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ARTIFICIAL INTELLIGENCE AND NURSING: CLINICAL APPLICATIONS, PATIENT SAFETY, HUMANIZATION, AND ETHICAL GOVERNANCE

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Abstract

Artificial intelligence (AI) is increasingly reshaping nursing practice by supporting clinical decision-making, patient monitoring, documentation, education, workflow management, and patient safety. This integrative literature review critically examines the principal applications, benefits, limitations, and ethical implications of AI in nursing, with emphasis on emergency triage, hospital data management, clinical decision support, humanized care, and safety governance. A structured search of PubMed/MEDLINE and major peer-reviewed journal platforms was conducted, prioritizing literature published from 2020 onward while retaining seminal works required for the theoretical framework. Peer-reviewed original studies, systematic and integrative reviews, umbrella reviews, and authoritative institutional guidance were considered. The evidence indicates that AI can improve risk stratification, early recognition of clinical deterioration, medication-safety processes, documentation quality, and access to simulation-based education. Nevertheless, the literature remains heterogeneous, and many applications lack prospective validation across diverse health systems and populations. Major concerns include algorithmic bias, privacy, opacity, automation bias, alert fatigue, unequal technological access, and unclear accountability. The findings support a human-in-the-loop model in which AI augments rather than replaces nursing judgment. Sustainable adoption therefore requires local validation, continuous performance monitoring, AI literacy, interdisciplinary

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governance, and explicit protection of patient autonomy and relational care. For Brazil, further multicenter research is needed to evaluate AI under the organizational, demographic, and infrastructural conditions of the Unified Health System. AI should ultimately be assessed not only by technical performance, but by its capacity to strengthen safe, equitable, evidence-based, and person-centered nursing care.

Keywords: artificial intelligence; nursing; clinical decision support; patient safety; health ethics

1. Introduction

Modern nursing has long combined observation, data, and relational care. Florence Nightingale's systematic use of health statistics is often cited as an early expression of evidence-informed nursing, while the later development of nursing informatics established digital information management as an important professional domain (Saba et al., 2015). The contemporary expansion of AI represents a further step in this trajectory because computational systems can now identify patterns in large clinical datasets, generate predictions, summarize records, and support decisions at the point of care (Topol, 2019).

Nursing is strategically positioned in this transition. Nurses maintain continuous contact with patients, coordinate care, document clinical changes, administer medications, educate patients and families, and frequently make time-sensitive judgments. Recent reviews describe applications of AI across patient monitoring, clinical decision support, education, workflow optimization, and documentation, while also emphasizing that implementation must remain aligned with professional accountability and patient-centered care (Hassanein et al., 2025; Wei et al., 2025).

The promise of AI is accompanied by important uncertainties. Performance reported in controlled datasets may not generalize to different hospitals or populations; biased

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training data can reproduce inequities; opaque models can weaken professional trust; and automation may shift attention away from the relational dimensions of care. These issues are particularly important in nursing because clinical judgment includes contextual, ethical, and interpersonal knowledge that is not reducible to statistical prediction (Rony et al., 2025; World Health Organization [WHO], 2021).

This review therefore examines how AI can support nursing without displacing the profession's clinical and human foundations. Its objective is to synthesize evidence concerning five interconnected domains: patient triage, hospital data management, clinical decision support, humanization of care, and patient safety. It also discusses implementation barriers, ethical governance, and implications for nursing education and professional development, with particular attention to the need for context-sensitive research in Brazil.

2. Literature Review

2.1 Theoretical and Epistemological Foundations

A pragmatic perspective is useful for examining AI in nursing because it evaluates knowledge according to its capacity to address practical problems while allowing quantitative, qualitative, and interpretive evidence to coexist. In applied health disciplines, this orientation is compatible with questions that involve both measurable outcomes and contextual meanings (Pretorius, 2024). AI outputs can be understood as one source of evidence within a broader clinical reasoning process rather than as self-sufficient knowledge.

Nursing theories reinforce this boundary. Watson's caring science places the interpersonal relationship, dignity, presence, and meaning of the caring encounter at the center of practice (Watson, 2008). Orem's self-care framework emphasizes patient agency and the nurse's role in supporting individuals when self-care capacity is

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insufficient (Orem, 2001). In both perspectives, technology is ethically acceptable when it strengthens care, autonomy, education, and safety rather than replacing human responsibility.

Technology adoption also depends on perceived usefulness, usability, compatibility with existing workflows, organizational support, and professional trust. These considerations help explain why technically accurate systems may still fail in practice. Contemporary nursing reviews repeatedly identify AI literacy, workflow integration, interdisciplinary participation, and ethical governance as prerequisites for sustainable adoption (El Arab et al., 2025a; Wei et al., 2025).

2.2 AI Concepts Relevant to Nursing

AI is an umbrella term for computational approaches designed to perform tasks associated with learning, prediction, classification, language processing, or decision support. Machine learning models learn statistical relationships from data; deep learning uses multilayer neural networks and is especially prominent in image, signal, and language analysis. Generative AI produces new text or other content from learned patterns. In clinical environments, these approaches can be embedded in electronic health records, monitoring platforms, documentation tools, virtual assistants, and clinical decision support systems (Topol, 2019; Wei et al., 2025).

A critical distinction is between decision support and autonomous decision-making. Clinical decision support systems (CDSS) organize patient information and produce alerts or recommendations, but professional users remain responsible for interpreting those outputs. This distinction is central to nursing because model predictions may be wrong, incomplete, or poorly calibrated to a specific patient. Explainable AI seeks to make model outputs more interpretable, although explanation alone does not eliminate bias or guarantee clinical validity (Chen et al., 2023; Payrovnaziri et al., 2020).

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2.3 AI in Triage and Emergency Nursing

Emergency triage traditionally relies on structured systems such as the Manchester Triage System, Emergency Severity Index, and Canadian Triage and Acuity Scale. Although these frameworks improve standardization, classification still depends on professional interpretation and can be affected by workload, incomplete information, and inter-rater variability. AI models have therefore been investigated as tools for predicting acuity, admission, critical illness, and time-sensitive conditions (El Arab & Al Moosa, 2025).

Evidence suggests that machine-learning approaches can improve risk stratification in selected settings, but superiority is not universal and performance depends on the population, outcome definition, and available variables. Natural-language processing has also been applied to emergency records to identify sepsis risk at triage (Brann et al., 2024). These tools are most defensible when they function as a second layer of assessment and when nurses can override recommendations on the basis of clinical evidence.

2.4 Hospital Data, Documentation, and Decision Support

Electronic health records create the data infrastructure on which many AI applications depend. Predictive models can combine vital signs, laboratory results, diagnoses, medications, and longitudinal documentation to estimate deterioration, readmission, or other adverse outcomes. CDSS can also flag medication interactions, allergies, and potentially unsafe doses. However, excessive or poorly targeted alerts may produce alert fatigue and undermine safety (Chen et al., 2023).

Generative AI has renewed interest in automated clinical documentation. Potential benefits include summarization, draft generation, and reduction of repetitive administrative work. Yet generated text can contain unsupported statements or omit

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clinically important details. Nursing documentation created with AI therefore requires professional verification, traceability, and clear institutional rules concerning authorship and accountability (Rony et al., 2025).

2.5 Humanization, Education, and Patient Safety

AI creates a paradox for humanized care. Automation may free time for direct patient interaction, but poorly designed digital workflows can increase screen time and fragment communication. Watson's caring framework is particularly relevant here because technical efficiency cannot substitute for presence, listening, empathy, and moral responsibility (Watson, 2008). Reviews of AI in nursing similarly argue that human-centered implementation should be treated as an outcome rather than an assumption (Rony et al., 2025).

In education, virtual simulation already has an established role in nursing training, and AI can expand scenario generation, adaptive feedback, and virtual-patient interaction. Systematic evidence supports virtual simulation as a useful educational strategy, while newer reviews emphasize the need to teach AI literacy, source verification, ethics, and critical appraisal alongside technical skills (El Arab et al., 2025b; Foronda et al., 2020).

Patient safety is among the most promising areas of application. AI-enabled CDSS, smart infusion systems, barcode workflows, and automated validation can create additional safety barriers. A 2025 systematic review reported reductions in medication errors across several technology-supported interventions, while stressing that nursing verification remains necessary (Alqaraleh et al., 2025). Predictive systems have also been studied for deterioration, pressure injury, falls, and other adverse outcomes (Mikkonen et al., 2026).

3. Methodology / Materials and Methods

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This study used an integrative literature review design with qualitative thematic synthesis. The design was selected because the topic spans clinical effectiveness, professional practice, education, ethics, and organizational implementation, and therefore requires evidence from heterogeneous study designs rather than a single intervention model.

A structured search was conducted using PubMed/MEDLINE and peer-reviewed journal platforms including Frontiers, JMIR, Wiley Online Library, and Elsevier/ScienceDirect. The search strategy combined controlled or platform-appropriate terms for artificial intelligence and machine learning with nursing and the review domains of triage and risk classification, clinical decision support and monitoring, documentation, patient safety, education, ethics, governance, and humanization. Publications from 2020 onward were prioritized; earlier seminal sources were retained when necessary for nursing theory, informatics history, and foundational concepts. The manuscript was updated to include relevant peer-reviewed publications available through 2026. The preserved review files do not contain an auditable contemporaneous log establishing the exact date of the final original search run; therefore, no unverifiable exact historical search date is claimed. The platform-specific search strings documented for reproducibility are provided in Appendix A.

Eligible sources included peer-reviewed original studies, systematic reviews, integrative reviews, umbrella reviews, and authoritative institutional guidance directly related to nursing practice, nursing education, clinical decision support, patient safety, or AI governance in health care. News reports, Wikipedia, commercial blogs, conference abstracts without full papers, and sources without clear academic or institutional provenance were excluded. Sources focused exclusively on medical diagnosis without a meaningful nursing component were also excluded from the thematic synthesis.

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3.1 Search Retrieval and Study-Selection Accounting

The original review files did not preserve a contemporaneous search log containing platform-level hit counts, duplicate-removal totals, stage-by-stage screening counts, or a verifiable final search date. These historical values cannot be recovered reliably from the manuscript, bibliography, or earlier versions and therefore are reported as NR (not recorded) rather than retrospectively estimated. The final analytical corpus can be audited directly from the retained bibliography and contains 12 analytical sources, while seven additional references are used only for theoretical, conceptual, historical, regulatory, or institutional framing. Supplementary Tables S1 and S2 distinguish the unavailable historical retrieval/screening counts from the auditable final corpus. Full numerical compliance with a PRISMA-style retrieval flow would require a documented rerun of every search and a new screening audit; no unverifiable numbers or dates were inserted for revision purposes.

Supplementary Table S1. Search retrieval accounting

Database / platform	Historical records retrieved	Documentation status
PubMed/MEDLINE	NR	Original platform-level hit count was not retained; no retrospective estimate was made.
Frontiers	NR	Original platform-level hit count was not retained; no retrospective estimate was made.
JMIR	NR	Original platform-level hit count was not retained; no retrospective estimate was made.

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Database / platform	Historical records retrieved	Documentation status
Wiley Online Library	NR	Original platform-level hit count was not retained; no retrospective estimate was made.
Elsevier/ScienceDirect	NR	Original platform-level hit count was not retained; no retrospective estimate was made.

Note. NR = not recorded. No numerical value was inferred or invented retrospectively.

Supplementary Table S2. Study-selection flow

Selection stage	Count	Documentation status
Records identified across all searched sources	NR	Historical retrieval total not retained.
Duplicate records removed	NR	Historical duplicate-removal total not retained; duplicates were checked manually as described below.
Records screened by title/abstract	NR	Historical title/abstract screening total not retained.
Records excluded after title/abstract screening	NR	Historical exclusion total at this stage not retained.
Full-text records assessed for eligibility	NR	Historical full-text assessment total not retained.
Full-text records excluded, with reasons	NR	Historical reason-specific exclusion counts not retained; exclusion categories are reported below.

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Selection stage	Count	Documentation status
Sources included in the final analytical corpus	12	Auditable final corpus established from the retained bibliography; seven additional contextual/theoretical sources are reported separately.

Note. NR = not recorded. The final analytical corpus (n = 12) is auditable from the retained bibliography, but historical retrieval and screening counts were not preserved. These values must not be reconstructed by estimation; a fully numerical flow can only be produced through a documented rerun and rescreening of the searches.

The included literature was read comparatively and organized into five analytical themes: (1) triage and risk classification; (2) hospital data and documentation; (3) clinical decision support and monitoring; (4) humanization and education; and (5) patient safety, ethics, and governance. Because this review did not involve human participants, identifiable patient data, or experimental intervention, institutional ethical approval and informed consent were not applicable.

Duplicate-removal procedure. The review was conducted by a single reviewer. After retrieval, records were consolidated for screening and duplicate references were identified by comparing bibliographic information, particularly title, author(s), publication year, journal or source, and DOI or other persistent identifier when available. Apparent duplicates were manually checked before removal so that different publications addressing the same topic were not incorrectly treated as duplicate records. Because the original search log did not preserve a numerical duplicate count, the number removed is reported as NR (not recorded) in the study-selection accounting rather than retrospectively estimated.

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Full-text exclusion reasons. Full-text eligibility assessment was performed by the same single reviewer. Articles were excluded at this stage when the full text showed that the central focus was not nursing practice or nursing education; the source did not address an AI-related application relevant to the review domains; the publication type did not meet the eligibility criteria (for example, editorial, conference abstract without a full paper, commercial or non-academic material); the full text was unavailable for adequate assessment; or the source did not provide sufficient academic or institutional provenance for inclusion. Sources focused exclusively on medical practice without a meaningful nursing component were also excluded. The original review records did not preserve the number excluded under each reason; therefore, reason-specific counts remain NR (not recorded) and are not reconstructed retrospectively.

Exact corpus size. A source-level audit of the bibliography identified 19 unique references in the manuscript. Twelve sources constitute the analytical evidence corpus because they directly synthesize or empirically examine AI-related clinical, educational, operational, safety, or decision-support applications relevant to the review. Seven additional sources are retained exclusively as theoretical, conceptual, historical, regulatory, or institutional context and are not counted as analytical evidence. Accordingly, the final analytical corpus is n = 12, while the complete manuscript evidence base contains 19 unique cited sources.

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Supplementary Table S3. Characteristics of the Analytical Evidence Corpus (n = 12)

Source	Country/context	Study type	Nursing domain	Population /setting	AI application	Main finding	Limitation	Evidence type
Alqaraleh et al. (2025)	Jordan / nursing perspective	Systematic review	Medication safety	Nursing/medication processes	AI integration for medication-error reduction	Synthesizes evidence on AI-supported medication-safety interventions and reports reductions in selected medication-error outcomes across included studies.	Review-level evidence; included studies were heterogeneous and further experimental validation is needed.	Secondary review
Chen et al. (2023)	General clinical context	Review	Clinical decision support	Health-care systems	Clinical decision support systems	Synthesizes opportunities and implementation challenges of CDSS.	Not nursing-specific and largely secondary evidence.	Secondary review
El Arab & Al Moosa (2025)	Emergency departments	Integrative systematic review	Triage	Emergency care	AI-supported emergency triage	Synthesizes evidence on AI-assisted risk classification and triage performance.	Heterogeneous models/settings and limited prospective validation.	Secondary review

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El Arab et al. (2025a)	International / nursing	Integrative review	Education, practice, workload	Nursing	Multiple AI applications in nursing	Integrates clinical, educational, workload, and professional-perception findings.	Broad heterogeneous evidence base; much evidence is non-longitudinal.	Secondary review
El Arab et al. (2025b)	International / nursing	Umbrella review	Education and practice	Nursing	AI in nursing education and practice	Synthesizes review-level evidence and highlights AI literacy and critical appraisal needs.	Dependent on quality and overlap of included reviews.	Review of reviews
Foronda et al. (2020)	Nursing education	Systematic review	Education	Nursing students / education	Virtual simulation	Supports virtual simulation as an established educational strategy relevant to AI-enabled simulation.	Evidence predates much current generative-AI use.	Secondary review
Hassanein et al. (2025)	International / nursing	Integrative review	Clinical and operational	Nursing	AI applications in nursing	Synthesizes clinical and operational applications, benefits, and implementation issues.	Heterogeneous study designs and implementation contexts.	Secondary review

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Brann et al. (2024)	Emergency department	Retrospective cohort study	Triage / early warning	ED patients	NLP-based sepsis prediction	Provides primary evidence for AI-supported sepsis prediction at triage.	Retrospective single-context validation; prospective generalizability remains uncertain.	Primary empirical
Mikkonen et al. (2026)	International / nursing	Systematic review	Clinical decision-making	Nurses / clinical settings	AI technologies supporting nursing decisions	Synthesizes AI applications supporting nurses' clinical decision-making and adverse-outcome prediction.	Evidence heterogeneity and varying validation maturity.	Secondary review
Payrovnazir i et al. (2020)	EHR / health care	Systematic scoping review	Explainability / CDSS	Clinical EHR settings	Explainable AI using real-world EHR data	Maps explainable-AI approaches and transparency issues relevant to clinical decision support.	Not nursing-specific; scoping design does not establish effectiveness.	Secondary review
Rony et al. (2025)	International / nursing	Umbrella review	Nursing care	Nursing	AI in nursing care	Synthesizes review-level evidence and emphasizes	Dependent on underlying reviews; limited	Review of reviews

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						human-centered implementation.	direct causal evidence.	
Wei et al. (2025)	International / nursing	Review	Multiple nursing domains	Nursing	AI applications, challenges, future directions	Summarizes current nursing applications and implementation challenges.	Broad narrative/review-level evidence; limited prospective validation.	Secondary review

Note. The analytical corpus excludes sources used solely for theoretical, conceptual, historical, regulatory, or institutional framing.

Supplementary Table S4. Contextual and Theoretical Sources Excluded from the Analytical Corpus (n = 7)

Source	Source role/type	Use in the manuscript
European Union (2016)	Regulatory document	Privacy/data protection (GDPR)
Orem (2001)	Nursing theory	Self-care framework
Pretorius (2024)	Methodological/conceptual source	Pragmatism and research paradigms
Saba et al. (2015)	Foundational book chapter	History of nursing informatics
Topol (2019)	Conceptual/perspective article	Human–AI convergence in medicine
Watson (2008)	Nursing theory	Caring science / humanization

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World Health Organization (2021)	Institutional guidance	Ethics and governance of AI for health

Evidence-source classification. The reviewed material was classified according to its methodological role before thematic synthesis. The analytical corpus (n = 12) comprises one primary empirical study, nine secondary review-level sources (systematic, integrative, scoping, or other reviews), and two umbrella reviews/reviews of reviews. These analytical sources were used to support claims regarding clinical applications, education, medication safety, triage, decision support, and implementation. Seven additional references were retained only for theoretical, conceptual, historical, regulatory, or institutional framing and were not treated as analytical evidence. In particular, Watson's caring science and Orem's self-care theory informed the nursing framework; the World Health Organization, European Union, and Brazilian LGPD sources informed ethical, governance, privacy, and regulatory discussion; and foundational or conceptual sources supported nursing informatics history, pragmatism, and human-AI framing. This separation prevents normative or contextual sources from being interpreted as empirical evidence of AI effectiveness.

Quality appraisal and evidence maturity. Because the corpus contains heterogeneous designs, methodological appraisal was structured by evidence type rather than by a single quantitative risk-of-bias score. Primary empirical studies were considered in relation to design, setting, validation approach, outcome definition, potential bias, external validity, and nursing relevance. Review-level sources were considered in relation to review design, transparency of the evidence synthesis, scope, heterogeneity, and the extent to which conclusions were supported by primary evidence. Umbrella reviews were additionally interpreted with caution because their conclusions depend on the quality and overlap of the underlying reviews. The

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appraisal is summarized in Supplementary Table S5 and is used to qualify the strength of claims throughout the synthesis.

Reviewer and coding process. All search management, duplicate checking, title/abstract screening, full-text eligibility assessment, source classification, data extraction, and qualitative thematic coding were performed by one reviewer. Themes were developed through iterative comparison of findings across the included sources and organized around the predefined review domains of triage and risk classification, clinical decision support and monitoring, documentation, patient safety, education, ethics, governance, and humanization. Because no second independent reviewer participated, inter-rater reliability statistics such as Cohen's kappa or Krippendorff's alpha are not applicable and were not calculated. The synthesis should therefore be interpreted as a single-reviewer interpretive thematic synthesis, and the absence of independent duplicate screening/coding is acknowledged as a methodological limitation. No second reviewer was retrospectively introduced for revision purposes; the methodological description reflects the process actually performed.

Inter-rater reliability. Inter-rater agreement was not calculated because study selection and thematic classification were conducted by one reviewer rather than by two or more independent coders. Consequently, Cohen's kappa, Krippendorff's alpha, and percentage agreement would not provide a valid measure for this review. This criterion is therefore not applicable to the completed review process and is reported transparently rather than retrospectively estimated.

Supplementary Table S5. Structured Quality Appraisal and Evidence-Maturity Assessment

Source	Evidence design	Appraisal considerations	Evidence maturity	Interpretive use

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Alqaraleh et al. (2025)	Systematic review	PRISMA-based review of 12 heterogeneous studies on medication-safety technologies; conclusions depend on underlying study quality and design diversity.	Moderate	Supports medication-safety synthesis as secondary evidence; causal claims remain constrained by the underlying studies.
Brann et al. (2024)	Retrospective cohort	Defined ED prediction task and real-world data; retrospective validation; prospective and cross-site validation remain limited.	Moderate	Primary evidence for AI-supported sepsis prediction at triage.
Chen et al. (2023)	Review	Broad CDSS synthesis; clinically relevant but not nursing-specific; conclusions depend on heterogeneous underlying evidence.	Moderate	Context for CDSS opportunities and implementation challenges.
El Arab & Al Moosa (2025)	Integrative systematic review	Focused emergency-triage synthesis; heterogeneous algorithms/settings ; limited prospective validation across contexts.	Moderate	Supports triage benefits and limitations.
El Arab et al. (2025a)	Integrative review	Broad nursing scope and multiple outcomes; heterogeneous designs and settings reduce direct comparability.	Moderate	Supports cross-domain nursing synthesis.

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El Arab et al. (2025b)	Umbrella review	High-level synthesis across reviews; dependent on quality and overlap of underlying reviews.	Moderate	Supports education/practice synthesis; not treated as direct causal evidence.
Foronda et al. (2020)	Systematic review	Established nursing simulation evidence; predates current generative-AI applications.	Moderate	Supports educational simulation background, not current AI effectiveness alone.
Hassanein et al. (2025)	Integrative review	Nursing-specific clinical/operational scope; heterogeneous source designs and implementation maturity.	Moderate	Supports clinical and operational application mapping.
Mikkonen et al. (2026)	Systematic review	Nursing decision-making focus; heterogeneous AI technologies and validation stages.	Moderate	Supports nursing clinical decision-making synthesis.
Payrovnaziri et al. (2020)	Systematic scoping review	Transparent mapping of explainable AI using EHR data; not nursing-specific and not designed to establish effectiveness.	Moderate	Supports explainability/transparency discussion.
Rony et al. (2025)	Umbrella review	Nursing-care focus; conclusions depend on included reviews and may contain evidence overlap.	Moderate	Supports high-level nursing-care synthesis with cautious inference.

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Wei et al. (2025)	Review	Broad overview of applications/challenges; limited capacity to establish comparative effectiveness or causality.	Emerging-to-moderate	Supports application and governance context; claims kept non-causal.

Note. Evidence maturity is a structured interpretive appraisal for this heterogeneous integrative review, not a pooled quantitative risk-of-bias score. Theoretical, regulatory, institutional, and foundational sources are excluded from this table because they are not part of the analytical evidence corpus.

4. Results

The literature converged on a consistent overall pattern: AI can improve information processing, risk recognition, documentation, and selected safety processes, but benefits are conditional on data quality, local validation, workflow design, and human supervision. The strongest nursing-specific evidence was found in decision support, early warning, medication safety, and educational applications, whereas evidence concerning long-term workforce effects and relational outcomes remains less mature (Hassanein et al., 2025; Mikkonen et al., 2026; Rony et al., 2025).

Table 1. Main AI applications identified in nursing practice

Application	Potential contribution	Required nursing role
Triage and risk prediction	Prioritization and earlier recognition of high-risk patients	Confirm clinical context and override unsafe classifications
Early warning systems	Detection of deterioration from longitudinal clinical data	Assess the patient and determine escalation
Care planning and CDSS	Organize evidence and support diagnoses/interventions	Individualize the plan and validate recommendations

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Documentation	Drafting, summarization, and standardization	Review accuracy and assume responsibility for the record
Education and simulation	Adaptive scenarios and feedback	Critically appraise generated content and evidence
Medication safety	Additional checks for dose, interaction, and administration risk	Maintain independent medication-safety verification

Note. Synthesized by the authors from the literature reviewed in this study.

4.1 Clinical Decision Support and Continuous Monitoring

AI-enhanced monitoring can combine vital signs, laboratory trends, and electronic-record variables to generate risk alerts. A systematic review of AI technologies supporting nurses' clinical decision-making found improvements in several outcomes, including faster escalation, improved documentation, better pressure-injury prevention, and improved performance in selected clinical tasks (Mikkonen et al., 2026). Machine-learning early-warning systems therefore appear capable of strengthening surveillance, although external validation and calibration remain essential.

The practical implication is not autonomous decision-making but augmented vigilance. Nurses remain responsible for bedside assessment, interpretation of atypical presentations, communication with the multidisciplinary team, and decisions about escalation. This human-in-the-loop model reduces the risk that an algorithm becomes an unchallengeable authority.

4.2 Triage and Flow Management

AI-supported triage can integrate demographic information, symptoms, vital signs, and clinical history to estimate acuity and downstream resource needs. The integrative systematic review by El Arab and Al Moosa (2025) found substantial interest in machine-learning triage, with potential gains in consistency and identification of high-

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acuity cases. However, false negatives, dataset bias, and local differences in emergency populations limit generalizability. Natural-language processing approaches to sepsis prediction illustrate how unstructured triage text can add predictive information, but they also require careful prospective validation (Brann et al., 2024).

4.3 Medication Safety and Adverse-Event Prevention

Medication-related AI and automation can provide dose checks, interaction warnings, barcode verification, and smart-pump safeguards. Alqaraleh et al. (2025) identified meaningful reductions in medication errors across nursing-related applications, including smart infusion technologies. Predictive analytics can also support prevention of pressure injuries and other adverse events (Mikkonen et al., 2026). The evidence nonetheless supports layered safety: technology, institutional protocols, and professional checking should operate together rather than sequentially replacing one another.

Table 2. Safety risks associated with AI and mitigation strategies

Risk	Possible consequence	Mitigation
False negative	Delayed recognition of clinical risk	Human review, local validation, sensitivity monitoring
False positive	Unnecessary alarms and alert fatigue	Threshold calibration and alert-priority governance
Algorithmic bias	Unequal performance across patient groups	Representative data and equity audits
Automation bias	Uncritical acceptance of recommendations	Training, override pathways, and accountability rules
Data/privacy failure	Loss of confidentiality or inappropriate secondary use	Data minimization, access controls, and governance

Note. Synthesized by the authors from the literature reviewed in this study.

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4.4 Alert Fatigue, Automation Bias, and Safety Governance

Alert fatigue and automation bias represent distinct but interacting safety mechanisms. High false-positive rates can expose nurses to excessive low-value alerts, increasing cognitive burden and the likelihood that clinically important warnings are dismissed. Conversely, false negatives may create false reassurance when a system fails to identify a deteriorating patient. Governance therefore requires explicit sensitivity/specificity trade-offs, locally calibrated alert thresholds, prioritization by clinical severity, and escalation rules for high-risk signals. Nurses must retain a visible override pathway when bedside findings conflict with an automated recommendation, and clinically significant overrides should be documentable so that recurrent model or workflow failures can be reviewed (Chen et al., 2023; Mikkonen et al., 2026).

Automation bias occurs when users give disproportionate weight to algorithmic recommendations despite contradictory clinical evidence. Mitigation requires training that treats AI outputs as contestable evidence, not authority; interface designs that avoid presenting predictions as definitive decisions; periodic review of false-positive and false-negative patterns; monitoring for performance drift after deployment; and multidisciplinary incident review when AI contributes to delayed escalation, inappropriate prioritization, or other safety events. Thresholds should be reassessed when patient populations, workflows, documentation practices, or model versions change. These mechanisms operationalize the human-in-the-loop principle by linking professional override to continuous institutional learning (World Health Organization, 2021; Wei et al., 2025).

Supplementary Table S6. Operational Controls for Alert Fatigue and Automation Bias

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Safety issue	Mechanism	Operational control	Nursing accountability / monitoring
False positives / alert fatigue	Excessive low-value alerts compete for attention.	Calibrate thresholds locally; tier alerts by severity; suppress redundant alerts.	Review alert burden, response patterns, and clinically important overrides at defined governance intervals.
False negatives	The model fails to identify a clinically important risk.	Monitor sensitivity and missed-event patterns; preserve independent bedside assessment and escalation.	Escalate on clinical findings even when the model is negative; include missed events in incident review.
Automation bias	Users over-rely on algorithmic recommendations.	Train staff to challenge outputs; avoid definitive interface wording; maintain accessible override pathways.	Document clinically significant overrides and rationale when required by institutional policy.
Threshold miscalibration	A threshold does not fit the local population or workflow.	Validate before deployment and recalibrate after meaningful population/workflow change.	Nurses participate in usability review and report recurrent inappropriate alerts.

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Model drift	Performance changes as data, practice, or populations evolve.	Track performance over time and reassess after model/data/workflow updates.	Report suspected degradation; governance team reviews trend and determines recalibration or suspension.
AI-related safety incident	AI output contributes to delay, inappropriate prioritization, or unsafe action.	Multidisciplinary incident review with traceable model version/output and workflow context.	Preserve professional escalation authority and feed lessons into training, thresholds, and deployment policy.

Note. Controls are synthesized from the safety, governance, and human-in-the-loop principles reviewed in this study. Monitoring frequency should be defined by institutional risk governance and intensified after deployment changes or safety signals.

4.5 Education and Professional Development

AI-supported simulation can provide repeatable scenarios, adaptive feedback, and opportunities to practice clinical reasoning without exposing patients to risk. Virtual simulation has a substantial evidence base in nursing education (Foronda et al., 2020), while contemporary umbrella reviews show growing interest in AI literacy and intelligent educational tools (El Arab et al., 2025b). A recurrent result across the literature is that digital competence must include critical appraisal: nurses need to recognize hallucinated or biased outputs, verify evidence, protect confidential information, and understand when AI should not be used.

4.6 Humanization and Relational Care

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The evidence does not support treating AI-generated conversational fluency as equivalent to clinical empathy. Relational nursing involves contextual understanding, nonverbal interpretation, continuity, accountability, and moral engagement. AI may indirectly strengthen humanization if it reduces low-value administrative work, but this benefit depends on whether saved time is actually redirected to patient care. Human-centered implementation therefore requires explicit evaluation of patient experience, communication quality, autonomy, and accessibility in addition to technical performance (Rony et al., 2025; Watson, 2008).

Table 3. Digital competencies for nursing in the AI era

Competency	Practical application
AI literacy	Understand capabilities, limitations, and common failure modes
Critical data interpretation	Interpret predictions without abandoning clinical context
Ethics and privacy	Protect sensitive data and recognize inequitable outputs
Human supervision	Validate recommendations and identify model failure
Communication	Explain the role and limits of AI to patients and families
Quality improvement	Participate in monitoring, incident reporting, and model evaluation

Note. Synthesized by the authors from the literature reviewed in this study.

4.7 Operational Definition of Nursing Professional Judgment

For this review, nursing professional judgment is operationally defined as the accountable process through which the nurse integrates bedside assessment, prioritization of needs, contextual interpretation of clinical data, communication with patients and the multidisciplinary team, ethical reasoning, documentation, escalation of deterioration or safety concerns, and patient/family education to determine an

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appropriate nursing response. AI may support these functions by organizing data, identifying patterns, generating alerts, drafting documentation, or presenting recommendations; however, responsibility for validating the output against the patient's condition, deciding whether to accept or override it, communicating the decision, documenting the rationale when clinically relevant, and initiating escalation remains with the qualified professional. This operational boundary distinguishes computational support from professional accountability and makes nursing judgment observable through specific clinical activities rather than treating it as an abstract concept (Mikkonen et al., 2026; Rony et al., 2025).

4.8 Human-in-the-Loop AI Governance Model for Nursing Care

The thematic synthesis supports a human-in-the-loop governance model in which AI contributes information, predictions, or recommendations, but nursing professional judgment remains the mandatory interpretive and accountability layer before a clinical decision or action. Patient outcomes then feed post-deployment monitoring, incident review, recalibration, and governance. Safety, humanization, ethics, privacy, equity, accountability, transparency, local validation, professional override, and auditability operate across the entire pathway rather than as isolated technical requirements. This model integrates the review's clinical findings with Watson's caring perspective, Orem's emphasis on patient agency, and the ethical-governance principles discussed in the reviewed literature (Orem, 2001; Watson, 2008; World Health Organization, 2021).

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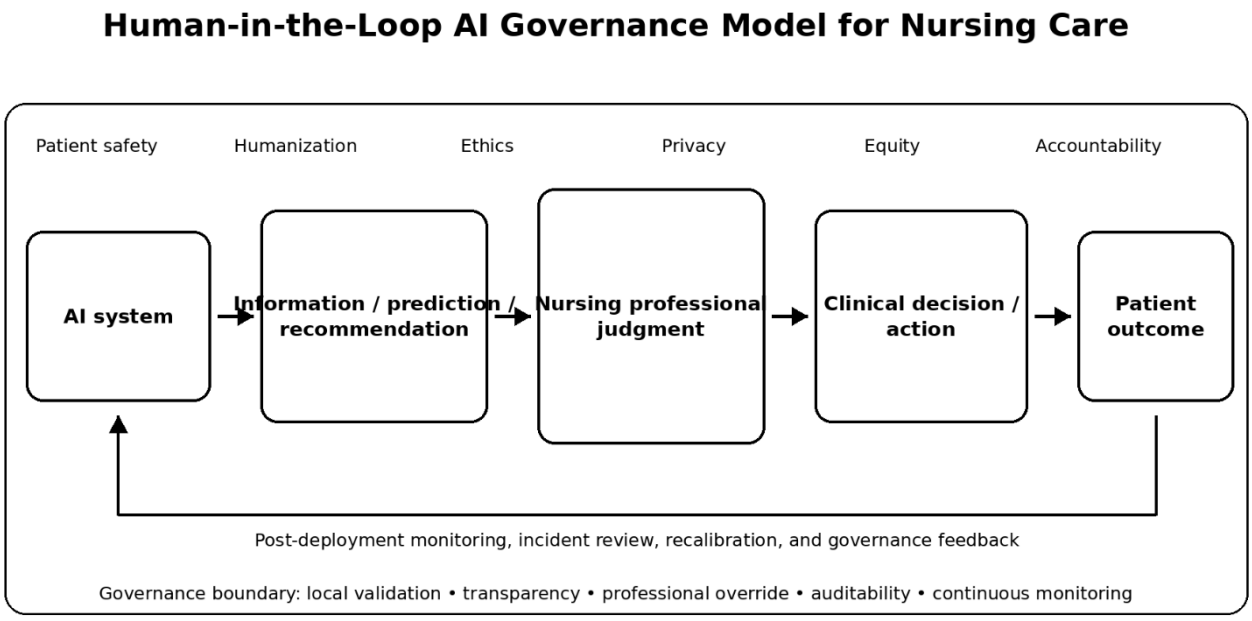

Figure 1. Human-in-the-Loop AI Governance Model for Nursing Care

Note. Conceptual synthesis developed from the evidence and theoretical framework reviewed in this study. AI = artificial intelligence.

5. Discussion

The synthesis indicates that the most appropriate role for AI in nursing is augmentation. Across triage, monitoring, documentation, medication safety, and education, the recurring advantage is computational scale: AI can process more variables, identify statistical patterns, and perform repetitive information tasks rapidly. The recurring limitation is contextual insufficiency: an algorithm does not independently possess the bedside knowledge, ethical responsibility, or relational understanding required for professional nursing judgment.

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This distinction helps reconcile technological innovation with nursing theory. Watson's emphasis on human caring and Orem's emphasis on patient agency do not require rejection of technology; rather, they establish criteria by which technology should be judged. A system that reduces documentation burden and increases meaningful patient contact may support caring practice. A system that obscures accountability, depersonalizes communication, or excludes vulnerable groups may undermine it even if its predictive accuracy is high (Orem, 2001; Watson, 2008).

The findings also reveal an evidence-quality problem. Recent reviews are encouraging, but many primary studies are retrospective, single-center, or focused on narrow technical outcomes. Mikkonen et al. (2026) found positive effects in experimental studies of nursing decision support, yet the number of eligible studies remained limited. Rony et al. (2025) similarly identified substantial promise alongside privacy, bias, literacy, and governance challenges. Consequently, claims of broad replacement of nursing work are not supported by the current evidence.

Implementation must therefore be treated as a sociotechnical process. A model may perform well statistically but fail because it generates too many alerts, does not fit nursing workflow, cannot explain clinically important outputs, or shifts responsibility without adequate authority. Nurses should participate in procurement, design, validation, deployment, and post-implementation monitoring because they understand both bedside workflow and the consequences of system failure (El Arab et al., 2025a; Wei et al., 2025).

Ethical governance is equally central. WHO guidance emphasizes autonomy, safety, transparency, accountability, inclusiveness, and sustainability in AI for health (WHO, 2021). In Europe, the General Data Protection Regulation establishes strong protections for personal data and data-subject rights (European Union, 2016). In nursing practice, these principles translate into data minimization, clear access rules,

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audit trails, patient information, bias monitoring, and defined escalation pathways when automated recommendations conflict with clinical assessment.

5.1 Brazilian Implementation Context: SUS, LGPD, and Health-System Heterogeneity

Brazil requires context-specific implementation because the Unified Health System (Sistema Único de Saúde, SUS) combines universal coverage with substantial heterogeneity in service capacity, digital infrastructure, staffing, interoperability, and local technological maturity. Evidence generated in high-income tertiary hospitals should therefore not be assumed to transfer directly to Brazilian primary care, emergency services, regional hospitals, or resource-constrained settings. Local and preferably multicenter validation should examine discrimination and calibration, subgroup performance, usability, workflow effects, alert burden, safety incidents, patient experience, and implementation costs before high-stakes deployment. Regional inequalities in connectivity, equipment, technical support, and workforce preparation also create an equity risk: an AI intervention that depends on infrastructure unavailable in less-resourced services may widen rather than reduce differences in access and quality.

Data governance must also be aligned with Brazil's Lei Geral de Proteção de Dados Pessoais (LGPD; Law No. 13,709/2018), particularly because health information is sensitive personal data. Institutions should define lawful and proportionate data use, access controls, security, traceability, retention practices, and responsibilities across data controllers, clinical services, technology suppliers, and professionals. Public and private institutions may differ in procurement capacity, infrastructure, staffing, and governance resources, but both require explicit accountability for AI-supported decisions and safeguards against secondary data use that is incompatible with the stated purpose.

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Workforce preparation is therefore a governance requirement rather than an optional educational benefit. Brazilian nurses should participate in procurement, workflow design, usability testing, local validation, deployment, incident review, and post-deployment monitoring. Training should include AI literacy, recognition of automation bias, privacy and data protection, interpretation of uncertainty, safe override and escalation, and communication with patients and families. A scalable Brazilian strategy is consequently not universal deployment of a model shown to work elsewhere, but staged adoption based on local validation, human-in-the-loop professional accountability, equity assessment, and continuous monitoring across the diversity of SUS and private-sector settings.

Table 4. Governance priorities for AI in nursing

Priority	Operational requirement	Responsible actor(s)	Evidence required	Monitoring frequency	Nursing accountability mechanism
Clinical validity	Prospective and local validation before high-stakes use.	Clinical governance; data/AI team; nursing leadership.	Discrimination, calibration, external/local validation, subgroup performance, workflow/usability evidence.	Before deployment; after major model/data/workflow changes; periodic risk-based review.	Nurses participate in validation and escalate discrepancies between model output and bedside assessment.

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Priority	Operational requirement	Responsible actor(s)	Evidence required	Monitoring frequency	Nursing accountability mechanism
Transparency	Document intended use, limitations, data sources, model/version history, and known failure modes.	Vendor/developer; information governance; clinical leadership.	Model documentation, intended-use statement, version/change log, explanation and audit records.	At procurement and deployment; review after each material update.	Nurses must be able to identify the tool/version used and document clinically relevant overrides or concerns.
Human oversight	Preserve professional override, escalation pathways, and non-AI alternatives for unsafe or uncertain outputs.	Nursing leadership; clinical governance; service managers.	Usability testing, override-pathway testing, escalation protocol, training records.	Continuous in clinical use; formal review after incidents or recurrent overrides.	Qualified nurses retain final responsibility for assessment, contextual interpretation, escalation, and action.

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Priority	Operational requirement	Responsible actor(s)	Evidence required	Monitoring frequency	Nursing accountability mechanism
Equity	Measure performance across demographic, clinical, geographic, and service subgroups.	Data/AI team; equity/quality committee; nursing representatives.	Subgroup sensitivity/specificity, calibration, error distribution, access and usability indicators.	Predeployment and periodically; intensified after population or workflow changes.	Nurses report recurrent subgroup-specific errors or access barriers and participate in equity review.
Privacy	Apply lawful, proportionate, secure, and purpose-limited processing of health data.	Data protection officer; information security; institutional governance.	Data-flow mapping, legal basis, access logs, security controls, retention rules, privacy impact assessment where applicable.	Continuous controls; scheduled audit; reassessment after material data-use changes.	Nurses follow minimum-necessary access, protect confidentiality, and report suspected inappropriate use or disclosure.

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Priority	Operational requirement	Responsible actor(s)	Evidence required	Monitoring frequency	Nursing accountability mechanism
Post-deployment monitoring	Track drift, incidents, false alerts, missed events, override patterns, and unintended workflow effects.	Clinical governance; quality/safety team; AI/data team; nursing leadership.	Performance dashboards, incident reports, alert burden, overrides, missed-event review, model/version traceability.	Continuous or scheduled risk-based monitoring; immediate review after safety signals.	Nurses report degradation and safety events, participate in incident review, and retain authority to escalate or suspend unsafe use through governance pathways.

Note. Governance roles and monitoring intervals should be adapted to institutional risk, local regulation, clinical setting, and model criticality. Nursing accountability remains centered on professional assessment, escalation, documentation, and participation in safety governance.

Supplementary Table S7. Evidence Maturity by Nursing AI Domain

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Domain	Evidence maturity	Basis for classification	Interpretive implication
Clinical decision support	Stronger	Multiple nursing-focused reviews and decision-support studies report benefits in selected clinical tasks, but validation remains heterogeneous.	Most defensible as decision augmentation with local validation and human oversight; not evidence for autonomous replacement.
Early warning / deterioration detection	Stronger	Predictive and monitoring applications are repeatedly represented in the reviewed evidence, including nursing decision-support synthesis.	Promising for surveillance and escalation support; calibration, missed-event review, and prospective local validation remain necessary.
Medication safety	Stronger	The corpus includes nursing-relevant evidence on medication-error reduction and technology-supported safety barriers.	Supports layered medication safety when professional checking remains independent and explicit.
Education and simulation	Moderate	Systematic and umbrella-review evidence supports virtual simulation and emerging AI literacy/educational applications, but much simulation evidence predates current generative AI.	Useful for training and adaptive learning, with source verification, ethics, and critical appraisal requirements.

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Domain	Evidence maturity	Basis for classification	Interpretive implication
Documentation / workflow support	Moderate	Review-level evidence identifies drafting, summarization, and workflow potential, but direct long-term nursing outcome evidence is limited.	May reduce repetitive work, but benefits should be measured with accuracy, workload, and time-allocation outcomes.
Humanization / relational care	Emerging	Current support is mainly theoretical or review-level; direct measures of empathy, patient experience, communication quality, autonomy, and relational outcomes are limited.	Claims should remain conditional; conversational fluency or automation-related time savings must not be treated as demonstrated humanization.
Workload redistribution / time redirected to care	Emerging	Reviews suggest potential efficiency gains, but evidence that saved time is consistently redirected to bedside care is limited.	Implementation studies should measure actual nursing workload, task redistribution, patient-contact time, and unintended digital burden.

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Domain	Evidence maturity	Basis for classification	Interpretive implication
Long-term workforce effects	Weak / insufficient	The reviewed corpus provides little longitudinal evidence on staffing, professional roles, deskilling, retention, or sustained organizational effects.	No strong conclusions about workforce replacement or long-term labor effects should be drawn from the current evidence base.

Note. Maturity categories are qualitative judgments based on the composition, consistency, directness, and validation maturity of the evidence synthesized in this integrative review. They are not pooled effect-size grades or formal GRADE ratings.

Domain-level evidence maturity. The corpus supports a differentiated interpretation rather than a uniform claim that AI improves nursing. Evidence is comparatively stronger for clinical decision support, early warning, and medication safety; moderate for education/simulation and documentation/workflow support; emerging for humanization and workload redistribution; and insufficient for firm conclusions about long-term workforce effects. This hierarchy is used to constrain the strength of claims in the discussion and conclusion and to distinguish technically promising applications from outcomes that remain largely theoretical or under-measured.

5.2 Empirical Evidence versus Theoretical and Normative Claims

Claims in this review were interpreted according to the evidentiary role of the source. Empirical claims about clinical performance, risk prediction, medication safety, education, workflow, or patient-safety outcomes were supported only by the analytical corpus, which consists of primary empirical or review-level evidence. Theoretical, historical, regulatory, and institutional sources were used to define

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professional values, ethical boundaries, governance duties, privacy principles, and conceptual interpretation; they were not treated as evidence that an AI intervention improves clinical outcomes.

This distinction is especially important for humanization. Watson's caring science and Orem's self-care framework provide a theoretical basis for interpreting dignity, presence, autonomy, agency, and relational responsibility, while WHO, GDPR, and LGPD materials provide normative and governance standards. However, the reviewed empirical literature contains limited direct measurement of empathy, patient experience, communication quality, autonomy, or sustained relational outcomes. Accordingly, statements that AI may support humanization are presented as conditional hypotheses or implementation goals, not as demonstrated effects. Evidence that automation saves time or that a conversational system produces fluent language is not treated as proof of more humanized nursing care.

5.3 Limitations of This Review

This review has limitations. It is an integrative synthesis rather than a meta-analysis, and the heterogeneity of technologies, outcomes, and clinical settings prevents direct quantitative comparison across all applications. The rapid pace of AI development also means that evidence may become outdated quickly. In addition, publication bias may favor successful implementations, and much of the available literature originates from technologically advanced health systems. These limitations reinforce the need for cautious interpretation and context-specific validation. In addition, all screening, eligibility assessment, source classification, data extraction, and thematic coding were conducted by a single reviewer; therefore, independent duplicate screening and inter-rater reliability assessment were not available, increasing the possibility of reviewer-dependent selection or interpretive bias. Accordingly, this work is explicitly classified as a single-reviewer interpretive thematic synthesis, which should be considered when

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assessing reproducibility of study selection and thematic interpretation. A further limitation is that the preserved historical search records do not contain platform-level retrieval counts, duplicate-removal totals, stage-specific screening and exclusion counts, reason-specific full-text exclusion totals, or an auditable exact date for the final original search run. Consequently, a complete numerical PRISMA-style flow cannot be reconstructed from the archived material without rerunning and rescreening the searches. The manuscript therefore reports these unavailable historical values as NR rather than estimating them retrospectively.

6. Conclusion

AI already has meaningful applications in nursing, particularly in triage, continuous monitoring, clinical decision support, documentation, education, and medication safety. Its most consistent contribution is the ability to organize large volumes of information and identify risk patterns that may support earlier and more standardized action. However, technical performance alone is insufficient to justify adoption.

Safe integration requires a human-in-the-loop model in which nurses retain authority and accountability for clinical interpretation. Institutions should combine local validation, privacy protection, bias auditing, clear responsibility structures, staff training, and continuous monitoring. Nursing education should incorporate AI literacy, evidence verification, data ethics, and communication about automated systems.

The future of nursing with AI is therefore better understood as professional transformation than professional replacement. Computational systems can extend information-processing capacity, while clinical judgment, empathy, ethical responsibility, and contextual understanding remain fundamentally human professional functions. In Brazil, further prospective and multicenter research is needed to determine how these technologies perform across the diversity of the Unified

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Health System. The guiding principle should remain clear: AI must serve care, safety, equity, and human dignity.

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Conflicts of Interest

The author declares no conflicts of interest.

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Appendix A. Search Strategy

The following strings document the platform-specific search strategy reported for this review and provide a reproducible basis for a future documented rerun. Because the contemporaneous historical search log was not preserved, these strings should not be interpreted as proof of a verifiable search run on a specific historical date.

Database / platform	Complete search string
PubMed/MEDLINE	(("Artificial Intelligence"[MeSH Terms] OR "artificial intelligence"[Title/Abstract] OR AI[Title/Abstract] OR "machine learning"[Title/Abstract]) AND ("Nursing"[MeSH Terms] OR nurs*[Title/Abstract]) AND (triage[Title/Abstract] OR "risk classification"[Title/Abstract] OR "clinical decision support"[Title/Abstract] OR monitoring[Title/Abstract] OR documentation[Title/Abstract] OR "patient safety"[Title/Abstract] OR education[Title/Abstract] OR ethics[Title/Abstract] OR governance[Title/Abstract] OR humanization[Title/Abstract] OR humanisation[Title/Abstract]))
Frontiers	("artificial intelligence" OR AI OR "machine learning") AND (nursing OR nurse OR nurses) AND (triage OR "risk classification" OR "clinical decision support" OR monitoring OR documentation OR "patient safety" OR education OR ethics OR governance OR humanization OR humanisation)
JMIR	("artificial intelligence" OR AI OR "machine learning") AND (nursing OR nurse OR nurses) AND (triage OR "risk classification" OR "clinical decision support" OR monitoring OR documentation OR "patient safety" OR education OR ethics OR governance OR humanization OR humanisation)
Wiley Online Library	("artificial intelligence" OR AI OR "machine learning") AND (nursing OR nurse OR nurses) AND (triage OR "risk classification" OR "clinical decision support" OR monitoring OR documentation OR "patient safety" OR education OR ethics OR governance OR humanization OR humanisation)
Elsevier/ScienceDirect	("artificial intelligence" OR AI OR "machine learning") AND (nursing OR nurse OR nurses) AND (triage OR "risk classification" OR "clinical decision support" OR monitoring OR documentation OR "patient safety" OR education OR ethics OR governance OR humanization OR humanisation)

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