

Advantages and challenges for utilization of generative artificial intelligence in clinical nursing practice: an integrative review

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Ga In Han, Hyeyeon Choi & Youn-Jung Son

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Title page

Advantages and challenges for utilization of generative artificial intelligence in clinical nursing practice: An integrative review

Ga In Han¹, Hyeyeon Choi², Youn-Jung Son^{3*}

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□ **Author information**

1. **Ga In Han**, RN, Doctoral student

Graduate school of Nursing, Chung-Ang University

84 Heukseok ro, Dongjak-gu, Seoul 06974, South Korea

Phone: +82-10-2364-5255 / ***Email:hangain079@gmail.com***

<https://orcid.org/0009-0000-0510-6136>

2. **Hyeyeon Choi**, RN, Master student

Department of Surgery Intensive Care Unit, Samsung Medical Center

81, Irwon-ro, Gangnam-gu, Seoul 06351, South Korea

Phone: +82-10-4947-3214 / ***Email:hyeyeon3214@gmail.com***

<https://orcid.org/0009-0007-0269-2767>

3*. **Youn-Jung Son**, Professor, PhD, RN, CCAPN (*Corresponding author)

Red Cross College of Nursing, Chung-Ang University

84 Heukseok ro, Dongjak-gu, Seoul 06974, South Korea

Phone: +82-2-820-5198 / ***Email:yjson@cau.ac.kr***

<https://orcid.org/0000-0002-0961-9606>

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Advantages and challenges for utilization of generative artificial intelligence in clinical nursing practice: An integrative review

Abstract

Background: Generative artificial intelligence (AI) has the potential to ease the administrative burden placed on nurses and to advance the quality and efficiency of care. Emerging nursing evidence suggests that increasing clinical complexity is associated with missed care, indicating that generative AI may play a role in supporting clinical judgment and streamlining nursing workflows. Despite these possibilities, its use within nursing area remains at an early developmental stage. This study aims to explore current applications of generative AI in clinical nursing, and to identify its advantages and challenges.

Methods: This integrative review followed the updated methodology of Whittemore and Knafl in 2005. Individual studies in this review were selected based on their relevance to the utilization of generative AI in clinical nursing practice. A literature search was conducted using PubMed, Cochrane, CINAHL, Web of Science, EMBASE, SCOPUS, and Google Scholar, covering the period from January 2000 to September 2025. A quality assessment was performed using a mixed-methods appraisal tool.

Results: The 15 included studies, which were published between 2023 and 2025, comprised randomized controlled trials, cross-sectional studies, qualitative studies, and mixed-methods studies. In clinical

nursing practice, generative AI is mainly utilized in three areas: clinical decision-making support, patient education and self-management support for chronic diseases, and efficiency of nursing work. The most common purpose of generative AI is to enhance nursing efficiency. ChatGPT is most frequently used in clinical decision-making support and enhancing nursing workflows, while task-oriented chatbots are primarily applied to patient education and self-management. Generative AI requires enhanced accuracy and reliability through continuous learning from new data, empathic conversations, and human interaction.

Conclusions: Our findings suggest that the use of generative AI in nursing practice has the potential to support clinical decision-making, educate patients and enable self-management, and improve nursing efficiency. By reducing documentation burdens, optimizing workflows and enabling personalized care, generative AI could enhance nursing practice. However, these findings should be interpreted cautiously given the heterogeneity of study designs and the predominantly exploratory nature of the available evidence. The integration of generative AI into nursing practice requires continued improvements in accuracy, reliability, empathic interaction and meaningful human involvement. These potential benefits can be realized by nurses, with appropriate competencies and a critical understanding of both the advantages and limitations of generative AI being fostered.

Keyword: Generative artificial intelligence; Hospitals; Nurses; Practical nursing; Review literature as topic

Background

Artificial intelligence (AI) encompasses computational systems capable of processing extensive datasets, recognizing patterns, and generating inferences to perform tasks typically carried out by humans [1]. Over the past decade, notable advances in AI have been achieved, with rapid growth in its applications to healthcare [2]. For example, AI-driven early warning systems can identify subtle physiological changes and support timely interventions, thereby improving patient outcomes and reducing risks such as diminished quality of life, hospital readmissions, and mortality [3,4].

In nursing, AI has evolved gradually alongside technological advances, initially supporting the analysis of clinical data and disease prediction [5-7]. More recently, its use has extended to domains central to nursing practice, including clinical decision support, patient education and self-management, and the coordination of administrative workflows [8], with emerging evidence suggesting that these applications may influence how nurses make clinical judgments, deliver patient education, and organize day-to-day care. A well-recognized example is the Rothman Index, an AI-based predictive tool integrating nursing assessment indicators with electronic health record data to identify patient deterioration risk [9,10]. Despite these contributions, conventional AI has shown limited capacity to deliver personalized, context-sensitive decision support, constraining its practical application in complex clinical settings [11-13].

To overcome these limitations, generative AI has recently gained attention, and interest in its application in the nursing field is growing [14,15]. Generative AI refers to systems designed not only to analyze data but also to generate novel outputs in text, image, voice, or video formats [16,17]. Unlike conventional AI that is confined to predictive tasks, generative AI can integrate heterogeneous data and synthesize new patterns through advanced deep learning architectures (e.g., generative adversarial networks, diffusion models, and large language models, LLMs) [18,19]. These advances allow generative AI to move beyond rule-based or task-specific approaches and synthesize novel, context-specific outputs [20,21]. While generative AI has been increasingly applied in diagnostics and treatment planning, its role in nursing remains exploratory and less clearly defined [22,23].

Nurses continue to face substantial workloads and time-intensive responsibilities, contributing to professional strain [24]. Although generative AI has the potential to automate repetitive tasks, assist decision-making, and improve workflow efficiency, empirical evidence guiding its implementation in clinical nursing practice remains limited [22,25,26]. Concerns regarding accuracy, reliability, and ethical implications further complicate its adoption [26,27]. Recent cross-sectional studies have shown that nurses' readiness for AI integration in clinical practice is accompanied by key concerns related to ethical issues, perceived barriers, and training needs [28]. These findings suggest that the evaluation of generative AI likewise needs to be grounded in nurses' professional perspectives and real-world clinical contexts.

This review defines generative AI as systems that can produce novel, open-ended outputs based on learned data distributions, such as large language models. Unlike previous scoping reviews, the focus of this review is on how these generative AI systems, which are distinct from rule-based or conventional AI, are being applied and evaluated in clinical nursing practice, and on the reported challenges and implications to date.

Methods

Study design

This review adhered to the updated methodology of Whitemore and Knafl [29], which comprises five systematic stages: problem identification, literature search, data quality appraisal, data analysis, and the presentation of findings. An integrative review was selected because research on generative AI in nursing is rapidly evolving and methodologically diverse. To enhance transparency, elements of the PRISMA 2020 statement were adapted for reporting [30], with non-applicable items retained in the checklist for completeness but not fully implemented. This approach aligns with recent integrative reviews that have incorporated PRISMA as a reporting aid while maintaining methodological coherence with the integrative framework [31,32]. Additionally, the review protocol was prospectively registered in the PROSPERO International database (CRD42024581809).

Search strategy and study selection

A comprehensive literature search was conducted using PubMed, Cochrane, CINAHL, Web of Science, EMBASE, SCOPUS, and Google Scholar. The initial searches were conducted in December 2024. Then, during February 2025, an updated search was performed using the same search strategy. This search strategy was developed using a concept-driven approach structured around three key domains: (1) generative AI technologies, (2) the nursing context and (3) clinical practice applications and outcomes. Within each domain, relevant synonyms and related terms were combined using Boolean 'OR' operators, and the domains were linked using 'AND' operators to ensure sensitivity and relevance. The same search terms were applied to Google Scholar, with results sorted based on relevance, and the first 52 records were screened.

Supplementary Table S1 provides detailed search strategies. During title/abstract and full-text screening, we distinguished studies on generative AI from those on non-generative or rule-based systems by examining the model description, AI-related keywords, and the methodological details reported in each article; studies classified as non-generative or rule-based were excluded.

Inclusion and exclusion criteria

This review considered English-language publications with full texts addressing the application of generative AI in clinical nursing practice (**Figure 1**). For this review, generative AI was defined as an AI model

capable of generating novel content (e.g., text or images) from learned data distributions, such as LLMs (e.g., ChatGPT and similar chatbots).

Since early studies in this emerging field did not consistently distinguish generative AI from other AI approaches using standardized terminology, the initial search employed a deliberately broad strategy. Terms such as “machine learning” and “deep learning,” combined with nursing- and clinical-context keywords, were included to capture early studies that did not explicitly identify their methods as generative AI. Studies were excluded if they were opinion pieces, conference abstracts, or other non-research papers, involved animal testing, or focused on techniques other than generative AI (e.g., conventional AI methods and non-generative machine learning models). The operational definition was applied consistently during title/abstract screening and full text review to determine study eligibility.

In total, 27,619 records were identified through database searches. After removing 8,286 duplicates, 19,333 records remained for title and abstract screening. Of these, 19,196 records were excluded at the title and abstract level because they were clearly unrelated to generative AI, did not pertain to the clinical nursing context, or were not original empirical studies. Consequently, 137 articles were selected for full-text assessment. Screening was conducted independently by two reviewers (GI and HY), followed by eligibility appraisal involving all authors. Discrepancies were resolved through discussion among three authors (GI, HY, and YJ). After full-text eligibility assessment, 122 studies were excluded for not meeting the predefined inclusion criteria, leaving

15 studies included in this integrative review. **Figure 1** shows the study selection process.

Data abstraction and synthesis

Data extraction was performed independently by two reviewers (GI and HY) using a standardized form developed by the author team. The form captured study characteristics, generative AI model type, clinical context, and reported outcomes, with predefined definitions and labels (**Supplementary Table S3**). Any discrepancies between reviewers were resolved through discussion; when consensus could not be reached, a third reviewer (YJ) adjudicated the final decision. Whitemore and Knafl [29] recommend using a systematic approach to analyze the relationships between studies when integrating research data. First, the main topics and findings of each study were categorized based on the extracted data, and recurring domains were identified. The data were then organized in Microsoft Excel to enable structured comparison across studies. A domain-oriented synthesis was performed to map the areas of utilization, as well as the advantages and challenges associated with generative AI in clinical nursing practice. Conclusions were derived from the integrated evidence, with coherence and accuracy maintained through ongoing cross-checking against the original data.

Quality appraisal

The outcomes of the quality appraisal are presented in **Supplementary Table S2**. For this review, study quality was evaluated using the Mixed Methods Appraisal Tool (MMAT), which provides criteria tailored to different designs, including qualitative studies, quantitative randomized controlled trials, quantitative non-randomized studies, quantitative descriptive studies, and mixed-methods research [33]. Two reviewers (GI and HY) independently applied the criteria to each study. Any discrepancies in scoring were resolved through discussion to reach consensus. Quality appraisal was conducted only for the included studies. Since the current evidence base predominantly consists of early exploratory studies with heterogeneous and evolving methodologies, all eligible studies were retained regardless of appraisal outcomes.

Results

Characteristics of included studies

The included studies provide early-stage evidence on the application of generative AI in nursing-related clinical settings and demonstrate substantial methodological heterogeneity (**Table 1**). Overall, the studies primarily focused on exploratory or short-term evaluations. Most were conducted in hospital-based settings, reflecting the current research emphasis on integrating generative AI into existing clinical workflows rather than in community-based or long-term care environments.

Across the included studies, generative AI was applied in diverse nursing practice domains, including patient education, mental health

support, nursing documentation, care planning, patient triage, and clinical decision-making. Intended users varied between patients and nurses, reflecting its deployment in patient-facing educational and clinician-facing support contexts. Notably, many studies focused on feasibility, acceptability, or usability outcomes rather than long-term clinical endpoints, indicating that research in this field remains at an early stage. Detailed characteristics of the randomized controlled trials—including intervention focus, target populations, and follow-up duration—are summarized in **Table 2**.

A diverse range of generative AI tools was employed, with some studies using multiple tools concurrently. This diversity reflects the rapid evolution of generative AI technologies and the current lack of standardization across interventions. Taken together, these characteristics suggest that existing research primarily focuses on proof-of-concept applications and short-term implementation outcomes, providing essential context for interpreting the findings synthesized in subsequent sections.

Domains of generative AI used and its advantages and challenges

The included studies demonstrate three primary domains of generative AI in clinical nursing practice: clinical decision-making support, patient education and self-management, and nursing workflow efficiency (**Table 3**). Nursing workflow efficiency was the most frequently reported

domain (n = 8, 53.3%), followed by clinical decision-making support (n = 4, 26.7%) and patient education and self-management (n = 3, 20.0%).

In this review, clinical decision-making support was defined as applications that help nurses assess patient status or determine appropriate interventions. Patient education and self-management support refer to tools that provide individualized information or coaching directly to patients. Nursing workflow efficiency encompasses systems primarily designed to reduce documentation burden, optimize workflows, or standardize nursing records and instructions.

Clinical decision-making support emerged as a domain in which generative AI was primarily applied in high-acuity settings requiring rapid assessment and protocol-driven responses, particularly emergency departments (EDs) and intensive care units (ICUs). Across studies, generative AI facilitated real-time patient monitoring, early detection of clinical deterioration, and prioritization of nursing interventions [34-37]. These findings were predominantly reported in studies of moderate methodological quality, and several reported limitations in contextual reasoning and clinical nuance [35-38]. Specifically, misclassification of patient severity was reported, with critically ill patients occasionally categorized as less severe, creating a potential risk of delayed intervention [34,35]. Across studies, generative AI functions as a decision-support tool, with clinical judgment remaining nurse-led.

Patient education and self-management support represent a distinct domain in which generative AI provides personalized information and coaching directly to patients, most commonly through conversational

chatbot systems. Several studies report that these tools complement traditional face-to-face patient education by offering continuous, individualized guidance after hospital discharge or treatment completion [38-40]. In clinical areas requiring long-term monitoring and intervention, such as postpartum depression, generative AI-based chatbots have been evaluated as effective tools that enhance accessibility through mobile applications and deliver evidence-based psychotherapeutic interventions [39]. While evidence consistently demonstrates improvements in the accessibility and personalization of patient education, conclusions regarding sustained clinical benefits remain limited. Most studies use exploratory designs, and the absence of long-term follow-up data constrains inferences regarding effectiveness, scalability, and ethical integration into routine clinical practice [38,39].

Nursing workflow efficiency is the most extensively reported domain, demonstrating relatively consistent findings across studies of varying methodological quality [41-45]. In this domain, generative AI primarily aims to reduce documentation burden through the automated generation of nursing records, care plans, and discharge instructions. Across multiple studies, these systems are reported to save time and improve the standardization of nursing documentation. Karacay et al. [37] report that generative AI could assist with specific tasks, such as pressure ulcer stage classification and wound management; however, final decision-making in more complex clinical situations remains dependent on the clinical judgement of the nurses. Several studies also report limitations in the accuracy, contextual relevance, and reliability of

generated content when applied to individual patient characteristics or rapidly changing clinical conditions, which are associated with risks of misclassification or overdiagnosis [37,46-48].

Discussion

Our integrative review reveals that generative AI has been applied across three primary domains of clinical nursing practice: clinical decision-making support, patient education and self-management, and nursing workflow. While conceptually distinct, these domains are closely interrelated in real-world clinical settings [49]. For example, generative AI supporting decision-making and documentation may indirectly enhance patient education and self-management by freeing up nurse time and cognitive resources, which, in turn, can influence the prioritization and delivery of nursing care [50,51].

Most studies included in this review are exploratory in design and demonstrate substantial methodological heterogeneity in study aims, implementation contexts, and outcome measures. Accordingly, rather than drawing confirmatory conclusions about the effectiveness of generative AI, the available evidence should be interpreted cautiously to understand how generative AI currently functions in nursing practice and the structural challenges and risks associated with its use [52]. Many generative AI systems continue to exhibit a “black box” nature, in which the rationale and reasoning processes underlying outputs are not clearly communicated to nurses or interprofessional health teams [52]. This

opacity may limit the ability of nurses to place clinical trust in AI-assisted recommendations and to explain or justify outputs to patients or colleagues [53]. Given that clinical judgment is a core component of professional nursing practice, the lack of explainability should be interpreted not merely as a technical limitation but as an issue directly related to nurse clinical accountability [54]. From this perspective, the opacity of generative AI is better understood not as an isolated system flaw but as an important context in which nurse clinical reasoning and cognitive judgment structures interact with and are reshaped by technology.

Generative AI hallucination has been identified as a factor that may pose direct risks to patient safety and clinical judgment in nursing practice [55,56]. In high-acuity environments such as ICUs and EDs, where time pressure and high-risk decision-making often coexist, inaccurate or fabricated AI-generated outputs may lead to delayed nursing interventions or inappropriate clinical decisions [55]. However, among the studies included in this review, no research systematically examined the frequency of hallucinations, their relationship to specific clinical contexts, or their effect on nursing task performance. This gap indicates that current evidence remains insufficient to adequately characterize or quantify safety-related risks associated with generative AI in clinical nursing settings [54,57].

This review also shows that generative AI has the potential to enhance nursing workflow efficiency by supporting nursing

documentation, information summarization, and other repetitive tasks. These efficiency gains may enable more time for direct patient care and therefore represent a positive opportunity for nursing practice [50,58]. Nevertheless, evidence supporting these efficiency improvements is largely based on short-term observations or exploratory evaluations, and connections to concrete clinical outcomes remain limited [59]. Patient education and self-management represent another important derivative domain of these changes. Generative AI has been explored as a complementary tool for nurse–patient communication, particularly in delivering repetitive or standardized educational content [58,59]. Several studies suggest that continuous access to AI-generated health information may reduce patient uncertainty and enhance understanding in chronic disease management [59,60,61]. These findings indicate potential benefits in improving the accessibility and consistency of patient education. At the same time, such approaches may inadequately capture the relational aspects of nursing practice, which require integrated consideration of patient comprehension, emotional responses, and lived contexts [55,59]. In complex or highly uncertain disease states, generative AI may fail to adequately account for individual patient circumstances or to clearly communicate information sources and reliability [55,56].

The technical limitations of generative AI repeatedly identified in this review can be broadly summarized as opacity, reliance on data and contextual constraints, and the risk of hallucinated outputs. These limitations should move beyond problem description and be translated

into concrete priorities for future research and technology design. Future studies should assess the scope and limits of generative AI contributions to nursing efficiency and patient education and self-management, and examine how these effects influence the quality and safety of nursing practice over time [56,59]. This will require an analysis of how generative AI intervenes in and shapes clinical reasoning and cognitive judgment of nurses. In addition, safety-focused empirical studies are needed to systematically evaluate the frequency of opaque or inaccurate outputs in real-world nursing practice and their clinical consequences [54,55,56]. Finally, design-oriented research on explainable AI is needed to develop more transparent and interpretable generative AI systems that can strengthen clinical trust of nurses in AI-assisted tools [53,62].

Overall, the findings of this review suggest that generative AI is an emerging and potentially transformative innovation in nursing practice, with applications spanning clinical decision support, patient education, and workflow efficiency. At the same time, significant methodological, technical, and ethical challenges remain. The current evidence base is largely exploratory and remains limited in its ability to balance assessments of benefits and risks associated with generative AI. Accordingly, generative AI should be positioned not as a replacement for professional nursing judgment but as a supportive technology, cautiously integrated within clearly defined role boundaries and human-centered collaborative structures. Future research should prioritize long-term, systematic evaluations in real-world clinical settings to identify

conditions under which generative AI can meaningfully enhance quality and safety in nursing practice.

Implication for nursing research and clinical practice

From a research perspective, this review identified recurrent limitations across the included studies, including insufficient accuracy, data bias, limited consideration of cultural diversity, and inadequate validation in real-world clinical settings. These issues were consistently reported in feasibility-focused and exploratory studies, highlighting the need for further international research to validate generative AI models and improve their generalizability prior to widespread clinical adoption [63,64]. Notably, only three studies included both hospital and community settings [38–40], indicating a lack of empirical evidence addressing transitional care. Future research should therefore prioritize generative AI applications that support continuity of care from hospital to home and reflect the needs of nurses across care settings. In addition, studies included in this review rarely reported robust clinical or patient-

centered outcomes, underscoring the need for future trials with adequate follow-up, transparent reporting of model characteristics, and mixed-methods designs that involve nurses and patients in development and evaluation.

From a clinical practice perspective, the findings of this review suggest that generative AI has primarily been explored as a supportive tool rather than a substitute for clinical judgment, reinforcing the central role of nurses in integrating AI with human-centered care. Studies frequently raised concerns regarding data privacy, ethical issues, and the reliability of AI-generated outputs [61,65], indicating that successful implementation will require clear governance structures, human verification processes, and competency-based training. At the individual level, nurses must be prepared to critically appraise AI-generated information, recognize potential biases, and communicate transparently with patients regarding the role and limitations of generative AI in clinical decision-making.

Strengths and limitations

This integrative review has several methodological strengths. First, a comprehensive, systematic search was conducted across multiple databases to capture the emerging literature on generative AI in clinical nursing practice. Second, a standardized data extraction framework enabled consistent comparison of study characteristics, types of

generative AI applications, and reported outcomes across heterogeneous study designs. Third, the integrative review approach allowed synthesis of evidence from diverse methodological traditions, providing a comprehensive overview of current research trends in this rapidly evolving field.

Nevertheless, some limitations should be acknowledged. First, the existing literature does not consistently distinguish between conventional AI and generative AI technologies in clinical nursing practice. Consequently, some relevant studies using generative AI may have been excluded due to the eligibility criteria. Second, while generative AI includes various modalities, the included studies predominantly focused on text-based technologies, so the findings may not fully reflect the acceptability or effectiveness of multimodal generative AI applications, such as image-based, voice-based, or interactive systems. Third, robust randomized controlled trials with long-term follow-up periods that evaluate generative AI across diverse clinical conditions and incorporate perspectives of nurses on sustained use remain scarce. In addition, most included studies focused on feasibility or perceived usefulness, with considerable variability in methodological rigor, limiting the strength of evidence synthesis. Furthermore, because this review included only English-language publications from selected databases, the possibility of publication or language bias cannot be excluded. Finally, given the rapid pace of generative AI development, the findings should be interpreted cautiously regarding their long-term applicability. Further validation

studies in real-world clinical environments across diverse healthcare settings are therefore warranted.

Conclusions

This integrative review identified three main domains of generative AI use in nursing practice:

clinical decision-making support, patient education and self-management, and efficiency of

nursing documentation. Across these domains, generative AI showed potential to reduce

documentation burden, assist in timely identification of high-risk patients, and provide

personalized health information, thereby augmenting both nurses' clinical work and patients

self-care. However, current evidence is constrained by important limitations. Generative AI

may misclassify patients in complex clinical contexts and generate biased or inaccurate

information, and most models remain insufficiently validated in real-world settings. In

addition, many included studies relied on relatively small and demographically restricted

samples—often older adults with specific conditions—which limits the generalizability of

these findings to broader and more diverse populations. Future research could further explore prospective, multi-site evaluations with transparent reporting of model characteristics, examine performance and acceptability across diverse user characteristics (e.g., age groups and levels of digital familiarity), and incorporate nurses' and patients' feedback into the refinement of generative AI tools.

By addressing methodological and ethical gaps, generative AI can progress from exploratory innovation toward safe and effective tools that enhance patient outcomes and strengthen nursing practice.

Abbreviations

AI: Artificial Intelligence

PRISMA: Preferred Reporting Items for Systematic Review and Meta-Analysis

MMAT: Mixed Methods Appraisal Tool

RCTs: Randomized Controlled Trials

ED: Emergency Departments

ICUs: Intensive Care Units

IRB: Institutional Review Board

Declarations

Clinical trial number: Not applicable

Ethics approval and consent to participate

This study was approved by the Institutional Review Board (IRB) of Chung Ang University (IRB No. 1041078-20240809-HR-210). The study was conducted in accordance with the Declaration of Helsinki. Consent to participate was not required, as this study did not involve human participants.

Consent for publication

Not applicable

Availability of data and materials

No datasets were generated or analyzed during the current study.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

GIH: Conceptualization, Data curation, Formal analysis, Investigation, Software, Validation, Writing – original draft, Writing – review & editing. **HYC:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **YJS:** Conceptualization, Formal analysis, Investigation, Funding acquisition, supervision, Writing – original draft, Writing – review & editing.

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Figure and Table Legends

Figure 1. PRISMA flow diagram of study selection process

Table 1 General characteristics and methodology of included studies

Table 2. Characteristics of RCT using generative AI

Table 3. Domains of generative AI used and its advantages and challenges in clinical nursing practice

Supplementary Table S1. Literature search strategy

Supplementary Table S2. Critical appraisal using MMAT checklist

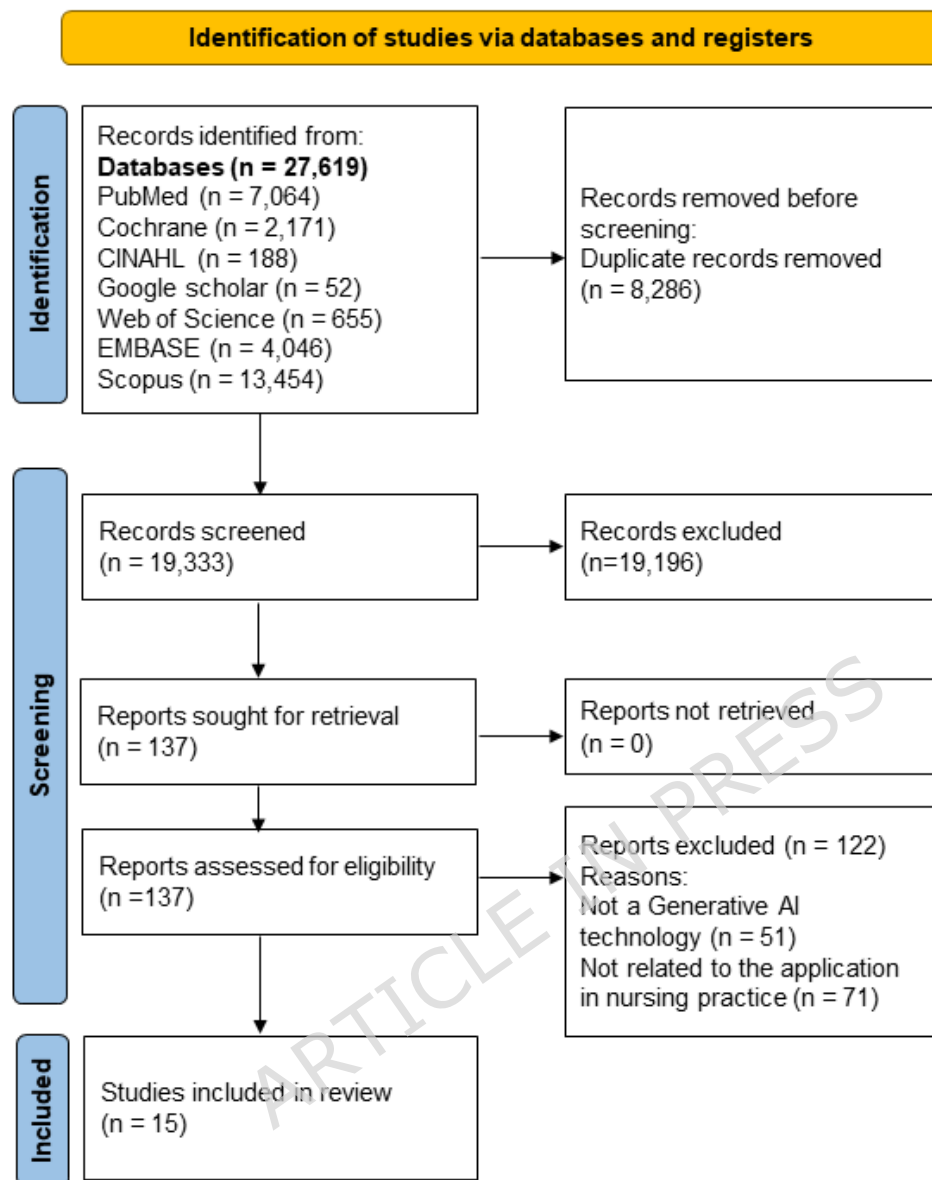


Figure 1. PRISMA flow diagram of study selection process.

Table 1. General characteristics and methodology of included studies ($N=15$)

Reference No	Author (year, Country)	Study aim	Study design	Study setting	Generative AI user	Generative AI tools	Application area	Results
[40]	Tawfik et al. (2023, Egypt)	To train cancer patients for self-management	Randomized controlled trial	Hospital & Community	Cancer patient	Chatbot	Patient education	ChemoFreeBot can improve self-care behavior and relieve symptoms through personalized learning.
[48]	Woodnutt et al. (2023, UK)	To develop mental health care plans	Qualitative case study	Hospital	Mentally health nurse	ChatGPT 3.5	Nursing care plans	ChatGPT produces patient empowerment in line with standard guidelines.
[39]	Suharwardy et al. (2023, US)	To manage postpartum women's moods	Randomized controlled trial	Hospital & Community	Postpartum patient	Chatbot	Mental health support	Text-based conversations allow you to track your mood at any time.
[38]	Cheng et al. (2023, Taiwan)	To train chronic disease patients for self-management	Cross-sectional study	Hospital & Community	PD patient	Chatbot	Patient education	Chatbots are more effective than traditional training methods that provide only one-sided knowledge.
[36]	Sheikh et al. (2024, US)	To manage CRRT alarms	Cross-sectional study	Hospital	ICU nurse	ChatGPT 3.5; ChatGPT 4	Nurse's decision-making	ChatGPT helps healthcare providers make informed decisions quickly and accurately.
[42]	Dos Santos et al. (2024, US)	To suggest nursing care plans	Qualitative case study	Hospital	Respiratory nurse	ChatGPT 3.5; ChatGPT 4	Nursing care plans	ChatGPT generated nursing care plans show potential as a decision support tool in cancer treatment.
[43]	Kim et al. (2024, Korea)	To evaluate nursing statements	Cross-sectional study	Hospital	Respiratory nurse	ChatGPT 4	Nursing statement	ChatGPT system performance has been inconsistent, and its high cost has limited its

								effectiveness for routine clinical use.
[35]	Levin et al. (2024, Israel)	To support patient assessment and decision-making	Mixed methods study	Hospital	ICU nurse	ChatGPT 4; Claude 2.0	Nurse's decision-making	LLMs are still limited in their ability to mimic human-like clinical reasoning.
[44]	Wan et al. (2024, China)	To support outpatient reception and admission	Randomized controlled trial	Hospital	Outpatient	Chatbot	Outpatient care	We received higher satisfaction feedback due to improved response quality.
[46]	Huang et al. (2024, US)	To provide discharge instructions.	Randomized controlled trial	Hospital	Outpatient	ChatGPT 4	Discharge education	LLM can improve the way personalized guidance is provided to patients.
[45]	Yahagi et al. (2024, Japan)	To educate and manage preoperative patient anxiety	Randomized controlled trial	Hospital	Preoperative patient	ChatGPT 3.5	Preoperative care	Anxiety decreased over time with GPT use.
[34]	Arslan et al. (2024, Turkey)	To provide preoperative education	Cross-sectional study	Hospital	ED patient	ChatGPT Plus; Copilot	Patient triage	The LLM outperformed traditional nurse triage in identifying acute patients.
[47]	Johnson et al. (2025, US)	To generate perinatal nursing care plans	Cross-sectional study	Hospital	Perinatal nurse	ChatGPT 4	Nursing care plans	ChatGPT can support perinatal nurses in developing care plans.
[37]	Karacay et al. (2025, Turkey)	To classify pressure injury stages	Cross-sectional study	Hospital	PI expert nurse	ChatGPT 4	Nurse's decision-making	Visual ChatGPT has limitations in unstageable and deep tissue pressure injuries.
[41]	Ju et al. (2025, Korea)	To evaluate nursing diagnosis and documentation	Cross-sectional study	Hospital	Clinical nurse	ChatGPT 4	Nursing diagnosis	ChatGPT significantly reduces the workload of nursing documentation and enhances efficiency.

Abbreviations: AI=Artificial intelligence; ChemoFreeBot= Chatbot created for self-education of breast cancer patients; Claude 2.0=Anthropic's conversational AI model; Copilot= AI assistant developed in collaboration with Microsoft and OpenAI; CRRT= Continuous Renal Replacement Therapy; ED= Emergency Department; GPT = Generative Pre-trained Transformer; ICU=Intensive

Care Unit; User are affected by the use of Generative AI technology; LLM= Large Language Model; PD= Peritoneal Dialysis; PI= Pressure injuries

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Table 2. Characteristics of RCT using generative AI ($N=5$)

Author (year, country)	Participants /Age (year)	Generative AI-Developers	Intervention group (n)	Control group (n)	Follow up period	Main findings
Tawfik et al. (2023, Egypt) [40]	Breast cancer women/ Age:>20	Microsoft team	ChemoFreeBot-based education (n=50)	Nurse-led education (n=50) and Usual care (n=50)	12 months	□ Women in the ChemoFreeBot group experienced a statistically significant less frequent, less severe and less distressing physical and psychological symptoms and higher effective self-care behaviors than those in the nurse-led education and routine care groups.
Suharwardy et al. (2023, USA) [39]	Postpartum women/ Age:>18	Woebot Health team	Woebot-based psychological counseling management (n=68)	Usual care (n=84)	5 months	□ At 6 weeks after intervention, the chatbot group showed a significantly greater decrease in PHQ-9 scores, while EPDS and GAD-7 scores remained unchanged. □ Chatbot use resulted in 91% satisfaction.
Wan et al. (China, 2024) [44]	Outpatients/ Age:20~60	Yantian Hospital research team	SSPEC based outpatient reception (n=1,080)	Usual care (n=1,084)	1 month	□ Large-scale language model (LLM)-assisted nurse-assisted admissions model was effective in increasing patient satisfaction, reducing the rate of repeat Q&R ($p < 0.001$), and reducing negative emotions during the visit ($p < 0.001$).
Huang et al. (2024, USA) [46]	Outpatients/ Age:>18	Yale University research team	GPT based discharge instructions (n=83)	Usual care (n=73)	4 months	□ Patients rated discharge instructions generated from GPT as more understandable and satisfactory and had higher “agree” and “strongly agree” ratings for interpretability in subsections including diagnosis, procedures, treatments, post-ED medications or changes, and return-to-care measures.
Yahagi et al. (2024, Japan) [45]	General anesthetic patients/ Age:>20	Not reported	GPT based education (n=44)	Usual care (n=41)	14 months	□ Decreased STAI scores in the intervention group (vs remained stable in the control group) □ Satisfaction and perceptions of the relevance of the information varied across participants.

Abbreviations: AI=Artificial intelligence; CSQ= Client Satisfaction Questionnaire; ED= Emergency Department; EPDS= Edinburgh Postnatal Depression Scale; F= Mixed design Repeated Measures ANOVA test; GAD= Generalized Anxiety Disorder-7; PHQ-9= Patient Health Questionnaire-9; Q&R= queries and responses; SD= Standard Deviation; SSPEC= Site-specific prompt engineering chatbot; STAI= State-Trait Anxiety Inventory.

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Table 3. Domains of generative AI used and its advantages and challenges in clinical nursing practice ($N=15$)

Domain [Reference No.]	Generative AI- enabled applications	Advantages	Challenges
Clinical decision-making support [34,35,36,37]	• ChatGPT Plus • Claude 2.0 • Copilot • ChatGPT 3.5 • ChatGPT 4 • GPT on Poe • Visual ChatGPT	• ChatGPT helps healthcare providers make informed decisions quickly and accurately. • LLMs outperform traditional nurse-led triage systems in identifying high-risk patients. • Generative AI could address knowledge imbalances in clinical practice settings. • Generative AI provides standardized responses based on clinical protocols.	• Generative AI demonstrated the need for trustworthy performance and sufficient explainability to reliably triage emergency patients in complex clinical contexts. • Generative AI must achieve consistent diagnostic performance and adequate generalizability to reliably augment nurses' holistic clinical judgment in highly complex settings such as intensive care units. • Generative AI requires a high level of accuracy and consistency and must be safely integrated into real-world clinical workflows in patient safety-critical situations, such as responding to continuous renal replacement therapy (CRRT) alarms.
Patient education and self-management support [38,39,40]	• ChemoFree Bot • PD AI Chatbot • Woebot	• Generative AI can enhance patients' self-care behaviors and alleviate symptoms through personalized learning. • Chatbots offer a more interactive and adaptive approach to patient education compared to usual care methods. • Generative AI facilitates rapid access to medical and educational information.	• Generative AI must provide personalized information that accounts for individual patient conditions and levels of health literacy in chronic disease populations, while systematically preventing and monitoring the dissemination of inaccurate or overly simplified explanations.

			• Generative AI requires the accumulation of long-term data with sufficient follow-up periods and clinically meaningful outcome measures to demonstrate improvements in mental health symptoms among populations, such as postpartum women. • Generative AI needs to be designed and operationalized to reliably maintain patient-level personalization in chronic disease management, such that it can complement nurse-led face-to-face education or approach its effectiveness.
Efficiency of nursing work [41,42,43,44,45, 46,47,48]	• ChatGPT 3.5 • ChatGPT 4 • SSPEC • SmartENR AI	• Generative AI supports patient empowerment by reinforcing evidence-based guidelines. • Generative AI systems augment documentation workflows, reducing administrative burden. • Generative AI can manage complex health conditions more accurately and efficiently.	• Generative AI must generate nursing care plans and clinical documentation in alignment with standardized nursing terminologies and documentation conventions, and its applicability and safety in real-world clinical settings require thorough validation. • Generative AI should be operationalized to efficiently share repetitive tasks, such as outpatient registration, while clearly defining points for nursing intervention in exceptional or complex situations to ensure both patient experience and safety. • Generative AI requires further refinement to reliably reproduce effects comparable to face-to-face nurse-patient interactions in reducing preoperative anxiety and improving patient understanding.

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- Generative AI should reduce the burden of discharge documentation while providing patients with clearer and more consistent information, thereby minimizing negative perceptions resulting from inaccurate explanations or omissions of critical content.
 - Generative AI must be implemented with appropriate safeguards and mandatory expert review processes to ensure that core principles of mental health nursing-relationality, ethics, and safety-are not compromised.
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Abbreviations: AI=Artificial Intelligence; GPT on Poe= NLP-based GPT on Poe; LLM= Large Language Model.