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The digital intelligent precise nursing framework: theory development in health recommender system

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Abstract

Background With the rapid integration of artificial intelligence, the Internet of Things, and big data into healthcare, Health Recommender Systems (HRS) have emerged as powerful tools to support personalized care. However, their application in the nursing field lacks a theoretical foundation grounded in nursing science.

Objective This study aims to develop the Digital Intelligent Precise Nursing Framework, a theory-driven conceptual model for HRS adoption in nursing, to guide the design of intelligent recommendation systems that align with the holistic, person-centered principles of nursing.

Methods Drawing upon interdisciplinary literature and nursing paradigms, this study proposes a framework consisting of three interrelated components: multidimensional data, solution bank, and recommendation. Multidimensional data includes sensing modalities, information modalities, data types, and information sources. The solution bank is structured across two axes—target users and function types. Recommendation engines integrate data and solution strategies to generate user-centered inferential conclusions, supportive measures, and individualized action suggestions.

Results The framework enables intelligent nursing systems to synthesize heterogeneous data and deliver personalized, real-time, and context-aware interventions. It provides a foundation for moving nursing practice from evidence-based care to precision-guided decision-making.

Conclusion The Digital Intelligent Precise Nursing Framework offers a structured foundation for advancing intelligent HRSs in nursing by bridging nursing theory, health technology, and clinical reasoning. It supports the development of systems that are adaptive, interpretable, and responsive to users' needs in diverse care settings.

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Keywords Digital technology, Intelligent systems, Nursing, Learning health system, Recommendation, health planning, Health recommender systems

Introduction

The term Fourth Industrial Revolution has been increasingly applied to both nursing education and practice, reflecting a broader shift toward the integration of information and computing technologies in addressing the complexities of modern, person-centered, and personalized care and research [1, 2]. The term personalized care refers to the design and adaptation of clinical treatment to the characteristics, needs, and individual preferences of the patient throughout all stages: care, prevention, diagnosis, treatment, and follow-up [3]. Within this evolving landscape, health recommender systems (HRSs) have emerged as promising tools for supporting personalized health-related decision-making. In a typical HRS, the recommended item of interest is a piece of health-related or medical information, such as a selected physician opinion or treatment option. These recommendations are typically generated using individualized health data documented in electronic health records (EHRs) or personal health records (PHRs) [4]. A specific subset of HRSs is designed to assist users in making preferred healthcare choices. The data that power these systems—commonly referred to as user profiles—may consist of patient information extracted from EHRs or PHRs, often structured as personalized health knowledge graphs [5], provider profiles [6], or a combination of both [7], or patient-reported outcomes and other health information.

Ricci et al. define recommender systems (RSs) as "software tools and techniques providing suggestions for items to be of use to a user," [8] with recommendations applicable to various decision-making processes, such as what products to buy, music to listen to, or online news to read. Extending this definition, Wiesner and Pfeifer [4] describe a health recommender system as "a specialization of an RS as defined by Ricci et al." In the context of an HRS, the recommendable item refers to a piece of nonconfidential, scientifically proven, or at least generally accepted medical information, such as IBM Watson health, or Amazon HealthLake.

HRSs offer the potential to motivate and engage users to change their behavior [9] and provide people with better choices and actionable knowledge based on observed behavior [10, 11]. The overall objective of the HRS is to empower people to monitor and improve their health through technology-assisted, personalized recommendations.

With the continued integration of technologies such as artificial intelligence, the Internet of Things, and big data into the nursing field, the functions, data sources, and modes of user interaction in health recommender systems have become increasingly complex and diverse. These technological advances not only enhance the system's capacity for personalized recommendation but also accelerate the transformation of nursing practice to one that is data-driven and guided by intelligent decision-making by applying Artificial Intelligence (AI) technology. Most existing systems are primarily technology-driven in the design of recommendation mechanisms [12], while reports on how to design and implement recommender systems specifically within the field of clinical nursing remain scarce. Our study seeks to address this gap by integrating nursing conceptual perspectives into the development of a theory-driven framework. An existing framework, termed the "Iron Triangle Theory," was introduced in 2023 to conceptualize the application of HRS in clinical practice by our research team [15]. However, this framework suffers from three major limitations: (1) it lacks a solid foundational theory to support its structural validity; (2) it inadequately addresses the role of digital technologies in shaping HRS functionalities; and (3) its functional description remains restrictive, failing to fully encompass the diverse capabilities of contemporary recommendation systems. To overcome these shortcomings and better harness the potential of AI, an enhanced framework is needed—one that seamlessly integrates AI into nursing practice, thereby enabling intelligent, precision-based patient care. Such an advancement would not only expand the breadth and depth of nursing services but also reinforce the development of digital intelligent precise nursing in the AI-driven healthcare era. The new definition of 'nursing' was proposed by The International Council of Nurses [13].

> *Nursing is a profession dedicated to upholding everyone's right to enjoy the highest attainable standard of health, through a shared commitment to providing collaborative, culturally safe, people-centred care and services. Nursing acts and advocates for people's equitable access to health and health care, and safe, sustainable environments.*
> *The practice of nursing embodies the philosophy and values of the profession in providing professional care in the most personal health-related aspects of people's lives. Nursing promotes health, protects safety and continuity in care, and manages and leads health care organizations and systems. Nursing's practice is underpinned by a unique combination of science-based disciplinary knowledge, technical capability, ethical standards, and therapeutic*

relationships. Nursing is committed to compassion, social justice and a better future for humanity.

To meet the needs of the new definition and scope of the nursing profession, there is an urgent need to conceptualize the Digital Intelligent Precise Nursing Framework. This study introduces a theoretical framework for Health Recommender Systems, grounded in the principles and context of the nursing discipline, which is strongly grounded in 'science' [13].

Methodology

This study adopted a narrative review approach to synthesize theoretical and empirical literature relevant to the construction of a conceptual framework for HRS in nursing. Unlike systematic or integrative reviews, a narrative review allows for a more flexible integration of diverse sources, making it particularly suitable for the development of new theories and conceptual models.

We conducted a structured search across multidisciplinary databases (e.g., PubMed, Web of Science, Wiley, Wangfang, CNKI) using keywords, such as ("recommendation system*" OR "recommender system*" OR "decision support system*" OR "clinical decision support" OR "intelligent recommendation" OR "personalized recommendation" OR "precision health" OR"Decision Support Systems, Clinical[Mesh] OR "Health Information Systems[Mesh]" OR "Artificial Intelligence[Mesh]") AND ("patient care" OR "precision health" OR "nursing[Mesh]"), we also search the theories, such as ("nursing theory" OR "nursing model" OR "conceptual framework" OR "theoretical framework" OR"Models, Nursing[Mesh]"OR "Philosophy, Nursing[Mesh]" OR "Nursing Theory[Mesh]") AND ("nursing practice" OR "clinical nursing" OR "nursing research").

The selection of literature prioritized seminal works, theoretical contributions, and empirical studies that informed the integration of nursing perspectives with digital intelligence. Articles were not limited by study design, as the primary aim was to identify conceptual gaps and synthesize cross-disciplinary insights rather than evaluate intervention effectiveness.

The results of this narrative review served as the foundation for constructing the Digital Intelligent Precise Nursing (DIPN) framework, which was subsequently refined through expert consultation and theoretical analysis.

Theoretical background

The theoretical foundation of this framework is grounded in the concept of Precision Nursing [14], the Iron Triangle Theory for Health Recommender Systems [15], and the key elements that should be explicitly addressed in studies on Health Recommender Systems, as summarized by De Croon et al. [16]. In terms of the complementarity of the theoretical system, these three collectively embody the complementarity and progressiveness of the theoretical system. The Nursing Science Precision Health Model (NSPH) [14] has established a scientific framework for individualized nursing in this research. Its core proposition, "achieving personalized health interventions by integrating multi-omics data with influencing factors such as individual lifestyles, social economy, and culture" [17], is highly consistent with the personalized recommendation needs of smart nursing systems and constitutes the underlying logic of the theoretical system. The Iron Triangle Theory of Health Recommendation Systems [15], as a theoretical framework previously developed by the team, provides preliminary framework for system construction from the perspective of feasibility, forming the intermediate support layer for theoretical application. The key elements of health recommendation systems summarized by De Croon et al. [16] have improved the technical implementation path from the methodological level, constituting the operational execution layer of the theoretical system.

Precision health "uses omic data within the context of lifestyle, social, economic, cultural, and environmental influences to help individuals achieve well-being and optimal health." Its primary goal is to deliver "individualized treatments to maximize the benefits of any particular intervention for one single individual" [18]. Derived from the concept of precision health (NIH proposed) [19], one of the theoretical foundations of this study is rooted in the NSPH [18], which was jointly developed in 2019 by researchers from multiple universities in the United States based on symptom science. This model comprises four core components of precision: (A) Precision in measures; (B) Precision in characterization of phenotype including life-style and environmental factors; (C) Precision in characterization of genotype and other biomarkers; and (D) Precision in intervention target discovery, design, and delivery. These four components reflect the unique attributes of nursing practice and emphasize interdisciplinary collaboration informed by scientific data and information (Fig. 1) [18]. Phenotypes are determined by a combination of individual behaviors, biological characteristics, and clinical data. Once phenotypic profiles are established, potential biomarkers are identified through genomics and other "omics" research. These findings are then integrated with physiological and behavioral data from the patient to support the prediction, treatment, and management of symptoms.

The second theoretical foundation of this study is the Iron Triangle Theory for Health Recommender Systems [15], proposed by Yuan et al. in 2023. With the rapid advancement of emerging technologies and artificial intelligence, this foundational theory must evolve to

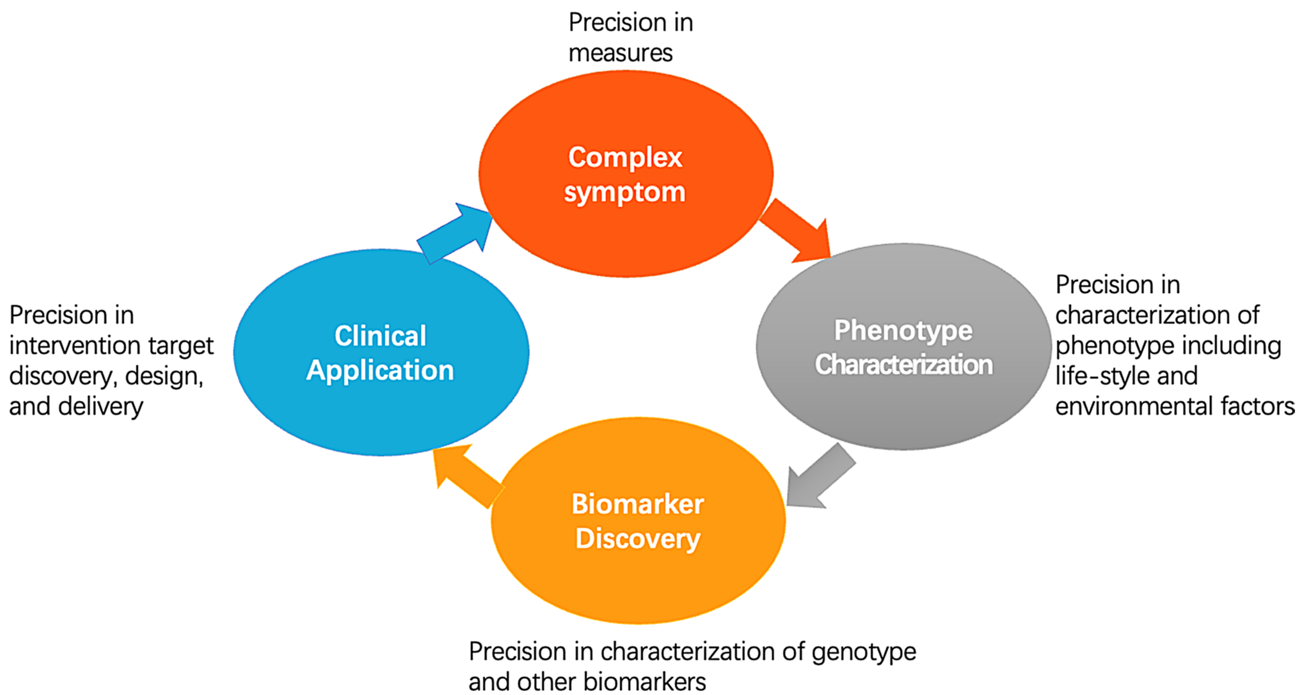

Fig. 1 Nursing science precision health model [18]

address the dynamic nature of healthcare—encompassing various data sources, intervention modalities, and the multiple professional roles of nurses [13], for example, the ICN redefined the nurse, 'Nurses enhance health literacy, promote health, prevent illness, protect patient safety, alleviate suffering, facilitate recovery and adaptation, and uphold dignity throughout life and at end of life. They work autonomously and collaboratively across settings to improve health, through advocacy, evidence-informed decision-making, and culturally safe, therapeutic relationships. Nurses provide people-centred, compassionate clinical and social care, manage services, enhance health systems, advance public and population health, and foster safe and sustainable environments. Nurses lead, educate, research, advocate, innovate and shape policy to improve health outcomes. Furthermore, nurses play a unique role in health and care for populations of all ages, and in all settings, building trust with individuals, families and communities and gaining valuable insights into people's experiences of health and illness.' Grounded in these principles of transparency, balance, and interdependence, the Iron Triangle Theory conceptualizes three interrelated components: accurate evaluation of multidimensional data, digital awareness solutions, and digital intervention [15] (Fig. 2). Collectively, these components form a cohesive, triangular model that encapsulates the inherent trade-offs among healthcare quality, access, and cost. This framework provides a structured, user-centered foundation for the development of data-driven, intelligent nursing systems that aim to enhance both clinical decision-making and patient engagement. This theory was developed by one of the authors (Yuan) research team based on the application of HRS to support symptom management in adult and pediatric cancer patients [20]. It proposed a conceptual framework comprising three core components, which interact with one another to form the model: accurate evaluation of multidimensional data, digital awareness solutions, and digital interventions. The original theory primarily focused on the process of conceptual development; As noted above, the 2023 Iron Triangle Theory framework has three major limitations: a weak theoretical foundation, insufficient integration of digital technologies, and a narrow functional scope. These shortcomings thus drive us to further develop this theory into the application of AI in HRS for nursing.

Notably, De Croon et al. emphasized that studies on HRSs should explicitly address several key elements: the intended target users and recipients of recommendations; the nature and format of the recommendations; the origin of the dataset; the algorithms employed to generate recommendations; and the evaluation protocols applied [16].

Therefore, based on the above theories and literature review, this paper presents the Digital Intelligent Precise Nursing Framework that aims to serve as a forward-looking theoretical tool to guide the scientific design and effective implementation of health recommender systems in intelligent nursing practice.

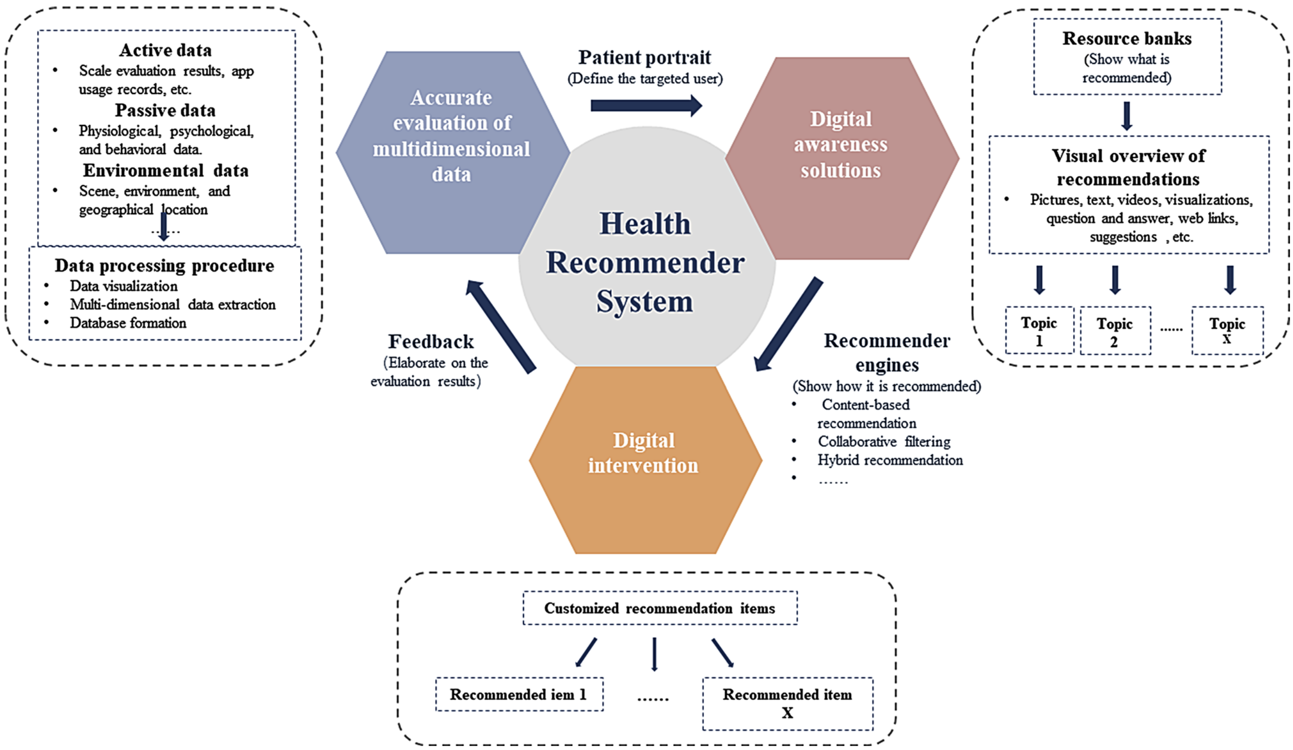

Fig. 2 Iron triangle theory for the health recommender system – extracted from the original paper [15]

Theoretical framework

Derived through a combination of gaps in existing nursing frameworks, and inspired by Clinical Decision Support Systems like IBM Watson Health and Google's Med-PaLM, we identified the need for: a solution bank to codify evidence-based interventions, a recommendation engine to translate data into actionable insights, similar to Amazon HealthLake's adaptive analytics. The Digital Intelligent Precision Nursing Framework centers on three core components: multidimensional data, solution bank, and recommendation. This triad mirrors the data-to-decision pipeline in AI systems: the input layer: addressing the question "what do we know about the current situation/patient?", drawing on the Nursing Science Precision Health Model, we have identified "multidimensional data" as the cornerstone for achieving "precision"; the knowledge layer: answering "what interventions work in similar cases?", we adopt the term "solution bank" from the field of computer science to embody the "intelligent" dimension of the framework; the output layer: responding to "what actions should be taken now?", this ultimately converges on the framework's overarching objective: generating recommendations.

Multidimensional data lays on the digital dimension, to acquire data from different sources; solution bank consists with a variety of response strategies or solutions to solve one or series of nursing issues by data-driven intelligent decision-making; to combine with/analysis/integrate multidimensional evaluation and solution bank, the recommendation can be developed (Fig. 3).

Component I –Multidimensional data

The digital dimension constitutes the foundational layer of the Digital Intelligent Precise Nursing Framework. It emphasizes the construction of data infrastructures and information platforms to digitize health information, services, and systems, thereby enabling the collection, integration, and analysis of multidimensional health data.

Situated within component I of the Digital Intelligent Nursing Triangle, this component underscores not only the diversity and richness of data sources but also the need for precision, sensitivity, and interpretability when delivering health recommendations through digital systems.

Multidimensional data refer to heterogeneous data types collected from diverse modalities and sources [21–23]. These include: (1) sensing modalities (information perception channels): sensors (e.g., physiological monitors, wearables), language/text (e.g., clinical narratives, user input), visual (e.g., wound images, facial expressions), auditory (e.g., voice patterns, digital speech); (2) information modalities (content domains): physical (e.g., gait, activity levels), behavioral (e.g., usage patterns, mobility,).

psychological (e.g., emotional states, stress levels), social (e.g., degree of social support, social interactions,

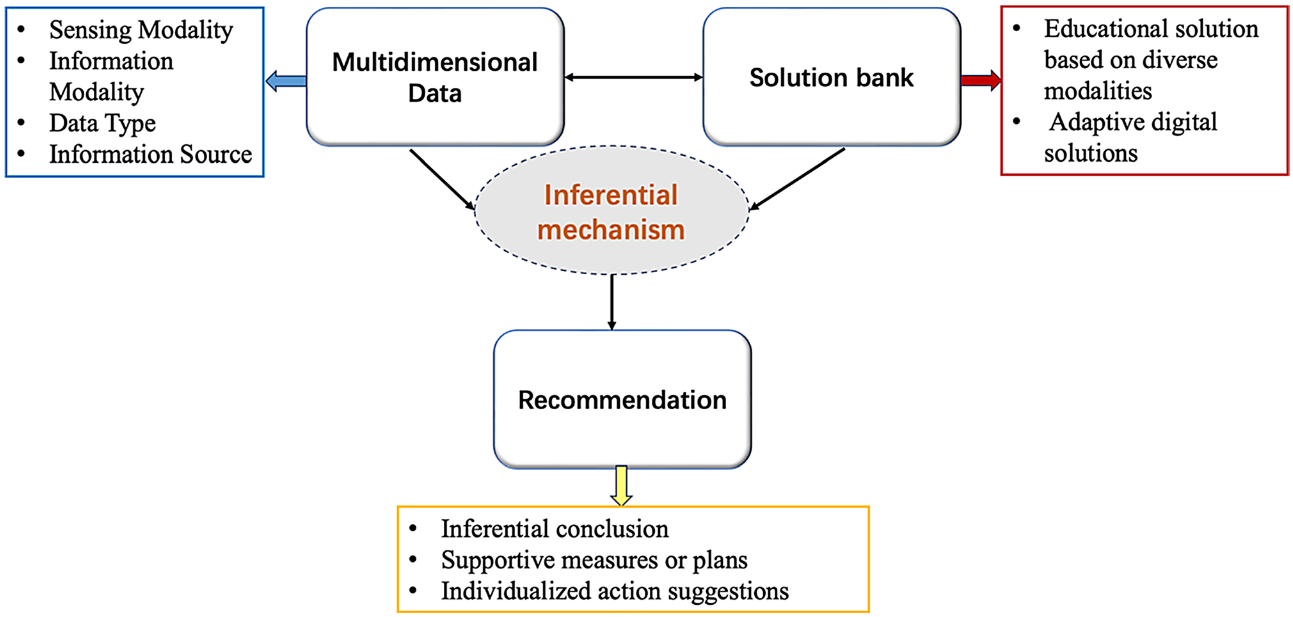

Fig. 3 The digital intelligent precise nursing framework

social determinants of health), environmental (e.g., geographic, meteorological, and built environment) [24]; (3) data types: structured data (e.g., EHRs, clinical records), unstructured data (e.g., free-text notes, social media), time-series data (e.g., ICU monitoring of ECG, heart rate), image data (e.g., diagnostic or wound images), textual data (e.g., nursing documentation); (4) information sources:

social media platforms (e.g., Weibo, Rednote), patient-generated health data (PGHD), including self-reported health and treatment histories, patient-reported outcomes.

(PROs), and biometric sensor data [25].

These data are captured through both active (e.g., survey responses, ePROs, clinician input) and innovative passive means to address psychological traits and social supports—key factors in treatment adherence. For example, psychological traits (e.g., stress resilience, emotional states) are supplemented via digital phenotyping: smartphone-based voice tone analysis and app usage patterns capture real-time emotional fluctuations [26], complementing traditional self-reports. Social supports are quantified through sociomarkers extended by ambient data, such as social network interaction frequency and neighborhood resource accessibility, enriching data beyond conventional surveys [27].

Increasingly, hybrid multimodal frameworks integrate these new data streams with existing sources to enhance ecological validity and granularity. This allows for the generation of PGHD, which—when integrated with clinical datasets—provides real-time, context-sensitive insights that extend beyond traditional medical records [28–31].

Notably, sociomarkers—quantifiable indicators of an individual's social context—have emerged as powerful predictors for tailored intervention. For instance, machine learning models using markers such as neighborhood poverty or housing instability have enhanced prediction of chronic disease risks [32–34]. This category of data is commonly acquired via community health information systems, self-reported measures, and data collection by healthcare staff.

Transforming these complex data streams—including qualitative data (e.g., patient narratives, interview transcripts)—into actionable intelligence relies on advanced analytics: qualitative data are structured via natural language processing to extract emotional polarity and need-related keywords, while real-time data mining, AI-driven classification, and digital biomarkers (objective physiological or behavioral metrics captured through digital means) process quantitative inputs. The textual information can also be sentiment analysis through multifaceted fine-grained sentiment analysis based on medical complaint texts [35–37]. These integrated features feed into multimodal AI models, where attention mechanisms weight data types (e.g., qualitative insights for assessing treatment acceptability) to enable descriptive, diagnostic, predictive, and prescriptive analytics—each supporting a different inferential mechanism of personalized recommendation [38, 39].

Nursing science, grounded in the meta-paradigm concepts of person, health, environment, and nursing [40], is uniquely positioned to guide this interpretive process.

This holistic approach enables the transformation of multidimensional data into meaningful, patient-centered indicators of well-being. Importantly, HRSs in nursing should not merely process raw data but interpret it through clinically relevant and theory-driven lenses. For example: descriptive patterns in physical activity may trigger motivational peer stories, diagnostic inferences from mood data may lead to stress-management content, predictive frailty scores may initiate preventive health education, prescriptive analysis may prompt real-time referrals or symptom-guided interventions. As biosensors, AI algorithms, and mHealth applications increasingly permeate clinical and community care, the nursing discipline bears a critical responsibility to ensure ethical, valid, and human-centered interpretation.

Ultimately, accurate, context-aware collection and interpretation of multidimensional data is not only the analytical backbone of HRSs but also a moral imperative—ensuring recommendations are not only evidence-based but also equitable, relevant, and responsive to the lived realities of diverse patient populations.

Component II - Solution bank

The intelligent dimension constitutes the methodological core of the Digital Intelligent Precise Nursing Framework. It centers on the computational transformation of data into actionable, personalized health recommendations by leveraging AI, big data analytics, and algorithmic modeling. The solution bank is designed to integrate evidence-based nursing interventions, clinical practice guidelines, and standardized nursing terminologies (e.g., North American Nursing Diagnosis Association International nursing diagnoses, Nursing Interventions Classification interventions, Nursing Outcomes Classification outcomes). This ensures that the generation of care plans is grounded in established nursing taxonomies and can be systematically adapted to different patient groups. This component ensures precision, timeliness, and contextual sensitivity in nursing interventions, thereby enhancing clinical decision-making, behavior change, and outcome prediction.

Building upon existing digital health frameworks [41], the second component—solution bank—embodies a semantically structured, behaviorally informed, and dynamically adaptive content ecosystem. It supports diverse health goals by addressing users' medical conditions, emotional needs, behavioral patterns, and digital literacy levels via intuitive, accessible, and multimodal formats. These include text, video, animations, infographics, decision trees, hyperlinks, and real-time prompts, which accommodate varying learning preferences and facilitate equitable access—especially for populations with limited health literacy [42].

To comprehensively reflect its utility, the solution bank is structured across two axes: target users (patients or caregivers vs. nurses) and function types (educational vs. adaptive digital solutions). This results in four functional categories, each aligned with specific goals of health recommendation systems.

(1) Patient-facing or caregiver-facing educational solutions: enhancing health literacy and self-management.

These solutions offer accessible health content aimed at empowering patients with knowledge and self-care strategies: health education materials: disease knowledge, postoperative care, dietary advice, emotional regulation; symptom management guidance for pain, fatigue, nausea, insomnia, etc.; medication instructions, such as reminders, adverse effect alerts, auto-generated medication plans; lifestyle modification advice: sleep, exercise, nutrition, smoking/alcohol cessation; psychological support: mindfulness training, meditation videos, mood self-assessment tools; rehabilitation and care skills: exercise videos (e.g., stoma care, limb exercises); health assessment tools: screening for depression, pressure injuries, or nutritional risk; health service navigation: hospital wayfinding, referral suggestions, follow-up alerts; peer experience sharing: testimonials, group support, recovery stories.

(2) Patient-facing or caregiver-facing adaptive digital solutions: behaviorally adaptive and personalized interventions.

Driven by AI and behavioral modeling, this category delivers context-aware and dynamically personalized content [33, 43, 44]: proactive content recommendation based on interaction patterns and behavior prediction; stage-matched interventions tailored to motivational readiness (e.g., vaccine uptake, exercise adherence); real-time prompts and nudges triggered by wearable or app-tracked data; personalization engines that adapt to evolving preferences and digital literacy levels.

(3) Nurse-facing educational solutions: supporting clinical competence and practice consistency.

Designed for professional development and clinical workflow optimization, these resources assist nurses in delivering standardized and evidence-based care: nursing pathway templates based on diagnosis or surgical procedures; evidence updated notifications: guidelines, summaries, clinical tips; assessment tool recommendations: Numerical Rating Scale [45], Braden [46], Activities of Daily Living [47], and other validated scales; skill training modules: instructional videos, procedure checklists, documentation tutorials; case repositories: typical case reviews with intervention strategies; communication guidance: language prompts and strategies for difficult conversations [42].

(4) Nurse-facing adaptive digital solutions: intelligent support for decision-making and patient management.

These systems integrate advanced algorithms to assist in risk monitoring, patient stratification, and adaptive planning: real-time alerts for high-risk symptoms or deteriorating behavior patterns; adaptive care plan generation based on nursing diagnoses and patient data; prioritized patient lists informed by predictive analytics (e.g., fall risk, delirium); knowledge-graph-enabled reasoning to align patient conditions with optimal interventions [48, 49].

To ensure clinical relevance and safety, solution bank recommendations must be grounded in validated datasets and expert-developed ontologies. The realization of personalized content customization relies on user profiling and recommendation rule algorithms—such as deep neural network models and association rule mining—to deliver targeted content recommendation [20]. Iterative updates based on real-world feedback enhance adaptability. Additionally, human-in-the-loop mechanisms allow healthcare professionals to review or refine recommendations prior to deployment, addressing the limitations of algorithmic opacity, cold-start problems, and data sparsity.

As healthcare shifts toward decentralized care models—including telehealth, mHealth coaching, and home-based monitoring—the solution bank serves as a central vehicle for distributing personalized, scalable, and contextually relevant support [50]. It bridges the informational gap between users and providers, strengthens nurse-patient interactions, and promotes continuity of care across digital environments.

The solution bank embodies the nursing profession's commitment to personalized education, empowered participation, and equitable care delivery [51–53]. By structuring content around both user roles and intelligent functionalities, it forms a critical infrastructure for intelligent nursing systems—one that not only informs but actively transforms the digital health experience.

Inferential mechanism

Leveraging multidimensional data and the solution bank, recommendation engines transform complex user profiles into actionable health guidance through diverse inferential mechanisms. For example, collaborative filtering, content-based filtering, knowledge-based rules, association rules and hybrid models to match users with the most relevant resources. Inputs include medical history, psychosocial background, behavioral trends, treatment responses, device-tracked metrics [48] and so on, which derived from component I - multidimensional data. With the incorporation of knowledge graphs and semantic reasoning, the system enables more nuanced and individualized recommendations, as demonstrated in domains like HPV vaccination and dementia care [33, 48, 49]. Similarly, digital self-monitoring of symptoms or behaviors (e.g., ecological momentary assessments [EMA]) enables the collection of ecologically valid data on mental health outcomes and allows for more precise clinical assessments [54–57]. Based on multidimensional, real-time data streams from EMA (including emotional states, perceived stressors, coping strategies, and prior intervention engagement) and wearable sensors (e.g., heart rate variability, sleep patterns, activity levels), the system's inferential mechanism—tailored to the specific research problem—generates personalized JITAI/EMI content. This content dynamically adapts to users' contextual characteristics (e.g., time, location, social environment) [58, 59] and demographic profiles by incorporating gender-specific nuances: adjusting language framing (e.g., emphasizing communal vs. individual resilience), addressing stigma-related barriers, and prioritizing health concerns relevant to specific gender groups; accounting for age-related differences: modifying content complexity, example relevance (e.g., school vs. workplace stressors), and delivery formats (e.g., gamification for adolescents vs. structured guidance for older adults) [60].

This contextual and demographic adaptation aligns with JITAI's core principles of timely (intervening only when risk thresholds are met) and adaptive (tailoring to individual needs) interventions, aiming to reduce fatigue, improve engagement, and enable rigorous evaluation of effectiveness [61].

The Digital Intelligent Precise Nursing Framework embodies the core principles of JITAI. Unlike traditional approaches that demand participants modify their routines to fit rigid intervention schedules, this framework dynamically tailors support to individual needs and evolving contexts—ensuring timely and precisely dosed delivery of interventions. JITAIs in mHealth have demonstrated success across diverse public health applications, including physical activity promotion, mental health support, weight management, smoking cessation, and substance use reduction [60, 62]. For instance, Santa Maria et al. [63] tested the MY-RID JITAI in a randomized controlled trial, demonstrating its efficacy in fostering HIV risk reduction behaviors among homeless young adults.

Therefore, researchers can select diverse inferential approaches based on the specific demands of their research problems.

Component III- recommendation

The third component of the Digital Intelligent Precise Nursing Framework—Recommendation—corresponds to the intelligent and precision, which represents the framework's ultimate goal: to translate personalized insights into evidence-based, actionable guidance tailored to individual needs. This dimension emphasizes the alignment of nursing care with personal characteristics and continuously evolving health data, aiming to deliver optimized interventions at the right time, in the right form, and for the right individual.

As the operational culmination of the Digital Intelligent Precise Nursing Framework, the recommendation component synthesizes outputs from the first two dimensions—multidimensional data and the solution bank—into dynamic, user-centered inferential conclusions, supportive measures or plans, individualized action suggestions.

In this framework, recommendations are conceptualized not merely as digital prompts but as data-driven, individualized guidance that can span both digital and traditional care modalities. These may include lifestyle modifications, in-person consultations, or nurse-led behavioral counseling—any form of intervention that aligns with the user's clinical profile and contextual needs. Thus, the essence of precision lies not in the mode of delivery, but in the personalization and appropriateness of the intervention itself. The Digital Intelligent Precise Nursing Framework serves as an intelligent mediator that bridges digital and conventional care pathways, dynamically aligning recommendations with real-time patient data and clinical reasoning.

This approach has demonstrated utility across a range of chronic conditions, including diabetes, cardiovascular disease, cancer, and mental health disorders. Nurse-led digital interventions, in particular, have shown strong effectiveness across diverse clinical settings, reinforcing the role of nursing leadership in operationalizing intelligent and personalized care strategies [64, 65]. By integrating PGHD with evidence-based algorithms, the framework enhances the timeliness, accuracy, and responsiveness of care—thereby improving care continuity and overall outcomes.

The effectiveness of such digital interventions depends not only on data and algorithmic precision, but also on their theoretical underpinnings. Interventions grounded in behavior change theories—such as Social Cognitive Theory or Cognitive Behavioral Therapy—consistently demonstrate improved engagement and sustained behavior change [66, 67]. Features like goal setting, gamification, real-time feedback, and motivational prompts further support adherence, addressing common challenges in digital health implementation. In addition to promoting behavior change, recommendation systems are increasingly applied in symptom monitoring, emotional support, and shared decision-making. Through continuous data collection—via wearable devices, digital self-reports, or passive sensing — can adapt the content, intensity, or format of interventions, ensuring relevance as patient needs evolve.

The emergence of PGHD and real-world evidence has further transformed digital intervention into a participatory and co-creative process. Through wearable and sensor-based platforms, patients continuously contribute data—such as heart rate, physical activity, and symptom reports—which enables dynamic risk assessments and adaptive recommendation delivery [68, 69]. This feedback loop not only enhances the precision of interventions but also fosters patient empowerment and engagement.

However, the effectiveness of precision-driven recommendations in nursing practice depends on their usability, accessibility, and perceived relevance. Key influencing factors include digital literacy, age, socioeconomic status, and interface design [70]. To ensure equitable and sustainable implementation, it is critical to apply inclusive design principles, offer user-centered customization, and maintain human-in-the-loop mechanisms to support diverse populations.

In summary, "recommendation" plays a pivotal role in the Digital Intelligent Precise Nursing Framework. By translating individualized insights into high-quality, actionable care, this component moves HRSs beyond passive information delivery. It enables continuous, context-sensitive, and theory-informed engagement—driving meaningful behavioral and clinical outcomes and advancing the practice of intelligent nursing.

Integration and functional synergy of core components

The Digital Intelligent Precise Nursing Framework comprises three interrelated components—multidimensional data, solution bank, and recommendation—which align with the digital, intelligent, and precision dimensions. These components operate in a progressive and synergistic sequence: robust data provides the foundation; the solution bank is composed of health resources; and under the inferential mechanism, the recommendation component converts insights into actionable, context-specific care strategies. Collectively, they form a unified architecture that enables Health Recommender Systems to deliver intelligent, individualized, and evidence-based support within nursing practice.

Expert opinions from nursing education and clinical fields

To better engage the framework into the real world, we consulting the expert advisory, the three questions are about the suggestions to the whole framework, challenges in application in the real world, the feasibility and generalizability of the framework.

A total of 10 experts ultimately participated in the consultation, including 4 clinical nursing experts and 6 nursing education faculty members from higher education institutions. The experts were aged 32–55 years (mean ± SD: 38.20 ± 7.00). Their working experience ranged from 5 to 32 years (mean ± SD:12.10 ± 8.74), of which 9 experts had specialized experience in stoma care ranging from 1 to 30 years (mean ± SD:9.53 ± 10.00). In terms of educational background, one held a master's

Table 1 Characteristics of the consulting experts

Number	Age	Education level	Expert source	Years of working experience	HRS design experience	Title/Position
1	36	Doctorate	University Faculty	8	Yes	Associate Senior Title
2	33	Doctorate	University Faculty	5	Yes	Associate Research Fellow
3	41	Master	Clinical Nurse Specialist, Nursing Administrator	14	Yes	Associate Senior Title
4	37	Doctorate	University Faculty	12	Yes	Associate Research Fellow
5	32	Doctorate	University Faculty	6	Yes	Associate Senior Title
6	34	Doctorate	University Faculty	5	Yes	Intermediate Title
7	35	Doctorate	Clinical Nurse Specialist	10	Yes	Intermediate Title
8	44	Doctorate	Clinical Nurse Specialist, Nursing Administrator	22	Yes	Senior Title
9	55	Doctorate	Clinical Nurse Specialist, Nursing Administrator	32	Yes	Senior Title
10	36	Doctorate	University Faculty	8	Yes	Associate Senior Title

Fig. 4 Implementation guideline

degree and nine held doctoral degrees. Regarding professional titles, there were 2 with intermediate titles, 4 with associate senior titles, 2 with senior titles, and 2 young associate researchers. The detailed characteristics of the consulting experts are presented in Table 1.

The consulted experts generally agreed that the framework demonstrates strong innovativeness and feasibility in integrating nursing with digital intelligence, and that it can provide theoretical support for advancing the transformation of nursing practice. However, the experts also highlighted several limitations of the framework. First, it remains overly macro-level, lacking refined indicators and robust logical underpinnings. Second, some core concepts lack standardized terminology and clear definitions, which may hinder consistent understanding and application across different contexts. Third, the recommendation and inference mechanisms are still relatively abstract, with insufficient contextualization and personalization. Fourth, issues of multimodal data governance, security, and ethical compliance have not been adequately addressed. In addition, some experts emphasized that the framework lacks sufficient operability, as nursing professionals may encounter difficulties in comprehending specialized digital-intelligence terminology, thereby necessitating the development of more intuitive guidance tools.

Based on the above expert feedback, we developed an implementation guideline accompanied by illustrative cases to enhance the framework's practicality and scalability.

Implementation guideline

To enhance its adoption by interested nursing leaders, we develop the implementation guideline (Fig. 4.) and provide the example by applying the Digital Intelligent Precise Nursing Framework.

Step 1: Preparation.

1. Define objectives: clarify the ultimate goal and value of developing the recommendation system.

   Example: This study aims to develop a personalized education recommendation system for ostomy patients to enhance their self-management ability and adaptation.

2. Specify application scope: define the target population and application scenarios.

   Example: The system is designed primarily for ostomy patients living at home.

3. Establish a multidisciplinary team: form a cross-disciplinary development team, provide necessary training, and develop standardized terminology with unified core concepts.

   Example: The team consists of colorectal surgeons, nutrition specialists, IT and software engineers, clinical nursing experts (including stoma therapists), and nursing managers. The team should jointly define standardized terminology and core concepts for ostomy patient education to lay the foundation for system development.

Step 2: Project Design.

1. Establishment of a multimodal evaluation index system: on the premise of data availability and security, construct a multimodal assessment and indicator system based on relevant theoretical frameworks or models.

   Example: In developing the personalized education recommendation system for ostomy patients, the bio–psycho–social medical model is adopted to establish an indicator system across three dimensions:

• *Physiological: peristomal skin score, leakage, complications, comorbidity index, emergency visits.*

• *Psychological: anxiety and depression scales, self-efficacy scale, ostomy adjustment scale.*

• *Social: social support score, caregiver availability, healthcare accessibility (distance, cost, follow-up punctuality), participation in patient support groups, and return-to-work status.*

Each dimension can be synthesized into indices such as a Physiological Burden Index, Psychological Distress Index, and Social Support Index. Using unsupervised clustering, patients may be categorized into groups (e.g., ① low-risk/well-adapted; ② high physiological burden; ③ high psychological distress; ④ socially isolated; ⑤ globally high-risk). *These categories highlight significant differences in complications, educational needs, and self-management capacity, thus supporting stratified health education and intervention strategies.*

2. Solution Library Construction: Build a personalized education content library aligned with project goals.

   Example: The project will develop a knowledge base in illustrated formats covering key aspects of ostomy health education. Content will be validated through evidence-based retrieval, expert consultation, and patient participation to ensure scientific accuracy and authority.

3. Establishment of recommendation mechanisms: generate personalized recommendations by integrating multimodal assessment results with expert judgment, using suitable recommendation algorithms.

   Example: The project will adopt association rule-based recommendation to determine the frequency and content of educational materials for different patient groups, implemented through collaboration between software engineers and nursing researchers.

4. Determination of an evaluation index system: establish outcome measures aligned with project goals.

   Example: Indicators will include patient self-management ability, system usability, adherence, and satisfaction.

Step 3: Pilot Implementation.

Conduct small-scale pilot studies in tertiary hospitals with a high level of digitalization/intelligent infrastructure to test feasibility and effectiveness.

Example: This study will conduct a randomized controlled trial at the author's affiliated hospital as an initial validation.

Step 4: Evaluation and Optimization.

Engage approximately 10–15 users to test the system, collect application data and feedback, and refine the system through iterative optimization and upgrades.

Step 5: Promotion and Expansion.

Adopt a tiered promotion strategy by initially implementing the system in well-prepared institutions, followed by gradual expansion to additional healthcare settings, with the ultimate goal of establishing a widely applicable and scalable model for dissemination.

Application challenges of the framework

Based on expert feedback, the framework faces several challenges in real-world implementation. First, subsequent research should incorporate concept analysis of the framework's indicators. Second, the framework requires enrichment with concrete application cases to enhance its practical utility and relevance. Third, nursing professionals may encounter difficulties in understanding the specialized terminology related to digital intelligence, which increases the threshold for application.

In addition, mechanisms for personalized recommendation and context awareness require further refinement, while human–machine collaboration is constrained by issues such as data quality, information silos, high implementation costs, and limited digital literacy among nursing staff. Integration into existing nursing workflows also poses challenges, necessitating organizational readiness, adequate resource allocation, and continuous training to strengthen nurses' digital competencies. Variability in the level of digital infrastructure across healthcare institutions further restricts the framework's scalability. Finally, data security and ethical considerations remain potential risk factors that demand greater attention in future research.

Conclusion

In summary, the Digital Intelligent Precise Nursing Framework offers a robust framework for understanding, designing, and implementing health recommender systems in intelligent nursing. By structuring digital innovation around data accuracy, contextual awareness, and actionable intervention, this framework holds great potential for advancing personalized, equitable, and high-quality care in an increasingly complex healthcare landscape. Future research directions include piloting the framework in digitally advanced hospitals to evaluate its feasibility, as well as refining and optimizing the model through empirical validation.

Abbreviations

HRS(s)	Health recommender system(s)
HER(s)	Electronic health record(s)
PHR(s)	Personal health record(s)
RS(s)	Recommender system(s)
NSPH	Nursing Science Precision Health Model
AI	Artificial intelligence
PGHD	Patient-generated health data
EMA(s)	Ecological momentary assessment(s)
EMI(s)	Ecological momentary intervention(s)
JITAI(s)	Just-in-time adaptive intervention(s)

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Author contributions
Y.C. and KY.H. wrote the main manuscript text, prepared visualizations (Figs. 1, 2 and 3), performed formal analysis, and curated data. X.Z. contributed to methodology development, validation, and visualization preparation. Y.W. performed validation and formal analysis.C.Y. and J.Y. supervised the research, acquired funding, and contributed to conceptualization and methodology. All authors reviewed the manuscript.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
This study was conducted in accordance with the Declaration of Helsinki. The theoretical framework was developed through literature review and expert consultations, and the protocol which was approved by the Ethical Committee of School of nursing in Fudan University (Approval No.IRB # TYSQ 2023-2-5.) on March 8, 2023. Informed consent was obtained from all experts prior to their participation. All expert data were anonymized to ensure confidentiality.

Generative AI and AI-assisted technologies in the writing process
During the preparation of this work the authors used Chat-GPT4.0 in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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