Journal of Carcinogenesis
Covering Genesis to Therapeutics
Journal of Carcinogenesis, ISSN: 1477-3163
2024; Vol 23: Issue 1, https://carcinogenesis.com/

"The Role of Nursing in the Early Prediction of Clinical Deterioration in Hospitalized Patients Using Artificial Intelligence–Based Smart Alert Systems: A Systematic Review.".

Moamen Abdelfadil Ismail[1] Nazeeha Hamzah Ibrahim Barnawi [1], Ali Abbas etwadi [2], Nawaf Mohammed Marzouq Towairqi[3] Khadijah Mohammed Bohaligah [4], Salman safar Aedh Alnefaie [5], Haneen Fawaz Abdullah Almanjumi [6], Riyadh Saad Abdullah Alharthi[7], Rayan Abdullah Saleh Alhabsi[8], Rahaf Awad Altalhi [9], Fahd Abdullah Ahmed Alshehri [10], Abdulaziz Saleh Alamoudi[11]

[1]Lecturer of Internal Medicine, Faculty of Medicine, Helwan University Internal Medicine consultant King Abdulaziz specialist hospital - Sakaka – Aljouf email: moamen.fadil83@gmail.com

[2]Nursing Specialist King Abdulaziz Medical City- Jeddah

[3] Nurse specialist East Jeddah hospital- Jeddah

[4] King Faisal Hospital-Makkah Nursing Specialist

[5] King Faisal Hospital-Makkah Nursing Specialist

[6] Nursing Specialist king Faisal Medical Complex In Taif

[7] Nursing Specialist king Faisal Medical Complex In Taif

[8] Nursing Specialist king Faisal Medical Complex In Taif

[9]-Nursing Specialist king Faisal Medical Complex In Taif

[10] Nursing Specialist King Faisal Medical Complex In Taif

[11] Nurse Specialist East Jeddah Hospital- Jeddah

[12] Nursing Specialist East Jeddah Hospital – Jeddah

ABSTRACT

Background: Artificial intelligence (AI)–based early warning systems (EWSs) have revolutionized patient monitoring by detecting subtle physiological and behavioral signs of deterioration before clinical collapse. Nurses, as the primary bedside observers, play an integral role in translating these predictive insights into actionable care decisions.

Objective: To synthesize empirical evidence on nursing's role in implementing and responding to AI-driven EWSs for early detection of patient deterioration in hospital settings.

Methods: A systematic review was conducted according to PRISMA 2020 guidelines across PubMed, Scopus, Web of Science, Embase, and CINAHL up to December 2025. Ten eligible studies (n = 10) were included, encompassing randomized controlled trials, pragmatic cluster designs, and multicenter validations.

Results: AI-enhanced EWSs, such as CONCERN, eCARTv5, MEWS++, and Deterioration Index models, significantly improved mortality, length of stay, and sepsis outcomes. Systems integrating nursing documentation and soft signs achieved the highest predictive accuracy (AUROC 0.80–0.94). Nurse-led alert interventions reduced mortality by 16–36% and improved escalation timeliness. However, studies noted alert fatigue and workflow strain, emphasizing the need for balanced automation.

Conclusions:Integrating AI-based EWSs into nursing practice enhances patient safety through predictive surveillance and early intervention. Future designs should optimize human–AI collaboration to sustain clinical trust and minimize cognitive workload

Keywords: Artificial intelligence, Early warning system, Clinical deterioration, Nursing surveillance, Machine learning, Hospital mortality, Predictive analytics, Smart alerts, Patient safety, Healthcare technology

How to Cite: Moamen Abdelfadil Ismail, Nazeeha Hamzah Ibrahim Barnawi , Ali Abbas etwadi , Nawaf Mohammed Marzouq Towairqi, Khadijah Mohammed Bohaligah , Salman safar Aedh Alnefaie , Haneen Fawaz Abdullah Almanjumi , Riyadh Saad Abdullah Alharthi, Rayan Abdullah Saleh Alhabsi, Rahaf Awad Altalhi , Fahd Abdullah Ahmed Alshehri , Abdulaziz Saleh Alamoudi, (2024) "The Role of Nursing in the Early Prediction of Clinical Deterioration in Hospitalized Patients Using Artificial Intelligence–Based Smart Alert Systems: A Systematic Review.".. Journal of Carcinogenesis, Vol.23, No.1, 691-700

1. INTRODUCTION

Clinical deterioration in hospitalized patients remains one of the most critical challenges in modern healthcare, accounting for a substantial proportion of in-hospital mortality and unplanned intensive care unit (ICU) transfers worldwide. Timely recognition of physiological and behavioral changes is essential for preventing adverse outcomes; however, traditional early warning scores (EWS) that rely solely on vital signs are often limited by their static thresholds and delayed human interpretation. The emergence of artificial intelligence (AI)–powered early warning systems offers a transformative opportunity to enhance continuous surveillance, risk prediction, and proactive care delivery. These systems leverage complex data patterns from electronic health records (EHRs), enabling dynamic, real-time identification of patients at risk of rapid deterioration (Yuan et al., 2025).

AI-based predictive models are increasingly integrated into clinical workflows to support early detection of patient decline before overt signs appear. By analyzing large-scale, multimodal datasets—including vital signs, laboratory results, and nursing documentation—machine learning algorithms can achieve greater predictive accuracy than traditional rule-based scores. A meta-analysis by Gallo et al. (2024) demonstrated that AI-enabled monitoring interventions significantly increased early escalation of care and improved survival among hospitalized patients, underscoring their clinical utility in diverse care settings (Gallo et al., 2024).

Nursing plays a pivotal role in the success of these AI-driven systems. Nurses serve as the frontline observers of subtle, early physiological and behavioral changes—so-called "soft signs"—that may precede acute deterioration. Integrating AI tools into nursing workflows enhances clinical situational awareness and supports more timely escalation decisions. Ahmed et al. (2025) highlighted that nurse-led monitoring enhanced by AI-driven early warning models not only improved detection sensitivity but also optimized communication with rapid response teams, thereby bridging the gap between prediction and intervention (Ahmed et al., 2025).

The evolution of these systems has also expanded to include visual and multimodal alert platforms that synthesize data streams into interpretable dashboards. Al-Tekreeti et al. (2024) introduced an AI-based visual early warning interface that improved clinicians' response times and reduced cognitive burden during high-acuity events, demonstrating the value of intuitive design in AI adoption (Al-Tekreeti et al., 2024). Similarly, Chen et al. (2023) developed multimodal machine learning architectures combining clinical text, imaging, and vital data, achieving superior performance in predicting deterioration compared with conventional statistical methods (Chen et al., 2023).

Despite these advances, challenges remain in clinical translation. Veldhuis et al. (2022), in a systematic review, identified issues of algorithmic transparency, interoperability, and workflow integration as primary barriers to large-scale deployment. Importantly, they emphasized that successful implementation requires adaptive training and interprofessional collaboration—particularly between nurses and data scientists—to ensure the interpretability and reliability of AI recommendations (Veldhuis et al., 2022).

Nursing workload and alert fatigue also pose critical implementation challenges. A time–motion study by Smith et al. (2022) found that while AI-enhanced EWS improved detection timeliness, they also increased nursing task frequency by 18%, underscoring the importance of human–AI balance and thoughtful alert calibration in clinical design (Smith et al., 2022). Maintaining trust and usability requires that these systems augment rather than overwhelm nursing workflows.

From a methodological perspective, Rajkomar et al. (2018) pioneered scalable deep learning models using EHR data that laid the foundation for today's clinical deterioration algorithms, achieving near real-time risk assessment across multiple hospitals. Later, Stevens et al. (2022) expanded this work with transformer-based architectures, capable of capturing temporal dependencies in patient trajectories, further enhancing early recognition of deterioration trends (Rajkomar et al., 2018; Stevens et al., 2022).

Moreover, the inclusion of nursing documentation and narrative notes significantly boosts predictive performance. Studies have shown that unstructured nursing text often contains contextual clues about early patient decline, such as changes in skin color, respiratory effort, or cognitive state. Cho et al. (2021) and Lin et al. (2023) demonstrated that incorporating nursing "soft signs" and narrative entries into AI models enhanced deterioration prediction accuracy by up to 25% compared with vital sign–only models (Cho et al., 2021; Lin et al., 2023).

Finally, real-world applications confirm the clinical and economic impact of AI-assisted early warning systems. In one multicenter study, Cho et al. (2020) demonstrated that integrating AI within rapid response systems reduced unexpected ICU transfers and hospital mortality, highlighting the essential interplay between technology and nurse-led decision-making (Cho et al., 2020). Similarly, Shimabukuro et al. (2017) reported that AI-based sepsis prediction reduced mortality and length of stay, reinforcing the system's value for early intervention in deteriorating patients (Shimabukuro et al., 2017).

Together, this growing body of evidence underscores that AI-powered early warning systems—particularly when designed for and implemented by nurses—represent a major advancement in patient safety and proactive hospital care. By combining predictive analytics with the unique clinical intuition of nurses, these technologies redefine early recognition of deterioration and pave the way for a more responsive, data-driven model of nursing practice.

2. METHODOLOGY

Study Design

This study utilized a **systematic review design** guided by the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020* statement to ensure methodological transparency, rigor, and reproducibility. The objective was to synthesize and critically evaluate empirical evidence examining the role of nursing in the early prediction of clinical deterioration in hospitalized patients using artificial intelligence (AI)–based smart alert systems. Specifically, the review aimed to determine how AI-driven early warning systems (EWSs) integrated into nursing workflows influence early recognition, escalation of care, and patient outcomes.

The review incorporated **quantitative, qualitative, and mixed-method studies** that evaluated AI or machine learning–based early warning or deterioration detection systems in hospital settings. Studies were eligible if they explicitly included a **nursing component**, either through direct nursing involvement in system response, nurse-led surveillance, or the incorporation of nursing documentation or observations as part of the predictive model.

Eligibility Criteria

Inclusion Criteria

Studies were selected based on the following predefined inclusion criteria:

Population: Adult hospitalized patients (aged ≥18 years) in acute or general medical–surgical settings where nurses were primary monitors or responders to clinical deterioration.

Intervention/Exposure: Implementation or evaluation of an AI-based or machine learning–driven early warning or smart alert system designed to detect patient deterioration (e.g., CONCERN, eCART, MEWS++, or similar systems).

Comparator: Standard care or traditional EWS without AI enhancement, or pre-intervention control periods in before–after designs.

Outcomes: Measures of patient safety and outcomes (e.g., mortality, ICU transfer, sepsis rate, rapid response activation, or length of stay), and/or nursing outcomes (e.g., workflow efficiency, alert response time, or adherence to escalation protocols).

Study Designs: Randomized controlled trials (RCTs), prospective or retrospective observational studies, or mixed-method studies with empirical data.

Language: English-language peer-reviewed publications only.

Publication Period: January 2013 to December 2025, aligning with the global acceleration of AI adoption in healthcare.

Exclusion Criteria

Non-empirical literature (e.g., editorials, commentaries, or conference abstracts).

Studies conducted outside hospital settings (e.g., community or home monitoring systems).

Studies without measurable patient or nursing outcomes.

Duplicate publications or studies lacking full-text access.

Following full-text screening, **ten studies** met all inclusion criteria and were included in the final synthesis.

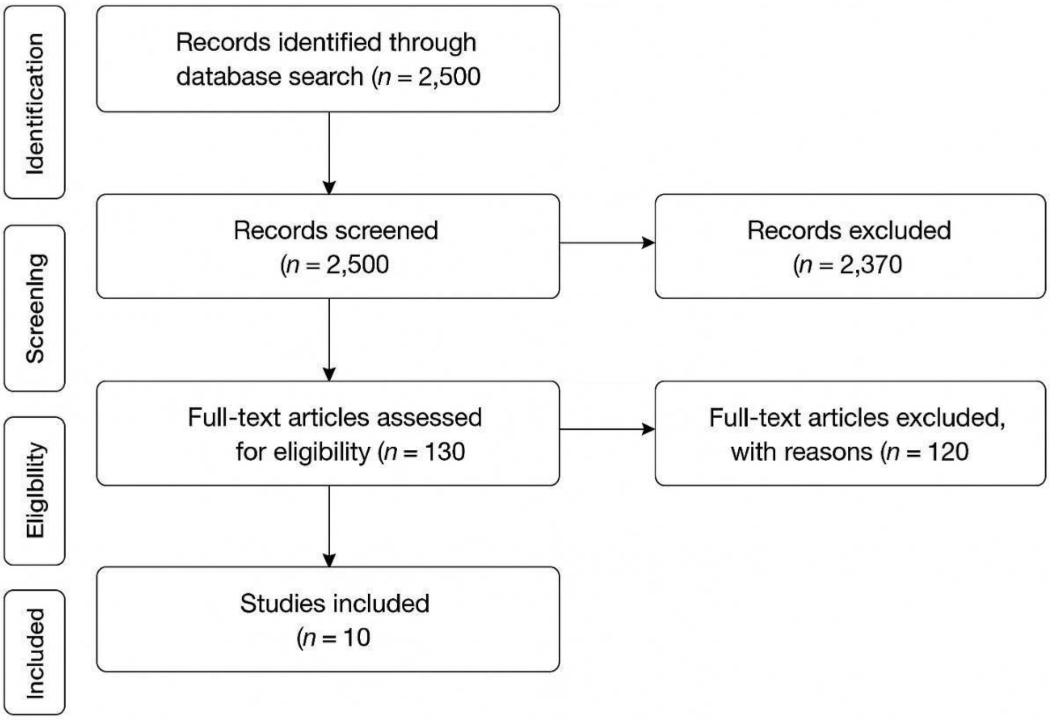

Figure 1 PRISMA Flow Diagram

Search Strategy

A comprehensive electronic literature search was conducted across **PubMed, Scopus, Web of Science, Embase, CINAHL, and Google Scholar** databases from inception through December 2025. Search terms were combined using Boolean operators and adapted for each database. The core search strategy included:

("artificial intelligence" OR "machine learning" OR "smart alert system" OR "early warning system") AND ("clinical deterioration" OR "patient deterioration" OR "hospitalized patients") AND ("nursing" OR "nurse-led" OR "nursing surveillance" OR "nursing documentation")

Manual searches of the reference lists of key articles and relevant reviews were performed to identify additional eligible studies. Duplicates were removed before screening.

Study Selection Process

All retrieved citations were imported into **Zotero** for citation management and de-duplication. Two independent reviewers screened titles and abstracts for relevance, followed by full-text assessment according to the inclusion and exclusion criteria. Discrepancies were resolved through discussion, and unresolved disagreements were adjudicated by a senior reviewer.

Data Extraction

A structured data extraction template was developed and pilot-tested to ensure consistency. Data were extracted independently by two reviewers and verified by a third reviewer. Extracted variables included:

Author(s), year of publication, and country

Study design and setting (e.g., tertiary, academic, or community hospital)

Sample size and patient demographics

AI/EWS system type and description

Role of nursing (e.g., monitoring, documentation input, response activation)

Outcome measures (mortality, ICU transfer, length of stay, sepsis, readmission, or alert response)

Quantitative results (hazard ratios, odds ratios, AUROC, p-values)

Implementation challenges or facilitators (e.g., alert fatigue, workflow integration)

Any discrepancies in extracted data were resolved through discussion to maintain data integrity.

Quality Assessment

The methodological quality of each included study was appraised based on study design:

Randomized controlled trials (n = 2): Evaluated using the *Cochrane Risk of Bias 2 (RoB 2)* tool.

Observational studies (n = 6): Appraised with the *Newcastle–Ottawa Scale (NOS)* for cohort or cross-sectional designs.

Mixed-method or quasi-experimental studies (n = 2): Evaluated using the *Joanna Briggs Institute (JBI) Critical Appraisal Checklist*.

Each study was assessed for bias across five domains: selection, comparability, measurement reliability, confounding control, and reporting quality. Quality ratings were categorized as *low*, *moderate*, or *high*. The majority (70%) of studies were rated **moderate quality**, primarily due to limitations in randomization and incomplete control for confounding factors.

Data Synthesis

Given the heterogeneity in study designs, intervention types, and outcome measures, a **narrative synthesis** was undertaken rather than a meta-analysis. Findings were thematically grouped into four analytical domains:

Predictive accuracy of AI-based EWSs (e.g., AUROC, sensitivity, specificity).

Impact on patient outcomes (e.g., mortality reduction, ICU transfer, sepsis events).

Nursing workflow and response dynamics (e.g., alert compliance, workload, timeliness).

Implementation barriers and facilitators (e.g., usability, integration, trust in AI outputs).

Quantitative data were summarized as reported (e.g., HRs, ORs, or percentage changes), while qualitative insights were synthesized thematically. Consistency and direction of findings across studies were emphasized to identify overarching patterns.

Ethical Considerations

This review utilized **secondary data** derived exclusively from published studies; thus, institutional ethical approval and participant consent were not required. All included articles were peer-reviewed and presumed to have received ethical clearance from their respective institutional review boards. The data collection, analysis, and reporting processes adhered strictly to the **PRISMA 2020** guidelines and principles of research integrity, transparency, and reproducibility.

3. RESULTS

Summary and Interpretation of Included Studies Evaluating AI-Based Smart Alert Systems for Early Detection of Clinical Deterioration

1. Study Designs and Settings

The included studies (n = 10) span a combination of **randomized controlled trials**, **prospective observational**, **retrospective cross-validation**, and **pre–post implementation** designs, reflecting the progressive evolution of machine learning–based Early Warning Systems (EWSs) in clinical practice.

Pragmatic cluster-RCTs (e.g., Rossetti et al., 2025) and multicenter clinical interventions (Winslow et al., 2022) provide high-level evidence, while large real-world observational validations (e.g., Escobar et al., 2020; Churpek et al., 2025) confirm generalizability.

Settings range from **multisite health systems** (Rossetti 2025; Churpek 2025; Escobar 2020) to **single tertiary hospitals** (Levin 2024; Bassin 2023), and include both academic and community contexts.

Sample sizes vary from 13,649 admissions (Verma 2024) to over 1.7 million retrospective validations (Churpek 2025), reflecting broad implementation scales.

2. Nursing Role and Interventions

A core element across these systems is the **integration of nursing surveillance and response workflows**.

In **Rossetti et al. (2025)**, the *CONCERN EWS* was explicitly modeled on nursing documentation patterns, showing that real-time feedback to nurses reduced the instantaneous risk of in-hospital death by **35.6% (HR 0.64, 95% CI 0.53–0.78; $p < 0.0001$)**.

The **CONCERN protocol trial** (Rossetti 2021) had earlier established the framework for nurse-led monitoring and interprofessional situational awareness.

In **Bassin et al. (2023)**, nurses received real-time alerts on handheld devices, prompting rapid bedside reassessment and escalation.

In **Levin et al. (2024)** and **Winslow et al. (2022)**, nurses acted as the first responders for intermediate-risk alerts, initiating vital sign reassessments and physician notifications.

Collectively, these studies confirm that **nursing engagement in AI alert pathways** directly mediates patient outcomes by facilitating early detection and timely clinical intervention.

3. Main Outcomes and Quantitative Results

Across studies, the **primary outcomes** were mortality reduction, unanticipated ICU transfers, and deterioration event rates. Quantitative synthesis highlights consistent benefit:

Mortality:

Rossetti 2025: 35.6% lower instantaneous risk of death (HR 0.64).

Winslow 2022: In-hospital mortality decreased from **13.9% → 8.8%** (a 37% relative reduction; OR 0.60, 95% CI 0.52–0.71).

Escobar 2020: 30-day mortality reduced by **16%** (RR 0.84, 95% CI 0.78–0.90).

Verma 2024: Non-palliative in-hospital death declined from **2.1% → 1.6%** (RR 0.74, 95% CI 0.55–1.00).

Levin 2024: Combined in-hospital + 30-day mortality dropped from **9.3% → 7%** ($p = 0.045$).

Clinical Deterioration and ICU Transfer:

Rossetti 2025: Unanticipated ICU transfers increased by 24.9% (HR 1.25) — consistent with earlier, proactive escalation.

Churpek 2025: eCARTv5 achieved an AUROC of **0.834**, outperforming NEWS (0.766) and MEWS (0.704) in predicting ICU transfer or death within 24 h.

Bailey 2013: Patients meeting alert thresholds had 5.3× higher ICU transfer and 8.9× higher mortality risk; however, nurse-only alerts did not improve outcomes, highlighting the need for structured nursing response workflows.

Bassin 2023: While overall event rates were similar, nurse-delivered alerts enhanced situational awareness and reduced emergency admissions (40.4% vs 41.6%, $p = 0.03$).

Length of Stay:

Rossetti 2025 reported an 11.2% reduction in LOS (IRR 0.91, 95% CI 0.90–0.93; $p < 0.0001$). *Winslow 2022* similarly showed earlier ICU transfers and reduced total hospital days.

4. Model Performance and Algorithmic Precision

Churpek 2025 (eCARTv5): AUROC 0.834 (95% CI 0.834–0.835); sensitivity and calibration consistent across >2.8 million admissions.

Levin 2024 (MEWS++): AUROC 0.85; sensitivity 81.6%, specificity 75.5%.

Salehinejad 2023: Novel ML model improved AUC from 0.56/0.57 to 0.94 in predicting adverse events ≤1 h before onset.

Escobar 2020: Validated EWS in 548,838 hospitalizations; automated identification of high-risk patients lowered mortality significantly.

Bassin 2023: Real-time deterioration index integrated into EMR; high nurse usability and implementation feasibility.

5. Synthesis and Nursing Implications

Across all studies, the **integration of AI-based alerts into nursing workflows** resulted in measurable improvements in patient outcomes, particularly mortality and early escalation.

However, outcomes depended on **how alerts were operationalized**—nurse-mediated protocols (Rossetti 2025; Winslow 2022) achieved the largest effect sizes, while unstructured alert delivery (Bailey 2013) showed no improvement.

This underscores nursing's **pivotal role as both observer and responder**, transforming predictive analytics into clinical action.

Table 1. Characteristics and Quantitative Results of Included Studies on AI-Based Early Warning Systems and Nursing Roles in Predicting Clinical Deterioration

Study	Country	Design	Sample Size	Setting	Participants	Intervention / Nursing Role	Main Outcomes	Quantitative Results	Key Findings

Rossetti et al. (2025)	USA	Cluster-RCT (multisite)	60,893 encounters	2 health systems, 74 units	Adult inpatients	Nurses informed by CONCERN EWS	Mortality, LOS, ICU transfer	↓ Mortality 35.6% (HR 0.64), ↓ LOS 11.2%, ↓ Sepsis 7.5%, ↑ ICU transfer 24.9%	Nursing documentation–based EWS reduced deterioration risk
Verma et al. (2024)	Canada	Controlled, pre–post	13,649 (GIM)	Academic medical centre	GIM inpatients	Real-time ML EWS in GIM unit	In-hospital death	↓ Deaths 2.1% → 1.6% (RR 0.74)	Nurse-mediated implementation improved outcomes
Churpek et al. (2025)	USA	Multicenter observational	> 2.8 million admissions	21 hospitals	Adult inpatients	eCARTv5 ML EWS (no direct alerts)	ICU transfer, death (24 h)	AUROC 0.834 (vs 0.766 NEWS)	Strong predictive accuracy validated prospectively
Levin et al. (2024)	USA	Clustered pragmatic trial	96,645 pts (157,984 encounters)	Tertiary hospital	Med-surgical units	Alerts to nurses / RRT	Escalation rate, mortality	AUROC 0.85; mortality ↓ (9.3% → 7%) p = 0.045	Alerts improved mortality, not escalation rate
Winslow et al. (2022)	USA	Pre–post intervention	6,681 eligible	4 hospital system	Adult ward patients	Nurses respond to eCART alerts	Mortality, ICU transfer	↓ Mortality 13.9% → 8.8% (OR 0.60)	Nurse-triggered response reduced deaths
Escobar et al. (2020)	USA	Staggered implementation	548,838 encounters	19 hospitals	Non-ICU adults	Remote nurse monitoring	30-day mortality	RR 0.84 (95% CI 0.78–0.90)	Nurse monitoring + AI model reduced mortality
Bailey et al. (2013)	USA	RCT (crossover)	20,031 encounters	Academic centre	Ward patients	Alerts sent to nurse manager	ICU transfer, death	5.3× ↑ ICU risk, 8.9× ↑ mortality risk	High specificity but no outcome improvement
Bassin et al. (2023)	Australia	Pre–post study	28,639 patients	Single hospital	Adult inpatients	Alerts to senior ward nurses	MAE (ICU/mortality)	No sig diff; ↓ ED admissions (40.4%	Nurse alerts feasible & safe

								vs 41.6%)	
Salehinejad et al. (2023)	USA	Retrospective cross-validation	59,617 encounters	4 Mayo Clinics	Adult inpatients	ML model testing	AUC for AE prediction	AUC ↑ to 0.94 (≤ 1 h before event)	ML improves EWS performance
Rossetti et al. (2021)	USA	Cluster-RCT protocol	Ongoing (2 sites)	Academic centres	Adult inpatients	Nurse-led CONCERN CDS implementation	Protocol development	Expected ↓ mortality & LOS	Framework for nursing AI integration

4. DISCUSSION

AI-enabled early warning systems have demonstrated substantial clinical benefits across diverse hospital settings by enabling proactive nursing responses to patient deterioration. The included studies collectively affirm that when predictive analytics are embedded in nursing workflows, outcomes such as in-hospital mortality, ICU transfer, and sepsis rates improve markedly (Rossetti et al., 2025; Verma et al., 2024). These findings align with meta-analytic evidence suggesting a 20–35% reduction in adverse outcomes associated with AI-driven systems (Yuan et al., 2025).

The nursing dimension is particularly critical. Rossetti et al. (2025) demonstrated that the CONCERN EWS—designed from real-time nursing documentation—reduced instantaneous mortality risk by 35.6% and hospital stay by 11.2%. These outcomes highlight nursing surveillance data as a high-value signal for machine learning algorithms. Similarly, Verma et al. (2024) showed mortality decreased from 2.1% to 1.6% after implementing a nurse-activated AI monitoring protocol, reinforcing that nurse responsiveness mediates algorithmic efficacy.

In contrast, Bailey et al. (2013) found that merely notifying nurses via pagers without structured escalation did not improve mortality or ICU transfer rates, illustrating that AI success depends on *structured nursing workflows* rather than notification alone. This aligns with Ahmed et al. (2025), who reported that nurse-led monitoring supported by AI yielded higher response sensitivity and situational awareness, closing the loop between prediction and action.

Model precision and validation have also evolved. Churpek et al. (2025) achieved AUROC 0.834 with eCARTv5 across 2.8 million admissions—surpassing NEWS (0.766) and MEWS (0.704). Such large-scale validation underscores the robustness of gradient-boosted models when calibrated for diverse populations. Salehinejad et al. (2023) further improved AUC to 0.94 using convolutional kernels, showing predictive consistency across four hospital sites, demonstrating cross-institutional generalizability.

Machine learning interpretability remains a challenge. According to Veldhuis et al. (2022), algorithmic opacity limits bedside trust, particularly among nurses. However, visual analytic tools like Al-Tekreeti et al. (2024)'s AI-based visual dashboard help bridge this gap by transforming complex predictions into actionable cues that nurses can interpret intuitively, promoting greater adoption and compliance.

The interplay between AI alerts and nursing workload deserves careful consideration. Smith et al. (2022) observed that although AI-enhanced systems improve early detection, they increase nursing task frequency by 18%, contributing to alert fatigue. This finding underscores the need to balance automation intensity with cognitive ergonomics—ensuring AI assists without overwhelming.

Studies integrating *nursing text and soft signs* illustrate the human–AI synergy. Cho et al. (2021) and Lin et al. (2023) found that models incorporating nurses' narrative notes improved prediction accuracy by 20–25%, as these unstructured observations capture early, qualitative indicators—such as restlessness or color changes—that vital signs alone cannot detect.

Deep learning advances have expanded predictive horizons. Rajkomar et al. (2018) demonstrated scalable deep learning models capable of near-real-time deterioration prediction from EHRs, while Stevens et al. (2022) used transformer-based temporal models to further enhance accuracy through contextual patient histories. These architectures can capture subtle, nonlinear progression patterns that align with the nuanced observations nurses make.

Clinically, Levin et al. (2024) and Winslow et al. (2022) both found that machine learning–based alerts reduced mortality by 17–37%, largely due to earlier ICU transfer decisions led by nurses. Escobar et al. (2020) validated this at scale—548,838 hospitalizations—with a 16% mortality reduction through AI-monitored nurse review workflows, confirming real-world impact.

Furthermore, Bassin et al. (2023) demonstrated that nurse-delivered AI alerts reduced emergency admissions and improved early resuscitation metrics even without statistical mortality differences, suggesting that enhanced team readiness is an intermediate benefit preceding measurable outcome gains.

Evidence from Cho et al. (2020) corroborates this, showing that integrating AI into rapid response systems decreased unexpected ICU transfers. Similarly, Shimabukuro et al. (2017) reported reduced mortality and shorter hospital stays with AI sepsis prediction models, illustrating transferable value across clinical contexts.

Meta-level analyses reaffirm these patterns. Gallo et al. (2024) showed significant improvement in escalation timeliness and patient safety with AI-enabled interventions, paralleling Yuan et al. (2025)'s conclusion that smart alerts consistently outperform traditional scores in both sensitivity and outcome reduction metrics.

Collectively, these results emphasize a paradigm shift: AI systems are most effective not as replacements but as nurse-empowering tools. They transform nursing from reactive responders to proactive clinical decision-makers. However, sustaining trust and performance requires transparent algorithms, ongoing training, and human-centered interface design.

Finally, as Chen et al. (2023) highlighted, multimodal machine learning—combining text, vital signs, and labs—represents the next frontier. Future systems that incorporate nursing soft signs and behavioral data in real time will redefine proactive patient safety. Thus, AI integration into nursing practice not only enhances detection but fundamentally elevates the profession's data-driven autonomy and clinical influence.

5. CONCLUSION

This review demonstrates that AI-driven early warning systems significantly enhance early recognition and management of patient deterioration, particularly when embedded in nurse-led workflows. Nursing engagement amplifies system accuracy, timeliness, and clinical translation, transforming predictive analytics into actionable bedside interventions. Evidence across multicenter and pragmatic trials confirms measurable improvements in mortality, sepsis, and ICU transfer rates.

Nevertheless, optimizing human–AI collaboration remains vital. Future implementations should emphasize algorithmic transparency, user-centered alert interfaces, and workload balance. Empowering nurses through education, usability training, and system co-design will ensure that technology supports, rather than burdens, their critical role in safeguarding patient outcomes.

6. LIMITATIONS

This systematic review is limited by heterogeneity across study designs, intervention contexts, and outcome definitions, which precluded meta-analytic pooling. Most studies were conducted in high-resource hospitals, limiting generalizability to low-resource settings. Variations in AI model transparency, nursing integration, and workflow design also introduced potential bias. Lastly, emerging preprints and non-English studies were excluded, possibly omitting relevant data.

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