialists, and both (2/2, 100%) care centralists. Furthermore, of the 24 participants, 18 (75%) were female, and 6 (25%) were male. The mean age of the participants was 41 (SD 12.8; range 21-61) years, and on average, the participants had 16 (SD 11.4; range 3-40) years of occupational experience in health care.

Procedure and Materials

All interviews were conducted digitally via video calls, with screen sharing used to provide visual support for the interview questions. The interviews were conducted between May 2022 and February 2023, with a mean duration of 79 (range 58-119) minutes. Of the 24 interviews, 17 (71%) were conducted by pairs of researchers, and 7 (29%) were conducted by a single researcher. A multidisciplinary group of researchers (DRML, NES, SIA, HHN, WPCB, and AP) developed the interview protocol. Minor adaptations were made to the protocol after pilot testing with the first 2 participants. The interviews were conducted in Dutch.

The interview protocol (Multimedia Appendix 1) was structured as follows. In the first part of the interviews, a general introduction was given about the AI-DSS developed in the HAAL project. This concerns a dashboard that acquires, presents, and uses data generated by various digital care and well-being technologies that can be deployed in the homes of older adults. When used, these technologies collect data on the physical activity, eating and sleeping patterns, cognitive functioning, mood, social contact, and medication intake of older adults. All technologies were explained and shown to participants using a visual illustration, and questions were asked about the perceived relevance of and the familiarity of participants with the various technologies and data.

In the second part, participants were invited to reflect on the opportunities of AI-assisted decision-making in LTC. A description and visual illustration were provided, and questions related to the 2 developed imaginary scenarios were asked. The first scenario describes a dashboard with descriptive analytical functions only. The dashboard provides an overview of the data collected over time via a tailored selection of digital care and well-being technologies. In the dashboard, specific collected data are marked by a color (red, orange, or green) to signify varying levels of risk or urgency associated with them. Apart from the application of this coloring scheme, the data are not interpreted by algorithms. The primary goal of this dashboard is to make the data generated by various technologies available to caregivers in one place to prevent them from looking at separate overviews and apps.

The second scenario describes a more advanced dashboard with descriptive, predictive, and prescriptive functions. In this scenario, the data generated by the selected care technologies are not only integrated into one system and color marked to signify risk levels but also automatically processed into actionable insights by algorithms. Actionable insights could entail predictions of the risk for future emergency situations, such as a fall, and recommendations about possible follow-up actions, such as stimulating the physical activity of a client if the data indicate a relatively inactive period.

Both scenarios left room for the interview participants to indicate whether, and for which types of caregivers and other stakeholders in LTC, the respective dashboard might be relevant and why. After questions in this regard, participants were asked which of the 2 dashboards they would prefer and why. In addition, a short explanation was provided about the term *AI*, including everyday examples, after which the participants were asked what role they hope AI will play in the future of LTC.

In the third part, the participants were asked about the risks related to the use of AI-DSSs in LTC, as well as mitigation strategies. Participants were first invited to openly discuss any risks or concerns linked to both scenarios and consider whether they perceived any explicit differences in the risks associated with more advanced AI-DSSs compared to low-complexity AI-DSSs. Subsequently, targeted questions about risks were asked by using the 6 probing themes based on the responsible AI principles from the WHO [43]. After a brief explanation of each principle, participants were asked about their views on the respective principle in the context of AI-assisted decision-making in LTC. During discussions of potential risks, participants were encouraged to brainstorm possible strategies and actions to address or mitigate these risks in the design, use, and implementation of AI-DSSs. Finally, the participants were asked whether they had any other suggestions or topics that they wanted to discuss regarding the implications of using AI-DSSs in LTC.

Ethical Considerations

Before the interviews, general information about the goal and procedure was provided, and the participants were asked to read and sign an informed consent form. The authors of this study followed the guidelines in the Declaration of Helsinki and the Dutch code of conduct for scientific integrity. Ethical approval for the interviews, not subject to the medical scientific research act involving human subjects, was granted by an independent board of the lead author's department (Vilans), including a privacy officer and legal expert [44]. The recorded interviews were transcribed verbatim using a professional transcription service. The transcripts were thereafter coded for confidentiality, and identifying information was removed.

Analyses

A thematic analysis was independently performed by 4 researchers using the MAXQDA 2022 (VERBI GmbH) analysis software. One researcher (DRML) analyzed all 24 transcripts, and 3 researchers (NES, SIA, and BMH) analyzed 8 transcripts each. While distributing tasks, the goal was to give each researcher the broadest possible view of the data set. Therefore, NES and SIA, who were involved in conducting some of the interviews, analyzed transcripts of interviews in which they had not been involved themselves. The transcripts were analyzed through a stepwise construction of codes. On the basis of our research objective, three initial main codes were established: (1) opportunities for AI-assisted decision-making in nursing practice, which were represented by potential supportive roles of AI-DSSs in this context; (2) risks of AI-assisted decision-making, which provide indications of factors that need to be addressed for the responsible embedding of AI-DSSs in practice; and (3) associated prerequisites for responsible

AI-assisted decision-making, which were represented by strategies to mitigate specific risks in the design, implementation, and use of AI-DSSs. Our in-depth analysis of the transcripts followed the 6 steps outlined by Braun and Clarke [45] and comprised a largely inductive thematic analysis to identify, analyze, and report repeated patterns across the interview transcripts [46]. The WHO principles provided a predefined theoretical framework that informed our thematic analysis, yet, apart from the 3 initial main codes, the development of codes and subcodes was largely inductive and reflective for the pertinent issues raised by the data. During the coding process and after initial coding, all 4 researchers engaged in 3 consultation sessions to exchange and cross-validate interpretations and coding decisions among themselves, thereby fostering intercoder reliability. Some of the results were presented through illustrative quotes, which were translated from Dutch to English and carefully selected to represent the arguments presented in the interviews and justify the various perspectives shown in the interviews. During the selection process, we considered whether the quotes could be understood without the context in which they were originally uttered.

Results

Overview

This section presents the perspectives of participants on prerequisites for responsible AI-assisted decision-making in nursing practice. First, we thoroughly discuss the anticipated opportunities and risks of AI-assisted decision-making in nursing practice, as these established a foundation for the participants in exploring prerequisites for responsible innovation in this area. Thereafter, we discuss the associated prerequisites for responsible AI-assisted decision-making in nursing practice that were inductively identified.

Opportunities and Risks of AI-Assisted Decision-Making in Nursing Practice

Overview

On the basis of their substantial experience and domain knowledge of LTC, all participants were able to make explicit representations of potential supportive roles of AI-DSSs in the nursing process. Most participants also discussed a diverse array of risks of using AI-DSSs in nursing practice, even though multiple participants shared that they lacked experience in contemplating the risks and disadvantages of using AI-DSSs and AI more broadly. Comments about risks were frequently raised spontaneously when participants were prompted to reflect on the 2 imaginary scenarios outlining different types of AI-DSSs. However, in most cases, these comments were shared as a response to either open or targeted (principle-based) interview questions about risks. Through our thematic analysis, involving open coding, it became evident that the identified opportunities and risks of AI-assisted decision-making in nursing practice coexist as complementary yet contradictory elements within 4 (interrelated) thematic domains: the early identification of care needs, guidance in devising care strategies, shared decision-making, and the workload and work experience of caregivers. For each of the domains, we discuss the opportunities and risks in the subsequent subsections.

Early Identification of Care Needs

Most participants anticipated that AI-DSSs could support caregivers in the remote and early anticipation of care needs, thereby enabling them to proactively initiate appropriate interventions. As multiple participants discussed, various existing care technologies enable caregivers to monitor the health, well-being, and behavior of clients remotely. The data generated by such technologies can provide insights into the changing care needs of specific clients. Such data could not only be remotely accessed and evaluated by caregivers but might also be automatically processed through AI into actionable insights, such as signals and alarms for caregivers about increased risks. Given that an increasing amount of data is being collected through various care technologies, multiple participants explicitly expressed optimism that AI could enable and optimize the use of these increasing amounts of data, thereby enhancing the already implemented and more stand-alone forms of remote monitoring. Furthermore, some participants perceived that insights gained through continuous technology-based monitoring might contribute to more adequate and complete information about care needs because, for instance, clients may not always (be able to) share all relevant information, the observations of caregivers when visiting clients generally provide only a limited view of the entire situation, and caregivers might inconsistently report on the same situation. One of the nurses shared the following:

> *If you think there is a specific care need but you are not sure what is actually happening in the client's room or house, we now often still ask about the nurse's gut feeling, which is often correct, of course, but now [with an AI-DSS] we can check with data what is really the case.* [Participant 14]

In this line, some participants suggested that AI-DSSs could assist caregivers in targeted risk assessments or attempts to gain insights into specific unexplained behavior of clients. Furthermore, some participants anticipated that AI, with its ability to discern subtle patterns from data, could swiftly uncover emerging trends or potentially overlooked areas of attention regarding the health, well-being, or behavior of a client.

Notwithstanding these opportunities, participants shared multiple concerns regarding the identification of care needs based on personal data. For instance, multiple participants stated that a false sense of security may be created when caregivers heavily rely on or excessively trust the outputs of AI-DSSs, assuming that these outputs encompass all relevant patterns regarding the health, well-being, and care needs of clients. In addition, some participants stated that numerous issues or concerns related to older adult data could be flagged as potentially problematic. As suggested, this might result in caregivers adopting care interventions, possibly under pressure from other stakeholders, such as the families of clients. However, these interventions may be perceived as unnecessary or even undesirable by stakeholders such as the clients themselves. Therefore, the use of AI-DSSs might lead to the over-problematization of old age and stigmatizing stereotypes, impacting both the quality of life of older adults and the workload of caregivers. One of the care coordinators stated the following:

> *The system may ignore the norms and values of a particular client...Sometimes things that may seem very problematic may actually not be that problematic to a client.* [Participant 22]

In addition, multiple participants commented that potential misuse of or unauthorized access to personal data could jeopardize the individual privacy of older adults; their ability to make their own decisions (ie, autonomy); and, consequently, their trust in their care network. Moreover, some participants suggested that the potential opacity of AI algorithms may complicate the understanding of both clients and caregivers of certain outcomes of AI-DSSs and care-related decisions made with the assistance of AI-DSSs. As suggested, this may diminish their trust and confidence in the collection and use of personal data. Furthermore, some participants commented that shifts toward data- and AI-assisted remote care might not be widely accepted. According to 2 participants, this raises questions regarding the extent to which enforcing these changes on clients or caregivers who are hesitant or unwilling to adopt these new approaches can be justified. One of the nurses expressed this as follows:

> *It [using AI-DSSs] becomes part of the foundation of your profession...It becomes an important part of determining your actions. But if someone does not want that, then you suddenly need your old-fashioned skills again, which requires a different way of caregiving that may no longer fit in with regular work processes or the zeitgeist...And then it could also be that the health insurer says: "We will no longer pay for that, because there is a better alternative."* [Participant 20]

Guidance on Devising Care Strategies

Multiple participants anticipated that by pointing caregivers to possible care needs and providing inspiration or substantiation for suitable care strategies, AI-DSSs might increasingly guide or direct caregivers in decision-making regarding person-centered care strategies. As some participants commented, AI-DSSs might thereby act as a type of personal coach, mentor, or advisor with 3 apparent, related functions. First, multiple participants suggested that AI-DSSs may offer inspiration or evidence for tailored person-centered interventions aimed at improving the health and well-being of a client, thereby helping caregivers devise care strategies to address specific issues. Second, multiple participants envisioned that AI-DSSs could facilitate the substantiation and validation of the initial ideas of caregivers about care strategies by using objective data to reinforce why these strategies should be implemented or explored further. Third, some participants anticipated that AI-DSSs might increasingly support caregivers in evaluating whether certain person-centered interventions were, in retrospect, suitable and whether adjustments should be made. Thus, the AI-DSSs were anticipated to enable iterative data-informed deliberation on person-centered care strategies. Some participants suggested that AI-DSSs may be particularly useful for relatively inexperienced caregivers who may overlook certain matters or possible care strategies owing to a lack of experience or for temporary substitute workers who are less familiar with the behavior, daily rhythm, and personal needs or preferences of a client. Others stated that more experienced caregivers may also find value in such AI assistance because of their potentially deeply rooted approaches to understanding care needs and implementing care strategies that could be challenged by the output of AI-DSSs.

Despite these potential benefits, most participants also shared concerns that guidance by AI-DSSs in devising care strategies could lead to the overreliance of caregivers on these systems. Multiple participants stated that heavy reliance on AI-DSSs by caregivers may gradually diminish their capacity for independent decision-making and critical thinking about person-centered care. One of the nurses said the following:

> *What I find a bit scary when a system is many times more intelligent than you, is that it does not always necessarily make you smarter...The more you are facilitated with knowledge and interpretations and so on, the less you have to think for yourself.* [Participant 21]

In addition, some participants suggested that caregivers who rely heavily on AI-DSSs may insufficiently consider broader contextual factors or crucial nuances in the characteristics and needs of individual clients. One of the nurses explained this as follows:

> *For instance, a male client who is very autistic may often retreat to his room and feel good about that. I can imagine that the system would then say: "This client rarely leaves his room, there is a risk of loneliness." Then you may think that is a good conclusion, while it is actually good for this man that he often withdraws himself. Otherwise, he would be seriously overstimulated.* [Participant 11]

As some participants expressed, heavy reliance on AI-DSSs might result in misguidance toward unsuitable care strategies and negative impacts on the overall quality of care owing to the reduced adaptability of caregivers and the care system as a whole to unforeseen circumstances or erroneous or suboptimal recommendations by AI-DSSs.

Shared Decision-Making

Several participants anticipated that AI-DSSs would support shared decision-making by older adults and their formal and informal caregivers. Multiple participants mentioned that AI-DSSs could support caregivers in conversations with clients and their care network, including informal and other formal caregivers, by helping clarify care needs, identify unaddressed care needs, and reveal and substantiate necessary adjustments in the care plan. Similar to the broader spectrum of data and technology, AI-DSSs are perceived as potential conversational tools, fostering a more collective approach to decision-making in nursing practice. A few participants also mentioned that the use of AI-DSSs could support the shared responsibility of different caregivers in providing good care. One of the nurses suggested the following:

> *A psychological side effect of sharing information amongst all care professionals is that care coordinators no longer feel solely responsible for difficult decisions such as scaling down care. It is increasingly becoming a shared responsibility. By sharing information and anchoring it in the process, there is much more support for difficult measures.* [Participant 3]

Simultaneously, it emerges from the comments of some participants that, instead of using data and AI-DSSs outcomes as input for shared decision-making, people might also intentionally or unintentionally use these outcomes against one another. As some participants expressed, in contexts where AI-DSSs collect, store, and use sensitive personal data, multiple interests could be intertwined and conflicting, such as the interest of a client in protecting their dignity and personal boundaries, the interest of professional caregivers in anticipating and understanding care needs, the interest of informal caregivers in monitoring (the quality of) formal care provided, and the interest of health insurers in exercising control over the care provided. Ultimately, conflicts of interest can result in mistrust.

Workload and Work Experience

Most participants suggested that the use of AI-DSSs might alleviate the cognitive load of caregivers and improve their work experience. Most participants envisioned that AI-DSSs could relieve caregivers of or even enable the processing of large amounts of pertinent data gathered in the care context. Some participants perceived it to be increasingly unrealistic to expect caregivers to invest time in tasks involving the analysis of substantial amounts of data, considering the high workload, the increasing amount of data gathered in the care context, and the lack of analytical skills to interpret these data. Accordingly, multiple participants suggested that AI-DSSs could relieve the workload of caregivers by automating routine tasks such as monitoring the daily rhythm or medication intake of the clients. In addition, some participants stated that by AI-DSSs taking on data-intensive and repetitive tasks, caregivers might experience a substantial decrease in mental strain and a more sustainable work environment. Furthermore, a few participants mentioned that a decrease in cognitive load resulting from the use of AI-DSSs might allow caregivers to dedicate more time and attention to empathetic aspects of caregiving and nuanced decision-making about person-centered care, rooted in thorough research into the specific care needs of clients.

In contrast, multiple participants suggested that the use of AI-DSSs might lead to an increased workload and deteriorate the work experience of caregivers. Some participants anticipated that caregivers using AI-DSSs might be unable to comprehend (some of) the outcomes of the systems or feel overwhelmed by the number of AI-generated insights, alarms, and recommendations for follow-up. Some participants also stated that caregivers might feel pressured to follow-up on the outcomes of the AI-DSSs. One of the nurses commented on this as follows:

> *I see the risk that if you as a care professional decide to ignore a system, like "I'll let this one go" or "I don't recognize this [problem] at all," then it could become a difficult story...To what extent will you, as a care professional, still have the right to say: "I will not do this," or "I see it differently?"* [Participant 20]

Furthermore, multiple participants mentioned that the heavy reliance of caregivers on AI-DSSs might diminish their active role and autonomy in investigating care needs and devising person-centered care strategies. Consequently, as some participants suggested, job satisfaction and the sense of professional fulfillment or purpose that caregivers could derive from person-centered and empathetic aspects of caregiving might be reduced.

Prerequisites for Responsible AI-Assisted Decision-Making in Nursing Practice

Overview

Building upon the anticipated opportunities and risks of AI-assisted decision-making, participants discussed a broad array of factors that should be considered to responsibly embed AI-DSSs in nursing practice and optimally balance opportunities and risks. These factors can be roughly divided into 7 interrelated categories of prerequisites for responsible AI-assisted decision-making in nursing practice.

Regular Deliberation on Data Collection

Stakeholders in data practices, including clients, should regularly deliberate on the data required as inputs for AI-DSSs. Despite the potential of AI-DSSs to provide better insights as they acquire more (eg, more diverse or more long-term) data, most participants stressed that only essential data should be acquired to, for instance, limit privacy infringements, counteract the over-problematization of old age, and prevent the cognitive overload of caregivers. One of the nurses stressed this as follows:

> *What I personally find troubling is that we want to keep an eye on people all day long...I would rather like us to look more closely at specific points about which we say: we might want some extra attention on that. So, for example you might want to know more about—I'll name it—the medication moment around ten o'clock. What happens around that moment that makes that the client may or may not do something with it? Or a fall incident, what happens before that makes the person fall every time?* [Participant 21]

Along this line, multiple participants advocated that the collection of data should always relate to specific objectives (ie, care needs or life goals) agreed upon by clients and caregivers. Some participants also proposed regular deliberation by stakeholders, including clients, on the necessity and implications of specific data collection, as care needs, the personal values of stakeholders, and technological possibilities change over time.

A Balanced Proactive Nature of AI-DSSs

AI-DSSs should have a balanced proactive nature, implying that they should proactively support the nursing process while avoiding decision automation. On the one hand, multiple participants stressed that AI-DSSs should ease data-intensive analytical tasks by processing data into actionable insights that encourage caregivers to implement certain care strategies or delve deeper into identified concerns. Some participants proposed that it is crucial to avoid overwhelming caregivers with excessive insights that, from a practical perspective (eg, owing to limited time and resources), cannot be acted upon or are not necessarily problematic.

On the other hand, there was a broad consensus among participants that human agency in decision-making should not be overshadowed and that ample space should be created for caregivers to devise person-centered care strategies by themselves. Multiple participants suggested that the need for users to think critically for themselves should be explicitly communicated to users during implementation. Some participants proposed that users could also be informed about this via the user interface of AI-DSSs. Furthermore, multiple participants noted that it could be meaningful if AI-DSSs point caregivers to specific areas of concern but that caregivers should largely retain and take the responsibility to develop person-centered approaches to address specific issues. One of the nurses stated the following:

> *If you see that a client has been less mobile the entire week, I think you should look at it like: "okay, what have we observed ourselves in recent weeks?"...And what actions you take in response, I think, always depends on the client...Let caregivers think for themselves about the interventions that are appropriate, because of course you do not always have to implement the same interventions in a certain situation.* [Participant 7]

Incremental Advancements Aligned With Trust and Experience

Advancements in AI-DSSs should involve incremental steps that align with users' and other stakeholders' evolving trust in, and experience with, these systems. Despite the perceived need for proactive AI-DSSs that can transform potentially unmanageable data sets into actionable insights, multiple participants stressed that their operation and use should provisionally not entail excessive complexity or opacity. Caregivers, clients, and other stakeholders should gradually build trust as AI-DSSs prove their value during use. Multiple participants envisioned that, as trust in and experience with AI-DSSs deepens, gradual advancements in these systems could be implemented. For instance, it may be useful to introduce more advanced predictive and prescriptive analytical functionalities provided that users can interact with the system without diminishing their autonomy and critical thinking abilities. In addition, some participants posited that before broader deployment, significant adjustments to algorithms and the underlying logic within AI-DSSs may first need to be extensively tested in a secure setting and evaluated by an independent body. One of the data specialists stated the following:

> *I think we need a quality mark to establish that trust and that we as sector must agree that if such a system does not have such a quality mark and it is still under development, we will not use it.* [Participant 12]

Customization for All User Groups

The design and implementation of AI-DSSs should involve customization for all user groups, including clients and caregivers, such that users' interactions with AI-DSSs are tailored to their personal needs. Some participants stated that no one-size-fits-all approach exists for clients when deploying care technologies or collecting data related to their health, well-being, and care needs. Differences between clients regarding their views on what is important in life and what contributes to quality of care (eg, the best possible curative care, safety, freedom, and privacy) may need to translate into variations regarding the choice of care technologies to be deployed, the data collected as input for AI-assisted decision-making (see also prerequisite 1), and who can access the resulting insights. Similarly, multiple participants suggested that some degree of customization should also be applied to caregivers. The interaction of AI-DSSs with caregivers, for instance, the type of insights provided and the extent to which recommendations by the systems have already been concretized, and the training of caregivers to use AI-DSSs optimally may need to be tailored to the specific role, level of education, problem-solving capacities, and ability for critical reflection of the caregivers. One of the care coordinators stated the following:

> *I think it depends on the resolving power of the person viewing it...Non-medical caregivers level two can often care for people very kindly and can help with washing, dressing and providing pills. But you cannot expect that when a client is ill, they will understand what needs to be changed with those medicines. So then maybe there must be a signal [by an AI-DSS] saying "maybe you should discuss with the nurse or doctor what should be done with the medication." But if you make that suggestion to a higher educated nurse, she will say "yes, duh, I know that. That is my profession." It might quickly cause irritation if things go like that.* [Participant 1]

Measures to Counteract Bias and Narrow Perspectives

During the design and practical deployment of AI-DSSs, measures should be taken to counteract bias and narrow perspectives. In respect to the design of AI-DSSs, multiple participants suggested that transparency should be provided regarding the underlying functioning of AI-DSSs to ensure that caregivers can properly understand the generation of AI-based insights and assess the applicability and relevance of these insights in the context of an individual client. Simultaneously, some participants posited that, although a certain level of transparency is essential, it should not entirely hinder the advantages offered by advanced and potentially opaque AI analytics. Multiple participants suggested that transparency about AI-based outcomes could be fostered through explanations via the user interface of AI-DSSs about underlying trends in the data that led to a specific outcome or about the types of data and client characteristics considered to achieve certain outcomes. In addition, multiple participants proposed that the output of AI-DSSs be framed as advice rather than compelling information to prevent users from following AI-based outcomes without critical reflection. In addition, some participants suggested that, in cases where AI-DSSs provide caregivers with recommendations about interventions to address specific care needs, multiple possible strategies could be presented to prevent caregivers from fixating on a specific solution. Furthermore, some participants advocated incorporating contextual information about client characteristics, such as cultural and socioeconomic backgrounds, as well as the observations or interpretations of caregivers. Such information could provide a broader perspective on the relevance of specific AI-generated insights and might be crucial for caregivers to develop a nuanced understanding of the situation and care needs of a client. Moreover, multiple participants suggested that it might be relevant if AI-DSSs not only provide insight into areas of attention in the health and care of clients but also highlight positive trends that indicate, for instance, that a certain care intervention has been successful.

In respect to the practical deployment of AI-DSSs, most participants stressed that caregivers require training on the responsible use of these systems. For instance, multiple participants proposed training to critically evaluate the relevance of AI-generated insights and resist a potential tendency to accept supposedly “evidence-based” outputs from AI-DSSs as the truth. In addition, some participants stressed that training should counteract the possibility that caregivers overconcentrate on specific facets of health and well-being or particular care interventions to which AI-DSSs have guided their attention. One of the nurses stated the following:

> *I think it is important to indicate very clearly in the training, for example, that options are presented for what you can do, but that you are supposed to think for yourself about what fits. Are you going to adjust the action slightly, are you going to take a completely different action, or aren’t you going to anything at all?* [Participant 17]

Human-Centric Learning Loops

AI-assisted decision-making should involve human-centric learning loops, meaning that caregivers should be involved in both the design of AI-DSSs and their implementation and use in practice. One suggested aspect of such involvement is that caregivers could assist designers in determining and iteratively improving the underlying logics of AI-DSSs during both the initial design and practical use of these systems. Multiple participants advocated that caregivers with domain-specific knowledge and an affinity to technology assist designers, who may lack such contextual knowledge, in drawing up and testing assumptions regarding the conversion of specific data into meaningful insights to support nursing practice. In addition, a few participants suggested that caregivers could be involved in labeling or annotating data in the training data sets for AI-DSSs. Furthermore, some participants proposed that caregivers could reinforce the learning process of AI by assisting designers in ensuring that adaptive AI-DSSs adequately refine their outputs based on new data and user feedback. Similarly, multiple participants mentioned that caregivers who actually use AI-DSSs in practice should have the option to review AI-generated outcomes and provide feedback that reinforces their learning capabilities. For instance, some participants suggested enabling caregivers to set the specific threshold values from which a certain alarm should be generated for specific clients, indicate how they followed up on specific AI-generated insights and why, and manually enter relevant matters overlooked by the system. A nurse stated the following:

> *It may be good to have the possibility to also add information as a professional, important data that may affect the client and care...If someone does absolutely not want physiotherapy, but that is recommended by the system every time, then you want to be able to indicate somewhere that this is no longer an option, so that the system can take that into account, and look for a second best option.* [Participant 6]

Another suggested aspect of human-centric learning loops is that caregivers can support each other in the use of AI-based insights in practice. Several participants commented that caregivers who are progressive with and at the forefront of using AI-DSSs could be assigned the responsibility of facilitating the use of AI-DSSs by other caregivers who may lack experience, be hesitant to use AI-DSSs, or not know how to handle certain outcomes. Similarly, some participants suggested that, in the context of AI-assisted decision-making, it might be relevant or necessary to involve interdisciplinary care professionals who act as intermediaries between care and technology. As suggested, these professionals could assist less data-savvy caregivers in interpreting data and AI-based outputs to formulate care strategies.

Routinization of Using AI-DSSs

Finally, the use of AI-DSSs should become routine, promoting a commitment to naturally consider AI-based insights when making decisions. Several participants posited that caregivers are responsible for critically examining what care is needed and appropriate in the context of an individual client and for using all available inputs, including insights generated by AI-DSSs. This might imply that consulting AI-DSSs might become the norm over time as more evidence becomes available about the added value of these systems for the quality and efficiency of care and trust increases. Multiple participants mentioned that AI-DSSs should be adequately integrated into the broader work processes of caregivers to optimally use AI-based insights. A data specialist put this as follows:

> *I think you should arrange implementations of algorithms in such a way that caregivers cannot work around them. You have to make the process foolproof. For example, as we have done here...We have arranged that every client with a positive outcome on the algorithm must be discussed by the coordinating practitioner and the manager. Then caregivers are still the ones who decide about what happens and the manager is the one who asks questions.* [Participant 23]

In addition, the participants mentioned multiple factors that are important for the routinization of AI-DSSs. For instance, several participants mentioned that caregivers should have the freedom to deviate from or disregard the outcomes of AI-DSSs, provided that they do so thoughtfully. Accordingly, some participants suggested that it might be essential for caregivers to comprehensively report their decisions and actions in the care process. It was also suggested that care protocols and agreements within care organizations, or the care sector more broadly, regarding the authority and decision-making power of caregivers should be regularly evaluated.

Discussion

Principal Findings

This study aimed to gain insights into the perspectives of nurses and other professional stakeholders in LTC on prerequisites for responsible AI-assisted decision-making in nursing practice. By first examining stakeholders' perspectives on the opportunities and risks of AI-assisted decision-making, the groundwork was established for exploring their perspectives on prerequisites for responsible innovation in this area. As our results demonstrate, the stances of LTC professionals toward the use of increasingly advanced AI-DSSs are not a matter of purely positive or negative expectations but rather a nuanced interplay of positive and negative elements that lead to a weighed perception of prerequisites for responsible AI-assisted decision-making in nursing practice. Our findings provide insights into potential supportive roles of AI-DSSs in nursing practice. For instance, AI-DSSs can elevate the remote and early anticipation of care needs by harnessing data from various sources (eg, care technologies) and swiftly uncovering overlooked issues or emerging trends related to the health, well-being, or behavior of a client. In addition, AI-DSSs are expected to foster adaptive, data-informed decision-making about person-centered care strategies as well as shared decision-making by clients and their formal and informal caregivers. Furthermore, the use of AI-DSSs is expected to alleviate the cognitive load of caregivers and improve their work experience by saving time that would otherwise be spent on repetitive, intricate, and burdensome analytical and monitoring tasks. AI-DSSs are not regarded as potential decision makers in the nursing process but rather as instruments, and by some even as anthropomorphized agents, such as personal coaches or mentors, that could proactively aid caregivers in becoming aware of certain care needs and adaptively responding to these needs. While these perspectives do not necessarily cover the entire spectrum of opportunities of AI-assisted decision-making, they correspond with previous studies on the expectations, opportunities, and applications of AI in LTC (eg, the studies by Mukaetova-Ladinska et al [2], Seibert et al [7], Buchanan et al [8], and Neves et al [47]).

Our findings also provide insight into perceived risks of AI-assisted decision-making in nursing practice. Notwithstanding the positive perspectives regarding the opportunities of using AI-DSSs, the care professionals generally expressed caution about its potential impacts. Despite their limited prior knowledge and expertise regarding the risks of AI, the care professionals shared a diverse array of interrelated concerns about risks associated with AI-assisted decision-making, which mirror findings from previous studies on the ethical implications of using AI-DSSs in health care (eg, the studies by Sutton et al [21], Skuban-Eiseler et al [35], and Schlicht and Räker [36]). For a large part, these concerns revolved around the heavy reliance of caregivers on AI-DSSs, which might, for instance, cause caregivers to overlook crucial nuances that are beyond the grasp of AI-DSSs. AI-DSSs might also perpetuate or exacerbate biases or cause a false sense of security, as certain people and care needs might not be adequately represented in the data and rules that are fed to AI-DSSs. Ultimately, caregivers who heavily rely on AI-DSSs might be led astray toward unsuitable care strategies. These perspectives tie in with how Nyholm [48] sketches the dual effects of AI on human intelligence: the prospect that AI technologies might serve as a form of cognitive enhancement and the cautionary notion that heavy reliance on AI technologies might make people less intelligent. Furthermore, in our study, concerns were expressed related to privacy infringements, conflicts of interest, and the deterioration of the work experience of caregivers owing to increased cognitive load or a reduced sense of professional fulfillment.

Expanding on both the opportunities and risks of AI-assisted decision-making in nursing practice, the care professionals participating in this study were able to articulate factors that might be important for responsibly embedding AI-DSSs into nursing practice. Overall, the reasoning of care professionals about the responsible design, implementation, and use of AI-DSSs in nursing practice centered on seven interrelated categories of prerequisites: (1) regular deliberation on data collection; (2) a balanced proactive nature of AI-DSSs; (3) incremental advancements aligned with trust and experience; (4) customization for all user groups, including clients and caregivers; (5) measures to counteract bias and narrow perspectives; (6) human-centric learning loops; and (7) routinization of using AI-DSSs. These findings extend beyond merely mitigating the risks of AI-DSSs deployment in nursing practices, as they provide insights into the envisioned interactions between people and technology and how these interactions can be responsibly shaped and reshaped as both technology and the needs and values of people evolve.

Implications for Research and Practice

An overarching lesson to be learned from the identified prerequisites for responsible AI-assisted decision-making in nursing practice is that care professionals perceive that despite the advancing capabilities of AI, AI-DSSs should serve as tools that support shared decision-making by clients and their care networks. Responsible AI-assisted decision-making hinges on mutual reinforcement between users and technology. To maximize the benefits and minimize the negative implications of AI-assisted decision-making, the ways in which AI-DSSs support nursing practice and interact with caregivers and other stakeholders require continuous refinement "in context." This implies the need to iteratively tailor the design, implementation, and use of increasingly advanced AI-DSSs to the interests, experiences, and roles of individual clients and caregivers in the care process and to the physical care environment.

The prevailing perspective suggests that inundating nurses, care coordinators, and other care professionals with excessive (aggregations of) data could impede, rather than enhance, their decision-making capabilities. This aligns with previous studies that show that too much information [49,50] and insufficient time can lead to information overload [51]. In this line, it is anticipated that the use of AI-DSSs can ease caregivers from data-intensive analytical tasks, proactively direct their attention to issues and trends in data that may need their attention, and possibly even guide them toward certain care strategies (see prerequisite 2). These findings align with previous studies that posit the use of AI as a “technical fix” to mitigate existing risks related to the remote monitoring of older adults, such as the potential cognitive overload of caregivers [32,52]. However, the anticipated utility of proactive AI-DSSs must be carefully balanced against the predominant perspective that the automation of decision-making in nursing practice should be avoided (prerequisite 2); that AI-DSSs might be introduced in practice only through incremental steps that are aligned with users’ evolving trust in, and experience with, using these systems (prerequisite 3); and that vigilance is required to prevent caregivers from becoming overly reliant on AI-DSSs and being led astray toward unsuitable care strategies (see also the studies by Parasuraman and Riley [53] and Goddard et al [54]). In this regard, our findings highlight the importance of and ways to actively counteracting bias and narrow perspectives during both the design and use of AI-DSSs (prerequisite 5; see also the studies by de Hond et al [55], Fosch-Villaronga et al [56], and Rubeis [57]). These findings complement previous studies showing that AI tools can contribute to the over-problematization and overdiagnosis of health issues [58] and perpetuate racial, gender, and age-related biases [24,47,59,60]. Moreover, in close connection to this, our findings emphasize the importance of establishing human-centric learning loops through which caregivers can actively contribute to the meaningful and responsible design, implementation, and use of AI-DSSs (prerequisite 6) [57,61]. These findings resonate with Hindocha and Cosmin Badea [34], who suggested that care professionals can act as moral exemplars for the virtuous machine and will, therefore, be integral to the responsible design, deployment, and use of AI in health care. Moreover, caregivers play an important role in collecting data that might eventually be used by AI tools [61]. Overall, these findings underscore the notion that responsible AI-assisted decision-making requires an approach that extends beyond merely the design and technical aspects of AI-DSSs. The development and use of AI-DSSs should be supported by caregivers capable of adeptly interacting with these technologies (see also the study by Sand et al [62]). The enhancement of capabilities calls for effective educational strategies to prepare caregivers for this evolving technological landscape [63]. However, as our findings suggest, caregivers may not contribute equally to responsible innovation in this area. Although all caregivers are obliged to justify their own decisions and actions [64], some may need practical assistance in the optimal and responsible use of AI-DSSs. Meanwhile, other caregivers can take on active intermediary roles between care and technology [61] by providing practical assistance to fellow caregivers and supporting designers in shaping and iteratively improving AI-DSSs.

Although our findings suggest that the overall potential of AI and AI-DSSs grows with the availability of pertinent data, they also show reservations against the unrestrained collection and use of data by AI-DSSs. The predominant perspective of care professionals was that specific data and associated AI-based insights should be generated only in accordance with established goals agreed upon by key stakeholders, including clients (prerequisite 1). The collection and use of specific data should be proactively and continuously balanced against potential harms, such as privacy infringement, cognitive overload, and the over-problematization of old age (see also the studies by Wang et al [65], Blasimme and Vayena [66], and Palmer and Schwan [67]). Although our findings emphasize the importance of generating only relevant data as input for AI-DSSs, they also suggest that once it has been decided to generate certain data and have them processed by AI-DSSs, it should be routine practice to use the resulting insights (prerequisite 7). In this context, Heyen and Salloch [22] stressed that the more routinized the use of AI-DSSs becomes in practice, the more critically caregivers need to focus on soft factors in individual client cases that cannot be comprehensively considered by AI-DSSs, such as the personality, life situation, or cultural background of a client (see also prerequisite 5). Similarly, a notable skepticism was present among the care professionals participating in this study regarding the future capacity of AI to comprehensively anticipate the care needs of people. After all, it may be difficult or even impossible to fully capture in data and decision rules for AI what contributes to good care and quality of life for an individual person [35,36,68]. Hence, in the context of AI-assisted decision-making, it may become increasingly important to engage in shared decision-making to get to know clients and respond optimally to their personal needs, goals, interests, preferences, and values [22,69]. Simultaneously, the shared decision-making model is subject to pressure, for instance, owing to the potential opacity of algorithms, leading to an insufficient understanding of the rationale behind AI-based insights into care needs and possible interventions [64]. Moreover, shared AI-assisted decision-making may be particularly challenging in the care of older adults, particularly those with cognitive impairment. This may hinder the ability of older adults to express their feelings and wishes and amplify the risk that nurses and other formal and informal caregivers consciously or unconsciously enforce what they think is right [35,36,70,71]. A fruitful direction for future studies could be to explore the effective integration of AI-DSSs into shared decision-making processes with older adults and their formal and informal caregivers.

Responsible Innovation: A Balancing Act

As our findings and the implications drawn earlier indicate, initial opportunities for AI-assisted decision-making in nursing practice could turn into drawbacks, contingent upon the specific shaping of both the design and deployment of AI-DSSs. The interrelatedness of the identified prerequisites for responsible AI-assisted decision-making suggests that addressing one factor alone may not be sufficient because of its tight link with others. Moreover, addressing risks such as privacy infringement, for instance, by limiting data collection, affects the possibilities of remote care and prevention supported by AI. Hence, we call for technology developers; caregivers using AI-DSSs; and other stakeholders, including older adults, to engage in ongoing public discourse (see also the study by Buhmann and Fieseler [72]) and work together to *cohesively* address different factors important to the responsible embedding of AI-DSSs in practice. In doing so, we recommend viewing the responsible use of AI-DSSs as a *balancingact* (see also the study by Wehrens et al [52]). Potential or proven positive and negative impacts could be carefully weighed against each other, or stated differently, trade-offs could be made among the effects of using AI-DSSs on values such as quality of life, autonomy, privacy, transparency, and fairness (see also the study by Sanderson et al [73]). Further research could explore at what level and by which means such trade-offs can be made effectively.

While trade-offs need to be made in context, in the care of individual clients, there are also trade-offs to be made at a higher level between the interests of individual people and broader public interests. Our findings suggest that responsible AI-assisted decision-making requires customization, for instance, regarding specific care technologies to be used and data to be collected [74], the processing of these data by AI, who gets access to the data and AI-based insights, the explanation of AI-based insights to users [75], and the extent to which AI-DSSs proactively advise caregivers about care needs and strategies (see prerequisite 4). In other words, there might be a desire to comprehensively address context-specific needs and preferences regarding privacy protection, transparency about the outcomes of AI-DSSs, and the protection of caregivers from potential overreliance on AI-DSSs and the erosion of professional autonomy (eg, the studies by Egelman and Peer [76] and Wilkinson et al [77]). One might suggest that the responsible deployment and use of AI-DSSs in practice requires customization at the level of individual clients and caregivers. Simultaneously, full customization might be at odds with the need to offer somewhat standardized solutions, universalize applicability, and foster scalability [78-80]. Future studies could explore how trade-offs could be made between the seemingly contrasting needs for contextualization and customization and for the decontextualization and standardization of AI-DSSs. In addition, it would be valuable to examine the implications of such trade-offs for the development of AI-DSSs and their deployment in practice.

Several studies have been conducted on the (potential) supportive roles of AI-based technologies in nursing practice [5-8] and the high-level requirements for responsible AI innovation [28-30]. This study builds upon previous studies in both research fields by examining the perspectives of various experienced nurses and other LTC professionals on the opportunities and risks of AI-assisted decision-making in nursing practice, thereby laying the groundwork for exploring associated prerequisites for responsible innovation in this area. This is particularly relevant because nurses and other caregivers do not always have a say in the design of AI tools, while they play a pivotal role in their implementation and use [5,8,57,61]. Along this line, we recommend that future studies continue to engage with the perspectives of caregivers and other stakeholders on striking a balance between the opportunities and risks of AI-assisted decision-making. This could contribute to a more comprehensive analysis and deeper understanding of ways to ensure the responsible embedding of AI-DSSs and other AI-based technologies in specific contexts. Another avenue worth exploring in future studies involves the demonstration of effective methodologies and metrics for an in-depth evaluation of the positive and negative impacts of AI-DSSs on the dynamics of nursing practices and the tensions between these impacts. Research endeavors of this nature could offer initial steps for diverse stakeholders in working together on the responsible embedding of specific AI-DSSs in practice.

Study Limitations

No study comes without limitations, and the main limitations of this study are related to the participants involved. For instance, by focusing *only* on the perspectives of LTC care professionals, this study does not consider the perspectives of *other* key stakeholders in AI-assisted decision-making in LTC, such as older adults and informal caregivers. Moreover, within LTC, an increasing number of caregiving responsibilities may transition to informal care networks. This highlights the need for future studies to include both formal and informal caregivers and care recipients to gain a comprehensive understanding of the prerequisites for responsible AI-assisted decision-making in nursing practice [36]. In addition, our findings may guide responsible innovation in AI-DSSs outside the context of Dutch LTC, but caution should be exercised in generalizing our findings, given the diversity of health care systems across countries. The results obtained from this study can be further examined in future studies using a quantitative approach or a larger and more diverse sample of LTC stakeholders from different geographic and cultural backgrounds, thereby evaluating and enhancing their robustness. Furthermore, despite the diverse group of care professionals participating in this study, biases may exist owing to varying experiences with digital innovation, potentially skewing views toward the desirability and implications of AI-assisted decision-making. In addition, the targeted (principle-based) interview questions may have influenced the responses of participants by guiding specific conceptualizations of risks. While this guidance may have positively contributed to gaining in-depth insights into prerequisites for responsible innovation, it may also have caused omissions of crucial factors, such as the impact of AI on the environment, digital inequality, and the caregiver-client relationship, which should also be considered in contexts of AI-assisted decision-making. Finally, to enhance the comprehension of the prerequisites for responsible AI-assisted decision-making, future studies might also consider and enlighten sociotechnical biases and potentially skewed perceptions of care professionals and other stakeholders about the opportunities and risks presented by AI-DSSs (eg, see the study by Neves et al [47]).

Conclusions

This study provides insights into prerequisites for responsible AI-assisted decision-making in nursing practice from the perspectives of nurses and professional stakeholders with whom they closely collaborate. While care professionals see broad opportunities in the use of AI-DSSs to improve the quality of care and workload and experience of caregivers, positive perspectives on AI-assisted decision-making are generally accompanied by a wide array of concerns about risks. Our findings indicate that opportunities for AI-assisted decision-making in nursing practice could turn into drawbacks depending on the specific shaping of the design and deployment of AI-DSSs. To optimally balance opportunities and risks of AI-assisted decision-making, seven interrelated categories of prerequisites were identified for responsible AI-assisted decision-making in nursing practice: (1) regular deliberation on data collection; (2) a balanced proactive nature of AI-DSSs; (3) incremental advancements aligned with trust and experience; (4) customization for all user groups, including clients and caregivers; (5) measures to counteract bias and narrow perspectives; (6) human-centric learning loops; and (7) routinization of using AI-DSSs. These prerequisites emphasize that regardless of their advancing capabilities, AI-DSSs should be used as tools to support shared decision-making by clients and their care network, and the ways in which AI-DSSs support the nursing process need continuous contextual refinement. Although this study focuses on the use of AI-DSSs in LTC, the findings may also be relevant to different sectors, contexts, and AI-based technologies. Finally, this study demonstrates the relevance of engaging care professionals in exploring the opportunities and risks of AI, as well as factors important to the responsible embedding of AI-based technologies into practice. These actors not only play a pivotal role in the future use of AI-based technologies in care practice but can also actively contribute to the articulation of strategies that ensure meaningful, responsible, and sustainable embedding of technologies in practice.

Acknowledgments

The authors gratefully acknowledge support from the Active Assisted Living program, cofinanced by the European Commission through the Horizon2020 Societal Challenge Health, Demographic Change and Wellbeing. In particular, the work reported here has been supported by the Active Assisted Living Healthy Ageing Eco-system for People with Dementia project (AAL-2020-7-229-CP). The authors would like to thank Editage for English language editing.

Authors' Contributions

DRML contributed to conceptualization, methodology, validation, investigation, formal analysis, writing the original draft, reviewing and editing the manuscript, and funding acquisition. NES contributed to methodology, investigation, formal analysis, and reviewing and editing the manuscript. SIA contributed to methodology, investigation, formal analysis, and reviewing and editing the manuscript. BMH contributed to formal analysis and reviewing and editing the manuscript. HHN contributed to conceptualization, methodology, validation, reviewing and editing the manuscript, project administration, and funding acquisition. WPCB contributed to conceptualization, methodology, and reviewing and editing the manuscript. AP contributed to conceptualization, methodology, and reviewing and editing the manuscript. EHMM contributed to conceptualization, methodology, and reviewing and editing the manuscript. MMNM contributed to conceptualization, methodology, and reviewing and editing the manuscript. All authors contributed to writing (original draft).

Conflicts of Interest

None declared.

Multimedia Appendix 1
Interview protocol (translated to English).
[DOCX File , 372 KB - nursing_v7i1e55962_app1.docx]

References

1. Ienca M, Jotterand F, Elger B, Caon M, Scoccia Pappagallo A, Kressig RW, et al. Intelligent assistive technology for Alzheimer's disease and other dementias: a systematic review. J Alzheimers Dis 2017;60(1):333 [FREE Full text] [doi: 10.3233/JAD-179005] [Medline: 28869482]
2. Mukaetova-Ladinska EB, Harwood T, Maltby J. Artificial intelligence in the healthcare of older people. Arch Psychiatr Ment Health 2020 Mar 20;4:007-013 [FREE Full text] [doi: 10.29328/journal.apmh.1001011]
3. Xie B, Tao C, Li J, Hilsabeck RC, Aguirre A. Artificial intelligence for caregivers of persons with Alzheimer's disease and related dementias: systematic literature review. JMIR Med Inform 2020 Aug 20;8(8):e18189 [FREE Full text] [doi: 10.2196/18189] [Medline: 32663146]
4. Rubeis G. The disruptive power of artificial intelligence. Ethical aspects of gerontechnology in elderly care. Arch Gerontol Geriatr 2020;91:104186 [FREE Full text] [doi: 10.1016/j.archger.2020.104186] [Medline: 32688106]
5. von Gerich H, Moen H, Block LJ, Chu CH, DeForest H, Hobensack M, et al. Artificial intelligence -based technologies in nursing: a scoping literature review of the evidence. Int J Nurs Stud 2022 Mar;127:104153 [FREE Full text] [doi: 10.1016/j.ijnurstu.2021.104153] [Medline: 35092870]
6. Martinez-Ortigosa A, Martinez-Granados A, Gil-Hernández E, Rodriguez-Arrastia M, Ropero-Padilla C, Roman P. Applications of artificial intelligence in nursing care: a systematic review. J Nurs Manag 2023 Jul 26;2023:1-12 [FREE Full text] [doi: 10.1155/2023/3219127]

7. Seibert K, Domhoff D, Bruch D, Schulte-Althoff M, Fürstenau D, Biessmann F, et al. Application scenarios for artificial intelligence in nursing care: rapid review. J Med Internet Res 2021 Nov 29;23(11):e26522 [FREE Full text] [doi: 10.2196/26522] [Medline: 34847057]
8. Buchanan C, Howitt ML, Wilson R, Booth RG, Risling T, Bamford M. Predicted influences of artificial intelligence on the domains of nursing: scoping review. JMIR Nurs 2020 Dec 17;3(1):e23939 [FREE Full text] [doi: 10.2196/23939] [Medline: 34406963]
9. Dubuc N, Brière S, Corbin C, N'Bouke A, Bonin L, Delli-Colli N. Computerized care-pathways (CCPs) system to support person-centered, integrated, and proactive care in home-care settings. Inform Health Soc Care 2021 Mar 02;46(1):100-111 [FREE Full text] [doi: 10.1080/17538157.2020.1865969] [Medline: 33406972]
10. Thoma-Lürken T, Bleijlevens MH, Lexis MA, Hamers JP. Evaluation of a decision support app for nurses and case managers to facilitate aging in place of people with dementia. A randomized controlled laboratory experiment. Geriatr Nurs 2018 Nov;39(6):653-662 [FREE Full text] [doi: 10.1016/j.gerinurse.2018.04.019] [Medline: 29858041]
11. Kihlgren A, Svensson F, Lövbrand C, Gifford M, Adolfsson A. A decision support system (DSS) for municipal nurses encountering health deterioration among older people. BMC Nurs 2016 Nov 08;15:63 [FREE Full text] [doi: 10.1186/s12912-016-0184-0] [Medline: 27833455]
12. Lindgren H. Towards personalized decision support in the dementia domain based on clinical practice guidelines. User Model User Adapt Interact 2011 Jan 9;21(4-5):377-406 [FREE Full text] [doi: 10.1007/s11257-010-9090-4]
13. van de Loo B, Linn AJ, Medlock S, Belimbegovski W, Seppala LJ, van Weert JC, et al. AI-based decision support to optimize complex care for preventing medication-related falls. Nat Med 2024 Mar;30(3):620-621 [FREE Full text] [doi: 10.1038/s41591-023-02780-z] [Medline: 38273147]
14. Hunink MM, Weinstein MC, Wittenberg E, Drummond MF, Pliskin JS, Wong JB, et al. Decision Making in Health and Medicine: Integrating Evidence and Values, Second Edition. Cambridge, UK: Cambridge University Press; 2014.
15. Akbar S, Lyell D, Magrabi F. Automation in nursing decision support systems: a systematic review of effects on decision making, care delivery, and patient outcomes. J Am Med Inform Assoc 2021 Oct 12;28(11):2502-2513 [FREE Full text] [doi: 10.1093/jamia/ocab123] [Medline: 34498063]
16. Yeung K. Recommendation of the council on artificial intelligence (OECD). Int Leg Mater 2020 Mar 12;59(1):27-34 [FREE Full text] [doi: 10.1017/ilm.2020.5]
17. Russell SJ, Norvig P. Artificial Intelligence: A Modern Approach, Third Edition. London, UK: Pearson Education; 2009.
18. Explanatory memorandum on the updated OECD definition of an AI system. OECD Publishing. 2024 Mar. URL: https://www.oecd-ilibrary.org/docserver/623da898-en.pdf?expires=1718864105&id=id&accname=guest&checksum=C7425CED5968520597F4424F309F050A [accessed 2024-06-26]
19. Lee S. Features of computerized clinical decision support systems supportive of nursing practice: a literature review. Comput Inform Nurs 2013 Oct;31(10):477-95; quiz 496-7 [FREE Full text] [doi: 10.1097/01.NCN.0000432127.99644.25] [Medline: 23958964]
20. Middleton B, Sittig DF, Wright A. Clinical decision support: a 25 year retrospective and a 25 year vision. Yearb Med Inform 2016 Aug 02;Suppl 1(Suppl 1):S103-S116 [FREE Full text] [doi: 10.15265/IYS-2016-s034] [Medline: 27488402]
21. Sutton RT, Pincock D, Baumgart DC, Sadowski DC, Fedorak RN, Kroeker KI. An overview of clinical decision support systems: benefits, risks, and strategies for success. NPJ Digit Med 2020 Feb 06;3:17 [FREE Full text] [doi: 10.1038/s41746-020-0221-y] [Medline: 32047862]
22. Heyen NB, Salloch S. The ethics of machine learning-based clinical decision support: an analysis through the lens of professionalisation theory. BMC Med Ethics 2021 Aug 19;22(1):112 [FREE Full text] [doi: 10.1186/s12910-021-00679-3] [Medline: 34412649]
23. Petersen C, Smith J, Freimuth RR, Goodman KW, Jackson GP, Kannry J, et al. Recommendations for the safe, effective use of adaptive CDS in the US healthcare system: an AMIA position paper. J Am Med Inform Assoc 2021 Mar 18;28(4):677-684 [FREE Full text] [doi: 10.1093/jamia/ocaa319] [Medline: 33447854]
24. Berridge C, Grigorovich A. Algorithmic harms and digital ageism in the use of surveillance technologies in nursing homes. Front Sociol 2022 Sep 16;7:957246 [FREE Full text] [doi: 10.3389/fsoc.2022.957246] [Medline: 36189442]
25. Morley J, Machado CC, Burr C, Cowls J, Joshi I, Taddeo M, et al. The ethics of AI in health care: a mapping review. Soc Sci Med 2020 Sep;260:113172 [FREE Full text] [doi: 10.1016/j.socscimed.2020.113172] [Medline: 32702587]
26. Chu CH, Nyrup R, Leslie K, Shi J, Bianchi A, Lyn A, et al. Digital ageism: challenges and opportunities in artificial intelligence for older adults. Gerontologist 2022 Aug 12;62(7):947-955 [FREE Full text] [doi: 10.1093/geront/gnab167] [Medline: 35048111]
27. Stypińska J. AI ageism: a critical roadmap for studying age discrimination and exclusion in digitalized societies. AI Soc 2023;38(2):665-677 [FREE Full text] [doi: 10.1007/s00146-022-01553-5] [Medline: 36212226]
28. Jobin A, Ienca M, Vayena E. The global landscape of AI ethics guidelines. Nat Mach Intell 2019 Sep 02;1(9):389-399 [FREE Full text] [doi: 10.1038/s42256-019-0088-2]

29. Fjeld J, Achten N, Hilligoss H, Nagy A, Srikumar M. Principled artificial intelligence: mapping consensus in ethical and rights-based approaches to principles for AI. Berkman Klein Center for Internet & Society. 2020. URL: https://dash.harvard.edu/handle/1/42160420 [accessed 2024-06-26]
30. Hagendorff T. The ethics of AI ethics: an evaluation of guidelines. Minds Mach 2020 Feb 01;30(1):99-120 [FREE Full text] [doi: 10.1007/s11023-020-09517-8]
31. Mittelstadt B. Principles alone cannot guarantee ethical AI. Nat Mach Intell 2019 Nov 04;1(11):501-507 [FREE Full text] [doi: 10.1038/s42256-019-0114-4]
32. Lukkien DR, Nap HH, Buimer HP, Peine A, Boon WP, Ket JC, et al. Toward responsible artificial intelligence in long-term care: a scoping review on practical approaches. Gerontologist 2023 Jan 24;63(1):155-168 [FREE Full text] [doi: 10.1093/geront/gnab180] [Medline: 34871399]
33. Goirand M, Austin E, Clay-Williams R. Implementing ethics in healthcare AI-based applications: a scoping review. Sci Eng Ethics 2021 Sep 03;27(5):61 [FREE Full text] [doi: 10.1007/s11948-021-00336-3] [Medline: 34480239]
34. Hindocha S, Badea C. Moral exemplars for the virtuous machine: the clinician’s role in ethical artificial intelligence for healthcare. AI Ethics 2021 Sep 12;2(1):167-175 [FREE Full text] [doi: 10.1007/s43681-021-00089-6]
35. Skuban-Eiseler T, Orzechowski M, Denkinger M, Kocar TD, Leinert C, Steger F. Artificial intelligence-based clinical decision support systems in geriatrics: an ethical analysis. J Am Med Dir Assoc 2023 Sep;24(9):1271-6.e4 [FREE Full text] [doi: 10.1016/j.jamda.2023.06.008] [Medline: 37453451]
36. Schlicht L, Räker M. A context-specific analysis of ethical principles relevant for AI-assisted decision-making in health care. AI Ethics 2023 Jul 24 [FREE Full text] [doi: 10.1007/s43681-023-00324-2]
37. Noortman R, Schulte BF, Marshall P, Bakker S, Cox AL. HawkEye - deploying a design fiction probe. In: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. 2019 Presented at: CHI '19; May 4-9, 2019; Glasgow, UK. [doi: 10.1145/3290605.3300652]
38. Nathan LP, Klasnja PV, Friedman B. Value scenarios: a technique for envisioning systemic effects of new technologies. In: Proceedings of the CHI '07 Extended Abstracts on Human Factors in Computing Systems. 2007 Presented at: CHI EA '07; April 28-May 3, 2007; San Jose, CA. [doi: 10.1145/1240866.1241046]
39. Carrol JM. Five reasons for scenario-based design. In: Proceedings of the 32nd Annual Hawaii International Conference on Systems Sciences. 1999 Presented at: HICSS-32; January 5-8, 1999; Maui, HI. [doi: 10.1109/hicss.1999.772890]
40. Risnes M, Thorstensen E, Mirtaheri P, Berg A. Exploring value dilemmas of brain monitoring technology through speculative design scenarios. J Responsible Technol 2024 Mar;17:100074 [FREE Full text] [doi: 10.1016/j.jrt.2023.100074]
41. El Morr C, Ali-Hassan H. Healthcare, data analytics, and business intelligence. In: Analytics in Healthcare. Cham, Switzerland: Springer; Jan 22, 2019.
42. Sadat Mosavi N, Filipe Santos M. How prescriptive analytics influences decision making in precision medicine. Procedia Comput Sci 2020;177:528-533 [FREE Full text] [doi: 10.1016/j.procs.2020.10.073]
43. Ethics and governance of artificial intelligence for health: WHO guidance. World Health Organization. 2021 Jun 28. URL: https://www.who.int/publications/i/item/9789240029200 [accessed 2024-06-26]
44. Your research: Is it subject to the WMO or not? Central Committee on Research Involving Human Subjects. URL: https://english.ccmo.nl/investigators/legal-framework-for-medical-scientific-research/your-research-is-it-subject-to-the-wmo-or-not [accessed 2024-07-23]
45. Braun V, Clarke V. Using thematic analysis in psychology. Qual Res Psychol 2006;3(2):77-101 [FREE Full text] [doi: 10.1191/1478088706qp063oa]
46. Kiger ME, Varpio L. Thematic analysis of qualitative data: AMEE guide no. 131. Med Teach 2020 Aug;42(8):846-854 [FREE Full text] [doi: 10.1080/0142159X.2020.1755030] [Medline: 32356468]
47. Neves BB, Petersen A, Vered M, Carter A, Omori M. Artificial intelligence in long-term care: technological promise, aging anxieties, and sociotechnical ageism. J Appl Gerontol 2023 Jun;42(6):1274-1282 [FREE Full text] [doi: 10.1177/07334648231157370] [Medline: 36799089]
48. Nyholm S. Artificial intelligence and human enhancement: can AI technologies make us more (artificially) intelligent? Camb Q Healthc Ethics 2024 Jan;33(1):76-88 [FREE Full text] [doi: 10.1017/S0963180123000464] [Medline: 37646146]
49. Hiltz SR, Turoff M. Structuring computer-mediated communication systems to avoid information overload. Commun ACM 1985 Jul 01;28(7):680-689 [FREE Full text] [doi: 10.1145/3894.3895]
50. Rosekind MR, Gander PH, Miller DL, Gregory KB, Smith RM, Weldon KJ, et al. Fatigue in operational settings: examples from the aviation environment. Hum Factors 1994 Jun;36(2):327-338 [FREE Full text] [doi: 10.1177/001872089403600212] [Medline: 8070796]
51. Schick AG, Gordon LA, Haka S. Information overload: a temporal approach. Account Organ Soc 1990;15(3):199-220 [FREE Full text] [doi: 10.1016/0361-3682(90)90005-f]
52. Wehrens R, Stevens M, Kostenzer J, Weggelaar AM, de Bont A. Ethics as discursive work: the role of ethical framing in the promissory future of data-driven healthcare technologies. Sci Technol Hum Values 2021 Nov 08;48(3):606-634 [FREE Full text] [doi: 10.1177/01622439211053661]
53. Parasuraman R, Riley V. Humans and automation: use, misuse, disuse, abuse. Hum Factors 1997;39(2):230-253 [FREE Full text] [doi: 10.1518/001872097778543886]

54. Goddard K, Roudsari A, Wyatt JC. Automation bias: empirical results assessing influencing factors. Int J Med Inform 2014 May;83(5):368-375 [FREE Full text] [doi: 10.1016/j.ijmedinf.2014.01.001] [Medline: 24581700]
55. de Hond AA, Leeuwenberg AM, Hooft L, Kant IM, Nijman SW, van Os HJ, et al. Guidelines and quality criteria for artificial intelligence-based prediction models in healthcare: a scoping review. NPJ Digit Med 2022 Jan 10;5(1):2 [FREE Full text] [doi: 10.1038/s41746-021-00549-7] [Medline: 35013569]
56. Fosch-Villaronga E, Drukarch H, Khanna P, Verhoef T, Custers B. Accounting for diversity in AI for medicine. Comput Law Secur Rev 2022 Nov;47:105735 [FREE Full text] [doi: 10.1016/j.clsr.2022.105735]
57. Rubeis G. Guardians of humanity? the challenges of nursing practice in the digital age. Nurs Philos 2021 Apr;22(2):e12331 [FREE Full text] [doi: 10.1111/nup.12331] [Medline: 32996687]
58. Vogt H, Green S, Ekstrøm CT, Brodersen J. How precision medicine and screening with big data could increase overdiagnosis. BMJ 2019 Sep 13;366:l5270 [FREE Full text] [doi: 10.1136/bmj.l5270] [Medline: 31519649]
59. Stypińska J, Franke A. AI revolution in healthcare and medicine and the (re-)emergence of inequalities and disadvantages for ageing population. Front Sociol 2022;7:1038854 [FREE Full text] [doi: 10.3389/fsoc.2022.1038854] [Medline: 36755564]
60. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science 2019 Oct 25;366(6464):447-453 [FREE Full text] [doi: 10.1126/science.aax2342] [Medline: 31649194]
61. Ronquillo CE, Peltonen LM, Pruinelli L, Chu CH, Bakken S, Beduschi A, et al. Artificial intelligence in nursing: priorities and opportunities from an international invitational think-tank of the Nursing and Artificial Intelligence Leadership Collaborative. J Adv Nurs 2021 Sep;77(9):3707-3717 [FREE Full text] [doi: 10.1111/jan.14855] [Medline: 34003504]
62. Sand M, Durán JM, Jongsma KR. Responsibility beyond design: physicians' requirements for ethical medical AI. Bioethics 2022 Feb;36(2):162-169 [FREE Full text] [doi: 10.1111/bioe.12887] [Medline: 34089625]
63. Long D, Magerko B. What is AI literacy? competencies and design considerations. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. 2020 Presented at: CHI '20; April 25-30, 2020; Honolulu, HI URL: https://doi.org/10.1145/3313831.3376727 [doi: 10.1145/3313831.3376727]
64. Grote T, Berens P. On the ethics of algorithmic decision-making in healthcare. J Med Ethics 2020 Mar;46(3):205-211 [FREE Full text] [doi: 10.1136/medethics-2019-105586] [Medline: 31748206]
65. Wang RH, Tannou T, Bier N, Couture M, Aubry R. Proactive and ongoing analysis and management of ethical concerns in the development, evaluation, and implementation of smart homes for older adults with frailty. JMIR Aging 2023 Mar 09;6:e41322 [FREE Full text] [doi: 10.2196/41322] [Medline: 36892912]
66. Blasimme A, Vayena E. Becoming partners, retaining autonomy: ethical considerations on the development of precision medicine. BMC Med Ethics 2016 Nov 04;17(1):67 [FREE Full text] [doi: 10.1186/s12910-016-0149-6] [Medline: 27809825]
67. Palmer A, Schwan D. More process, less principles: the ethics of deploying AI and robotics in medicine. Camb Q Healthc Ethics 2024 Jan 24;33(1):121-134 [FREE Full text] [doi: 10.1017/S0963180123000087] [Medline: 37092348]
68. Ho A. Are we ready for artificial intelligence health monitoring in elder care? BMC Geriatr 2020 Sep 21;20(1):358 [FREE Full text] [doi: 10.1186/s12877-020-01764-9] [Medline: 32957946]
69. McDougall RJ. Computer knows best? the need for value-flexibility in medical AI. J Med Ethics 2019 Mar;45(3):156-160 [FREE Full text] [doi: 10.1136/medethics-2018-105118] [Medline: 30467198]
70. Grigorovich A, Kontos P, Jenkins A, Kirkland S. Moving toward the promise of participatory engagement of older adults in gerotechnology. Gerontologist 2022 Mar 28;62(3):324-331 [FREE Full text] [doi: 10.1093/geront/gnab026] [Medline: 33675641]
71. Suijkerbuijk S, Nap HH, Cornelisse L, IJsselsteijn WA, de Kort YA, Minkman MN. Active involvement of people with dementia: a systematic review of studies developing supportive technologies. J Alzheimers Dis 2019 Jun 18;69(4):1041-1065 [FREE Full text] [doi: 10.3233/jad-190050]
72. Buhmann A, Fieseler C. Towards a deliberative framework for responsible innovation in artificial intelligence. Technol Soc 2021 Feb;64:101475 [FREE Full text] [doi: 10.1016/j.techsoc.2020.101475]
73. Sanderson C, Douglas D, Lu Q. Implementing responsible AI: tensions and trade-offs between ethics aspects. arXiv Preprint posted online on April 17, 2023 [FREE Full text] [doi: 10.1109/ijcnn54540.2023.10191274]
74. Berridge C, Demiris G, Kaye J. Domain experts on dementia-care technologies: mitigating risk in design and implementation. Sci Eng Ethics 2021 Feb 18;27(1):14 [FREE Full text] [doi: 10.1007/s11948-021-00286-w] [Medline: 33599847]
75. Du Y, Antoniadi AM, McNestry C, McAuliffe FM, Mooney C. The role of XAI in advice-taking from a clinical decision support system: a comparative user study of feature contribution-based and example-based explanations. Appl Sci 2022 Oct 13;12(20):10323 [FREE Full text] [doi: 10.3390/app122010323]
76. Egelman S, Peer E. The myth of the average user: improving privacy and security systems through individualization. In: Proceedings of the 2015 New Security Paradigms Workshop. 2015 Presented at: NSPW '15; September 8-11, 2015; Twente, The Netherlands URL: https://doi.org/10.1145/2841113.2841115 [doi: 10.1145/2841113.2841115]
77. Wilkinson D, Namara M, Badillo-Urquiola K, Wisniewski PJ, Knijnenburg BP, Page X, et al. Moving beyond a "one-size fits all": exploring individual differences in privacy. In: Proceedings of the Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems. 2018 Presented at: CHI EA '18; April 21-26, 2018; Montreal, QC URL: https://doi.org/10.1145/3170427.3170617 [doi: 10.1145/3170427.3170617]

78. Peine A, Moors EH. Valuing health technology – habilitating and prosthetic strategies in personal health systems. Technol Forecast Soc Change 2015 Apr;93:68-81 [FREE Full text] [doi: 10.1016/j.techfore.2014.08.019]
79. Peine A. Understanding the dynamics of technological configurations: a conceptual framework and the case of Smart Homes. Technol Forecast Soc Change 2009 Mar;76(3):396-409 [FREE Full text] [doi: 10.1016/j.techfore.2008.04.002]
80. Fischer B, Östlund B, Peine A. Of robots and humans: creating user representations in practice. Soc Stud Sci 2020 Apr;50(2):221-244 [FREE Full text] [doi: 10.1177/0306312720905116] [Medline: 32037966]

Abbreviations

AI: artificial intelligence
AI-DSS: artificial intelligence–based decision support system
HAAL: Healthy Ageing Eco-system for People With Dementia
LTC: long-term care
WHO: World Health Organization

Edited by E Borycki, K Cato; submitted 01.01.24; peer-reviewed by L Schlicht, B Neves, S Mitra; comments to author 21.02.24; revised version received 16.04.24; accepted 24.05.24; published 25.07.24.

Please cite as:
Lukkien DRM, Stolwijk NE, Ipakchian Askari S, Hofstede BM, Nap HH, Boon WPC, Peine A, Moors EHM, Minkman MMN
AI-Assisted Decision-Making in Long-Term Care: Qualitative Study on Prerequisites for Responsible Innovation
JMIR Nursing 2024;7:e55962
URL: https://nursing.jmir.org/2024/1/e55962
doi:10.2196/55962
PMID:39052315

Publisher:
JMIR Publications
130 Queens Quay East.
Toronto, ON, M5A 3Y5
Phone: (+1) 416-583-2040
Email: support@jmir.org