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HUMAN–AI COLLABORATION IN NURSING PRACTICE, EVALUATING THE IMPACT OF INTELLIGENT CLINICAL DECISION SUPPORT, AUTOMATED DOCUMENTATION, PREDICTIVE PATIENT MONITORING, AND AI-ASSISTED CARE PLANNING ON NURSING PERFORMANCE, PROFESSIONAL AUTONOMY, CLINICAL REASONING, AND PATIENT SAFETY

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Abstract

Abstract

The accelerated adoption of AI in nursing practice is a paradigmatic shift in the delivery of healthcare services, and intelligent systems are evolving from being a passive instrument of administration to an active cognitive agent in the 5IR healthcare system. We critically synthesize evidence across multiple domains to assess how four core AI types intelligent clinical decision support systems (CDSS), automated documentation through ambient clinical intelligence (ACI), predictive patient monitoring, and AI-assisted care planning affect nursing performance, professional autonomy, clinical reasoning, and patient safety. The results indicate that integration of the AI technology provides significant operational advantages, such as 28.8% to 30% reduction of time spent on documentation, 40% reductions in time taken for triage decisions, and 30% enhancement of efficiency in resource usage. But the positive effects of AI are balanced by profound cognitive and professional risks, including automation bias, cognitive deskilling, "never-skilling" of novice clinicians, and vigilance fatigue. The rise of the "liability sink"2 for algorithmic errors compounds asymmetrical legal risk as that algorithmic fallibility maps onto bedside nurses vicariously bearing the risk of algorithm errors absent corresponding administrative control. Moreover, patient and public safety and healthcare equity are at risk from algorithmic bias, hallucinations of large language models, and lack of adequate transparency. The GREAT PLEA system of nursing governance and participatory co-design processes provide avenues through which these risks may be addressed whilst

maintaining the person-centred heart of nursing. We propose that a way forward to maximizing human–AI collaboration in nursing is by implementing compulsory "AI-free" simulation training, adopting a reasoning-first pedagogy, designing transparent explainable interfaces in partnership with frontline nurses, and developing regulatory policies that clarify liability protections. In the absence of these protections, computational intelligence could undermine rather than augment clinical judgment, moral agency, and therapeutic presence the hallmarks of professional nursing practice.

1. INTRODUCTION

The modern healthcare ecosystem is undergoing a structural transformation. This transformation is marked by complexity that is rising patients who are increasingly acute severe shortages in the nursing workforce and widespread burnout among clinicians (Flores et al., 2013). In response to these pressures intelligence (AI) technologies are being quickly added to direct patient care workflows. Historically computational tools in settings acted as passive deterministic software that ran inside rigid electronic health record (EHR) systems (Aravazhi et al. 2025). However the rise of machine learning (ML) natural language processing (NLP) deep neural networks and generative artificial intelligence has sparked a shift toward Fifth Industrial Revolution (5IR) healthcare (Hirschberg & Manning 2015). Within this paradigm intelligent systems no longer serve only as administrative tools. Instead intelligent systems become cognitive partners and extensions of professional nursing practice (Wang et al. 2020).

Nursing practice is inherently sociotechnical. Nursing practice blends complex data interpretation with hands-on physical care, emotional presence and moral agency (Booth et al. 2016). The integration of AI across four functional areas—intelligent clinical decision support systems (CDSS) automated documentation through ambient clinical intelligence (ACI) predictive patient monitoring and AI-assisted care planning—completely changes how care is thought about delivered and assessed (Zhang et al. 2025). While technologies promise to boost efficiency lift burdens, sharpen diagnostic precision and reduce preventable clinical deterioration technologies also bring complex tensions around professional autonomy, cognitive deskilling, liability distribution and algorithmic bias (Lavoie-Gagne et al. 2025).

Understanding how human–AI collaboration affects nursing needs more than looking at technical speed or system accuracy. Human–AI collaboration requires a look at the cognitive, relational, legal and ethical mechanisms that guide human-machine interaction at the bedside (Rony et al., 2024). This review critically pulls together evidence, from fields to see how intelligent technologies influence nursing performance, professional autonomy, clinical reasoning and patient safety. This review also outlines the educational frameworks needed to keep nursing's humanistic core alive while using computational intelligence (Castro et al. 2023).



Figure 1: Multidimensional Framework of Artificial Intelligence Integration Across Professional Nursing Domains.

2. Typology and Operational Capabilities of Nursing AI Technologies

2.1 Intelligent Clinical Decision Support Systems (CDSS)

Today's AI-enabled CDSSs are a significant architectural departure from traditional deterministic alert-based rule sets. As a result of the integration of real-time multi-parameter human health data with machine learning algorithms and natural language processing, dynamic CDSS provide context-aware, personalized suggestions at the POC (Ouanes & Farhah, 2024). In critical care and acute care units, early detection of septic shock is facilitated by systems like InSight and the Epic Sepsis Model that utilize longitudinal EHR stream analytics (Papareddy et al., 2025). In mechanical ventilation, reinforcement learning for optimal lung protective ventilation with individualized oxygenation demand, and precision dosing algorithms for vasoactive agents and continuous sedatives in critical care are examples of such high dimensional challenges (Yousuf et al., 2026). Instead of static alerts, modern CDSS provide continuous risk-scoring dashboards and explainable interface designs that demonstrate parameter weighting and clinical rationale (Ikegwu et al., 2025).

2.2 Ambient Clinical Intelligence and Automated Documentation

Nurses now spend a large share of their working hours on paperwork, a burden linked to mental strain and staff turnover (Stults et al., 2025). Ambient Clinical Intelligence (ACI) uses voice recognition and language-processing tools to capture conversations between nurses and patients, then organize them into standard notes in the electronic health record (Hundal et al., 2025).

Studies suggest these tools can cut documentation time by about 29% to 30%, help clinicians finish notes 20% faster, and reduce charting after work by 30%. Early results have also shown a 40% drop in self-reported burnout among clinicians (Lim et al., 2025).

However, automation does not remove all the work; it changes what the work involves. Instead of entering information by hand, clinicians review and check what the system produces—a shift described as the "displacement-of-burden framework" (Sucharitrak, 2026). Whether this makes daily work easier depends on how usable and accurate the system is, and how much effort it takes to verify its notes (Dong et al., 2025).

2.3 Predictive Patient Monitoring and Early Warning Infrastructure

Predictive monitoring systems combine sophisticated algorithms with various sources of data such as continuous real-time telemetry, continuous physiological monitoring, and laboratory data to compute dynamic patient risk scores (Alam et al., 2020). As opposed to using individual vitals threshold-based alerts, which contribute to alarm fatigue then, predictive models evaluate hidden cross-parameter correlations to forecast possible clinical paths several hours prior. On a practical level, assessments indicate that predictive analytics monitoring enables the 30% more efficient utilization of clinical resources, such as triage and emergency nurses, and shortens the duration of triage decision-making by 40% through the reduction of the immediate cognitive decision burden on triage and emergency nurses (Pedersen et al., 2026). In the ICU, such algorithms integrate continuous hemodynamic data to predict acute kidney injury, respiratory failure, and cardiac arrest, redefining clinical care from reactive crisis management to proactive clinical stabilization (Boutin et al., 2026).

2.4 Generative AI and AI-Assisted Care Planning

Care planning is the theoretical link between nursing assessment and tailored nursing intervention. Platform for AI-enabled care planning make use of generative language models and predictive algorithms to evaluate patient history, social determinants of health (SDOH), comorbid conditions and evidence-based nursing interventions (Kitson, 2018). Such platforms take into account local resources and institutional policies to provide context aware, personalized nursing care plans (Ongenae et al., 2014) that may be adapted to a different care setting in the form of an established set of scenarios. AI care planners for scheduling interprofessional care coordination, by automating standardized nursing diagnoses, modify interventions and measurable patient outcomes, and ensuring that local care pathways continuously adjust to minute variations in patient condition (Chen et al., 2025).

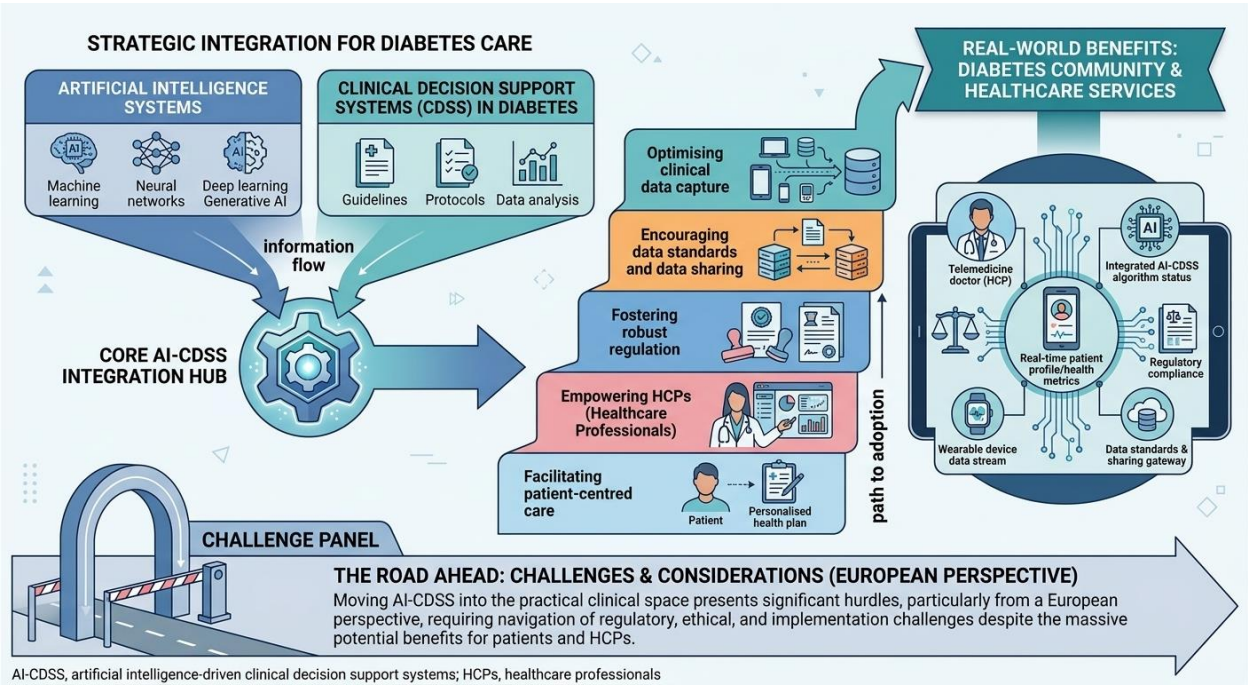


Figure 2: Strategic Architecture, Information Flow, and Implementation Pathways for AI-Driven Clinical Decision Support Systems (CDSS) in Diabetes Care.

Table 1 provides an architectural and operational comparison across these four primary AI implementation domains in professional nursing.

Technology Category	Core Underlying Architecture	Primary Clinical Applications	Quantitative Operational Impact Metrics	Key Workflow & Interface Integration Mechanisms
Intelligent Clinical Decision Support (CDSS)	Machine learning, NLP, reinforcement learning, deep neural networks.	Early sepsis detection, vasoactive medication titration, ventilator management.	Dynamic risk stratification; early intervention prior to clinical recognition.	EHR-integrated risk dashboards, interruptive pop-up alerts, explainable risk weighting.
Ambient Clinical Intelligence (ACI)	Ambient speech recognition, generative NLP, contextual text summarization.	Point-of-care nursing documentation, intake assessment, shift change handoff summaries.	28.8%–30% drop in charting time; 30% drop in after-hours charting; 40% burnout reduction.	Passive microphone capture, real-time draft generation, EHR field-mapping interfaces.
Predictive Patient Monitoring	Time-series deep learning, multi-parameter pattern recognition.	ICU deterioration tracking, triage risk scoring, cardiac arrest prediction.	30% increase in resource allocation efficiency; 40% reduction in triage time.	Continuous dashboard indicators, central monitoring station feeds, automated escalations.
AI-Assisted Care Planning	Large Language Models (LLMs), generative pattern analysis, clinical ontology mapping.	Individualized care plan assembly, interprofessional pathway alignment, localized constraint modeling.	Accelerated care plan formulation; enhanced standardization across shifts.	Interactive EHR care plan modules, automated nursing diagnosis suggestion feeds.

3. Impact on Nursing Performance and Workflow Dynamics

The integration of intelligence into nursing changes how performance works, moving the type of clinical productivity from doing physical tasks to doing mental control (Damarched, 2026). The main way of work that we see in cases is turning office work and data gathering into supervision. Gaining back hours that were spent on EHR charting gives nursing time for care at the bedside emotional help, teaching patients and engaging in therapy (Georgakopoulos et al., 1995). This time saving is very important in fields such as community health nursing and oncology navigation, where the therapeutic relationship and empathetic presence decide how well patients follow care and how good the results are (Avelino et al., 2025).

However, a deeper look shows that moving the task load does not always stop strain (Khan & Suhluli et al. 2025). According to the idea when AI does the first drafting tasks, such as writing nursing progress notes or making first care plans it creates a second mental job: supervision. Nurses must look over, check, change and approve AI outputs (Sucharitrak, 2026). If an AI system shows mistakes gives unclear summaries or works like a black box without clear clinical logic the mental effort of checking AI work can be as big as or bigger than doing the writing by hand (Kumar et al. 2026).

When supervision work is mixed with a lot of alerts from monitoring systems nurses feel heavy vigilance fatigue (Parasa, 2024). This mental state can cause two kinds of mistakes: alert suppression, where nurses

ignore the automated warnings because they see many wrong ones or passive checking, where tired nurses just approve unverified AI summaries (Van Der Sijs et al., 2009). For AI to bring performance benefits the way it fits into work must focus on low friction clear interfaces that are made together with practicing nurses. When the technology fits with the existing routines office stress goes down nurse job satisfaction goes up and keeping nurses, in the job steadies (Choi & Lee 2026).

4. Professional Autonomy, Agency, and the Liability Environment

Adding algorithms to everyday clinical choices creates big ethical and legal problems about professional autonomy and liability (Braun, 2026). Nursing autonomy depends on the power to use judgment read complex health information and stand up for patient welfare. In an environment nursing autonomy can be weakened if predictive algorithms are used as sole diagnostic engines instead of flexible clinical helpers (Lavoie, 2026).

When a predictive algorithm sends an alert that does not match a nurses bedside judgment the clinician faces a decision path (Rojas et al., 2023). If the nurse follows the system they carry out the suggested protocol and record agreement with the score. If the nurse chooses to override the algorithm because of an observation, physical exam or subtle context they must start a formal override process (Morris, 2000). This means writing a clinical reason and often sending the case to an interdisciplinary care team for formal review (Nebeker et al., 2004).

Both choices bring professional and systemic risks. Accepting predictions without careful review raises the danger of automation bias making clinicians follow strict protocols even when a patient's unique situation says otherwise. On the side overriding an automated tool puts the clinician under legal scrutiny if the patient later suffers a bad outcome (Branda & Ciccozzi 2026).

This clash creates the "liability sink" problem, a worry in health policy and malpractice law. Hospitals quickly adopt AI tools to boost efficiency and lower institutional risk (Issa et al., 2026). Still legal rules and tort cases usually see the bedside nurse as the human-in-the-loop" who must carry out the final care (Heimer, 1999). That creates a liability system where nurses take legal blame for computational mistakes even though they have no say in buying the system choosing software training the model or putting it into use (Jackson et al., 2026). If a nurse blindly follows a sepsis alert or medication dose that harms a patient they can be sued for not using independent judgment. If a nurse overrides the system and the patient gets worse they can be sued for straying from the automated rules (Mugamba, 2025).

Keeping nursing autonomy safe and lowering liability needs policy steps. The design of systems must keep the nurse's power to override machine outputs (Cao et al. 2025). Hospitals must set up EHR forms that let nurses note override choices and their reasoning without fear of harsh administrative checks (Sinha et al., 2012). In addition, regulators and lawmakers must add nursing protections showing that legal blame cannot stick to front-line nurses unless they have AI training and can see the clear explainable logic, behind decisions (Galatzan et al. 2025).

5. Cognitive Transformations: Clinical Reasoning, Automation Bias, and Deskilling

5.1 Cognitive Partnership and Distributed Intelligence

The incorporation of artificial intelligence into clinical practice redefines human cognition from an isolated internal process into a distributed cognitive partnership (Rad et al., 2025). In this dynamic model, the machine contributes high-bandwidth data synthesis, continuous multi-variable pattern recognition, and rapid guideline matching, while the nurse contributes contextual interpretation, qualitative observation, moral agency, and empathetic engagement (Ray, 2026). When properly balanced, this partnership elevates the floor of clinical performance, enabling early-career nurses to identify rare complications and supporting expert nurses in managing highly complex patient assignments (Kaplan et al., 2010).

5.2 Automation Bias and the Cognitive Deskilling Paradox

Yet repeated exposure to automated decision support systems poses substantial cognitive hazards, including automation bias and cognitive deskilling. Automation bias is the tendency of physicians to have an inflated trust in the automated system recommendation, which implies less attentiveness and

independent evaluation on the part of the physician (Heudel et al., 2026). Liu (2026) notes that in stressful, high-paced settings, cognitive weariness amplifies this bias so that nurses are more prone to trust machine recommendations without cross-checking of underlying physiological data.

Automated decision pathways over time result in cognitive deskilling. Clinical reasoning is based on the continual processing of implicit intuition through schema development and mental simulation based on experiential practice (Natali et al., 2025). Where algorithmic approaches increasingly take over the cognitive work of pattern recognition and diagnostic synthesis, there is a danger that clinicians may be less able to recognise subtle changes in physiology (Sunday, 2025).

This is compounded by the phenomenon of "never-skilling". Novice nurses and nursing students who are trained in clinical practice solely in the context of predictive CDSS and generative AI may be at risk for not acquiring the prerequisite intuitive pattern recognition, clinical diagnostic patterns, or foundational decision making skills needed to evaluate decisions versus the algorithm (Ke et al., 2026). Studies have revealed clinical performance of AI-supported clinicians worsens significantly when AI support is unexpectedly removed or the system fails (Guo, 2026).

Table 2 outlines these primary cognitive phenomena alongside their psychological mechanisms, impact on patient safety, and institutional mitigation strategies.

Cognitive Phenomenon	Operational Definition & Psychological Mechanism	Impact on Clinical Reasoning & Patient Safety	Pedagogical & Institutional Mitigation Strategies
Automation Bias	Overreliance on automated recommendations driven by cognitive offloading and high trust in system capability.	Omission errors (failing to notice unflagged patient decline) and commission errors (executing erroneous AI alerts).	Cognitive forcing functions requiring independent reasoning prior to viewing AI output; calibrated explainability interfaces displaying confidence intervals.
Cognitive Deskilling	Degradation of unassisted diagnostic reasoning, intuitive pattern recognition, and clinical skills over prolonged reliance on AI.	Impaired clinical performance during system downtime, network outages, or algorithmic failure modes.	Mandatory periodic "AI-free" clinical simulation practice; post-market monitoring of unassisted clinician competency.
"Never-Skilling"	The complete failure of novice clinicians to ever develop foundational intuitive diagnostic capabilities due to early reliance on AI.	Permanent loss of expert clinical intuition across incoming generations of practitioners.	Longitudinal competency models requiring mastery of manual diagnostic reasoning prior to AI integration.
Vigilance Fatigue	Exertion of high cognitive oversight energy required to continuously review, edit, and validate low-accuracy AI outputs.	Blind approval of automated documentation, elevated burnout, and delayed response to true clinical alerts.	Rigorous pre-deployment validation thresholds; dynamic filtering of non-actionable notifications.

5.3 Educational Frameworks and Pedagogical Innovations

Preventing cognitive degradation requires updating nursing education frameworks. Legacy curricula focus predominantly on basic technical literacy, failing to prepare nurses for the cognitive, relational, and ethical demands of human-AI collaboration (Herodotou et al., 2019). To address this gap, contemporary

education models integrate the 5IR Human–AI Collaborative Nursing Education Model and Rest's Four-Component Model of Moral Behavior (Pepito et al., 2026).

The 5IR Education Model establishes seven core competency domains: algorithmic literacy, technological fluency, ethical-legal acumen, digital empathy, critical thinking in AI-supported decision-making, interdisciplinary systems thinking, and adaptive practice (Calderone et al., 2025). Complementing this framework, Rest's Four-Component Model structures ethical reasoning under four progressive phases:

- Moral Sensitivity trains nurses to recognize hidden biases, privacy risks, and psychosocial impacts embedded in AI data feeds.
- Moral Judgment develops critical appraisal skills to evaluate algorithmic accuracy and identify hallucination or protocol deviations.
- Moral Motivation cultivates professional commitment to prioritize patient welfare over computational convenience.
- Moral Character builds agency and resilience to override faulty algorithmic alerts, escalate systemic errors, and maintain accountability (Harjika, 2026).

Pedagogy must enforce a "reasoning-first" sequence: nursing students must document independent diagnostic hypotheses and clinical interventions before consulting AI-generated care plans or CDSS recommendations (Wainwright, 2024). Furthermore, nursing curricula must embed mandatory, periodic "AI-free" simulation scenarios to ensure that clinicians maintain robust, unassisted clinical reasoning skills capable of operating during technical outages (Simoni et al., 2026).

6. Patient Safety, Algorithmic Governance, and Ethical Paradigms

6.1 Dual Impacts on Patient Safety

Artificial intelligence is a disruptive technology that has a dual impact on patient safety in nursing. Advanced predictive systems significantly enhance safety by eliminating diagnostic delays, standardizing risk scores, optimizing resource allocation, and allowing early stabilization of worsening patients (Schlosser et al., 2020). Conversely, the use of AI also creates new safety vulnerabilities due to model inaccuracies, dataset bias, software hallucinations, and data security breaches (Perez-Cerrolaza et al., 2024).

Predictive models, if trained on unrepresentative historical healthcare data, can learn and reinforce systemic socioeconomic, racial, and geographic disparities (Hasanzadeh et al., 2025). Biased models, when deployed at scale, can systematically under-score risk in marginalized patient populations, resulting in delayed escalations, lower resource allocation, and increased health inequities (Yu et al., 2026). In addition, large language models used in automated charting and care planning are still prone to "hallucinations" — generating plausible but factually incorrect clinical narratives or non-existent interventions (Beisheuvel et al., 2025). These mistakes, if not caught by nurses, become part of the permanent legal medical record, infecting future clinical decision-making and endangering patient health (Risser et al., 1999).

6.2 The GREAT PLEA Governance Architecture

To systematically address these safety and ethical risks, healthcare institutions must operationalize robust ethical frameworks (McNamara, 2004). The GREAT PLEA ethical architecture provides nine comprehensive principles tailored for AI integration in clinical settings:

- **Governability** mandates that systems maintain meaningful human control, incorporating explicit protocols and technical safeguards that allow nurses to instantly disengage or deactivate malfunctioning algorithms without disrupting core patient care.
- **Reliability** requires AI models to demonstrate continuous safety and performance efficacy, undergoing rigorous evaluation across explicit clinical use cases and patient populations (Rachmad, 2022).
- **Empathy** demands that technology be designed to preserve and amplify human relational capacity, ensuring automated tools support rather than replace compassionate bedside interaction.
- **Accountability** anchors legal and moral responsibility to identifiable human professionals and institutional leadership, preventing legal vacuums when algorithmic errors occur (Kong & Chang, 2026).

- **Transparency** mandates that algorithmic decision logic remain explainable and traceable, calibrating the depth of system explainability to the level of clinical risk involved (Chaudhary, 2024).
- **Privacy** enforces strict data protection standards, utilizing advanced techniques such as federated learning to train algorithms without exposing sensitive personal health information to breaches (Razi et al., 2025).
- **Legality** ensures full compliance with medical laws and data protection regulations, such as HIPAA and GDPR, while establishing clear organizational protocols for managing system errors (Isibor, 2024).
- **Equity** requires continuous monitoring and auditing to detect and eliminate algorithmic biases, ensuring fair treatment across diverse demographic groups (Metaxa et al., 2021).
- **Accessibility** focuses on expanding technological access to under-resourced, rural, and community health settings to prevent the widening of global healthcare disparities (Dang et al., 2024).

6.3 Participatory Co-Design and Human-in-the-Loop Architecture

Front-line nurses have been largely excluded from the technology development lifecycle, which is a key reason why many historical AI implementations have failed. Software procurement has long been driven by administrative and IT leadership, leading to the proliferation of tools that create more work at the bedside, add cognitive load, and are often clinically irrelevant (Mirzaei & Adibhesami, 2025).

Creating safe human-AI collaboration requires a shift toward participatory co-design ecosystems. Nurses must be involved throughout every step of system development: requirements analysis, model training, data annotation, interface design, clinical simulation testing, and ongoing post-implementation evaluation (Mushkani et al., 2025). Participatory design guarantees that explainable AI (XAI) interfaces offer information in easily understandable visual displays that align with the fast-paced clinical assessment practices of acute care nurses (Fouad et al., 2026). Incorporating direct nursing expertise into model development allows health systems to develop AI ecosystems that function as cognitive extensions, enhancing clinical decision-making and ensuring patient safety (Elish & Watkin, 2020).

Conclusion

This review shows that human–AI collaboration in nursing practice is a double-edged change. It offers chances to make work flow faster spot early signs of patient decline and cut down on paperwork. At the time it brings big thinking, moral and legal problems. The evidence from four kinds of AI – decision support systems, background clinical intelligence, predictive monitoring and AI-helped care planning – tells us that putting technology into nursing changes the job a lot. It moves the focus of nursing from doing tasks to watching over and checking the work. Numbers show that records can be done faster triage can be quicker. Resources can be used better.. These gains happen only when the tools are easy to use and clear and when they are made together with nurses who work every day. A key idea is the model. It says that when AI does the tasks nurses then need to think harder to check and approve the results. That extra thinking can be as hard or harder than doing the work by hand especially when the AI makes mistakes or its logic is not clear. Thinking problems such as trusting the machine much losing skill or never learning new skills endanger the experience that nurses rely on to make good decisions. Therefore nurses must do training that does not use AI and must learn to think first. The "liability sink" problem means that nurses need rules that let them stop the AI if it is wrong and that protect them from blame when they decide for themselves. The GREAT PLEA framework gives a set of moral rules that cover manageability, trust, care, responsibility, openness, privacy, law, fairness and reach. It helps guide how AI should be used in a way. Working together with nurses from the start from figuring out needs to checking the system after it is used is necessary so that AI feels like a helper, to the nurse's mind, not an obstacle. In the end keeping the caring heart of nursing – the hands-on care, the emotional presence and the moral power – means that AI should be a helper that supports not replaces, the nurse's own judgement. Hospitals must keep checking that nurses stay skilled that AI is fair and that every kind of care place can use the technology.

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