THE EUROPEAN SOCIETY OF MEDICINE
Medical Research Archives, Volume 13 Issue 10

REVIEW ARTICLE

# The Role of Artificial Intelligence in the Prediction, Diagnosis, and Management of Sepsis in the Intensive Care Unit (ICU)

**Ali Amirsavadkouhi [1], Seyed Bashir Mirtajani [2], Sara Razi [3]**

[1] Critical Care Medicine, Chairman of Iranian Critical Care Society, Mehrad Hospital, Tehran, Iran.
**ORCID ID:** 0000-0002-8954-5562
[2] Lung transplant Research Center, National Research Institute of Tuberculosis and Lung Diseases (NRITLD), Shahid Beheshti University of Medical Sciences, Tehran, Iran.
**ORCID ID:** 0000-0003-4373-1383
[3] Islamic Azad University of Tehran Tehran, IRAN
**ORCID ID:** 0009-0000-1697-6700

OPEN ACCESS

**PUBLISHED**
31 October 2025

**CITATION**
Amirsavadkouhi, A., Mirtajani, SB., et al., 2025. The Role of Artificial Intelligence in the Prediction, Diagnosis, and Management of Sepsis in the Intensive Care Unit (ICU). Medical Research Archives, [online] 13(10). https://doi.org/10.18103/mra.v13i10.6751



**DOI**
https://doi.org/10.18103/mra.v13i10.6751

**ISSN**
2375-1924

## ABSTRACT

**Background:** Sepsis is a leading cause of morbidity and mortality in intensive care units (ICUs) worldwide, contributing to millions of deaths annually. Delayed recognition and treatment remain the most critical factors associated with poor outcomes, as conventional diagnostic approaches such as SIRS, SOFA, and qSOFA often fail to capture the heterogeneity of sepsis. The dynamic physiology of critically ill patients, combined with the complexity of large-scale clinical data, underscores the urgent need for innovative approaches to improve early detection and personalized management.

**Objective:** This review examines the emerging role of Artificial Intelligence (AI) encompassing machine learning, deep learning, natural language processing, and reinforcement learning in predicting, diagnosing, and managing sepsis in ICU settings.

**Methods:** We conducted a comprehensive review of recent AI driven models applied to sepsis, focusing on their ability to predict onset, anticipate organ dysfunction, guide individualized therapy, and optimize antimicrobial stewardship. The analysis also included evaluation of commercially available and FDA-cleared tools, with attention to validation studies, clinical integration, and regulatory considerations.

**Conclusions:** AI has the potential to transform sepsis care in ICUs by enabling earlier diagnosis, supporting clinical decision-making, and personalizing treatment strategies. To realize this promise, future work should focus on enhancing explainability through explainable AI (XAI), conducting large-scale multicenter validation studies, and establishing clear regulatory frameworks. With these advances, AI-driven systems are likely to become integral components of critical care practice.

**Keywords:** Artificial Intelligence; Machine Learning; Deep Learning; Reinforcement Learning; Sepsis; Critical Care; Intensive Care Unit; Antimicrobial Stewardship; Predictive Analytics; Clinical Decision Support

## 1. Introduction

Sepsis is a complex and life-threatening syndrome that arises from a dysregulated host response to infection, frequently leading to organ dysfunction, septic shock, and death. Despite advances in intensive care medicine, sepsis continues to represent one of the leading causes of morbidity and mortality worldwide, accounting for millions of cases and deaths annually[1]. The global burden of sepsis places significant strain on healthcare systems, particularly in the intensive care unit (ICU), where timely recognition and intervention are critical for improving patient outcomes[2]. Early and accurate prediction of sepsis remains a major clinical challenge, as conventional diagnostic approaches often fail to capture the heterogeneity of the disease.

In recent years, Artificial Intelligence (AI) has emerged as a transformative tool in clinical medicine, offering new possibilities for the prediction, early diagnosis, and individualized management of sepsis. AI refers to computational systems designed to mimic human cognitive functions such as learning, reasoning, and decision-making[3,4]. Within this domain, Machine Learning (ML) techniques are especially powerful for processing large-scale and complex clinical datasets that exceed the capacity of traditional statistical methods[5]. By leveraging electronic health records, physiological monitoring data, and laboratory results, AI models are able to identify subtle patterns, recognize high-risk patients, and provide real-time decision support.

The application of AI is particularly valuable in the ICU, where patients' physiological parameters change rapidly and clinical deterioration may occur suddenly. AI-driven tools have shown promise in predicting the onset of sepsis hours before the appearance of overt clinical symptoms, thereby preserving a critical window for effective intervention[6–8]. Moreover, such systems can support personalized treatment strategies and optimize resource allocation in critical care environments.

The aim of this review is to synthesize current evidence on the role of AI in sepsis management, highlight prominent predictive models and their clinical applications, assess the strengths and limitations of these approaches, and outline future directions for integrating AI into routine critical care practice. In addition, commercially available and regulatory-approved tools for sepsis prediction will be discussed to provide a balanced perspective on their readiness for clinical adoption.

## 2. Sepsis in the ICU Challenges and the Necessity for Innovation

Sepsis continues to be one of the foremost causes of mortality and morbidity among critically ill patients, particularly in the intensive care unit (ICU). Despite decades of research, sepsis remains difficult to diagnose early because of its heterogeneous presentation and overlap with other life-threatening conditions such as acute respiratory distress syndrome, pneumonia, and septic shock [1,2]. Even widely adopted screening toolssuch as the Systemic Inflammatory Response Syndrome (SIRS), the Sequential Organ Failure Assessment (SOFA), and the quick SOFA (qSOFA) scores have demonstrated limited sensitivity and specificity, with a considerable proportion of patients failing to be identified at the initial stages of the disease[3,4]. The dynamic physiological changes observed in ICU patients, the time constraints faced by healthcare providers, and the continuous influx of complex heterogeneous data further complicate timely recognition and intervention[5].

In addition, the absence of universally standardized diagnostic criteria and the inconsistent use of sepsis definitions across institutions pose a major barrier to effective patient care. The transition from Sepsis-2 to Sepsis-3 criteria, while intended to improve diagnostic accuracy, has led to variability in clinical practice and research, generating uncertainty in patient stratification and outcome reporting^6. These discrepancies not only undermine the comparability of clinical studies but also delay the development of evidence-based protocols. Such challenges highlight the urgent need for novel, data-driven, and adaptive diagnostic methodologies that can harmonize detection strategies and ensure more precise and timely diagnosis of sepsis in critically ill populations[7,8].

## 3. The Role of Artificial Intelligence in the Early Detection of Sepsis

Artificial Intelligence (AI) has emerged as a transformative solution for the early detection and risk prediction of sepsis, addressing many of the limitations associated with conventional diagnostic approaches. Machine learning (ML) algorithms are particularly well suited to analyze large volumes of complex, multivariate clinical data, enabling the identification of patterns that would otherwise remain undetected by human clinicians or standard statistical models[9]. For example, ensemble models such as eXtreme Gradient Boosting (XGBoost) and Random Forests have demonstrated high predictive performance, often outperforming established clinical scoring systems in forecasting sepsis onset hours before overt clinical symptoms appear[10,11].

One of the landmark developments in this field is the InSight algorithm, which relies on only six vital signs yet surpasses SIRS and SOFA in predictive accuracy in real world ICU settings[12]. Similarly, the Risk Assessment Index Model (RAIM) integrates continuous physiological streams such as electrocardiograms and arterial blood pressure with irregular laboratory data, enabling more precise forecasts of sepsis and organ dysfunction progression[13]. Advances in Natural Language Processing (NLP) have further expanded AI's capabilities by extracting clinically relevant insights from unstructured sources such as nursing notes, triage logs, and physician narratives, thus complementing structured datasets and improving predictive accuracy[14].

Deep learning methods represent another promising frontier. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are particularly effective in capturing temporal dependencies and nonlinear relationships in high-frequency monitoring data, including heart rate variability and respiratory dynamics[15]. A notable example is the multi-output Gaussian Process RNN, which, when trained on continuous

ICU streams, outperformed standard baselines in the early detection of sepsis[16]. Such approaches underscore the potential of AI not only to enhance predictive power but also to function as early warning systems, thereby extending the therapeutic window for life-saving interventions.

## 4. AI-Guided Personalized Treatment for Sepsis Patients

Beyond early detection, AI is increasingly influencing therapeutic decision-making and personalized management strategies for sepsis patients. Reinforcement learning (RL) models, such as the AI Clinician, have been trained on millions of historical ICU treatment decisions to recommend optimal strategies for fluid resuscitation, vasopressor titration, and antibiotic initiation[17]. These models have demonstrated that deviations from AI-recommended treatment pathways are associated with increased mortality, emphasizing their potential utility as real-time decision-support systems in critical care[18].

Recent innovations have also aimed to enhance transparency and clinical trust. The DeepAISE model, for example, incorporates explainable AI principles to provide interpretable risk assessments, enabling physicians to better understand the rationale behind algorithmic recommendations[19]. This transparency is crucial for clinician adoption, ensuring that AI augments rather than replaces human judgment.

AI based approaches are also shaping the field of risk stratification and biomarker-guided therapy. The Sepsis ImmunoScore, a tool that integrates vital signs, laboratory biomarkers, and clinical parameters, stratifies patients into risk categories to guide individualized treatment plans[20]. Importantly, in April 2024, the U.S. Food and Drug Administration (FDA) granted de novo clearance to the Prenosis Sepsis ImmunoScore, making it the first FDA-authorized AI tool for predicting sepsis within 24 hours of ICU admission[21]. This approval marks a significant milestone, signaling the readiness of AI applications to transition from research to routine clinical practice.

AI has also shown promise in antimicrobial stewardship, an essential component of sepsis care. By analyzing pathogen genomics, resistance profiles, and patient treatment responses, AI systems can recommend targeted antibiotic regimens that minimize adverse drug events while reducing the emergence of multidrug-resistant organisms[22]. Integrating such AI-driven antimicrobial stewardship programs into ICU workflows has the potential to optimize outcomes while preserving the long-term efficacy of available antibiotics.

## 5. Benefits and Challenges of AI in Sepsis Management

The integration of Artificial Intelligence (AI) into sepsis management has generated significant interest due to its potential to transform clinical workflows and patient outcomes in the intensive care unit (ICU). Among the most widely recognized benefits is the ability of AI systems to enable faster and more accurate diagnosis of sepsis compared with conventional clinical tools[23-26]. By continuously analyzing large volumes of physiological and laboratory data, AI can detect subtle changes in patient status, allowing for earlier initiation of life-saving interventions. This improvement in diagnostic timeliness translates into reduced delays in antibiotic administration, which is a key determinant of survival in septic patients. Studies have demonstrated that timely administration of appropriate antimicrobials is directly associated with decreased mortality, and AI-driven early warning systems may help clinicians meet this critical therapeutic window more consistently[27].

Another major advantage of AI applications lies in their impact on healthcare resource utilization. By identifying high-risk patients earlier, AI can contribute to a reduction in ICU length of stay, thereby alleviating the burden on overstretched critical care units. Optimized allocation of resources, such as ventilators, vasopressors, and renal replacement therapy, not only improves patient outcomes but also enhances system-wide efficiency. Furthermore, AI tools can support healthcare providers by streamlining clinical decision-making, reducing cognitive load, and improving overall efficiency. In this context, AI-based antimicrobial stewardship programs can also play a pivotal role by assisting clinicians in selecting the most appropriate antibiotics, minimizing unnecessary exposure, and combating the global threat of antimicrobial resistance. Collectively, these benefits underscore the transformative potential of AI to improve both individual patient care and broader healthcare system performance.

Despite these advantages, several challenges must be addressed before AI can be fully integrated into routine sepsis management. One of the most pressing concerns is the limited interpretability of certain machine learning and deep learning models. Complex “black-box” algorithms often fail to provide clear explanations for their predictions, making it difficult for clinicians to trust and adopt their recommendations in high-stakes settings such as the ICU. Another significant challenge involves privacy and data security, as AI relies on vast amounts of sensitive patient information. Without advanced encryption and strict governance policies, the risk of data breaches and unauthorized access could undermine confidence in AI solutions[28].

In addition, the lack of standardized definitions of sepsis across institutions and studies continues to complicate algorithm development and validation. The coexistence of Sepsis-2 and Sepsis-3 criteria has created inconsistencies in clinical datasets, making it difficult to train models that are both generalizable and reliable[29]. Equally important is the need for robust external validation of AI models across diverse clinical settings, patient populations, and geographic regions. Many algorithms that show promise in controlled environments fail to reproduce similar performance in real-world practice, underscoring the importance of large, multicenter trials. Finally, technical barriers to integration with existing electronic health record (EHR) systems further slow adoption. AI tools must be seamlessly embedded into clinicians’ workflows to be useful, yet interoperability issues and varying IT infrastructures often hinder this process[30].

Several strategies have been proposed to overcome these barriers. Explainable AI (XAI) frameworks, using techniques such as SHAP (Shapley Additive Explanations), allow clinicians to visualize the contribution of individual variables to a model's prediction, thereby improving transparency and trust. Enhanced cybersecurity protocols, including encryption, decentralized storage, and secure data-sharing agreements, can mitigate privacy concerns. To address usability issues, developing clinician-friendly interfaces and offering targeted training programs are essential steps toward improving adoption. Ultimately, fostering collaboration between data scientists, clinicians, and healthcare administrators will be critical to designing AI systems that are not only technically robust but also aligned with the practical realities of patient care.

## Successful AI Models in Clinical Practice

Several AI models have been successfully deployed in clinical settings:

Epic Sepsis Model (ESM), despite widespread adoption, has shown low sensitivity and high false alarm rates.

Sepsis Watch (Duke Health): Realtime deep learning alerts in ED and ICU. Integrated in 2018, associated with a 27% reduction in sepsis deaths at Duke. A 2025 multisite validation confirmed its strong AUROC (0.906–0.960) and portability across different hospitals.

InSight (Dascena): FDA approved, predicts sepsis up to 48 hours prior to symptom onset.

COMPOSER (UCSD): Analyzes >150 clinical variables in real time to identify high-risk patients.

TREWS: A real-time alert system; a prospective multisite study showed decreased mortality, organ failure, shorter length of stay, and improved antibiotic timeliness.

Emerging models for pediatric and neonatal ICUs leverage age-specific physiological and developmental data to enhance detection accuracy in these vulnerable populations.

## Conclusion

Artificial Intelligence represents a transformative advancement in the management of sepsis within ICU settings. From early detection to personalized therapeutic strategies, AI serves as a powerful adjunct to healthcare professionals, enhancing clinical decision-making, improving patient outcomes, and reducing mortality. With ongoing efforts to address regulatory, ethical, and technical hurdles, AI is poised to become an increasingly integral component of critical care, helping redefine sepsis management toward more effective, efficient, and patient-centered outcomes.

## Author Contribution

All the authors met the standard criteria of authorship based on recommendations of the international committee of medical journal editors.

## Funding

The authors declare there is no funding support was included in the study.

## Conflict of Interest

The authors declare there is no conflict of interest

## References


1. Purkayastha S, Gichoya JW, Siva A, Addepally A. Implementation of a single sign-on system between practice, research and learning systems. Appl Clin Inform. 2017;8(2):639–647.
2. Hazelzet JA. Can fuzzy logic make things more clear? Crit Care. 2009;13(1):116. PMID:19291252.
3. Bali J, Garg R, Bali R. Artificial intelligence (AI) in healthcare and biomedical research: why a strong computational/AI bioethics framework is required? Indian J Ophthalmol. 2019;67(1):3–6.
4. Panch T, Szolovits P, Atun R. Artificial intelligence, machine learning and health systems. J Glob Health. 2018;8(2):020303.
5. Yu KH, Beam AL, Kohane IS. Artificial intelligence in healthcare. Nat Biomed Eng. 2018;2(10):719–731.
6. Miotto R, Wang F, Wang S, Jiang X, Dudley JT. Deep learning for healthcare: review, opportunities and challenges. Brief Bioinform. 2018;19(6):1236–1246.
7. Mahapatra D, Schueffler P, Tielbeek JAW, Buhmann JM, Vos FM. A supervised learning based approach to detect Crohn's disease in abdominal MR volumes. In: MICCAI 2012. Berlin, Heidelberg: Springer; 2012. p. 97–106.
8. Gottesman O, Johansson F, Komorowski M, et al. Guidelines for reinforcement learning in healthcare. Nat Med. 2019;25(1):16–18.
9. Clermont G. Artificial neural networks as prediction tools in the critically ill. Crit Care. 2005;9(2):153–154.
10. Dybowski R, Weller P, Chang R, Gant V. Prediction of outcome in critically ill patients using artificial neural network synthesised by genetic algorithm. Lancet. 1996;347(9009):1146–1150.
11. Dellinger RP, Levy MM, Rhodes A, et al. Surviving sepsis campaign: international guidelines for management of severe sepsis and septic shock, 2012. Crit Care Med. 2013;41(2):580–637.
12. Singer M, Deutschman CS, Seymour CW, et al. The third international consensus definitions for sepsis and septic shock (Sepsis-3). JAMA. 2016;315(8):801–810.
13. Seymour CW, Kennedy JN, Wang S, et al. Derivation, validation, and potential treatment implications of novel clinical phenotypes for sepsis. JAMA. 2019;321(20):2003–2017.
14. Quinten VM, van Meurs M, Ligtenberg JJ, Ter Maaten JC. Prehospital antibiotics for sepsis: beyond mortality? Lancet Respir Med. 2018;6(3):e8.
15. Goulden R, Hoyle MC, Monis J, et al. qSOFA, SIRS and NEWS for predicting in-hospital mortality and ICU admission in emergency admissions treated as sepsis. Emerg Med J. 2018;35(6):345–349.
16. Anand V, Zhang Z, Kadri SS, Klompas M, Rhee C. Epidemiology of qSOFA criteria in undifferentiated patients and association with suspected infection and sepsis. Chest. 2019;156(6):1287–1296.
17. Quinten VM, van Meurs M, Wolffensperger AE, Ter Maaten JC, Ligtenberg JJM. Sepsis patients in the emergency department: stratification using the clinical impression score, predisposition, infection, response and organ dysfunction score or quick sequential organ failure assessment score? Eur J Emerg Med. 2018;25(5):328–3.
18. Gulshan V, Peng L, Coram M, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA. 2016;316(22):2402–2410. doi:10.1001/jama.2016.17216.
19. Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017;542(7639):115–118.
20. Melendez-Torres GJ, O'Mara-Eves A, Thomas J, Brunton G, Caird J, Petticrew M. Interpretive analysis of 85 systematic reviews suggests that narrative syntheses and meta-analyses are incommensurate in argumentation. Res Synth Methods. 2017;8(1):109–118.
21. Lu X, Xue L, Sun W, et al. Identification of key pathogenic genes of sepsis based on the Gene Expression Omnibus database. Mol Med Rep. 2018;17(2):3042–3054.
22. Moons KG, Wolff RF, Riley RD, et al. PROBAST: a tool to assess risk of bias and applicability of prediction model studies. Ann Intern Med. 2019;170(1):51–58.
23. Delahanty RJ, Alvarez J, Flynn LM, Sherwin RL, Jones SS. Development and evaluation of a machine learning model for the early identification of patients at risk for sepsis. Ann Emerg Med. 2019;73(4):334–344.
24. Barton C, Chettipally U, Zhou Y, et al. Evaluation of a machine learning algorithm for up to 48-hour advance prediction of sepsis using six vital signs. Comput Biol Med. 2019;109:79–84. doi:10.1016/j.compbiomed.2019.04.027.
25. Van Steenkiste T, Ruyssinck J, De Baets L, et al. Accurate prediction of blood culture outcome in the intensive care unit using long short-term memory neural networks. Artif Intell Med. 2018;95:27–39.
26. Oonsivilai M, Mo Y, Luangasanatip N, et al. Using machine learning to guide targeted and locally-tailored empiric antibiotic prescribing in a children's hospital in Cambodia. Wellcome Open Res. 2018;3:131.
27. Lamping F, Jack T, Rübsamen N, et al. Development and validation of a diagnostic model for early differentiation of sepsis and non-infectious SIRS in critically ill children using machine-learning algorithms. BMC Pediatr. 2018;18(1):112.
28. Ratzinger F, Haslacher H, Perkmann T, et al. Machine learning for fast identification of bacteraemia in SIRS patients treated on standard care wards: a cohort study. Sci Rep. 2018;8(1):12233.
29. Aushev A, Ripoll VR, Vellido A, et al. Feature selection for the accurate prediction of septic and cardiogenic shock ICU mortality in the acute phase. PLoS One. 2018;13(11):e0199089.
30. García-Gallo JE, Fonseca-Ruiz NJ, Celi LA, Duitama-Muñoz JF. A machine learning-based model for 1-year mortality prediction in patients admitted to an intensive care unit with a diagnosis of sepsis. Med Intensiva. 2018;42(5):263–270.