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Applications of Artificial Intelligence for Patient Monitoring in the Intensive Care Unit: A Comprehensive Narrative Review

Ameer Abbas Al-Moosewy [1*]

[1]Department of Anesthesia Techniques and Intensive Care, Al -Zahraa University for Women, Karbala, Iraq.
E-mail: ameer.abbas@alzahraa.edu.iq

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Abstract— Intensive Care Units (ICUs) require continuous, high-resolution monitoring to detect early clinical deterioration. Artificial intelligence (AI) has emerged as a transformative tool capable of enhancing predictive accuracy and supporting real-time clinical decision-making. This review aims to critically evaluate current applications of AI in ICU patient monitoring, identify performance trends across different clinical domains, and address existing gaps in validation, implementation, and clinical integration. Using databases including PubMed, Scopus, and Google Scholar, a systematic literature review was carried out. Studies that concentrated on AI - based monitoring systems used in intensive care unit settings that were published between 2015 and 2025 were considered. After being extracted, pertinent data was grouped thematically. AI models demonstrated strong predictive performance across multiple ICU applications. Sepsis prediction models achieved AUROC values ranging from 0.83 to 0.94, while ventilator weaning models reported AUROC values between 0.76 and 0.93, with sensitivity reaching up to 91% for extubation success prediction. Hemodynamic monitoring systems, particularly those based on waveform analysis, achieved AUROC values around 0.89 for hypotension prediction. Multimodal AI platforms integrating electronic health records (EHR), physiological signals, and wearable data achieved AUROC values between 0.76 and 0.82. Despite these promising results, fewer than 30% of models underwent external validation. AI-based monitoring systems significantly enhance early detection of clinical deterioration and support proactive ICU management. However, their clinical implementation remains limited by challenges in external validation, interpretability, and workflow integration. Future research should prioritize prospective multicenter trials, development of explainable AI models, and integration into real-time ICU systems to improve patient outcomes and ensure safe adoption in clinical practice.

Keywords— Artificial intelligence, ICU monitoring, machine learning, deep learning, early warning systems, critical care.

1. INTRODUCTION

In order to offer patients with life - threatening diseases with continuous, high - acuity monitoring and intervention, the Intensive Care Unit (ICU) is the epitome of contemporary critical care. [1 - 3] Preventing morbidity and death in this high - stakes setting requires prompt identification of clinical deterioration. [1, 4] In order to make quick, life - saving choices, intensive care unit monitoring has historically mostly depended on bedside clinicians to analyze physiological data in real time, including heart rate, blood pressure, oxygen saturation, and lab results. [5, 6] However, the limitations of human alertness and response capacity have

* Corresponding author : Radhwan Adnan Dakhil

become more apparent as patient acuity increases and healthcare systems experience greater strain. [7]

Artificial Intelligence (AI) is a broad field encompassing computational systems designed to perform tasks that typically require human intelligence. Within AI, Machine Learning (ML) refers to algorithms that learn patterns from data to make predictions or decisions without explicit programming. Deep Learning (DL), a subset of ML, utilizes multi-layered neural networks to model complex, non-linear relationships in large datasets. Predictive analytics involves the use of statistical and ML techniques to forecast clinical events, while early warning systems (EWS) are clinical tools designed to detect patient deterioration using predefined or data-driven criteria. In this review, these terms are used consistently according to these definitions. In parallel, the past decade has witnessed a rapid evolution in artificial intelligence (AI), particularly in machine learning (ML), deep learning (DL), and data - driven predictive analytics. [4, 8] These technologies offer the potential to analyze complex physiological datasets with a level of speed and analytical depth that exceed human capabilities. [5, 6, 9] By identifying subtle, nonlinear patterns in vital signs or laboratory trends, AI can predict clinical events such as sepsis, acute kidney injury, respiratory failure, and cardiac arrest hours before traditional monitoring systems would detect them. [10]

The application of AI in ICU monitoring is no longer a distant futuristic vision it is rapidly becoming an emerging reality. [11] Numerous AI - powered platforms and prediction models have been created and assessed, showing encouraging outcomes in pilot clinical implementations as well as research settings. [3, 12] However, there are still many obstacles to overcome in terms of thorough validation, moral implementation, physician acceptance, and smooth incorporation into current clinical workflows, especially in healthcare settings with limited resources. [13]

There is currently a dearth of comprehensive literature that systematically analyzes how AI is being used in ICU monitoring, which technologies show the highest effectiveness, and what obstacles stand in the way of wider implementation, despite an increasing number of studies and prototype systems. [14, 15] Thus, by offering a thorough summary of the state of AI applications in ICU patient monitoring, this review aims to close that gap.

Despite the rapid expansion of AI-driven ICU monitoring systems, existing reviews often focus on isolated applications such as sepsis prediction or early warning systems, without providing an integrated evaluation across multiple monitoring domains. Furthermore, limited attention has been given to comparative performance metrics, validation strategies, and real-world implementation challenges. This review addresses these gaps by offering a comprehensive synthesis of AI applications across diverse ICU monitoring domains, with emphasis on quantitative performance (e.g., AUROC, sensitivity), clinical applicability, and barriers to large-scale adoption.

2. Materials and Methods

We looked through every review paper that discussed the use of AI in ICU patient monitoring, including the usefulness of different AI technologies and implementation issues. A comprehensive literature search was conducted across multiple online databases, including Medline, EMBASE, PubMed, Web of Science, Scopus, and the Google search engine. To guarantee the inclusion of current and pertinent technological developments in AI related to

ICU patient monitoring, the search encompassed research published between January 2015 and June 2025.

Boolean operators (AND/OR) were used to combine search phrases in order to guarantee a thorough search approach. "Artificial Intelligence," "Machine Learning," or "Deep Learning," along with "Intensive Care Unit," "Critical Care," and "Patient Monitoring," "Clinical Deterioration," "Early Warning System," or "Vital Signs Prediction," were among the search terms.

Study Design

In order to summarize the body of research on the application of artificial intelligence (AI) technologies for patient monitoring in intensive care units (ICUs), this study was carried out as a narrative literature review. The narrative style preserves an organized and critical approach to the literature while permitting greater investigation and contextual interpretation of the available findings, in contrast to systematic reviews that necessitate protocol registration and stringent inclusion criteria.

Inclusion criteria

Studies that were authored in English, published in peer - reviewed publications between 2015 and 2025, that particularly addressed AI applications for patient monitoring in intensive care units or other critical care settings were eligible for inclusion. Studies that reported clinical deployment, retrospective analysis, or validation of AI systems such neural networks, predictive models, or warning systems were all eligible as long as they supplied enough methodological information to evaluate their quality and applicability.

Exclusion criteria

Studies that addressed AI in administrative or non - clinical roles, such as hospital resource planning, or that concentrated on AI applications outside of the intensive care unit (ICU), such as emergency rooms or outpatient care, were disqualified. Studies that did not provide a clear explanation of AI models or their clinical significance for ICU monitoring were also disqualified, as were editorials, opinion articles, and non - peer - reviewed preprints.

Data analysis

The type of AI technology or model used, the clinical application (e.g., respiratory monitoring or sepsis prediction), performance metrics (e.g., AUROC, sensitivity, and accuracy), the validation method (either prospective, retrospective, or real - world), and the reported benefits and limitations were among the pertinent data that were extracted from the chosen articles. The results were then thematically synthesized, with a focus on the real - world applications of AI in intensive care unit monitoring, common trends found in various technologies, and recurrent issues mentioned in the literature.

Ethical considerations

Ethical approval was not necessary for this review because it was carried out using secondary data that was solely obtained from academic sources that were openly accessible.

3. Results

Overview of the Literature

This narrative review summarizes the results of 37 peer - reviewed and preprint papers that looked into the use of AI in intensive care unit patient monitoring and were published between 2015 and 2025. Predictive early warning systems, ventilatory control, hemodynamic surveillance, multimodal dashboards, and robotic assistance are only a few of the several AI roles covered in the chosen literature. Citations of at least 15 core studies are expressly included, and thematic analysis was used to group studies according to clinical use and technological methodology. The following section provides a summary of the key features of the chosen studies:

Predictive Early Warning Systems (EWS)

AI enhanced early warning systems (EWS) leverage continuous physiological data including heart rate, respiratory rate, blood pressure, oxygen saturation, temperature, and laboratory results to identify early signs of patient deterioration. At the highest level of evidence, Stylianides et al., through a meta - review, demonstrated that AI - EWS reduced in - hospital mortality and unplanned ICU admissions, underscoring their clinical impact. [16] In support of this, Park et al. found that bio signal - based AI systems were highly accurate in identifying deterioration hours before it started. [17] Nemati et al. made a significant contribution by creating Deep AISE, which demonstrated great performance in predicting sepsis up to six hours ahead of time. [18] In addition to these developments, the AI - SEWS framework decreased false alarms and increased specificity when compared to more conventional tools like NEWS and MEWS. However, only 26% of the 572 machine learning models evaluated by Rockenschaub et al. received external validation, indicating persistent difficulties with reproducibility. [19] All things considered, AI - EWS systems are maturing, providing early detection and less alarm fatigue; nonetheless, broader external validation and physician education are still necessary for a successful practice integration.

Ventilatory Monitoring and Extubation Prediction

The use of AI algorithms in ventilator weaning, extubation scheduling, and respiratory failure avoidance has grown. Using MIMIC - III data, Zhang et al. created a neural network with a 91% sensitivity in predicting successful extubation at the strongest evidence level. [20] More recently, BoXHED showed strong performance (AUROC: 0.86) in predicting the need for invasive breathing by combining structured ICU data with clinical notes. [21] Yoosoofsah et al. examined interpretable LSTM and TCN models in order to support these findings, and they were able to predict extubation failure with moderate discriminating (AUC 0.60 - 0.72). [22] Strong predictive ability has also been demonstrated by conventional machine learning techniques like SVM and Random Forest, which have reported AUROCs ranging from 0.76 to 0.93 across a variety of ventilator - related datasets. Furthermore, when applied to accelerometer data, deep convolutional neural networks (VGG and ResNet) showed 69 - 75% accuracy in mobility and acuity categorization, offering a fresh viewpoint on respiratory patient monitoring. [23] While generalizability across various ICUs and patient populations continues to be a major obstacle to wider adoption, AI - supported respiratory monitoring as whole shows promise for increasing extubation safety and tailoring weaning techniques.

Hemodynamic and Cardiovascular Monitoring

By providing real - time risk prediction, especially in patients in the intensive care unit who are unstable, AI models have improved cardiovascular monitoring. The clinical efficacy of waveform - based models utilizing LSTM and CNN architectures was supported by an AUROC of roughly 0.89 for hypotension predicting published in the Annals of Intensive Care (2025). [24] Similar to this, the Hypotension Prediction Index (HPI) showed that it might forecast hemodynamic instability up to 60 minutes ahead of time, enabling the early introduction of vasopressors and possibly leading to better patient outcomes. [25] In support of these results, Mollura et al. used deep learning to analyze arterial waveform data and were able to diagnose sepsis and hypotension with an AUROC of 0.92. [26] Notwithstanding these encouraging outcomes, issues with algorithm openness, real - time responsiveness, and data leakage risk in dynamic intensive care units still exist. Overall, these models mark a paradigm shift in cardiovascular surveillance; nevertheless, before they can be routinely incorporated into critical care practice, extensive prospective and real - world validation is still desperately needed.

Multimodal ICU Monitoring Platforms

Using artificial intelligence (AI), multimodal intensive care unit (ICU) solutions combine data streams from wearable sensors, bedside monitors, electronic health records (EHRs), and even video feeds to create a thorough and up - to - date clinical picture. In order to promote early intervention, commercial systems like Philips IntelliVue Guardian and CLEWICU offer real - time dashboards that automatically produce alerts for patient deterioration. Similarly, to support centralized clinical decision - making, the ICU Cockpit system combines AI models with continuous EHR data. [27] The integration of multimodal inputs, such as video, waveform, EHR, and wearable data, was more recently proven by the MANGO Transformer Model (2025), which achieved an AUROC of 0.82 for predicting ICU acuity and 0.76 for forecasting life - support requirements. When taken as a whole, these systems show how AI - driven multimodal monitoring might improve critical care situational awareness. To guarantee dependability and patient safety, its effective implementation necessitates a strong IT infrastructure, interoperability across diverse data sources, and stringent cybersecurity measures.

Robotic Automation and Assistive AI

Robotics and AI - enabled automation are emerging in critical care as tools for task support and telepresence. A 2024 scoping review in JMIR identified 21 robotic interventions in ICUs, ranging from medication delivery to patient rehabilitation, reflecting the expanding scope of robotic applications. [28] Nurse - assistive robots, in particular, have shown promise in reducing repetitive tasks and facilitating physical distancing during pandemic conditions. Despite these advances, challenges remain, including cost - effectiveness, ethical considerations, and varying levels of acceptance among patients and clinicians. Overall, while still largely experimental, robotic systems may offer valuable supplemental support in ICU care, particularly in resource - limited or high - risk environments.

Meta - Analyses, Reviews, and Big Data Studies

Important information about the effectiveness and generalizability of AI in intensive care unit practice can be found in large datasets and systematic reviews. According to a 2024 MDPI analysis, deep learning models routinely performed better in predicting sepsis and mortality than conventional scoring methods like SOFA and SAPS II. [29] This was corroborated by Gao et al. (2024), who showed that AI models based on MIMIC - IV could obtain AUROC values of up to 0.94 for septic outcomes. [30] while Chen et al. (2025) applied XGBoost to predict AKI - related ICU mortality with strong discrimination (AUROC: 0.878). [31] But in their analysis of 61 machine learning models developed using MIMIC datasets, Syed et al. (2021) discovered that just 30% of them included clinician interpretability variables, underscoring persistent issues with usability and reliability. [32] The therapeutic potential of AI is confirmed by numerous meta - analyses and large data research taken together, which also continuously highlight the significance of interpretability, clinician training, and organized integration into intensive care unit processes.

Table 1: Performance Summary.

Domain	AI Techniques	AUROC Range	Key Applications
Sepsis Prediction	Deep learning, XGBoost	0.83 - 0.94	Early detection, mortality reduction
Ventilator Weaning	Neural nets, SVM, Random Forest	0.76 - 0.93	Extubation prediction
Hypotension Forecasting	LSTM, CNN	~ 0.89	Proactive hemodynamic intervention
ICU Deterioration Scoring	Logistic regression + deep models	0.75 - 0.88	Dynamic risk assessment
Multimodal Acuity Prediction	Transformer models (e.g., MANGO)	0.76 - 0.82	Holistic ICU status tracking
Mobility Monitoring	Deep CNN + accelerometers	0.69 - 0.75	Patient movement and acuity stratification

The assessed studies shared a number of similar weaknesses. Because prospective validation is still rare, a strong dependence on retrospective designs restricts the findings' real - time applicability. Clinician trust and legal defensibility are diminished by the fact that many models still operate as black - box systems with no capacity for explanation. Further impeding smooth deployment are integration gaps with standard intensive care unit (ICU) workflows and electronic health record (EHR) systems. Widespread adoption is further complicated by the disparity in physician confidence and familiarity with AI - generated outcomes. Strong governance and transparency are necessary since ethical issues including data privacy, algorithmic bias, and accountability are still unresolved.

In general, AI - based intensive care unit monitoring has great clinical promise in a variety of fields. These technologies, which range from early warning systems to integrated multimodal dashboards, improve prediction accuracy and facilitate prompt decision - making. Nonetheless, successful incorporation into routine practice still requires human - centered design, workflow integration, and real - time validation. ICU monitoring in the future will probably rely on hybrid systems that integrate clinical judgment, algorithmic insight, transparency, and individualized care to guarantee efficacy and confidence in critical care settings.

4. Discussion

Principle Findings

This review demonstrates that artificial intelligence (AI) significantly enhances patient monitoring in the ICU across multiple domains, including early warning systems, ventilatory management, hemodynamic prediction, and multimodal data integration. AI models achieved strong predictive performance, with AUROC values up to 0.94 in sepsis prediction, 0.93 in ventilator weaning, and approximately 0.89 in hemodynamic forecasting [(33)]. These findings highlight AI's ability to detect clinical deterioration earlier and more accurately than conventional monitoring approaches.

Advanced multimodal platforms further support real-time integration of diverse clinical data streams, enhancing situational awareness and decision-making in ICU settings (34).
However, despite these promising results, most studies remain retrospective, and fewer than one-third have undergone external validation.
Compared to previous reviews, this study provides a more comprehensive and quantitatively driven synthesis by integrating performance metrics across multiple ICU monitoring domains rather than focusing on a single application. Additionally, this review highlights gaps in external validation and real-world implementation, which are often underreported in prior literature. The inclusion of multimodal AI systems and recent transformer-based models further distinguishes this work from earlier reviews that primarily focused on traditional machine learning approaches.

Comparison with Traditional ICU Monitoring

Compared to traditional scoring systems such as SOFA, APACHE II, and MEWS, AI models offer superior temporal resolution and personalization. Conventional tools rely on static thresholds, whereas AI systems continuously analyze dynamic physiological data to generate real-time predictions. Despite these advantages, AI has not replaced traditional systems due to ongoing challenges related to interpretability, reliability, and clinical accountability.

Strengths and Contributions of This Review

This review provides a comprehensive and performance-oriented synthesis of AI applications across multiple ICU monitoring domains. Unlike previous reviews that focus on isolated applications, this study integrates early warning systems, ventilatory monitoring, hemodynamic prediction, and multimodal platforms within a unified framework. In addition, it emphasizes quantitative performance metrics, including AUROC and sensitivity, while highlighting key gaps in external validation and real-world implementation. The inclusion of recent multimodal and deep learning models further strengthens the clinical relevance of this review.

Clinical and Ethical Implications

The integration of AI into ICU monitoring raises important ethical and clinical considerations. Limited model interpretability may affect clinician trust and decision-making transparency, while data privacy and algorithmic bias remain critical concerns. Ensuring the use of explainable AI (XAI) and establishing clear regulatory frameworks are essential to support safe and accountable clinical implementation.

5. Limitations

Several limitations affect the current evidence base. Most studies rely on retrospective datasets, limiting real-time applicability. External validation remains insufficient, reducing generalizability across diverse ICU settings. In addition, many AI models function as “black-box” systems with limited interpretability. Integration challenges with existing ICU workflows and electronic health record systems further restrict widespread adoption.

6. Conclusion and Recommendation

AI-based ICU monitoring systems demonstrate strong predictive performance across multiple domains, with AUROC values reaching up to 0.94 in sepsis prediction, 0.93 in ventilator weaning, and approximately 0.89 in hemodynamic forecasting. These technologies enable earlier detection of clinical deterioration and support data-driven decision-making.

However, translation into routine clinical practice remains limited due to insufficient external validation, lack of interpretability, and integration challenges within ICU workflows.

To advance clinical adoption, future research should focus on:
(1) prospective multicenter validation studies,
(2) development of explainable AI models to enhance clinician trust, and
(3) seamless integration into real-time ICU monitoring systems.

AI is best positioned as a decision-support tool that augments, rather than replaces, clinical expertise, with the potential to significantly improve patient outcomes when implemented safely and effectively.

7. Implications

The results have critical ramifications for low - resource and LMIC settings, where AI has great potential to improve patient care and ICU monitoring. Scalable and automated artificial intelligence models have the potential to fill service delivery gaps in areas with a dearth of clinicians and limited diagnostic capacity. However, a number of obstacles need to be overcome, such as a lack of digital infrastructure, issues with legacy system interoperability, and different clinicians' levels of experience with cutting - edge technologies. Mobile - based ICU alert systems and customized low - computation AI models may offer workable and long - term answers to these problems. To optimize adoption and equity in various situations, it will be crucial to ensure ethical, cultural, and linguistic localization.

Conflict of interest: None.

Authors' contributions

Ameer A.J. was responsible for the study's conception or design; Ameer A.J. prepared the draft manuscript and analyzed the data; Ameer A.J. critically revised the paper; Research supervision: Ameer A.J.; Ameer A.J. gave his final clearance for the version that would be published.

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