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Artificial Intelligence and the Changing Role of Nurses in Clinical Decision-Making: A Narrative Review

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Abstract

Artificial intelligence (AI) is increasingly embedded in clinical decision support, early warning systems, documentation tools, and conversational agents, reshaping how nurses assess, prioritize, and act on patient information. This narrative review synthesizes literature published between 2017 and 2024 on AI and the changing role of nurses in clinical decision-making. Evidence was organized around four themes: applications of AI in nursing-relevant decisions, the evolving nursing role in human–AI collaboration, ethical and equity considerations, and implementation and governance. Findings indicate that AI-enabled deterioration and sepsis alerts can improve outcomes when nurses are central to the response workflow, yet poorly validated models, alert fatigue, and limited explainability undermine trust. Nurses increasingly act as interpreters, verifiers, and advocates rather than passive recipients of algorithmic output. Priorities include nurse participation in design, AI literacy, transparent governance, equity auditing, and rigorous evaluation of nursing-sensitive outcomes.

Keywords: artificial intelligence; nursing; clinical decision-making; clinical decision support; digital health ethics.

Introduction

Clinical decision-making is the core cognitive work of nursing. Every shift, nurses interpret streams of observations, recognize subtle change, decide whom to reassess first, judge when to escalate, and tailor education and support to individual patients. These decisions have traditionally relied on education, experience, intuition, and institutional protocols. Artificial intelligence now enters this space. AI can be understood broadly as computational systems that perform tasks historically associated with human intelligence, such as pattern recognition, prediction, and language processing, and it has moved rapidly from research laboratories into routine care (Topol, 2019). Early syntheses described applications in imaging, genetics, and the diagnosis and treatment of conditions such as stroke (Jiang et al., 2017). Subsequent work emphasized that advances in machine learning depend on large electronic datasets and computing capacity, and that these methods are most valuable when they augment rather than replace clinical judgment (Rajkomar et al., 2019). Commentators have also argued that AI is likely to automate many administrative and some analytic tasks, while the relational, ethical, and integrative work of clinicians will remain essential in most care contexts (Davenport & Kalakota, 2019).

Nurses are positioned at the point where much of this technology meets the patient. They form the largest segment of the health workforce in most countries, they are present around the clock, and they generate and act on the observations, such as vital signs, assessments, and symptom reports, that feed many algorithms. Predictive alerts, risk scores, and

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automated recommendations frequently reach the bedside nurse before any other clinician. Yet nurses have historically been underrepresented in the design, validation, and governance of these tools. A scoping review of the literature predicted that AI would influence all domains of nursing practice, including clinical care, administration, education, and research, while also drawing attention to the limited visibility of nursing perspectives in the AI literature (Buchanan et al., 2020). Descriptive accounts of the field have traced how AI is changing nursing work, from predictive analytics and virtual assistants to robotics and automated monitoring (Robert, 2019). Others have argued that the profession must proactively adapt to a digital future and claim a role in shaping it, rather than waiting to receive technologies designed without nursing input (Booth et al., 2021).

The international nursing community has begun to articulate priorities. An international think-tank of nursing informatics and AI leaders identified the need for nurses to participate in AI design and governance, for AI-related education across the career span, and for policy attention to the implications of AI for nursing practice (Ronquillo et al., 2021). At the same time, scholars have cautioned that technology should serve, not displace, the fundamentals of care, and that futurist enthusiasm needs to be balanced by attention to the relational essence of nursing (Archibald & Barnard, 2018).

Despite growing interest, the literature on AI and nursing decision-making is fragmented. Evidence is spread across informatics, nursing, medicine, ethics, and implementation science, and it spans technical validation studies, qualitative explorations, policy statements, and early implementation reports. There is a need to bring these strands together and to examine what is changing in the nursing role, not only what AI can do. The purpose of this narrative review is therefore threefold: (a) to describe the principal applications of AI that influence nursing clinical decisions; (b) to analyze how the nursing role is changing in relation to AI-supported decision-making; and (c) to identify ethical, equity, implementation, and educational considerations and research priorities. The review is intended for nurses, nurse leaders, educators, informaticists, and policymakers.

2. Methods

This article is a narrative review. Narrative reviews offer an interpretive and integrative synthesis of broad and heterogeneous literature and are suited to topics in which concepts, designs, and outcomes differ too widely for quantitative pooling (Sukhera, 2022). The topic of AI and nursing decision-making fits this description, because it combines technical, clinical, ethical, and organizational questions studied with very different methods.

A structured, non-exhaustive search was conducted in PubMed/MEDLINE, CINAHL, Embase, Scopus, IEEE Xplore, and Google Scholar for publications from January 2017 to December 2024. Search terms combined concepts for artificial intelligence (artificial intelligence, machine learning, deep learning, predictive analytics, large language model, clinical decision support), nursing (nurse, nursing, nursing informatics), and decision-making (clinical judgment, clinical decision-making, early warning, deterioration, sepsis, documentation). Reference lists of key reviews, position statements, and policy documents were also screened.

Publications were included if they addressed AI or machine-learning tools relevant to nursing decisions, nurses' experiences with or roles in relation to such tools, or ethical, regulatory, and implementation issues bearing on nursing practice. Systematic and scoping reviews, trials, implementation studies, qualitative studies, expert commentaries, reporting guidelines, and professional or international guidance were eligible. Purely technical papers without clinical relevance were excluded. Findings were organized thematically, and the strength of the evidence in each theme was appraised qualitatively, considering study design, real-world validation, consistency, and relevance to nursing practice. No formal risk-of-bias scoring or meta-analysis was undertaken, and the conclusions should be read as an expert synthesis rather than a quantitative estimate.

3. Conceptual Foundations

3.1 Nursing clinical decision-making

Nursing clinical judgment is commonly described as a cycle of recognizing cues, analyzing and interpreting them, prioritizing hypotheses, generating and taking action, and evaluating outcomes. The cycle is iterative and context dependent. A nurse noticing that a patient is slightly more restless than at the previous assessment, has a marginally faster respiratory rate, and looks "not quite right" is integrating quantitative and qualitative cues that may not yet cross any numeric threshold. This tacit, relational knowledge is a distinctive strength of experienced nurses and is difficult to encode in data. It is also exactly the kind of knowledge that algorithmic systems, trained on recorded and structured data, can overlook.

3.2 From rule-based decision support to machine learning

Clinical decision support has existed for decades in the form of rule-based alerts, order sets, and drug-interaction checks. An overview of clinical decision support systems describes both their benefits, such as improved guideline adherence and error reduction, and their risks, including excessive alerts, workflow disruption, and unintended consequences, and it emphasizes that success depends on usability, integration, and ongoing evaluation (Sutton et al., 2020). The era of AI adds a new layer. Machine-learning models learn patterns from data rather than following explicitly programmed rules, and they can generate probabilistic predictions from complex inputs. Commentators have noted that this shift raises

new demands for transparency, because clinicians must be able to understand and, where appropriate, explain the basis of a recommendation to patients and colleagues (Shortliffe & Sepúlveda, 2018). Deep-learning methods applied to electronic health record data can model longitudinal patient trajectories, free-text notes, and multimodal inputs, which creates opportunities for earlier detection but also dependence on the quality and completeness of documentation (Shickel et al., 2018).

For nursing, three kinds of AI matter most. Predictive models estimate risk, for example of deterioration, falls, pressure injury, or readmission. Language-based systems, including speech recognition and large language models, generate or summarize text. Perception and monitoring systems, including sensors and computer vision, observe patients or environments. Each type interacts differently with nursing judgment: predictive models propose priorities, language systems alter the burden and content of documentation and communication, and monitoring systems extend the nurse's senses.

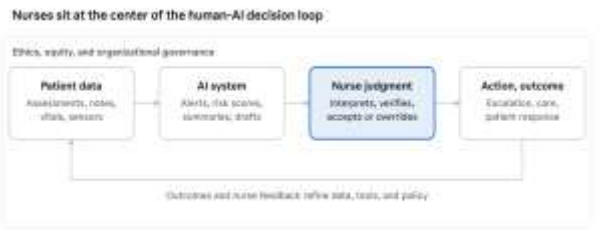
3.3 Technology and caring

A recurring theme in the nursing literature is that technological competence and caring are not opposed but intertwined. Pepito and Locsin (2019) argued that nurses can remain relevant in a technologically advanced future by integrating technological competency with caring as the expression of nursing's purpose, so that technology enhances the nurse's ability to know the person as a whole. This perspective frames AI as a tool that should free nurses for the human work that machines cannot perform, and it provides a normative standard against which AI implementations can be judged: does a given tool strengthen or weaken the nurse's capacity to know and care for the patient?

3.4 An organizing framework

To structure the review, a framework of human–AI collaborative decision-making in nursing is proposed. In this framework, patient data generated at the bedside and in the record feed AI systems, which produce outputs such as alerts, risk scores, summaries, or suggested actions. The nurse receives these outputs and, drawing on clinical context and knowledge of the patient, interprets, verifies, accepts, modifies, or overrides them before acting. The outcomes of those actions, and the nurse's feedback, return to the system and the organization, where governance, education, and monitoring shape the next cycle. Ethical, equity, and organizational conditions surround the loop. The framework is shown in Figure 1.

Figure 1. Framework of Human–AI Collaborative Decision-Making in Nursing Practice



4. Applications of AI in Nursing-Relevant Decisions

The applications of AI that bear on nursing decisions are diverse. This section examines three clusters: early warning and deterioration detection, documentation and language-based tools, and the broader landscape of nursing-focused AI studies. Table 1 summarizes the applications, the nursing decisions they touch, and their principal risks.

4.1 Early warning, deterioration, and sepsis

The most mature use of AI in inpatient nursing is the early identification of patients at risk of deterioration. Models continuously analyze vital signs, laboratory results, and other data to estimate the probability of events such as intensive care transfer, sepsis, or death. The evidence illustrates both promise and peril, and in each case the role of the nurse is decisive.

A large implementation across a hospital network used an automated model to identify adults at risk of in-hospital deterioration and routed alerts to remote nurses, who reviewed them and contacted the bedside team when appropriate. The program was associated with lower mortality, which shows that a prediction model coupled with a nurse-led human response can change outcomes (Escobar et al., 2020). Similarly, the implementation of a deep-learning sepsis detection tool in routine care depended on a sociotechnical design in which rapid response nurses took ownership of the alerts, engaged with the bedside team, and shaped how the information was presented and used. The authors emphasized that technical performance alone is not sufficient and that integration into clinical workflow and relationships is central (Sendak et al., 2020).

The peril is equally instructive. An external validation of a widely deployed proprietary sepsis prediction model found much poorer performance than that reported by its developer, with the tool missing a majority of sepsis cases while generating a large number of alerts (Wong et al., 2021). When tools of this kind reach the bedside, nurses absorb the cost of false alarms and the risk of missed warnings. A study of clinician perceptions of a machine-learning early warning system found that nurses and physicians questioned the credibility of alerts, wanted more actionable and interpretable information, and experienced alert burden as a barrier to use (Ginestra et al., 2019). Taken together, these studies show that the same technology can improve or degrade care depending on validation, workflow design, and the position of nurses within the response pathway. Figure

2 depicts a nurse-in-the-loop response to an AI-generated deterioration alert.

Figure 2. Nurse-in-the-Loop Response to an AI-Generated Deterioration Alert



4.2 Documentation, language models, and communication

Documentation consumes a considerable share of nursing time. A scoping review of studies that measured clinical documentation burden among physicians and nurses using electronic health records found substantial time spent on documentation tasks and considerable heterogeneity in how burden is measured, which complicates efforts to evaluate solutions (Moy et al., 2021). Language-based AI promises relief. Ambient AI scribes, which listen to clinical encounters and draft notes, have been evaluated in early deployments, where physician users reported a reduction in documentation burden; evidence specific to nursing workflows, however, remains sparse (Sezgin et al., 2023). Nurses engage in different forms of documentation than physicians, including flowsheets, care plans, handoff reports, and assessments, so tools cannot be assumed to transfer without adaptation.

Large language models extend the possibilities beyond transcription. A review of their use in medicine described applications in summarization, question answering, and patient communication, along with risks that include fabricated content, bias, privacy concerns, and the difficulty of verifying output (Thirunavukarasu et al., 2023). One widely discussed study found that evaluators rated chatbot responses to patient questions posted on a public forum as higher in quality and empathy than those written by physicians (Ayers et al., 2023). The finding is provocative for nursing because patient education, symptom triage, and emotional support are core nursing functions. It does not show that chatbots can replace nurses, since the comparison was made on text responses outside a care relationship and without accountability, but it signals that patients may increasingly encounter AI-generated advice and that nurses will need to help them interpret it.

4.3 The broader nursing AI evidence base

Several reviews have mapped the nursing-specific literature. A scoping review of the role of AI in enhancing clinical nursing care identified applications in assessment, prediction, monitoring, and workload management, and noted that many studies were at the stage of model development rather than clinical evaluation (Ng et al., 2022). A rapid review of application scenarios for AI in nursing care similarly described a wide range of potential uses, from care planning and documentation support to monitoring and robotics, while observing that the evidence of real-world benefit was limited (Seibert et al., 2021). A systematic review of AI in nursing and midwifery concluded that the evidence base was small and heterogeneous, concentrated in early-stage studies, and often lacking involvement of nurses in development and evaluation (O'Connor et al., 2023).

The pattern across these reviews is consistent. Interest is high, technical studies are plentiful, but rigorous evaluation of nursing-sensitive outcomes, such as failure to rescue, pressure injury, falls, patient experience, and nurse workload, is rare. This evidence gap is a major obstacle to responsible adoption, because decisions to purchase and deploy AI are being made in the absence of the outcome data that nurse leaders require.

Table 1. Applications of AI Relevant to Nursing Clinical Decisions

Application	Nursing decision supported	Typical nursing role	Representative evidence	Principal risk
Deterioration and sepsis early warning	Whom to reassess first and when to escalate	Reviews alert, verifies at the bedside, activates response	Alert-based program with nurse review associated with lower mortality (Escobar et al., 2020)	False alarms, missed cases, alert fatigue
Documentation and ambient scribes	What to record and how to summarize care	Reviews and corrects drafts, retains accountability for content	Early physician deployments report reduced burden (Sezgin et al., 2023)	Inaccurate or fabricated content, privacy
Risk prediction (falls, pressure injury, readmission)	Which patients need preventive interventions	Interprets risk score, individualizes the care plan	Mostly development-stage studies; see Section 4.3	Bias, over-reliance, limited outcome evidence

Conversational agents and patient-facing tools	How to educate, triage, and support patients	Helps patients interpret advice, escalates concerns	Evaluator ratings of chatbot answers; see Section 4.2	Misinformation, loss of relational care
Sensor and vision-based monitoring	Observation of movement, falls, and behavior	Responds to prompts, balances safety and dignity	Emerging; see Section 4.3	Surveillance concerns, consent, false alerts

5. The Changing Role of the Nurse in AI-Supported Decision-Making

5.1 From recipient to interpreter, verifier, and advocate

The introduction of AI does not eliminate nursing decision-making; it changes its structure. Nurses become interpreters who translate algorithmic output into the context of an individual patient, verifiers who check whether a recommendation fits what they see at the bedside, and advocates who speak for the patient when the algorithm is wrong, biased, or silent. Surveys and interviews with nursing professionals suggest a mix of optimism and apprehension. In one study, nurses anticipated gains in efficiency, accuracy, and time for patient care, but they also voiced concerns about privacy, job displacement, the erosion of human contact, and inadequate training (Rony et al., 2024). These findings echo the broader professional conversation and suggest that acceptance is conditional on the way AI is introduced.

The new role carries a paradox. As algorithms assume responsibility for pattern recognition in large datasets, the distinctive contribution of the nurse shifts toward what the algorithm cannot see: the patient's story, preferences, family context, subtle behavioral change, and values. At the same time, nurses must develop new competence in questioning data quality, recognizing model limits, and communicating uncertainty to patients and colleagues.

5.2 Trust, calibration, and explainability

Trust is central to effective human–AI collaboration, but more trust is not always better. A review of artificial intelligence and human trust in healthcare highlighted that clinicians' trust should be calibrated to the actual performance and limits of the system, since both undertrust and overtrust can harm patients, and that trust is shaped by transparency, reliability, and organizational context (Asan et al., 2020). Evidence from other clinical fields shows why calibration matters. In a study of human–computer collaboration for skin cancer recognition, AI support improved the accuracy of many clinicians, but incorrect AI advice could mislead them, and the benefit varied with experience and with the design of the interface (Tschandl et al., 2020). Although this study involved physicians, it is directly relevant to nurses, who also face the temptation to defer to a confident-looking output.

Explainability is one way to support calibrated trust. A study of what clinicians want from explainable machine learning concluded that needs depend on the clinical context, and that explanations are most useful when they help clinicians validate a model's output against clinical knowledge and decide on an action, rather than when they simply expose technical detail (Tonekaboni et al., 2019). For a nurse deciding whether to escalate a patient at the end of a long shift, a short, clinically meaningful explanation, such as which vital sign trends drove an alert, is more useful than an opaque score.

5.3 Alert fatigue and workload

Because nurses receive a high volume of alerts, the design of AI-enabled decision support has direct implications for cognitive load and safety. Research on clinical decision support has shown that workload, task complexity, and repeated alerts are associated with alert fatigue, in which clinicians become less likely to accept alerts as their number increases (Ancker et al., 2017). If AI simply multiplies alerts, it may increase rather than reduce the risk of missed warnings. The implication for nursing leaders is that AI deployment should be accompanied by deliberate alert governance: thresholds should be set with nurse input, alerts should be tiered by urgency, and the burden on nurses should be monitored as a safety metric.

5.4 Professional identity, autonomy, and accountability

As AI becomes embedded in decision support, questions arise about who is accountable when a nurse follows or overrides a recommendation. Professional norms hold that the nurse remains accountable for judgments made, which means that nurses need the authority to override algorithmic advice and the protection to do so without penalty. Equally, they need the opportunity to give feedback that improves the system. Where organizations pressure nurses to comply with algorithmic recommendations, professional autonomy is threatened, and so are patients. Preserving the nurse's role as a clinical decision-maker, not an operator of the algorithm, is therefore both an ethical and a safety requirement.

6. Ethics, Equity, and Governance

6.1 Bias and equity

AI systems learn from historical data, which reflect historical inequities. A landmark analysis of an algorithm widely used to guide care management found that it systematically underestimated the health needs of Black patients, because it used health care costs as a proxy for need, and unequal access to care meant that less had been spent on Black patients at the same level of illness (Obermeyer et al., 2019). The lesson for nursing is twofold. First, nurses should not

assume that algorithmic outputs are neutral. Second, nurses, who often see the consequences of structural inequity most directly, are well placed to detect when a tool performs differently for different groups. Early discussions of machine learning in health care warned that models can encode biases in training data and that ethical challenges, including transparency, consent, and fairness, need to be addressed before implementation (Char et al., 2018).

6.2 Ethical principles and professional accountability

A mapping review of the ethics of AI in health care identified recurring concerns about privacy, transparency, accountability, fairness, and the potential for harm, and noted that practical guidance on how to resolve these concerns lagged behind the proliferation of principles (Morley et al., 2021). The World Health Organization has issued guidance on the ethics and governance of AI for health that sets out principles including protecting human autonomy, promoting well-being and safety, ensuring transparency and explainability, fostering responsibility and accountability, ensuring inclusiveness and equity, and promoting responsive and sustainable AI (World Health Organization [WHO], 2021). Within nursing, the American Nurses Association (ANA) (Douthit et al., 2022) has stated that AI should support, and not replace, the relationships and judgment that define nursing, and that nurses remain accountable for their professional decisions when using AI-enabled tools. Such statements establish expectations: nurses must be able to understand enough of a tool to use it responsibly; patients should be informed when AI influences their care, and organizations must not use AI to erode safe staffing or professional discretion.

6.3 Governance

Governance determines whether AI is introduced safely. A proposed governance model for AI in health care emphasized the need for structures that address the whole lifecycle of a tool, from evaluation of need and validation, through deployment, to monitoring and decommissioning, with multidisciplinary oversight and clear accountability (Reddy et al., 2020). For nursing, this implies that nurses must have seats at the committees that select, validate, and monitor AI tools, and that governance must include mechanisms for frontline nurses to report problems and to see that reports lead to action. Figure 3 illustrates a lifecycle model of nurse-engaged AI governance.

Figure 3. Lifecycle of Nurse-Engaged Governance for AI in Clinical Practice



7. Implementation and Evaluation

Translating AI from promising prototype to improved care is difficult. A synthesis of the key challenges for delivering clinical impact with AI identified obstacles including the gap between technical performance and patient benefit, the difficulty of integrating tools into clinical workflow, the need for prospective evaluation, and uncertainty about regulation and liability (Kelly et al., 2019). These challenges are acutely relevant to nursing, where workflow is complex, interruptions are frequent, and technology has often been introduced without sufficient consultation.

A framework developed to explain the non-adoption, abandonment, and failure to scale and sustain health technologies offers a useful lens. It proposes that success depends on the interaction of multiple domains, including the condition, the technology, the value proposition, the adopters, the organization, the wider system, and change over time (Greenhalgh et al., 2017). Applied to AI, the framework warns against treating a model as a plug-in solution. A model that performs well in a validation study may fail in a unit where staffing, documentation habits, or the patient population differ. Implementation should therefore include local validation, co-design with the nurses who will use the tool, phased roll-out, and continuing evaluation.

Rigorous evaluation requires appropriate study designs and transparent reporting. Reporting guidance for clinical trials of AI interventions seeks to ensure that trial reports describe the AI intervention, the way it is integrated, the input data, and the handling of errors in sufficient detail to permit appraisal and replication (Liu et al., 2020). Updated guidance for reporting clinical prediction models that use machine learning promotes transparency about data, modeling, and performance, including fairness considerations (Collins et al., 2021). Nurse researchers and leaders can use these frameworks both to appraise vendor claims and to design their own evaluations.

Evaluation should also look beyond accuracy. A systematic review of the role of AI in patient safety outcomes concluded that AI has potential to improve safety, for example by supporting error detection and reducing adverse events, but that the evidence is uneven and that safety must be examined as an outcome, not assumed (Choudhury & Asan, 2020). For nursing, a balanced set of indicators would include patient outcomes, nursing-sensitive quality indicators, alert burden, time on documentation, nurse experience and moral distress, and equity measures stratified by patient characteristics. Without such measures, an AI program may seem successful by technical criteria while worsening the working conditions that sustain safe care.

8. Education, Competencies, and Workforce Implications

Preparing nurses for AI-supported practice requires changes in education and professional development.

Nursing curricula have traditionally given limited attention to data science, algorithmic reasoning, and the ethics of automated decision-making. Nurses do not need to become programmers, but they need enough literacy to ask critical questions of the tools they use: What data was the model trained on? In which populations has it been validated? What happens when it is wrong? Who is accountable? Table 2 outlines competencies that nurses and organizations should cultivate, mapped to the roles described in this review.

Table 2. Competencies and Responsibilities for Nurses and Organizations in AI-Supported Decision-Making

Nursing role	Core competencies	Organizational responsibility	Example of safe practice
Interpreter	Understanding model inputs, outputs, uncertainty, and limits	Provide plain-language documentation and training for each tool	Explains to a colleague why an alert fired and what it does not show
Verifier	Cross-checking alerts against bedside assessment and context	Protect time and authority to verify before acting	Reassesses a patient who is flagged low risk but looks unwell
Advocate	Recognizing bias, protecting patient preferences, raising concerns	Offer non-punitive reporting and visible follow-up on concerns	Reports that a tool performs poorly for a specific patient group
Communicator	Discussing AI use and uncertainty with patients and families	Set disclosure standards for AI-influenced care	Tells a patient that a recommendation came from an AI-supported tool
Co-designer and evaluator	Participating in selection, validation, and monitoring	Include nurses in governance committees and trial design	Joins a validation review before an alert is switched on
Learner and leader	Continuous learning, data literacy, and change leadership	Fund education and informatics career pathways	Leads a unit-level audit of alert burden

Workforce implications are significant. If AI reduces documentation and routine monitoring burden, nurses could reclaim time for direct patient care, but history suggests that efficiency gains are often absorbed by increased workload rather than reinvested in care. Nurse leaders and policymakers should therefore be explicit that any time savings should be protected for clinical and relational work, and they should monitor whether AI is being used to justify reductions in staffing. Equally, new roles are emerging, such as clinical informatics nurses, AI implementation specialists, and nurse data scientists, and career pathways should be developed so that these roles remain connected to clinical practice.

9. Limitations and Research Priorities

This review has limitations. As a narrative review, it is subject to selection bias, since the search was structured but not exhaustive and the quality of the included studies was appraised qualitatively. The field is changing quickly, and publications after 2024, including advances in large language models and ambient documentation, are outside its scope. Much of the evidence concerns physicians or mixed clinician groups, and extrapolation to nursing requires caution. Studies are concentrated in high-income settings, with well-resourced informatics infrastructure, which limits generalizability.

Several research priorities emerge. First, prospective and pragmatic studies should evaluate AI tools on nursing-sensitive outcomes, workload, and patient experience, not just model accuracy. Second, nurse-specific qualitative and mixed-methods research is needed to understand how nurses actually use, override, and adapt to AI recommendations, including the cognitive and emotional effects of working with algorithms. Third, equity audits should be a standard part of evaluation, with outcomes reported across race, ethnicity, language, age, disability, and socioeconomic groups. Fourth, research on explainability and interface design should be conducted with nurses in realistic clinical situations. Fifth, educational interventions to build AI literacy should be tested for their effect on safe and effective use. Sixth, studies of governance models should examine how nurse participation affects tool selection, safety, and sustainability. Finally, economic evaluations should consider the cost of nurse time, training, and monitoring, as well as potential savings.

10. Conclusion

Artificial intelligence is changing the context in which nurses make clinical decisions, but it is not replacing the need for nursing judgment. The evidence reviewed here suggests that AI can improve outcomes when it is validated, integrated into workflows, and paired with a skilled nursing response, and that it can cause harm when it is poorly validated, opaque, biased, or deployed without nurses' participation. The nursing role is evolving toward interpreting, verifying, and advocating within human–AI partnerships, and this evolution calls for new competencies, stronger governance, and rigorous evaluation. By taking an active role in design, validation, policy, and education,

nurses can ensure that AI strengthens the relational and ethical core of care rather than eroding it. The task for the profession is to move from being the recipients of technology to being its co-authors.

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