AI-Driven Early Warning Systems in Intensive Care Unit Nursing: Current Applications and Clinical Challenges

Ao LI, Chan WANG, Gang ZHANG, Wenyan YAN, Rui WANG*

Taihe Hospital, Hubei University of Medicine, Shiyan 442000, China

Abstract [**Objectives**] To summarize the current applications, clinical value, and challenges of artificial intelligence-driven early warning system (AI-EWS) in intensive care unit (ICU) nursing. [**Methods**] A literature review was conducted using major medical databases, including PubMed, Web of Science, Embase, and Scopus. The review focused on studies related to AI-EWS in intensive care settings, with particular emphasis on their clinical applications, nursing implications, and implementation challenges. [**Results**] AI-EWS demonstrated improved predictive capability compared to conventional early warning tools by integrating multidimensional clinical data. Current evidence suggests that AI-EWS can facilitate the early detection of sepsis, acute kidney injury, respiratory deterioration, and hemodynamic instability, thereby enabling earlier recognition of patient deterioration and more timely nursing interventions. Beyond improving prediction accuracy, AI-EWS has the potential to enhance nursing decision-making, optimize resource allocation, and support a shift toward more proactive and data-informed critical care nursing. Nevertheless, limitations related to data quality, model interpretability, workflow integration, and ethical issues remain important barriers to clinical implementation. [**Conclusions**] AI-EWS shows considerable potential to advance ICU nursing toward predictive and precision-based care. Further multicenter validation, improved explainability, and better integration with nursing workflows are essential for broader clinical implementation.

Key words Artificial intelligence-early warning system (AI-EWS), Intensive care unit (ICU) nursing, Clinical prediction

1 Introduction

Patients admitted to intensive care units (ICUs) are typically in highly unstable conditions, characterized by dynamic and rapidly changing physiological parameters. Nursing staff are required to continuously monitor a large volume of data, including heart rate, blood pressure, oxygen saturation, and laboratory indicators, and to identify potential risks within a limited time frame. Traditional monitoring systems mainly rely on threshold-based alarms that are univariate and often fail to capture complex multivariate interactions[1]. Conventional scoring systems such as Acute Physiology and Chronic Health Evaluation II (APACHE II) and Sequential Organ Failure Assessment (SOFA) offer some utility in assessing disease severity, but exhibit limited predictive performance. Johnson *et al.* [2] analyzed the MIMIC database and reported that traditional scoring systems often show a significant delay in the real-time prediction of clinical deterioration. Furthermore, these scoring systems are generally based on static data and are unable to capture dynamic changes in patient status.

With advancements in artificial intelligence (AI), machine learning models have become capable of processing high-dimensional time-series data, significantly improving predictive accuracy. Thorsen-Meyer *et al.* [3] developed a deep neural network model that achieved an area under the curve (AUC) exceeding 0.90 in multicenter validation, demonstrating superior predictive capability compared to traditional approaches. This breakthrough enables a transition from reactive to predictive nursing in ICU settings.

2 Literature review methods

This review was conducted following the general principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. Relevant literature was systematically retrieved from the PubMed, Web of Science, Embase, and Scopus databases. The search focused on studies published in English that investigated AI, machine learning, or deep learning-based early warning systems in intensive care settings.

The main search terms included "artificial intelligence", "machine learning", "deep learning", "early warning system", "intensive care unit", "critical care", and "nursing". Studies focusing on sepsis, acute kidney injury, respiratory deterioration, hemodynamic instability, and other forms of clinical deterioration were included. After screening titles, abstracts, and full texts, relevant studies were reviewed and synthesized to provide a comprehensive overview of the current applications, clinical value, and implementation challenges of AI-EWS in ICU nursing.

3 Technical foundations and advantages of AI-EWS

AI-EWS is generally developed using machine learning or deep learning algorithms to predict risks through integration of multi-source data. Commonly used models include Random Forest, XGBoost, and recurrent neural networks such as Long Short-Term Memory (LSTM). At the data level, AI-EWS can integrate multiple types of information, including real-time vital signs (*e.g.*, heart rate, blood pressure), laboratory data (*e.g.*, lactate, creatinine), treatment information (*e.g.*, medications, ventilator settings), and clinical text (*e.g.*, nursing records). Rajkomar *et al.* [4] reported that deep learning models integrating electronic

Received: April 16, 2026 Accepted: June 12, 2026

Supported by Hospital-level Research Project of Taihe Hospital "Effects of Moxibustion at Guanyuan (CV4) on Immune Function in Healthy Rats: A Gut Microbiota-Based Study" (2024JJXM073).

Ao LI, master's degree, nurse-in-charge. *Corresponding author. Rui WANG, master's degree, senior rehabilitation therapist.

health record (EHR) data can significantly improve prediction accuracy while reducing reliance on manual feature engineering. Compared to traditional EWS, AI systems offer several advantages, including the capacity to capture nonlinear relationships, support for time-series analysis, individualized risk assessment, and extended prediction lead time. These features make AI-EWS particularly advantageous in complex ICU environments.

4 Clinical applications of AI-EWS in ICU nursing

4.1 Early detection of sepsis Sepsis is a highly complex clinical syndrome encountered in the ICU, characterized by a dysregulated inflammatory response, microcirculatory dysfunction, and multi-organ failure. Delays in antimicrobial therapy significantly increase mortality, making early identification critical. Recent AI-based models have achieved breakthroughs in early sepsis prediction. Nemati *et al.* [1] developed a deep neural network model that predicts sepsis 4 – 6 h prior to clinical diagnosis, achieving an AUC of 0.93, outperforming the traditional SOFA score. Henry *et al.* [5] developed the TREWScore system using gradient boosting algorithms, achieving an AUC of 0.83 in real clinical settings and reducing patient mortality in prospective studies. Desautels *et al.* [6] proposed the InSight model with a multicenter AUC of 0.88, showing good generalizability.

From a nursing perspective, AI systems can continuously analyze subtle changes in vital signs, allowing the early identification of high-risk patients and supporting the timely execution of sepsis bundles, including blood culture collection, antibiotic administration, and fluid resuscitation. AI can dynamically update risk scores to evaluate treatment responses and guide nursing interventions. Excessive alarm frequency may increase nurse workload; therefore, thresholds and priority rankings must be optimized to mitigate this issue[7].

4.2 Prediction of acute kidney injury Acute kidney injury (AKI) is highly prevalent among ICU patients and is frequently associated with mechanical ventilation, infection, and hemodynamic instability. Conventional diagnosis relies on elevations in serum creatinine levels or reductions in urine output; however, these indicators typically lag behind the actual onset of kidney injury.

Tomašev *et al.* [8] developed a deep learning model trained on millions of patient records, enabling the prediction of AKI up to 48 h in advance, with an AUC exceeding 0.90. Koyner *et al.* [9] utilized a Random Forest model to predict AKI in ICU patients, achieving an AUC of 0.87 and demonstrating robust performance in clinical validation. Moreover, a systematic review conducted by Gameiro *et al.* [10] indicated that most AKI prediction models achieve AUC values ranging from 0.80 to 0.90, suggesting strong clinical applicability.

In nursing practice, AI-EWS supports AKI management at multiple levels. For risk identification, the system integrates hemodynamic parameters, incldluing mean arterial pressure, laboratory indicators such as lactate and creatinine levels, and medication data to identify high-risk patients at an early stage. In terms of nursing intervention, predictive outputs enable nurses to optimize fluid management strategies, such as avoiding fluid overload or ensuring timely fluid resuscitation to maintain renal perfusion. Regarding medication safety, AI systems can alert clinicians to potential exposure to nephrotoxic drugs, thereby facilitating monitoring and interdisciplinary communication. Additionally, continuous risk tracking enables the dynamic assessment of disease progression, allowing the timely recognition of improvement or deterioration. It should be noted that most existing models primarily depend on structured data and underutilize unstructured nursing documentation, highlighting the need for multimodal data integration.

4.3 Prediction of respiratory deterioration Respiratory failure and extubation failure are common and severe complications in ICU patients, directly influencing clinical outcomes and the duration of hospital stay. Traditional assessment methods rely largely on clinical experience and simple indicators such as arterial blood gas analysis, which lack predictive capability.

AI models can predict respiratory deterioration by analyzing continuous respiratory parameters, including tidal volume, respiratory rate, and oxygenation indices. Thorsen-Meyer *et al.* [3] reported that their deep learning model achieved an AUC exceeding 0.85 in predicting respiratory deterioration. Additionally, Goh *et al.* [11] demonstrated that machine learning models outperform conventional approaches in predicting extubation failure.

In clinical nursing practice, AI predictions can guide the optimization of ventilator settings, including positive end-expiratory pressure (PEEP) and oxygen concentration, thereby reducing the risk of ventilator-induced lung injury. AI systems also assist in identifying patients at high risk of extubation failure, thereby preventing premature extubation and subsequent reintubation. Furthermore, the early detection of respiratory deterioration enables timely interventions, such as patient repositioning and airway management. Importantly, AI can identify "occult respiratory failure" prior to the manifestation of overt clinical signs, enhancing nursing sensitivity to early physiological changes.

4.4 Prediction of hemodynamic instability Hemodynamic instability, including hypotension and shock, is a common and life-threatening condition in ICU patients. Conventional monitoring relies on blood pressure measurements and urine output, which often change only after significant deterioration has occurred.

Komorowski *et al.* [12] proposed a reinforcement learning-based model, termed the "AI Clinician", which optimizes strategies for fluid resuscitation and vasopressor therapy and is associated with reduced mortality. Hatib *et al.* [13] developed the Hypotension Prediction Index (HPI), which can predict hypotension events up to 15 min in advance with an AUC of 0.95.

AI systems can detect subtle hemodynamic variations, such as pulse waveform characteristics, enabling the early identification of instability. Nurses can use these predictions to prepare for fluid resuscitation and adjust vasopressor therapy proactively, preven-

ting severe hypotensive events. Continuous risk monitoring further supports the optimization of nursing frequency and prioritization. However, the clinical application of reinforcement learning models remains limited due to issues of interpretability and ethical considerations.

4.5 Nursing workflow and alarm optimization Alarm systems in ICUs are complex and generate alarms at a high frequency, with studies indicating that approximately 80% of these alarms are false or clinically insignificant[14]. Prolonged exposure to such alarm environments may lead to alarm fatigue, which reduces nurses' responsiveness to critical alerts.

AI-EWS improves alarm specificity through multivariate analysis and dynamic risk scoring. Sendak *et al.*[7] reported that AI systems can adjust alarm thresholds based on overall patient status, thereby reducing the incidence of false alarms. By stratifying patient risk, nurses can prioritize high-risk individuals and optimize resource allocation. Additionally, reducing unnecessary alarms can alleviate cognitive workload and fatigue among nurses. However, inadequate integration of these systems into clinical workflows may lead to information overload; thus, system design should emphasize usability, clear prioritization, and effective visualization.

5 Challenges and limitations of AI-EWS in ICU nursing

5.1 Data quality and model generalizability Despite the promising performance of AI-EWS, their clinical application remains constrained by issues related to data quality and model generalizability. Most AI models are developed using single-center datasets or publicly available databases, such as MIMIC-III/IV, which may introduce "center-specific bias" and limit their external validity across different clinical settings[15].

Furthermore, ICU data are often characterized by missing values, inconsistent sampling frequencies, and variability in monitoring devices, all of which can adversely affect model performance. In clinical nursing practice, reduced predictive accuracy across different patient populations or care units may result in an increased incidence of false alarms or missed detections, ultimately compromising decision-making efficiency.

5.2 Model interpretability and nursing trust Another significant limitation is the lack of interpretability in many AI models, particularly deep learning systems that are often considered "black boxes". Topol emphasized that insufficient interpretability may hinder clinical adoption and reduce trust among healthcare professionals[16].

In nursing practice, understanding the relationship between model outputs and clinical indicators is essential for informed decision-making. Therefore, the development of explainable AI (XAI) techniques, such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), is crucial for improving transparency and facilitating acceptance among nursing staff.

5.3 Integration with nursing workflows The effective integration of AI systems into existing ICU nursing workflows remains a significant challenge. If AI-generated alerts are frequent, poorly prioritized, or misaligned with clinical processes, they may lead to information overload and disrupt clinical workflows.

To ensure practical utility, AI systems should be designed using a user-centered approach, incorporating clear alert prioritization, intuitive interfaces, and efficient data visualization. Proper integration can enable AI to function as a supportive tool rather than an additional burden for nursing staff.

5.4 Ethical, legal, and accountability issues The implementation of AI in healthcare also raises important ethical and legal concerns. These include data privacy protection, potential algorithmic bias, and ambiguity in responsibility attribution when adverse outcomes occur.

For example, when incorrect predictions lead to adverse clinical events, it is unclear whether accountability should be attributed to the algorithm developers, healthcare institutions, or clinical staff. Establishing regulatory frameworks and ethical guidelines is therefore essential to ensure the safe and accountable use of AI in ICU nursing.

6 Future directions

The future development of AI-EWS in ICU nursing should prioritize their integration into routine nursing practice. Rather than functioning solely as predictive technologies, AI-EWS should be designed as clinical decision-support tools that assist nurses in early risk identification, care prioritization, and timely intervention. User-centered system design, optimized alert strategies, and seamless integration with existing nursing workflows may help reduce alarm fatigue and improve clinical usability. Future studies should further evaluate the impact of AI-EWS on nursing efficiency, response time, and patient outcomes in real-world ICU settings.

In addition, the widespread adoption of AI technologies highlights the need to enhance nurses' competencies in data interpretation and AI-assisted decision-making. Nursing education and training programs should incorporate fundamental AI literacy to support effective human-AI collaboration. Furthermore, multicenter prospective studies are needed to validate the effectiveness and generalizability of AI-EWS across diverse clinical settings. Addressing issues related to interpretability, ethical use, and professional accountability is essential to ensure the safe and sustainable implementation of AI-EWS in critical care nursing.

7 Conclusions

AI-EWS has demonstrated considerable potential in enhancing the early detection of clinical deterioration in intensive care units by enabling timely predictions of conditions such as sepsis, acute kidney injury, respiratory deterioration, and hemodynamic instability. By integrating large volumes of patient data and providing real-time risk assessment, AI-EWS can support more proactive and in-

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theless, the current reform exhibits certain limitations: teaching resources, task complexity, and assessment methods require further enhancement. In particular, it is essential to more carefully select cases and projects appropriate for lower-grade students, regulate the difficulty and quantity of open-ended tasks, and accumulate more process materials that reflect students' learning development. The applicability of this model warrants further validation through ongoing teaching practice, with continuous adjustments and improvements aligned with course implementation.

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dividualized nursing interventions, thereby contributing to improved patient safety and more efficient allocation of nursing resources.

Beyond their predictive capabilities, AI-EWS has the potential to facilitate a transition from reactive nursing to predictive and precision-based nursing care. However, challenges related to data quality, model interpretability, workflow integration, and ethical considerations continue to limit their widespread implementation. Future efforts should focus on strengthening the integration of AI-EWS into nursing practice, enhancing nurses' competencies in AI-assisted decision-making, and generating high-quality clinical evidence through multicenter studies. With ongoing technological advancements and appropriate clinical adoption, AI-EWS is expected to become a valuable tool for supporting intelligent, patient-centered critical care nursing.

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