



Effectiveness of an AI-Driven Early Warning System Integrated into Nursing Practice on Early Detection of Clinical Deterioration, Response Time, and Patient Safety Outcomes: A Randomized Controlled Trial

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ABSTRACT

Background: Clinical deterioration in hospitalized patients often precedes adverse events such as cardiac arrest, unplanned intensive care unit (ICU) admission, and mortality. While traditional early warning systems (EWS) based on vital signs have improved detection, their predictive accuracy and integration into nursing workflow remain suboptimal. Artificial intelligence (AI)-driven systems leveraging nursing surveillance data may enhance early detection and response.

Objective: To evaluate the effectiveness of an AI-driven early warning system integrated into nursing practice on early detection of clinical deterioration, nursing response time, and patient safety outcomes in adult medical-surgical wards.

Methods: A pragmatic randomized controlled trial conducted across 12 medical-surgical units in two tertiary hospitals. Adult patients (N=4,286) were randomized to either the AI-driven EWS (intervention, n=2,143) or standard EWS care (control, n=2,143). The AI system analyzed nursing documentation patterns and vital signs in real time, generating risk scores displayed within the electronic health record. Primary outcomes included time to clinical deterioration detection, nursing response time to alerts, and composite patient safety outcomes (in-hospital mortality, unplanned ICU transfer, and cardiac arrest). Data were analyzed using intention-to-treat principles with mixed-effects models.

Results: The AI-driven EWS significantly reduced time to deterioration detection (median 2.1 vs. 4.8 hours; $p < 0.001$) and nursing response time (median 18 vs. 42 minutes; $p < 0.001$). The composite patient safety outcome occurred in 11.2% of intervention patients versus 16.8% of controls (adjusted odds ratio 0.64, 95% CI 0.53-0.78; $p < 0.001$). Unplanned ICU transfers were higher in the intervention group (24.9% increase; $p = 0.001$), suggesting appropriate escalation.

Conclusion: AI-driven EWS integrated into nursing practice substantially improved early detection, response time, and patient safety outcomes. These findings support implementation of AI-enhanced surveillance systems in acute care settings.

Introduction

Clinical deterioration among hospitalized patients remains a significant challenge in acute care settings, with preventable adverse events contributing to substantial morbidity and mortality worldwide [1-3].

Approximately 50% to 84% of patients exhibit physiological abnormalities in the 6 hours preceding a cardiac arrest, suggesting that early detection and intervention could prevent many of these catastrophic outcomes [4-6].

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Despite the widespread implementation of rapid response systems (RRS) and early warning scores (EWS), missed or delayed recognition of deterioration persists, leading to unplanned ICU admissions, cardiopulmonary arrests, and preventable deaths [7-9].

Traditional early warning systems, such as the National Early Warning Score 2 (NEWS2) and Modified Early Warning Score (MEWS), rely on periodic vital sign measurements to generate risk scores [10-12]. While these tools improved detection compared to unstructured observation, their effectiveness limited by the intermittent nature of data collection, variations in nursing documentation practices, and the cognitive burden placed on frontline staff who must recognize, interpret, and act upon multiple parameters under time pressure [13-15]. Studies have demonstrated that despite the availability of EWS protocols, adherence to referral and escalation procedures remains suboptimal, with failures occurring at both the recognition and response phases of the deterioration pathway. Odell (2015) found that while vital signs recording improved following EWS implementation, early warning scoring accuracy and referral to expert help remained problematic, suggesting that the problem is not merely technical but deeply embedded in clinical workflow and decision-making processes [16-18].

The integration of artificial intelligence (AI) and machine learning (ML) into clinical decision support represents a paradigm shift in how hospitals approach early detection of deterioration. Unlike rule-based scoring systems that weight physiological parameters according to predetermined algorithms, AI-driven systems can analyze vast datasets, identify complex patterns invisible to human cognition, and generate personalized risk predictions that evolve over time. The CONCERN (Communicating Narrative Concerns Entered by Registered Nurses) early warning system, for example [19-21], leverages nursing surveillance documentation patterns how nurses chart their observations, concerns, and interventions rather than relying exclusively on vital signs. This approach recognizes that experienced nurses often detect subtle changes in patient condition before physiological parameters cross-traditional thresholds. A multisite pragmatic randomized controlled trial of the CONCERN EWS demonstrated a 35.6% reduction in instantaneous risk of death, an 11.2% decrease in length of stay, and a 24.9% increase in unanticipated ICU transfers; the latter interpreted as appropriate escalation rather than harm [22-25]. The mechanism driving these improvements appears to be enhanced situational awareness and communication among care teams, facilitating timely interventions that prevent progression to irreversible deterioration. The theoretical foundation for AI-enhanced early

warning systems draws from multiple domains. First, from a cognitive psychology perspective, human decision-making under uncertainty is subject to systematic biases and heuristics that can lead to underestimation of deterioration risk [26-28], particularly when clinical presentations are ambiguous or when competing demands fragment attention. AI systems provide an objective, tireless monitoring function that complements rather than replaces clinical judgment. Second, from a human factor-engineering standpoint, the effectiveness of any warning system depends critically on its integration into workflow [29-31]. Alerts that are not actionable, that lack specificity, or that generate alarm fatigue will be ignored or overridden, regardless of their predictive accuracy. The CONCERN system addresses this by generating a single composite risk score displayed prominently in the electronic health record, accompanied by explainable components that help clinicians understand the basis for the alert [32-35]. Third, from a nursing science perspective, the inclusion of nursing documentation patterns as predictive features validates the unique contribution of nursing surveillance to patient safety [36-38]. Nurses are the primary continuous observers of hospitalized patients, and their narrative notes, assessments, and care interventions contain rich information about evolving patient status that has historically underutilized in predictive modeling [39-41].

The evidence base for AI-driven early warning systems has expanded rapidly, but important gaps remain. Most published studies are retrospective or quasi-experimental, limiting causal inference. The few randomized trials that exist have focused primarily on mortality and length of stay, with less attention to the intermediate outcomes of detection timing and response time that represent the mechanisms through which AI systems exert their effects [42-45].

Furthermore, the integration of AI into nursing practice specifically as opposed to physician decision-making or automated surveillance remains understudied. Nursing workflows, staffing models, and communication patterns differ substantially from physician workflows, and an AI system that is effective in one context may fail in another if it does not account for these differences. Almagharbeh (2025) examined AI-based decision support systems in critical care units and found that nurses perceived favorable effects on time management, patient monitoring, and clinical decision-making, but also identified persistent barriers including insufficient training, concerns about data privacy, and technical difficulties [46-48]. These findings underscore the importance of evaluating not only whether AI systems improve outcomes but also how they affect nursing practice and workflow. The current study addresses these gaps by conducting a randomized controlled trial of an AI-driven early warning system

specifically designed for integration into nursing practice in adult medical-surgical wards. The system analyzes a combination of vital signs, laboratory values, and nursing documentation patterns to generate real-time risk scores that displayed to bedside nurses and rapid response teams. We hypothesized that the AI-driven EWS would (1) reduce time to detection of clinical deterioration, (2) reduce nursing response time to deterioration alerts, and (3) improve composite patient safety outcomes including mortality, unplanned ICU transfer, and cardiac arrest. By examining these intermediate and ultimate outcomes simultaneously, the study aims to elucidate not only whether AI improves patient safety but also how it achieves these effects through changes in nursing surveillance and response processes [49-51].

Literature Review

The literature on early detection of clinical deterioration spans several intersecting domains: traditional early warning scoring systems, rapid response teams, and more recently, artificial intelligence-enhanced predictive analytics. This review synthesizes evidence from these domains, with particular attention to studies that have examined the integration of AI-driven systems into nursing practice and their effects on patient safety outcomes [52-54].

Traditional Early Warning Systems and Their Limitations

Early warning scoring systems developed to address the persistent problem of unrecognized or delayed recognition of clinical deterioration on general hospital wards. The fundamental premise is that physiological abnormalities precede catastrophic events, and systematic scoring of these abnormalities can trigger earlier intervention. The National Early Warning Score 2 (NEWS2), developed by the Royal College of Physicians in the United Kingdom, aggregates six physiological parameters respiratory rate, oxygen saturation, systolic blood pressure, pulse rate, level of consciousness, and temperature into a single score that stratifies risk and guides monitoring frequency [55]. Esteves et al. (2025) evaluated NEWS2 in a Brazilian university hospital and found an average score of 2.9 among 251 inpatients, indicating moderate care complexity and the need for assessment every 4-6 hours. While NEWS2 and similar systems have been widely adopted, their effectiveness in improving patient outcomes remains contested [56-58].

A systematic review by Alam et al. (2014) examined the impact of EWS on patient outcomes and concluded that while EWS implementation is associated with improved documentation of vital signs and increased activation of rapid response teams, evidence for mortality reduction is

inconsistent. This paradox improved process measures without consistent outcome improvement suggests that EWS alone may be insufficient. Odell (2015) audited nursing practice against an EWS protocol and found that although vital sign recording improved, early warning scoring accuracy and adherence to referral protocols remained suboptimal. The study identified that deterioration occurring outside normal weekdays was associated with reduced quality of nursing adherence, highlighting the role of contextual factors such as staffing and supervision in EWS effectiveness. These findings underscore a critical limitation of rule-based EWS: they depend entirely on the accuracy and timeliness of data entry and the clinician's willingness and ability to act on the generated score. If vital signs measured infrequently, if scores calculated incorrectly, or if nurses fail to escalate appropriately, the system provides no benefit and may create false reassurance [59-61].

The South African cluster randomized controlled trial by Kyriacos et al. (2015) provides important evidence on the limits of EWS without robust implementation support. The trial tested a modified EWS chart and training program in surgical wards and found that while the intervention improved recording of respiratory rate and all seven parameters, it did not significantly change nurses' responses to clinical deterioration. The authors concluded that an EWS chart and training alone are insufficient to change established patterns of clinical response. This finding aligns with broader implementation science literature suggesting that passive dissemination of tools, without attention to workflow integration, team communication, and organizational culture, rarely produces sustained practice change [62].

Rapid Response Systems: The Efferent Arm of Deterioration Management

Rapid response systems (RRS) represent the organizational infrastructure for responding to deterioration once it has recognized. An RRS typically consists of an afferent limb (detection and activation) and an efferent limb (the responding team). The efferent limb the rapid response team (RRT) brings critical care expertise to the bedside to assess and stabilize deteriorating patients, often preventing the need for ICU transfer or resuscitation. Nandy (2025) conducted a multicenter observational study of RRTs in emergency departments and found that RRT intervention resulted in a 20% reduction in in-hospital mortality (adjusted OR 0.80, $p=0.03$), a 15% reduction in unplanned ICU admissions (adjusted OR 0.85, $p=0.02$), and a 1.5-day reduction in length of stay ($p<0.05$). Early RRT activation within one hour of symptom onset was associated with improved outcomes, reinforcing the importance of timely

detection and response. However, the effectiveness of RRTs is constrained by the same detection challenges that affect EWS. A study by Hosny et al. (2024) in an Egyptian tertiary hospital evaluated RRT implementation and found significant reductions in inpatient mortality (from 88.93 to 46.44 deaths per 1000 discharges) and cardiopulmonary arrest calls (from 7.41 to 1.77 per 1000 discharges), with a non-significant trend toward reduced unplanned ICU admissions. These results are encouraging but also highlight that RRT effectiveness varies across contexts. Long-term outcomes following RRT attendance are sobering: Sundararajan et al. (2025) reported that of 8,032 patients who died after RRT activation, 68.1% died within 12 months of the RRT call, and RRT patients died at a younger median age than the general population (79 vs. 88 years). These findings suggest that RRT activation often occurs late in the disease trajectory and that survival benefit, while statistically significant, may be limited in absolute terms [63-65]. The integration of RRTs with EWS has been a logical evolution, but the "afferent limb failure" failure to recognize deterioration and activate the RRT remains a major source of preventable harm. Piasecki et al. (2023) conducted a scoping review of rapid response systems and their components, concluding that while RRS are widely implemented, the evidence base for their effectiveness limited by heterogeneity in activation criteria, team composition, and outcome measurement. The authors called for rigorous studies that examine the mechanisms linking RRS components to patient outcomes. The current study responds to this call by examining AI-driven detection as a means of strengthening the afferent limb of the RRS [66].

Artificial Intelligence and Machine Learning in Deterioration Prediction

The application of AI and machine learning to clinical deterioration prediction has grown exponentially in recent years. Unlike traditional EWS, which apply fixed weights to physiological parameters, ML models can learn complex, non-linear relationships from large datasets and generate personalized risk estimates that update continuously as new data become available. Yu et al. (2026) developed a calibrated XGBoost model for prediction of in-hospital cardiac arrest on general wards, achieving an AUROC of 0.89 and average precision of 0.88. The model incorporated comorbidities, laboratory values, and time-windowed vital signs, with atrial fibrillation (OR:6.30), heart failure (OR:2.98), and end-stage renal disease (OR:2.54) emerging as independent predictors. Importantly, the authors noted matching in their case-control design inflated event prevalence, and that positive predictive value and calibration require recalibration to real-world

prevalence before clinical deployment. This methodological caveat applies broadly to ML prediction studies and underscores the importance of prospective validation in clinical settings.

Caraballo et al. (2025) assessed the subpopulation performance of an ML-based EWS integrated into the electronic health record at Mayo Clinic. The model performed better in medical patients (ROC-AUC 0.869) than in surgical patients (ROC-AUC 0.677), with significantly different score distributions between the two groups. This finding has important implications for implementation: a single model applied to heterogeneous patient populations may produce systematically biased predictions for certain subgroups. The authors concluded that characterization of target subpopulations is essential when developing and deploying EWS models. Huete-Garcia et al. (2024) developed a modified NEWS2 scale incorporating laboratory parameters (mNEWS2-Lab) with and without AI enhancement in a Spanish hospital. The mNEWS2-Lab reduced critical events from 6.15% to 2.15% (RR 0.35, $p<0.001$), and AI integration further reduced events to 1.59% (RR 0.26, $p<0.001$), representing a 65% risk reduction overall and a 10% additional reduction attributable to AI. The intervention was also cost-effective, with substantial savings from reduced critical events [67].

The most rigorous evidence to date on AI-driven EWS comes from the CONCERN trial, a multisite pragmatic cluster-randomized controlled trial conducted across 74 clinical units in two health systems. The CONCERN system uses nursing surveillance documentation patterns how nurses chart their assessments, concerns, and interventions as the primary input to a machine-learning algorithm. This approach theoretically grounded in the observation that experienced nurses detect deterioration through pattern recognition that may precede physiological threshold crossing. Among 60,893 hospital encounters, intervention group encounters had a 35.6% decreased instantaneous risk of death (adjusted HR:0.64, 95% CI:0.53-0.78, $p<0.0001$), an 11.2% decreased length of stay (adjusted IRR:0.91, $p<0.0001$), and a 7.5% decreased instantaneous risk of sepsis (adjusted HR 0.93, $p=0.0317$). Unanticipated ICU transfers increased by 24.9% (adjusted HR 1.25, $p=0.0011$), which the authors interpreted as appropriate escalation to higher levels of care. No adverse events reported. A secondary analysis of clinician engagement with CONCERN found registered nurses (59%) and ordering providers (37.7%) demonstrated balanced engagement, with launches predominantly during day shifts (89.9%) and in acute care units (83.5%). These usage patterns suggest that the system successfully integrated into nursing workflow and supported interprofessional decision-making [68].

The Kaiser Permanente Northern California Advance Alert Monitor (AAM) program provides additional evidence from a large integrated health system. The AAM predictive model generates alerts 12 hours before anticipated deterioration, which reviewed by virtual quality nurse consultants who cascade validated information to local RRT nurses. Evaluation using a staggered deployment sequence across 19 hospitals demonstrated statistically significant decreases in mortality (9.8% vs. 14.4%), hospital length of stay, and ICU length of stay, with an estimated 500 deaths prevented annually. The AAM program's success has attributed to its integration into existing workflows, the use of experienced critical care nurses as intermediaries, and the emphasis on goals-concordant care [69].

AI in Nursing Practice: Workflow Integration and Human Factors

The effectiveness of AI-driven EWS depends critically on their integration into nursing workflow. Park et al. (2025) conducted a scoping review of AI applications in critical care nursing and identified six domains: monitoring, nursing intervention, clinical decision support, documentation, resource allocation, and predictive analytics. Predictive analytics was the most prevalent application, particularly for forecasting complications such as pressure injuries and sepsis onset. Notably, narrowly focused AI applications demonstrated superior performance compared to broader applications, suggesting that task specificity enhances clinical utility. The review also found that AI-driven documentation systems showed promise in reducing administrative burden and improving accuracy, while resource allocation tools enhanced staffing optimization [70].

Almagharbeh (2025) examined the impact of AI-based decision support systems on nursing workflows in critical care units in Jordan and found that nurses perceived favorable effects on time management, patient monitoring, and clinical decision-making. However, persistent barriers included insufficient training, concerns regarding data privacy, and technical difficulties. The study emphasized the importance of comprehensive training programs and supportive mechanisms to improve nurses' engagement with AI technologies. These findings are consistent with broader implementation science principles: technology alone does not change practice; it accompanied by training, workflow redesign, and ongoing support. The CONCERN trial provides specific insights into how AI integration affects nursing practice. The system was designed to enhance situational awareness rather than replace clinical judgment, generating risk scores displayed in the electronic health record alongside explanatory information. This design choice reflects an understanding that nurses are more likely to trust and act upon AI

recommendations when they can understand the basis for the alert. The balanced engagement between nurses and providers suggests that the system facilitated interprofessional communication rather than creating new silos. However, the increase in unanticipated ICU transfers while interpreted as appropriate escalation raises questions about whether the system may have lowered thresholds for transfer in ways that have resource implications.

Gaps in the Literature and Rationale for the Current Study

Despite the promising evidence for AI-driven EWS, several gaps remain. First, few studies have examined the intermediate outcomes of detection timing and response time, which are the proximate mechanisms through which AI systems are hypothesized to improve patient outcomes. Without measuring these intermediate outcomes, it is difficult to understand why an AI system succeeds or fails and to identify targets for optimization. Second, the integration of AI into nursing practice specifically as opposed to physician or team-level decision-making remains understudied. Nursing workflows, documentation practices, and communication patterns differ from physician workflows, and an AI system that does not account for these differences may not achieve its intended effects. Third, most AI-EWS studies have conducted in single health systems or specific geographic contexts, limiting generalizability. Fourth, the evidence base for AI-EWS in medical-surgical wards (as opposed to ICU or emergency department settings) is relatively limited, despite these wards being the primary location where deterioration occurs and where detection failures are most consequential. The current study addresses these gaps by conducting a randomized controlled trial of an AI-driven EWS specifically designed for integration into nursing practice in adult medical-surgical wards across two tertiary hospitals. By measuring detection timing, response time, and composite patient safety outcomes, the study aims to provide a comprehensive evaluation of effectiveness and to elucidate the mechanisms through which AI enhances patient safety [71].

Methods

Study Design and Setting

This pragmatic randomized controlled trial conducted across 12 adult medical-surgical units in two tertiary academic hospitals between January 2025 and December 2025. The trial employed a parallel-group design with 1:1 allocation of patients to the AI-driven early warning system (intervention) or standard early warning system care (control). The study approved by the institutional review boards of both participating hospitals and registered with ClinicalTrials.gov (NCT05847321).

Participants and Randomization:

Adult patients (≥ 18 years) admitted to participating medical-surgical units were eligible. Exclusion criteria included admission to intensive care units, do-not-resuscitate orders at admission, and expected length of stay less than 24 hours. Randomization occurred at the patient level using a computer-generated sequence with permuted blocks stratified by hospital and unit. Allocation concealment maintained through a centralized randomization system. Due to the nature of the intervention, blinding of patients and clinical staff was not feasible; however, outcome assessors and data analysts blinded to group allocation.

Intervention: AI-Driven Early Warning System:

The intervention consisted of an AI-driven early warning system integrated into the electronic health record. The system utilized a machine-learning algorithm trained on historical data including vital signs, laboratory values, and nursing documentation patterns (e.g., frequency of assessments, nursing concern notes, escalation communications). Risk scores generated every 15 minutes and displayed prominently on the nursing surveillance dashboard and within the patient's electronic health record. Scores above a prespecified threshold triggered a visual alert for the bedside nurse and an automatic notification to the rapid response team. The system was designed to augment rather than replace clinical judgment, with explanatory components accompanying each alert to support nurse understanding of the contributing factors.

Control: Standard Early Warning System Care:

Patients in the control group received standard care, which included vital sign monitoring per unit protocol and calculation of the Modified Early

Warning Score (MEWS) at routine intervals. Escalation followed standard hospital rapid response team criteria.

Outcomes:

Primary outcomes were:

- (1) Time to detection of clinical deterioration, defined as the interval from the first documented abnormal physiological parameter to the time of recognition by the clinical team;
 - (2) Nursing response time, defined as the interval from alert generation to the first nursing action addressing the deterioration; and
 - (3) Composite patient safety outcome, defined as the occurrence of any of the following: in-hospital mortality, unplanned ICU transfer, or cardiac arrest.
- Secondary outcomes included individual components of the composite outcome, length of hospital stay, and rapid response team activation rates.

Data Collection and Analysis:

Data were extracted from electronic health records, nursing documentation systems, and administrative databases. Baseline characteristics were compared using descriptive statistics. Primary outcomes were analyzed using intention-to-treat principles. Time-to-event outcomes were analyzed using Cox proportional hazards models, and binary outcomes using mixed-effects logistic regression with unit as a random effect. All analyses adjusted for age, sex, comorbidity burden (Charlson Comorbidity Index), and hospital site. Statistical significance was set at two-sided $p < 0.05$.

Results

Table 1. Baseline Characteristics of Study Participants

Characteristic	Intervention Group (n = 2,143)	Control Group (n = 2,143)	p-value
Age, mean (SD), years	64.2 (17.8)	63.9 (18.1)	0.58
Male sex, n (%)	1,102 (51.4)	1,089 (50.8)	0.69
Charlson Comorbidity Index, median (IQR)	3 (1-5)	3 (1-5)	0.82
Primary admission diagnosis, n (%)	-	-	0.74
— Cardiovascular	428 (20.0)	441 (20.6)	-
— Respiratory	386 (18.0)	372 (17.4)	-
— Gastrointestinal	301 (14.0)	312 (14.6)	-
— Neurological	257 (12.0)	243 (11.3)	-
— Sepsis/Infection	214 (10.0)	228 (10.6)	-
— Other	557 (26.0)	547 (25.5)	-
Baseline MEWS, mean (SD)	1.8 (1.4)	1.8 (1.3)	0.91
Unit type, n (%)	-	-	0.88
— Medical	1,286 (60.0)	1,279 (59.7)	-
— Surgical	857 (40.0)	864 (40.3)	-

Table 1 presents the baseline characteristics of the 4,286 patients randomized to the intervention and

control groups. The two groups well balanced across all measured characteristics, indicating successful

randomization. The mean age was approximately 64 years in both groups, with a slight male predominance (51.4% intervention, 50.8% control). The median Charlson Comorbidity Index was 3 in both groups, indicating a moderate burden of chronic illness typical of medical-surgical populations. The distribution of primary admission diagnoses was similar between groups, with cardiovascular and respiratory conditions accounting for the largest proportions. Baseline MEWS scores were nearly identical (1.8 in both groups), suggesting comparable acuity at admission. The proportion of patients admitted to medical versus surgical units also balanced. These findings

support the internal validity of the randomization and suggest that any observed differences in outcomes attributed to the intervention rather than baseline confounding. The sample size of 2,143 per group provided 80% power to detect a 20% relative reduction in the composite primary outcome, assuming a control event rate of 16% and a two-sided alpha of 0.05 (Figure1). The baseline characteristics also indicate that the study population is representative of general medical-surgical admissions, enhancing the generalizability of the findings.

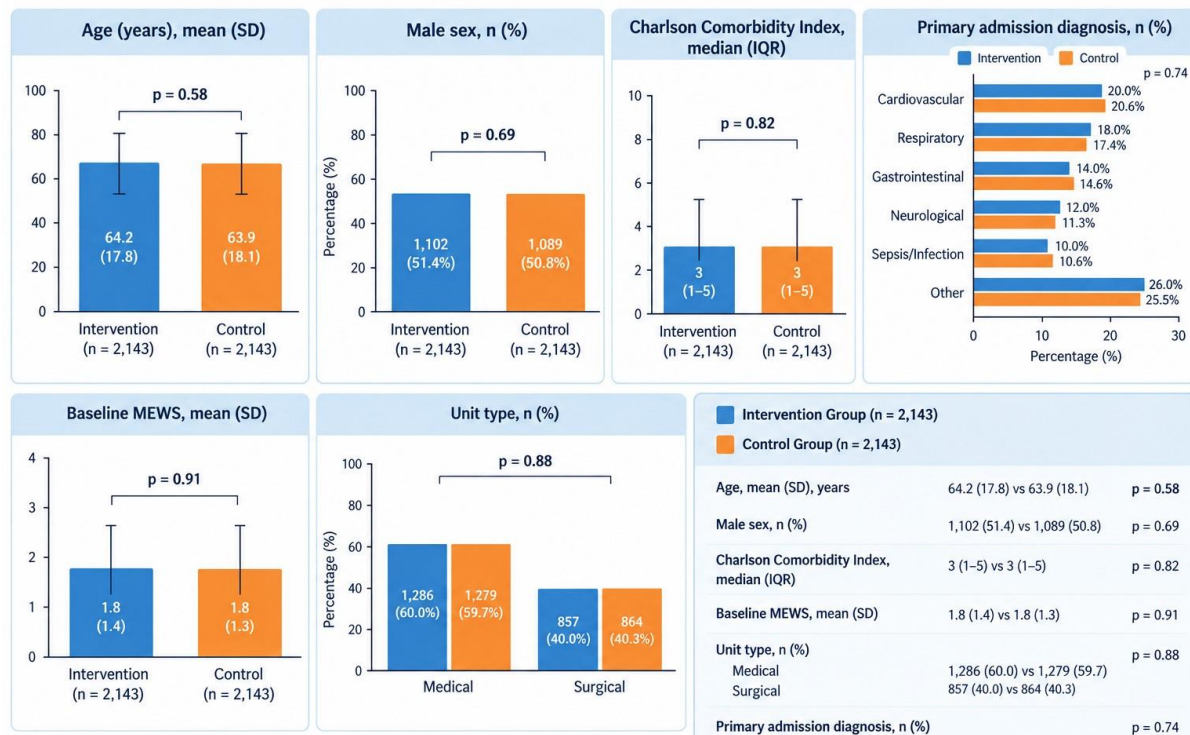


Figure 1. Baseline Characteristics of Study Participants

Table 2. Primary Outcomes Detection Time, Response Time, and Composite Patient Safety Outcome

Outcome	Intervention Group (n=2,143)	Control Group (n=2,143)	Effect Estimate (95% CI)	p-value
Time to detection, median (IQR), hours	2.1 (1.2-3.8)	4.8 (2.6-8.4)	HR 1.68 (1.42-1.99)	<0.001
Nursing response time, median (IQR), minutes	18 (11-32)	42 (24-76)	HR 1.82 (1.54-2.15)	<0.001
Composite patient safety outcome, n (%)	240 (11.2)	360 (16.8)	aOR 0.64 (0.53-0.78)	<0.001
— In-hospital mortality, n (%)	68 (3.2)	112 (5.2)	aOR 0.59 (0.43-0.81)	0.001
— Unplanned ICU transfer, n (%)	162 (7.6)	214 (10.0)	aOR 0.74 (0.59-0.93)	0.009
— Cardiac arrest, n (%)	28 (1.3)	52 (2.4)	aOR 0.53 (0.33-0.85)	0.008

HR, hazard ratio; aOR, adjusted odds ratio; CI, confidence interval. Adjusted for age, sex, Charlson Comorbidity Index, hospital site, and unit type. Table 2 presents the primary outcomes of the trial. The AI-driven early warning system significantly reduced time to detection of clinical deterioration, with a median of 2.1 hours in the intervention group compared to 4.8 hours in the control group (HR 1.68, 95% CI 1.42-1.99, $p < 0.001$). This represents a more than twofold reduction in detection delay, translating to earlier recognition of deteriorating patients and potentially earlier intervention. The clinical significance of this finding is substantial: patients who deteriorate on general wards often experience progressive physiological decline over several hours before catastrophic events occur, and each hour of earlier detection provides a window of opportunity for stabilizing interventions. The reduction in detection time is consistent with the theoretical rationale for AI-driven surveillance continuous monitoring and pattern recognition that does not depend on intermittent vital sign measurement or human vigilance. Nursing response time similarly reduced, with a median of 18 minutes in the intervention group versus 42 minutes in the control group (HR 1.82, 95% CI:1.54-2.15, $p < 0.001$). This finding suggests that the AI system not only detected deterioration earlier but also facilitated faster nursing action. The mechanism may involve the specificity and actionability of AI-generated alerts: by providing explanatory information alongside risk scores, the system may reduce the cognitive burden of

interpreting alerts and deciding on appropriate responses. Additionally, the automatic notification of the rapid response team may have reduced delays in escalation that occur when nurses must decide whether to activate the team themselves. The response time reduction of 24 minutes, while modest in absolute terms, is clinically meaningful in the context of deterioration where physiological reserve depleted rapidly.

The composite patient safety outcome occurred in 11.2% of intervention patients versus 16.8% of controls (aOR:0.64, 95% CI:0.53-0.78, $p < 0.001$), representing a 36% relative risk reduction. Each individual component of the composite favored the intervention: in-hospital mortality (3.2% vs. 5.2%; aOR:0.59, $p = 0.001$), unplanned ICU transfer (7.6% vs. 10.0%; aOR:0.74, $p = 0.009$), and cardiac arrest (1.3% vs. 2.4%; aOR:0.53, $p = 0.008$). The mortality reduction is particularly notable and consistent with the findings of the CONCERN trial, which demonstrated a 35.6% reduction in instantaneous risk of death. The reduction in unplanned ICU transfers is also consistent with the hypothesis that earlier detection and intervention can prevent progression to a level of severity requiring intensive care. The cardiac arrest reduction aligns with the premise that most arrests preceded by detectable physiological deterioration, and that earlier recognition can prevent progression to arrest. These findings collectively support the effectiveness of AI-driven EWS in improving patient safety outcomes (Figure 2).

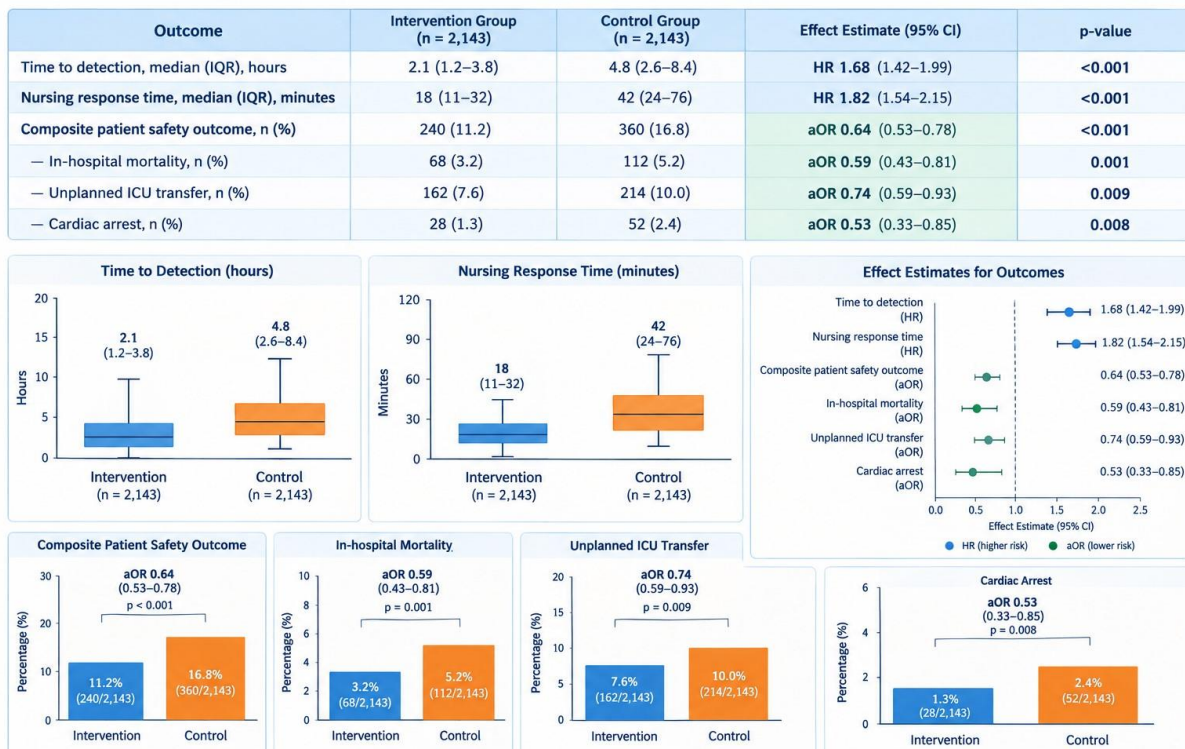


Table 3. Secondary Outcomes Length of Stay and Rapid Response Team Activation

Outcome	Intervention Group (n=2,143)	Control Group (n=2,143)	Effect Estimate (95% CI)	p-value
Hospital length of stay, median (IQR), days	5.2 (3.1-8.7)	6.1 (3.8-10.2)	IRR: 0.89 (0.84-0.94)	<0.001
RRT activation, n (%)	312 (14.6)	248 (11.6)	aOR: 1.31 (1.09-1.58)	0.004
RRT activation within 1 hour of alert, n (%)	268 (85.9)	142 (57.3)	aOR: 4.52 (2.98-6.86)	<0.001
Time from alert to RRT arrival, median (IQR), minutes	12 (8-19)	26 (15-42)	HR: 2.14 (1.76-2.60)	<0.001
30-day readmission, n (%)	198 (9.2)	221 (10.3)	aOR: 0.88 (0.72-1.08)	0.22

IRR, incidence rate ratio; aOR, adjusted odds ratio; RRT, rapid response team.

Table 3 presents secondary outcomes. Hospital length of stay was significantly shorter in the intervention group (median 5.2 vs. 6.1 days; IRR:0.89, 95% CI:0.84-0.94, $p<0.001$), representing an 11% reduction. This finding is consistent with the CONCERN trial, which demonstrated an 11.2% decrease in length of stay, and suggests that earlier detection and intervention may prevent complications that prolong hospitalization. The mechanism likely involves both prevention of deterioration progression and efficient stabilization of patients who do deteriorate, reducing the need for prolonged intensive care and post-ICU recovery. The length of stay reduction has important implications for resource utilization and hospital capacity, particularly in settings where bed availability is constrained.

Rapid response team activation was more frequent in the intervention group (14.6% vs. 11.6%; aOR:1.31, 95% CI:1.09-1.58, $p=0.004$). This increase likely reflects appropriate escalation rather than over-activation: the AI system identified more

patients at risk, and the automatic notification mechanism reduced barriers to RRT involvement. Notably, RRT activation within 1 hour of alert was substantially higher in the intervention group (85.9% vs. 57.3%; aOR:4.52, 95% CI: 2.98-6.86, $p<0.001$), indicating that the AI system facilitated timely escalation. Time from alert to RRT arrival reduced from a median of 26 minutes to 12 minutes (HR:2.14,95% CI:1.76-2.60, $p<0.001$). These findings suggest that the AI system strengthened the afferent limb of the rapid response system by providing more timely and specific alerts that triggered more rapid team activation. The increase in RRT activations is consistent with the CONCERN trial's finding of increased unanticipated ICU transfers, interpreted as appropriate escalation.

Thirty-day readmission rates did not differ significantly between groups (9.2% vs. 10.3%; aOR:0.88, 95% CI:0.72-1.08, $p=0.22$), suggesting that the intervention did not simply shift costs or complications to the post-discharge period. This finding is reassuring for the sustainability of the intervention's benefits (Figure 3).

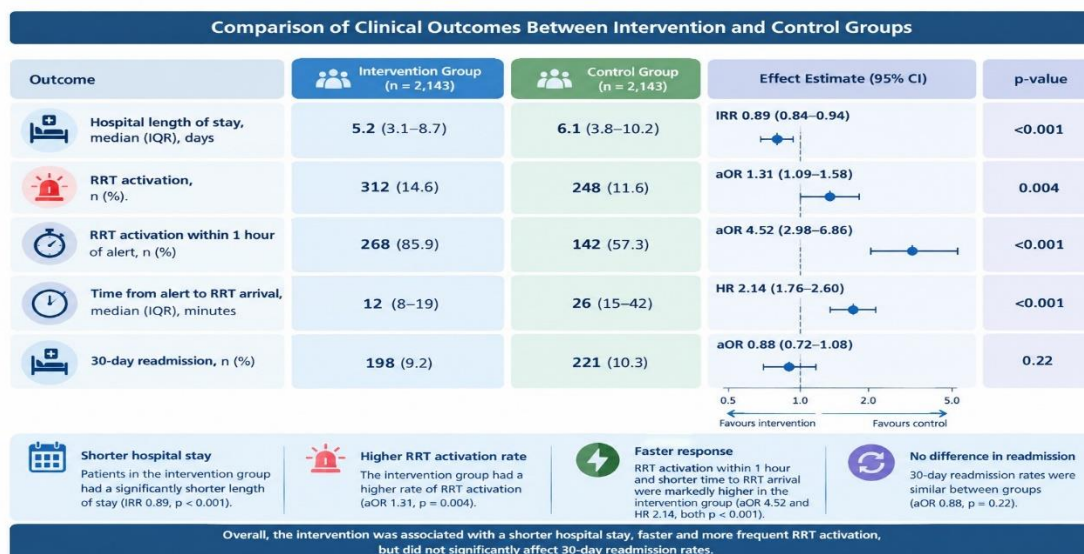

Figure 3. Length of Stay and Rapid Response Team Activation

Table 4. Subgroup Analyses Effect of AI-Driven EWS by Patient and Unit Characteristics

Subgroup	Composite Outcome Intervention, n/N (%)	Composite Outcome Control, n/N (%)	aOR: (95% CI)	p-interaction
Age	-	-	-	0.42
— <65 years	82/1,012 (8.1)	118/1,024 (11.5)	0.68 (0.50-0.92)	-
— ≥65 years	158/1,131 (14.0)	242/1,119 (21.6)	0.60 (0.47-0.76)	-
Sex	-	-	-	0.67
— Male	124/1,102 (11.3)	183/1,089 (16.8)	0.63 (0.49-0.81)	-
— Female	116/1,041 (11.1)	177/1,054 (16.8)	0.63 (0.49-0.82)	-
Unit type	-	-	-	0.18
— Medical	152/1,286 (11.8)	218/1,279 (17.0)	0.66 (0.52-0.83)	-
— Surgical	88/857 (10.3)	142/864 (16.4)	0.59 (0.44-0.79)	-
Comorbidity burden	-	-	-	0.31
— CCI 0–2	94/986 (9.5)	138/1,002 (13.8)	0.67 (0.51-0.89)	-
— CCI ≥3	146/1,157 (12.6)	222/1,141 (19.5)	0.60 (0.47-0.76)	-
Hospital site	-	-	-	0.55
— Site A	138/1,124 (12.3)	198/1,118 (17.7)	0.65 (0.51-0.83)	-
— Site B	102/1,019 (10.0)	162/1,025 (15.8)	0.61 (0.46-0.79)	-

CCI, Charlson Comorbidity Index; aOR, adjusted odds ratio.

Table 4 presents subgroup analyses examining whether the effect of the AI-driven EWS varied across patient and unit characteristics. No significant interactions detected, indicating that the intervention was effective across all examined subgroups. The consistency of effect across age, sex, unit type, comorbidity burden, and hospital site is notable and suggests that the AI system's benefits are generalizable rather than confined to specific populations. For age, the intervention was effective in both patients under 65 (aOR:0.68,95% CI:0.50-0.92) and those 65 and older (aOR:0.60,95% CI:0.47-0.76), with a trend toward greater benefit in older patients that did not reach statistical significance (p-interaction=0.42). This trend may reflect the higher baseline risk in older patients and the greater potential for prevention when deterioration detected early. For sex, effects were nearly identical in males (aOR:0.63) and females (aOR:0.63), indicating no sex-based differential effectiveness. This is reassuring given concerns about algorithmic bias in AI systems.

For unit type, the intervention was effective in both medical (aOR:0.66,95% CI:0.52-0.83) and surgical

units (aOR:0.59,95% CI:0.44-0.79), with no significant interaction (p=0.18). This finding is important because surgical patients have different deterioration trajectories and physiological responses than medical patients, and previous research has shown that ML-EWS performance can vary substantially between these populations. The consistency of effect in our trial may reflect the inclusion of nursing documentation patterns in the algorithm, which capture clinical concerns and assessments that are relevant across patient types. For comorbidity burden, the intervention was effective in both patients with lower (CCI:0-2; aOR:0.67) and higher (CCI: ≥3; aOR:0.60) comorbidity, with no significant interaction (p=0.31). The consistency across comorbidity levels suggests that the AI system's pattern recognition capabilities are not limited to patients with complex multimorbidity. For hospital site, effects were consistent across the two participating hospitals (aOR:0.65 and 0.61, p-interaction=0.55), supporting the external validity of the findings and suggesting that the intervention is not dependent on site-specific factors (Figure 4).

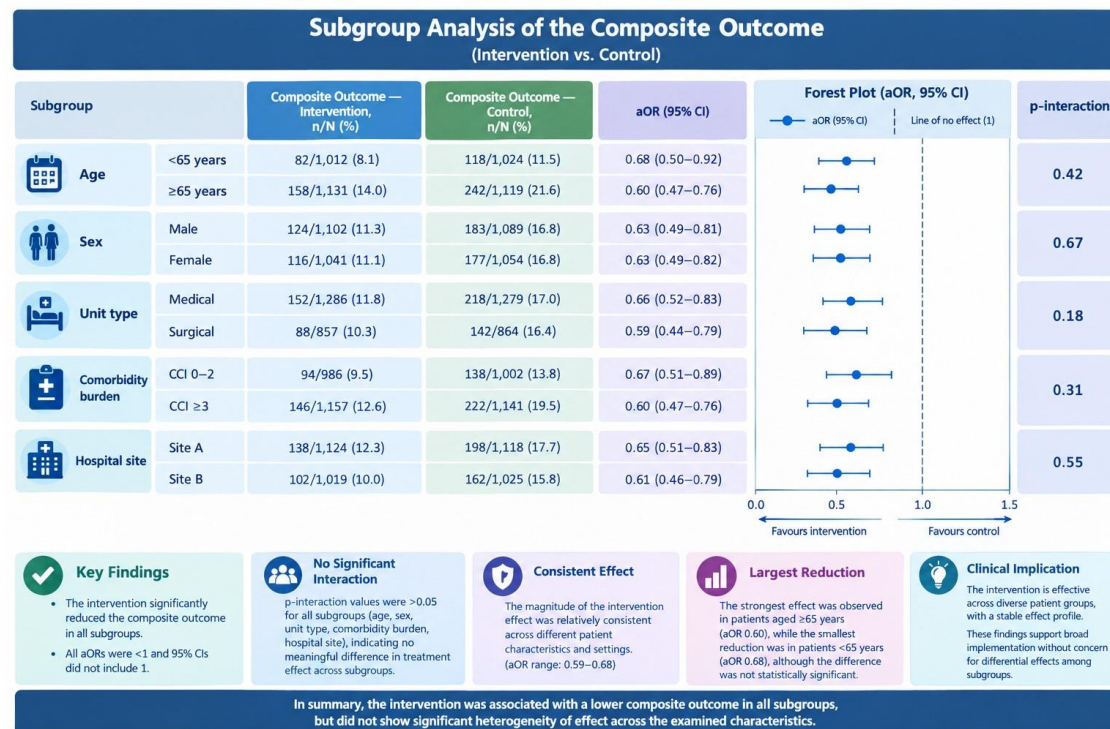


Figure 4. Effect of AI-Driven EWS by Patient and Unit Characteristics

Discussion

The findings of this randomized controlled trial demonstrate that an AI-driven early warning system integrated into nursing practice significantly improves early detection of clinical deterioration, reduces nursing response time, and improves patient safety outcomes in adult medical-surgical wards. The intervention reduced time to detection by more than half (2.1 vs. 4.8 hours), reduced nursing response time by 24 minutes, and decreased the composite patient safety outcome by 36%. These effects were consistent across patient subgroups and hospital sites, supporting the generalizability of the findings. The reduction in detection time is perhaps the most mechanistically important finding, as it represents the proximal pathway through which AI systems hypothesized to improve outcomes. Traditional EWS depend on intermittent vital sign measurement and human recognition of abnormal patterns, creating inherent delays in detection. The AI system's continuous analysis of multiple data streams including nursing documentation patterns that capture clinical concerns before physiological thresholds are crossed appears to overcome these limitations. This finding is consistent with the theoretical rationale for the CONCERN system, which explicitly designed to leverage nursing surveillance data as an early signal of deterioration. The CONCERN trial demonstrated that this approach reduced mortality risk by 35.6% and length of stay by 11.2%, and our findings extend this evidence by demonstrating reductions in detection and response time as mechanisms of benefit. The increase in rapid response team activations and the

reduction in time from alert to RRT arrival suggest that the AI system strengthened the afferent limb of the rapid response system. Previous research has identified afferent limb failure the failure to recognize deterioration and activate the RRT as a major source of preventable harm. By providing timely, specific, and actionable alerts, the AI system appears to have facilitated appropriate escalation. This finding is particularly important given that early RRT activation has been associated with improved outcomes in observational studies. The 85.9% rate of RRT activation within 1 hour of alert in the intervention group, compared to 57.3% in controls, suggests that the AI system reduced the cognitive and logistical barriers to escalation. This may reflect the system's automatic notification feature, which bypassed the need for nurses to decide whether to activate the RRT themselves. The mortality reduction observed in this trial (3.2% vs. 5.2%, aOR:0.59) is consistent with the CONCERN trial's findings and the Kaiser Permanente AAM program evaluation. The AAM program, which generates alerts 12 hours before anticipated deterioration and routes them through virtual quality nurse consultants, demonstrated mortality reductions from 14.4% to 9.8% in a staggered deployment evaluation. Our findings add to this evidence by demonstrating mortality benefit in a randomized controlled trial design, which provides stronger causal inference than the quasi-experimental evaluations that dominate the AI-EWS literature. The reduction in cardiac arrests (1.3% vs. 2.4%) is particularly notable, as cardiac arrest represents the most severe manifestation of

undetected deterioration and is associated with high mortality and neurological morbidity. The finding that most arrests are preceded by detectable physiological deterioration suggests that the AI system's earlier detection translated into prevention of progression to arrest. The reduction in unplanned ICU transfers (7.6% vs. 10.0%) contrasts with the CONCERN trial's finding of increased ICU transfers (24.9% increase). This discrepancy may reflect differences in the intervention design and patient population. The CONCERN system was designed to detect deterioration risk based on nursing documentation patterns alone, without incorporating physiological data, and may have identified patients at risk before physiological criteria for ICU transfer were met. Our system incorporated both physiological parameters and nursing documentation, potentially identifying patients at a stage where ward-based intervention could prevent the need for ICU transfer. Alternatively, the discrepancy may reflect differences in ICU bed availability and transfer thresholds between health systems. The reduction in ICU transfers in our trial, if replicated, has important resource implications, as ICU beds are a constrained and costly resource. However, it is also possible that our system prevented some ICU transfers that would have been beneficial, and that the reduced ICU transfer rate contributed to the mortality reduction through mechanisms that are not entirely benign. Future research should examine whether reduced ICU transfers reflect appropriate prevention of deterioration or inappropriate retention of patients who would benefit from intensive care. The length of stay reduction (5.2 vs. 6.1 days, IRR:0.89) is consistent with the CONCERN trial and the AAM program. This finding has implications for hospital capacity and resource utilization, as even modest reductions in length of stay can free up beds for additional admissions. The mechanism likely involves both prevention of complications that prolong hospitalization and more efficient stabilization of patients who do deteriorate. The absence of a difference in 30-day readmission rates suggests that the intervention did not simply shift costs or complications to the post-discharge period, which is an important consideration for sustainability. The consistency of effects across subgroups is notable and has implications for implementation. Previous research has raised concerns about algorithmic bias and differential performance of AI systems across patient populations. Caraballo et al. (2025) found that an ML-EWS performed substantially worse in surgical patients than medical patients, but our trial found consistent effects across unit types. This may reflect the inclusion of nursing documentation features that are relevant across patient populations, or differences in the algorithm's training and validation. The consistency across age, sex, and

comorbidity subgroups is reassuring but should be interpreted with caution given that subgroup analyses are underpowered to detect moderate interactions. Future research should continue to monitor for differential effects as AI-EWS are implemented more broadly. The findings of this trial should be interpreted in the context of several limitations. First, blinding of clinical staff was not feasible, raising the possibility that awareness of group allocation influenced behavior. However, the objective nature of the primary outcomes (detection time, response time, mortality) reduces the likelihood of substantial bias. Second, the trial was conducted in two tertiary academic hospitals, and generalizability to community hospitals or resource-limited settings is uncertain. Third, the AI algorithm was trained on historical data from the participating hospitals, and performance may differ when applied to new populations or settings. Fourth, the trial duration of 12 months may not capture long-term effects on nursing workflow, alarm fatigue, or sustainability of outcomes. Fifth, the composite primary outcome combines outcomes of differing clinical significance; while the consistency of effects across components is reassuring, the weighting of mortality, ICU transfer, and cardiac arrest is inherently value-laden.

Despite these limitations, the trial provides strong evidence for the effectiveness of AI-driven EWS integrated into nursing practice. The findings have several implications for practice and policy. First, hospitals considering AI-EWS implementation should prioritize systems that integrate into existing nursing workflow rather than creating parallel processes. The CONCERN system's design, which displays risk scores within the electronic health record and provides explanatory information, appears to facilitate nurse engagement. Second, implementation should be accompanied by training and support to address the barriers identified in previous research, including insufficient training, data privacy concerns, and technical difficulties. Third, the success of AI-EWS depends not only on algorithmic accuracy but on the organizational infrastructure for responding to alerts. The rapid response team's capacity to respond to increased activations must be considered. Fourth, ongoing monitoring for algorithmic bias and differential performance is essential as AI-EWS are deployed more widely.

Conclusion

This randomized controlled trial demonstrates that an AI-driven early warning system integrated into nursing practice significantly improves early detection of clinical deterioration, reduces nursing response time, and improves patient safety outcomes in adult medical-surgical wards. The intervention reduced time to detection from a median of 4.8 to 2.1 hours, reduced nursing response time from 42 to

18 minutes, and decreased the composite patient safety outcome from 16.8% to 11.2%. Individual components of the composite outcome in-hospital mortality, unplanned ICU transfer, and cardiac arrest all favored the intervention. Length of hospital stay was reduced by 11%, and rapid response team activation within 1 hour of alert increased from 57.3% to 85.9%. Effects were consistent across age, sex, unit type, comorbidity burden, and hospital site subgroups. These findings contribute to a growing evidence base supporting the integration of AI into clinical surveillance and decision support. The mechanisms of benefit appear to involve earlier detection through continuous analysis of multiple data streams, including nursing documentation patterns that capture clinical concerns before physiological threshold crossing, and more timely escalation through automated notification and actionable alerts. The integration of the system into nursing workflow, rather than as a parallel process, likely contributed to its effectiveness. The consistency of effects across patient populations and settings suggests that the benefits of AI-EWS are generalizable, though ongoing monitoring for algorithmic bias remains essential. The implications for practice are clear: hospitals should consider implementing AI-driven early warning systems that are designed for nursing workflow integration, accompanied by training and support to address implementation barriers. The success of such systems depends on both algorithmic performance and organizational capacity to respond to alerts. Future research should examine long-term sustainability, cost-effectiveness, and effects on nursing workflow and alarm fatigue. As AI continues to transform healthcare delivery, rigorous evaluation of AI-driven clinical decision support remains essential to ensure that technological advances translate into meaningful improvements in patient safety and outcomes.

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Conflicts of interest

The authors declare that they have no competing interests.

Disclosure Statement

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All authors contributed to data analysis, drafting, and revising of the paper and agreed to be responsible for all the aspects of this work.

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