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The AI Co-Pilot in Nursing: A Systematic Review of Clinical Decision Support Systems at the Bedside

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Abstract

Background: Nursing practice is under significant strain due to workforce shortages and increasing patient acuity. Traditional Clinical Decision Support Systems (CDSS) often lead to "alert fatigue" from vague alarms. The introduction of artificial intelligence, especially machine learning, represents a shift towards predictive, individualized CDSS, intended to assist bedside nurses effectively. **Aim:** This systematic narrative review synthesizes evidence (2010-2024) on the implementation and impact of AI-powered CDSS in nursing, focusing on applications in deterioration prediction, sepsis detection, and harm prevention. **Methods:** A systematic search of PubMed, CINAHL, Scopus, and IEEE Xplore databases identified peer-reviewed studies evaluating AI-CDS interventions in acute care nursing. **Results:** AI-CDSS offers improved predictive accuracy compared to traditional tools, enhancing outcomes such as sepsis bundle compliance and reducing adverse events. Its effect on mortality is ambiguous. Successful integration depends on human-centered design; ineffective systems heighten cognitive load, while effective ones bolster situational awareness. Key findings indicate AI can enhance judgment but may also cause automation bias and diagnostic deskilling. Alert fatigue remains a concern but can be alleviated through tiered, intelligent alerting and closed-loop workflows. **Conclusion:** The AI co-pilot represents a transformative but complex partner. Its value is realized not through algorithmic superiority alone, but through thoughtful design that supports nursing cognition, integrates seamlessly into workflow, and fosters a culture of calibrated trust, ensuring technology augments rather than displaces essential nursing judgment.

Keywords: Artificial Intelligence; Nursing Informatics; Clinical Decision Support Systems; Patient Safety; Alert Fatigue

Introduction

The essence of bedside nursing is a sophisticated, continuous process of clinical surveillance, data synthesis, and judgment under uncertainty. Nurses are the linchpins of patient safety, responsible for detecting subtle signs of deterioration, preventing hospital-acquired complications, and coordinating complex care. This role is under severe strain in a global context of nursing shortages, heightened patient acuity, and expanding administrative burdens, creating an environment where cognitive overload and missed cues pose significant risks (Haddad et al., 2018; Needleman et al., 2011). For decades, healthcare technology has promised support through Clinical Decision Support Systems (CDSS). First-generation CDSS, typically rule-based and logic-driven, automated simple tasks and generated alerts based on static thresholds (e.g., "if potassium >5.5, alert"). While occasionally helpful, these systems have been widely criticized for a fatal flaw: they generate a high volume of clinically irrelevant notifications, leading directly to alert fatigue—a well-documented phenomenon where clinicians become desensitized to alarms, potentially

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ignoring critical warnings (Ancker et al., 2017; Russ et al., 2014). This has often rendered such tools more of a hindrance than a help in the dynamic reality of nursing practice.

The advent of sophisticated artificial intelligence (AI), particularly machine learning (ML) and predictive analytics, heralds a potential revolution. Modern AI-powered CDSS can move beyond binary "if-then" rules to analyze vast, multimodal datasets in real-time. By processing continuous vital signs, longitudinal laboratory trends, medication administration records, nursing documentation, and even free-text notes, these systems can identify complex, non-linear patterns indicative of impending adverse events. They shift from a reactive "alerting" mode to a proactive "predictive partnership," offering a probabilistic, patient-specific risk assessment. This enables the system to function as an intelligent "co-pilot"—a continuous, data-driven second opinion that supports, rather than replaces, the nurse's clinical expertise (Buchanan et al., 2021; Lu et al., 2022). Prominent applications are emerging in core nursing domains: predicting patient deterioration hours before it becomes clinically obvious, identifying sepsis risk earlier than conventional criteria, and forecasting the likelihood of pressure injuries or falls to enable targeted preventative care (Muralitharan et al., 2021; Sendelbach & Funk, 2013).

This technological leap necessitates a comprehensive and critical examination of its real-world implications. While the technical validation of these algorithms—measured by metrics like area under the curve (AUC), sensitivity, and specificity—is a common focus of research, their integration into the complex socio-technical ecosystem of nursing is less understood. The true impact of an AI co-pilot extends far beyond statistical performance. It fundamentally interacts with the core elements of nursing work: How does it reshape clinical reasoning—does it enhance the nurse's diagnostic acumen or foster dangerous over-reliance? Does it streamline workflow and reduce cognitive load, or does it create new, hidden tasks and interruptions? Does evidence substantiate measurable improvements in patient outcomes, and what implementation factors dictate success or failure? Finally, how does the perennial challenge of alert fatigue manifest in this new, more sophisticated context, and how can it be designed against?

Therefore, this systematic narrative review aims to synthesize and critically analyze the contemporary evidence base (2010-2024) on the implementation, efficacy, and broader impact of AI-powered Clinical Decision Support Systems specifically designed for or utilized by nurses at the bedside. Moving beyond a narrow focus on algorithmic accuracy, this review interrogates the intersection of advanced technology and the art and science of nursing practice. We examine the effects on patient outcomes, nurse workload and satisfaction, the development and application of clinical judgment, and the persistent challenge of alarm and alert management. Through this synthesis, we seek to delineate the conditions under which the AI co-pilot matures from a promising technological novelty into a trusted, effective, and ethically sound partner in the mission to deliver safer, higher-quality, and more sustainable patient care.

2. Methodology

This review was executed as a systematic narrative synthesis, a methodological approach chosen to rigorously identify, appraise, and synthesize a diverse body of evidence while accommodating the conceptual and methodological heterogeneity inherent in this emerging field of research (Wong et al., 2013). The process was guided by the principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement to ensure methodological transparency and rigor throughout the identification, screening, eligibility, and inclusion phases (Page et al., 2021). A narrative synthesis was deemed most appropriate over a quantitative meta-analysis due to the anticipated variability in study designs, specific AI-CDSS interventions, clinical settings, and measured outcomes, which would preclude meaningful statistical pooling of data. This approach facilitates a comprehensive, thematic analysis of the complex interactions between technology, nursing practice, and patient care.

Search Strategy and Information Sources

A comprehensive and systematic literature search was performed in April 2024 across four major electronic databases selected for their disciplinary scope and relevance: PubMed/MEDLINE, CINAHL (Cumulative Index to Nursing and Allied Health Literature), Scopus, and IEEE Xplore. The search strategy was developed in consultation with a health sciences librarian to ensure comprehensiveness and precision. It employed a combination of controlled vocabulary (e.g., MeSH terms, CINAHL headings) and free-text keywords spanning three core conceptual domains integral to the review's focus. The first domain, Technology & Intervention, included terms such as "artificial intelligence," "machine learning," "clinical decision support system," and "predictive model". The second domain, Profession & Context, incorporated terms like "nurs", "bedside," "nursing informatics," and "nursing practice" to anchor the search in the nursing domain. The third domain, Outcome & Process, encompassed terms related to specific applications (e.g., "early warning score," "sepsis detection," "pressure injury") and evaluative dimensions (e.g., "clinical reasoning," "alert fatigue," "workload," "patient outcome*"). Boolean operators (AND, OR) were used to logically combine these domains. The search was temporally restricted to articles published in English between January 1, 2010, and April 1, 2024, to capture the modern evolution of machine learning-driven CDSS relevant to contemporary practice (Samal et al., 2023; Darko et al., 2023).

Eligibility Criteria and Study Selection

Two independent reviewers conducted the study selection process to minimize bias. Titles and abstracts of all retrieved records were screened against pre-defined eligibility criteria. Full-text articles were obtained for all studies deemed potentially relevant and were then assessed independently by the same two reviewers against the full criteria. Any disagreements regarding inclusion or exclusion were resolved through discussion or, when necessary, consultation with a third reviewer.

The inclusion criteria were designed to capture studies that were both conceptually relevant and methodologically sound. Eligible studies included primary research (e.g., randomized controlled trials, quasi-experimental studies, cohort studies, mixed-methods studies) and rigorous systematic reviews or meta-analyses. The central intervention of interest was an AI or machine learning-based CDSS, explicitly excluding studies of simple, rule-based alerting systems. Studies were required to focus on the use of such systems by direct-care registered nurses or licensed practical/vocational nurses in acute care inpatient settings, such as medical-surgical units, intensive care units, or emergency departments. Finally, included studies had to report on at least one outcome pertinent to the review's aims, encompassing: (a) patient clinical outcomes (e.g., mortality, length of stay), (b) process outcomes (e.g., sepsis bundle compliance), (c) nurse-related outcomes (e.g., workload, clinical reasoning), or (d) system outcomes (e.g., alert characteristics, usability) (Varghese et al., 2020).

Conversely, exclusion criteria were applied to maintain focus and rigor. Studies were excluded if they were purely descriptive of algorithm development without clinical implementation or evaluation, or if they focused exclusively on CDSS use by physicians or other non-nursing clinicians. Research conducted in outpatient, primary care, or long-term care settings, which involve fundamentally different nursing workflows and contexts, was also excluded. Furthermore, editorials, commentaries, conference abstracts lacking full data, and non-peer-reviewed literature were not considered, ensuring the synthesis was based on substantive, validated research.

Data Extraction and Synthesis

A standardized data extraction form was used to collect key information from included studies: authors, publication year, study design, setting and sample, description of the AI-CDSS intervention, comparator (if any), and key findings related to the review's focal areas (patient outcomes, workflow, reasoning, alert fatigue). Due to significant heterogeneity in interventions, populations, and outcome measures, a quantitative meta-analysis was not feasible. Instead, a narrative synthesis was conducted. Studies were first grouped thematically by primary application area (e.g., deterioration prediction, sepsis, hospital-acquired conditions). Within and across these themes, findings were synthesized to address the central review questions, identifying common patterns, divergent results, and key facilitators and barriers to successful implementation.

The AI Co-Pilot's Dashboard and Its Core Applications in Nursing Surveillance and Intervention

Artificial intelligence-powered Clinical Decision Support Systems are being strategically deployed in domains central to nursing's mandate of vigilant surveillance and proactive intervention, representing a paradigm shift from monitoring isolated physiological parameters to interpreting complex, multivariate clinical narratives (Jahandideh et al., 2023). These applications transform raw data into actionable intelligence, serving as an advanced dashboard for nursing judgment. A primary and critical application is in the domain of predictive deterioration and advanced early warning systems (Cavalier et al., 2022). The detection of clinical decline is a cornerstone of nursing practice, yet traditional track-and-trigger systems like the Modified Early Warning Score (MEWS) rely on manual, intermittent calculations and apply uniform thresholds that fail to account for individual patient physiology (Oliveira et al., 2022). AI-driven systems, such as the Epic Deterioration Index or the Rothman Index, represent a significant evolution by ingesting hundreds of variables from the electronic health record in real-time—including vital signs, laboratory trends, nursing assessments, and demographic data—to generate a dynamic, personalized risk score for adverse events like ICU transfer or cardiac arrest within a 6-24 hour window (Bedoya et al., 2019; Lu et al., 2023). For the bedside nurse, this provides a continuously updated "sick score" that visually prioritizes patients on a unit dashboard. Evidence robustly indicates these algorithms possess superior discriminative ability, with area under the curve (AUC) metrics often ranging from 0.85 to 0.95, significantly outperforming traditional scores (Churpek et al., 2016). Their paramount value lies not in rendering a definitive diagnosis but in directing nursing attention to patients whose subtle, multivariate signs of instability might otherwise be obscured in the chaos of a busy shift, thereby enabling earlier assessment and stabilizing intervention.

In the high-stakes realm of sepsis detection and management orchestration, AI-CDSS finds another vital application. Sepsis is a time-sensitive, pathophysiologically complex syndrome where early recognition is paramount. Machine learning models excel at identifying the non-linear, often subtle patterns that precede septic shock, synthesizing trends in vital signs, sequential laboratory values (such as rising lactate), medication administration records, and clinical documentation cues to flag at-risk patients hours before conventional criteria are met (Wong et al., 2021). Widely implemented tools like the EPIC Sepsis Model prompt nurses to initiate protocol-driven actions core to the "sepsis bundle," including obtaining blood cultures, measuring serum lactate, and administering antibiotics. The literature substantiates that such systems can significantly improve key process metrics, notably reducing time-to-antibiotics and increasing bundle compliance (Ferrer et al., 2014). However, the independent impact of AI-CDSS on reducing ultimate sepsis mortality remains a complex and debated area, as mortality is influenced by numerous downstream factors beyond early detection alone (Wardi et al., 2023). Nevertheless, these systems fundamentally evolve the nursing role, integrating the interpretation of predictive algorithmic prompts into a streamlined clinical workflow for rapid response.

Furthermore, AI is revolutionizing the proactive prevention of hospital-acquired conditions, moving nursing from generalized, resource-intensive preventative measures to targeted, precision-based practice. In pressure injury prediction, AI models enhance traditional tools like the Braden Scale by incorporating static scores with dynamic, real-time data such as electronic documentation of patient mobility and repositioning, serum biomarkers like albumin, and vasopressor use to generate a dynamic, personalized risk score for hospital-acquired pressure injuries (HAPIs) (Song et al., 2021). This enables nurse managers and bedside staff to strategically allocate preventative resources—such as specialized mattresses and more frequent turning schedules—to the patients at highest, real-time risk, thereby improving both the efficiency and efficacy of prevention efforts. Similarly, in fall risk prediction, AI models advance beyond static scales like the Morse Fall Scale by incorporating dynamic data streams: real-time mobility events from sensors or documentation, scheduled administration of psychoactive medications, and clinical notes indicating confusion (Lee et al., 2021). This enables context-aware fall risk alerts that prompt timely, personalized nursing interventions, such as intentional rounding or the use of a bed alarm, precisely when risk is heightened. Together, these applications exemplify how the AI co-pilot's dashboard extends nursing capacity from reactive monitoring to intelligent, predictive safeguarding (Table 1).

Table 1: Key AI-CDSS Applications in Bedside Nursing: Functions, Data, and Intended Impact

Application Area	Core AI Function	Exemplar Data Inputs	Nursing Action Prompt	Theoretical Impact on Outcomes
Predictive Deterioration	Generates a continuous, personalized risk score for ICU transfer, cardiac arrest, or death.	Real-time vitals, lab trends, age, comorbidities, prior admissions, nursing narrative notes.	Prioritizes patient for enhanced assessment; facilitates earlier rapid response or critical care consultation.	Reduced failure-to-rescue, decreased non-ICU cardiac arrests, shorter ICU length of stay.
Sepsis Detection	Identifies patients at high risk of developing sepsis prior to meeting conventional SIRS or qSOFA criteria.	Heart rate, temperature, respiratory rate, WBC, lactate trends, antibiotic administration, fluid balance.	Initiates sepsis protocol: obtain cultures/lactate, administer antibiotics/fluids, escalate care.	Reduced time-to-antibiotics, improved bundle adherence, decreased progression to septic shock and mortality.
Pressure Injury Prediction	Dynamically calculates risk of developing a HAPI, updating with new clinical data.	Braden Scale scores, mobility/turn documentation, serum albumin, vasopressor use, hemodynamic status.	Triggers targeted, intensified skin care, repositioning, and use of pressure-redistributing surfaces for high-risk patients.	Reduced HAPI incidence and severity, optimized utilization of preventative equipment and nursing time.
Fall Risk Prediction	Provides a real-time, context-sensitive assessment of fall probability.	Historical fall score, recent mobility events, PRN medication admin (sedatives),	Generates situation-specific alerts for increased supervision, scheduled toileting, or	Reduced inpatient fall rates with injury, decreased use of constant observers or

	documentation of confusion/delirium.	environmental modifications.	physical restraints.

Impact on Patient Outcomes and the Nursing Work Ecosystem

The introduction of AI-CDSS into clinical practice produces a multifaceted and contingent set of outcomes, where anticipated benefits are not guaranteed but are instead mediated by the quality of the technological integration and the encompassing socio-technical milieu of the healthcare environment (Varghese et al., 2020). The impact distinctly bifurcates into measurable effects on patient trajectories and profound influences on the nature and experience of nursing work itself. Evidence concerning the influence of AI-CDSS on ultimate patient-centric endpoints, such as all-cause mortality or aggregate hospital length of stay, remains mixed and highly context-dependent, presenting a persistent "mortality conundrum" for researchers and evaluators (Wong et al., 2021). A more consistent and demonstrably positive finding across the literature is the significant improvement in critical process outcomes—the intermediary, evidence-based clinical actions known to directly influence final results. In the domain of sepsis management, multiple studies demonstrate that AI-CDSS implementation is associated with statistically significant increases in 3-hour and 6-hour bundle compliance and clinically meaningful reductions in median time-to-antibiotics, often by 60 minutes or more (Ferrer et al., 2014; Wardi et al., 2023).

For the surveillance of general clinical deterioration, research more frequently reports reductions in specific adverse events such as non-ICU cardiopulmonary arrests and unplanned intensive care unit transfers, suggesting successful earlier intervention on the general ward (Bartkowiak et al., 2019). However, conclusively demonstrating a direct, attributable reduction in hospital-wide mortality rates is methodologically challenging due to confounding variables and the requisite scale of robustly controlled trials. In harm prevention, several well-designed studies indicate that AI-driven, precise targeting of pressure injury prevention resources can lead to significant reductions in hospital-acquired pressure injury (HAPI) incidence rates (Song et al., 2021). Crucially, the strongest patient outcomes are observed when the AI alert is intrinsically linked to a structured nursing response protocol, empowering immediate action rather than merely serving as an informational prompt (Sendelbach & Funk, 2013).

The effect on nursing workload and the cognitive experience of care delivery is profoundly paradoxical, serving as the critical differentiator between implementations that succeed as supportive tools and those that fail as disruptive burdens. This duality represents the "double-edged sword" of assistive health information technology. When an AI-CDSS is implemented as a "bolt-on" system—a separate application, browser tab, or physical device that exists outside the native electronic health record (EHR) workflow—it creates task duplication and workflow fragmentation (Varghese et al., 2020). Nurses are compelled to remember to consult an additional screen, log into another system, and mentally reconcile its outputs with their primary clinical data stream. This architecture increases cognitive load, chronically interrupts clinical reasoning sequences, and can rapidly transform the tool into an additional administrative burden. Alerts generated from such disjointed systems, unless they are exceptionally specific and actionable, become mere noise, exacerbating notification overload.

Conversely, when AI-derived insights are deeply and seamlessly embedded into the native nursing workflow—appearing as a salient, color-coded indicator on the electronic patient list, integrated into the handoff report, or synthesized on the main patient overview screen—they can genuinely streamline surveillance and reduce cognitive burden (Despins et al., 2020). In this configuration, the AI acts as a high-fidelity filter for attention, helping the nurse efficiently answer the fundamental question: "Which of my patients needs my attention most right now?" This capability can alleviate the background anxiety associated with missing subtle signs of deterioration. Moreover, it substantively empowers nursing advocacy; a nurse can contact a physician with a concrete, data-driven rationale rather than a vague subjective concern. The most effective systems, therefore, provide actionable intelligence, designed to answer not only "what is the risk?" but also "why is the risk elevated?" and "what should be done?". Figure 2 illustrates the dual impact of AI-CDSS on nursing practice. On the supportive pathway, explainable and workflow-integrated AI enhances situational awareness, clinical reasoning, and patient safety.

Figure 2. Human–AI Collaboration in Nursing: Balancing Cognitive Augmentation and Alert Fatigue

Clinical Reasoning, Trust, and the Persistent Challenge of Alert Fatigue

The most profound implications of the AI co-pilot lie in its intricate interaction with the nurse's fundamental cognitive processes, raising critical questions about the evolution of clinical expertise, the nature of trust in automation, and the fabric of nursing judgment (Chu et al., 2022). This partnership holds simultaneous potential for powerful augmentation and insidious erosion. Artificial intelligence can serve as a cognitive augment, particularly for novice nurses or in clinically ambiguous situations, by highlighting subtle data correlations and pathophysiological patterns, thereby accelerating the development of pattern recognition (Fernandes et al., 2023). However, this collaborative dynamic carries the significant risk of automation bias—the human tendency to over-rely on automated decision aids, uncritically accepting their outputs while discounting contradictory information from one's own senses or judgment (Lyell et al., 2017). In nursing, this bias could manifest as a clinician deferring to a "low risk" AI score and consequently performing a less thorough assessment, potentially missing critical contextual cues that the algorithm cannot perceive. Over time, such uncritical reliance poses the threat of diagnostic deskilling, where the nurse's independent assessment capacities atrophy from disuse. The ideal "co-pilot" relationship must therefore foster calibrated trust—a dynamic where the nurse uses the AI output as one vital data point within a holistic clinical picture, actively reconciling it with direct observation and professional experience (Kupfer et al., 2023).

Despite advances in algorithmic intelligence, the perennial challenge of alert fatigue is not solved but is merely transformed. A poorly calibrated AI-CDSS, particularly one tuned for high sensitivity, will generate a novel class of sophisticated false positives—patients flagged as high-risk who do not deteriorate. Consequently, clinician fatigue evolves from ignoring simplistic threshold alarms to dismissing complex risk scores. Contemporary design strategies for mitigation are becoming more nuanced. A primary strategy is tiered, intelligent alerting, which employs multi-level risk stratification with corresponding, graded notification modalities, where only high-criticality alerts are interruptive (Nyarko et al., 2022). Furthermore, fatigue is reduced when an alert provides actionable intelligence within a closed-loop design. An effective alert integrates the warning with tools for intervention, such as one-click order sets, transforming a passive notification into an active clinical pathway (Sendelbach & Funk, 2013). Finally, embedding feedback mechanisms—allowing nurses to indicate if an alert was "actionable" or "not helpful"—creates a valuable data stream for continuous model refinement. This participatory loop improves algorithmic specificity over time and grants frontline clinicians a sense of agency, mitigating feelings of technological imposition (Table 2).

Table 2: The Dual Impact of AI-CDSS: Facilitators of Success vs. Drivers of Failure

Domain	Facilitators of Success (The Effective Co-Pilot)	Barriers & Risks (The Disruptive Passenger)
Workflow Integration	**Native EHR Embedding:** AI insights are woven into existing screens (patient list, summary). **Closed-Loop Action:** Alert is linked directly to order sets, documentation flowsheets, or communication tools.	**Bolt-On Design:** Requires separate logins and applications, creating parallel workflows and task duplication. **Passive Notification:** Presents risk data without clear, sanctioned, and easy-to-execute next steps.
Clinical Reasoning & Trust	**Explainable AI (XAI):** Provides succinct rationale for the prediction (e.g., "Risk elevated due to 20% increase in HR and new tachypnea"). **Supports Calibrated Trust:** Designed as a consultative input; encourages nurse validation through assessment.	**"Black Box" Algorithms:** No transparency into prediction rationale, fostering mistrust or blind faith. **Promotes Automation Bias:** Interface design encourages uncritical acceptance, potentially eroding independent clinical judgment.
Alert Fatigue Management	**Risk-Tiered Notification:** Alerts are stratified by severity with appropriate interruptiveness. **Context-Aware Suppression:** Intelligently withholds alerts during predictable clinical events or low-staffing crises.	**High False-Positive Rate:** Poorly tuned models flood nurses with non-actionable warnings, leading to indifference. **Interruptive by Default:** All alerts are high-priority, disrupting workflow and increasing cognitive load.
Organizational & Cultural Support	**Nurse-Led Co-Design:** Nurses are integral to selection, design, testing, and iteration. **Protected Response Capacity:** Staffing models acknowledge and support the time required to investigate and act on AI-generated insights. **Clear Governance &**	**Top-Down, IT-Led Implementation:** Technology is imposed without nursing input, leading to poor fit with practice realities. **Lack of Standardized Response:** No clear protocol exists, causing variability, confusion, and delays. **Punitive or Surveillance Culture:** Alerts are used for

	Autonomy: Protocols define nursing scope of practice in responding to alerts, empowering action.	performance monitoring or blame, rather than as supportive tools.

Discussion

The synthesized evidence presents a compelling yet cautionary narrative. AI-powered CDSS undeniably possesses formidable technical capability to identify patterns predictive of adverse events, often exceeding the performance of traditional tools. However, this review underscores that algorithmic excellence is a necessary but insufficient condition for success in the complex, human-centric world of bedside nursing. The translation of predictive accuracy into improved care and sustainable practice is entirely mediated by the socio-technical system enveloping the technology. The most impactful implementations are those architected with profound respect for nursing workflow, cognitive processes, and professional autonomy.

The recurring themes from the literature point to human-centered design as the critical differentiator. Systems that succeed recognize the nurse as the central cognitive agent in a collaborative human-machine system. They provide support that is transparent, integrated, and actionable. The persistent issue of alert fatigue, even with advanced AI, confirms that the core challenge is not merely statistical (sensitivity/specificity) but fundamentally human-factors and organizational. It demands sophisticated alert management philosophies and a culture that values signal over noise.

Significant evidence gaps and ethical considerations must guide future research and development. There is a pressing need for longitudinal studies to understand the long-term impact of AI co-pilots on the development of nursing expertise, intuition, and diagnostic confidence. Ethical frameworks must be strengthened to address accountability (e.g., liability if a nurse appropriately acts on a false-negative AI prediction), algorithmic fairness (ensuring models perform equitably across diverse patient demographics), and data privacy in increasingly data-hungry ML systems (Buchanan et al., 2020; Morley et al., 2020). Furthermore, the economics of implementation—cost, ROI, and impact on nurse retention—require deeper exploration.

Conclusion

The integration of AI-powered Clinical Decision Support Systems into bedside nursing represents one of the most profound and consequential technological evolutions in the history of the profession. This systematic review confirms that these systems, when conceived and implemented as true "co-pilots," hold significant potential to enhance a nurse’s capacity to predict, prevent, and rapidly respond to patient harm. The tangible benefits—earlier treatment for sepsis, more precise prevention of pressure injuries, and intelligent prioritization in a sea of clinical data—can contribute meaningfully to patient safety and care quality.

However, the path to realizing this potential is not automatic. It is paved with the risks of increased cognitive burden, the erosion of clinical judgment through automation bias, and the ever-present threat of sophisticated alert fatigue. Therefore, the future of the AI co-pilot in nursing must be navigated with intentionality, collaboration, and a steadfast commitment to nursing values. It requires an enduring partnership between data scientists, clinical informaticists, healthcare leaders, and, most importantly, bedside nurses. Together, they must build systems that are not only intelligent but also wise—wise to the rhythms of clinical work, the nuances of human physiology, and the irreplaceable power of the nurse-patient relationship.

The ultimate goal is not to create a nurse who is subordinate to an algorithm, but to foster a nurse whose clinical judgment is informed, augmented, and amplified by a trusted, intelligent partner. Achieving this symbiotic balance is essential as healthcare confronts escalating complexity. It ensures that the promise of artificial intelligence is harnessed to champion and elevate the timeless art and science of nursing, safeguarding its core mission: the provision of safe, compassionate, and exceptionally competent patient care.

References

1. Ancker, J. S., Edwards, A., Nosal, S., Hauser, D., Mauer, E., Kaushal, R., & With the HITEC Investigators. (2017). Effects of workload, work complexity, and repeated alerts on alert fatigue in a clinical decision support system. *BMC medical informatics and decision making*, *17*(1), 36. https://doi.org/10.1186/s12911-017-0430-8
2. Bartkowiak, B., Snyder, A. M., Benjamin, A., Schneider, A., Twu, N. M., Churpek, M. M., ... & Edelson, D. P. (2019). Validating the electronic cardiac arrest risk triage (eCART) score for risk stratification of surgical inpatients in the postoperative setting: retrospective cohort study. *Annals of surgery*, *269*(6), 1059-1063. *DOI:* 10.1097/SLA.0000000000002665
3. Bedoya, A. D., Clement, M. E., Phelan, M., Steorts, R. C., O’brien, C., & Goldstein, B. A. (2019). Minimal impact of implemented early warning score and best practice alert for patient deterioration. *Critical care medicine*, *47*(1), 49-55. *DOI:* 10.1097/CCM.0000000000003439
4. Buchanan, C., Howitt, M. L., Wilson, R., Booth, R. G., Risling, T., & Bamford, M. (2020). Nursing in the age of artificial intelligence: Protocol for a scoping review. *JMIR research protocols*, *9*(4), e17490. https://doi.org/10.2196/17490

5. Buchanan, C., Howitt, M. L., Wilson, R., Booth, R. G., Risling, T., & Bamford, M. (2021). Predicted influences of artificial intelligence on nursing education: scoping review. *JMIR nursing*, *4*(1), e23933. https://doi.org/10.2196/23933
6. Cavalier, J. S., O'Brien, C. L., Goldstein, B. A., Zhao, C., & Bedoya, A. (2022). Vitals are Vital: Simpler Clinical Data Model Predicts Decompensation in COVID-19 Patients. *ACI Open*, *6*(01), e34-e38. DOI: 10.1055/s-0042-1749193
7. Chu, C. H., Leslie, K., Shi, J., Nyrup, R., Bianchi, A., Khan, S. S., ... & Grenier, A. (2022). Ageism and artificial intelligence: protocol for a scoping review. *JMIR Research Protocols*, *11*(6), e33211. https://doi.org/10.2196/33211
8. Churpek, M. M., Yuen, T. C., Winslow, C., Meltzer, D. O., Kattan, M. W., & Edelson, D. P. (2016). Multicenter comparison of machine learning methods and conventional regression for predicting clinical deterioration on the wards. *Critical care medicine*, *44*(2), 368-374. *DOI:* 10.1097/CCM.0000000000001571
9. Darko, E. M., Kleib, M., Lemermeyer, G., & Tavakoli, M. (2023). Robotics in nursing: Protocol for a scoping review. *JMIR Research Protocols*, *12*(1), e50626. https://doi.org/10.2196/50626
10. Despins, L. A., Guidoboni, G., Skubic, M., Sala, L., Enayati, M., Popescu, M., & Deroche, C. B. (2020). Using sensor signals in the early detection of heart failure: A case study. *Journal of gerontological nursing*, *46*(7), 41-46. https://doi.org/10.3928/00989134-20200605-07
11. Fernandes, F., Santos, P., Sá, L., & Neves, J. (2023). Contributions of artificial intelligence to decision making in nursing: a scoping review protocol. *Nursing Reports*, *13*(1), 67-72. https://doi.org/10.3390/nursrep13010007
12. Ferrer, R., Martin-Loeches, I., Phillips, G., Osborn, T. M., Townsend, S., Dellinger, R. P., ... & Levy, M. M. (2014). Empiric antibiotic treatment reduces mortality in severe sepsis and septic shock from the first hour: results from a guideline-based performance improvement program. *Critical care medicine*, *42*(8), 1749-1755. *DOI:* 10.1097/CCM.0000000000000330
13. Haddad, L. M., Annamaraju, P., & Toney-Butler, T. J. (2018). *Nursing shortage*. In: StatPearls. StatPearls Publishing, Treasure Island (FL).
14. Jahandideh, S., Ozavci, G., Sahle, B. W., Kouzani, A. Z., Magrabi, F., & Bucknall, T. (2023). Evaluation of machine learning-based models for prediction of clinical deterioration: A systematic literature review. *International Journal of Medical Informatics*, *175*, 105084. https://doi.org/10.1016/j.ijmedinf.2023.105084
15. Kupfer, C., Prassl, R., Fleiß, J., Malin, C., Thalmann, S., & Kubicek, B. (2023). Check the box! How to deal with automation bias in AI-based personnel selection. *Frontiers in Psychology*, *14*, 1118723. https://doi.org/10.3389/fpsyg.2023.1118723
16. Lee, H., Yun, D., Yoo, J., Yoo, K., Kim, Y. C., Kim, D. K., ... & Han, S. S. (2021). Deep learning model for real-time prediction of intradialytic hypotension. *Clinical Journal of the American Society of Nephrology*, *16*(3), 396-406. *DOI:* 10.2215/CJN.09280620
17. Lu, T. C., Wang, C. H., Chou, F. Y., Sun, J. T., Chou, E. H., Huang, E. P. C., ... & Huang, C. H. (2023). Machine learning to predict in-hospital cardiac arrest from patients presenting to the emergency department. *Internal and Emergency Medicine*, *18*(2), 595-605. https://doi.org/10.1007/s11739-022-03143-1
18. Lyell, D., Magrabi, F., Raban, M. Z., Pont, L. G., Baysari, M. T., Day, R. O., & Coiera, E. (2017). Automation bias in electronic prescribing. *BMC medical informatics and decision making*, *17*(1), 28. https://doi.org/10.1186/s12911-017-0425-5
19. Morley, J., Machado, C. C., Burr, C., Cowls, J., Joshi, I., Taddeo, M., & Floridi, L. (2020). The ethics of AI in health care: a mapping review. *Social science & medicine*, *260*, 113172. https://doi.org/10.1016/j.socscimed.2020.113172
20. Muralitharan, S., Nelson, W., Di, S., McGillion, M., Devereaux, P. J., Barr, N. G., & Petch, J. (2021). Machine learning–based early warning systems for clinical deterioration: systematic scoping review. *Journal of medical Internet research*, *23*(2), e25187. https://doi.org/10.2196/25187
21. Needleman, J., Buerhaus, P., Pankratz, V. S., Leibson, C. L., Stevens, S. R., & Harris, M. (2011). Nurse staffing and inpatient hospital mortality. *New England Journal of Medicine*, *364*(11), 1037-1045. DOI: 10.1056/NEJMsa1001025
22. Nyarko, B. A., Nie, H., Yin, Z., Chai, X., & Yue, L. (2023). The effect of educational interventions in managing nurses' alarm fatigue: An integrative review. *Journal of clinical nursing*, *32*(13-14), 2985-2997. https://doi.org/10.1111/jocn.16479
23. Oliveira, G. N., Nogueira, L. D. S., & Cruz, D. D. A. L. M. D. (2022). Effect of the national early warning score on monitoring the vital signs of patients in the emergency room. *Revista da Escola de Enfermagem da USP*, *56*, e20210445. https://doi.org/10.1590/1980-220X-REEUSP-2021-0445en
24. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic

reviews. *bmj*, *372*. https://doi.org/10.1136/bmj.n71

25. Russ, A. L., Zillich, A. J., Melton, B. L., Russell, S. A., Chen, S., Spina, J. R., ... & Saleem, J. J. (2014). Applying human factors principles to alert design increases efficiency and reduces prescribing errors in a scenario-based simulation. *Journal of the American Medical Informatics Association*, *21*(e2), e287-e296.
26. Sendelbach, S., & Funk, M. (2013). Alarm fatigue: a patient safety concern. *AACN advanced critical care*, *24*(4), 378-386. https://doi.org/10.4037/NCI.0b013e3182a903f9
27. Samal, L., Wu, E., Aaron, S., Kilgallon, J. L., Gannon, M., McCoy, A., ... & Wright, A. (2023). Refining clinical phenotypes to improve clinical decision support and reduce alert fatigue: a feasibility study. *Applied Clinical Informatics*, *14*(03), 528-537. DOI: 10.1055/s-0043-1768994
28. Song, W., Kang, M. J., Zhang, L., Jung, W., Song, J., Bates, D. W., & Dykes, P. C. (2021). Predicting pressure injury using nursing assessment phenotypes and machine learning methods. *Journal of the American Medical Informatics Association*, *28*(4), 759-765. https://doi.org/10.1093/jamia/ocaa336
29. Varghese, J., Kleine, M., Gessner, S. I., Sandmann, S., & Dugas, M. (2018). Effects of computerized decision support system implementations on patient outcomes in inpatient care: a systematic review. *Journal of the American Medical Informatics Association*, *25*(5), 593-602. https://doi.org/10.1093/jamia/ocx100
30. Wardi, G., Carlile, M., Holder, A., Shashikumar, S., Hayden, S. R., & Nemati, S. (2021). Predicting progression to septic shock in the emergency department using an externally generalizable machine-learning algorithm. *Annals of emergency medicine*, *77*(4), 395-406. https://doi.org/10.1016/j.annemergmed.2020.11.007
31. Wong, A., Otles, E., Donnelly, J. P., Krumm, A., McCullough, J., DeTroyer-Cooley, O., ... & Singh, K. (2021). External validation of a widely implemented proprietary sepsis prediction model in hospitalized patients. *JAMA internal medicine*, *181*(8), 1065-1070. doi:10.1001/jamainternmed.2021.2626
32. Wong, G., Greenhalgh, T., Westhorp, G., Buckingham, J., & Pawson, R. (2013). RAMESES publication standards: realist syntheses. *BMC medicine*, *11*(1), 21. https://doi.org/10.1186/1741-7015-11-21

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