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Review Article

Artificial Intelligence in Intensive Care: Applications, Challenges, and Future Directions – A Review

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Abstract

Artificial intelligence (AI) has emerged as a transformative technology in intensive care units (ICUs), where clinicians must process large volumes of rapidly evolving physiological, laboratory, and imaging data. This review aims to evaluate current AI applications in critical care, highlight organ- and syndrome-specific use cases, identify major implementation challenges, and outline future directions necessary for safe and effective integration of AI into ICU practice. A narrative review methodology was adopted. Relevant literature was identified through a non-systematic search of PubMed and major critical care journals, focusing on recent clinical, computational, and translational studies. Evidence was synthesized across functional domains-including diagnosis, risk stratification, prognostic modeling, decision support, and imaging analysis and across organ specific applications such as respiratory failure, acute kidney injury, cardiovascular dysfunction, sepsis, trauma, nutrition, and delirium. AI-driven tools demonstrated substantial potential in early detection of clinical deterioration, prediction of outcomes, optimization of mechanical ventilation, identification of acute kidney injury, enhanced cardiovascular monitoring, and improved detection of sepsis and traumatic injuries. AI-assisted imaging systems, including those integrated within PACS, have shown marked improvements in diagnostic accuracy and workflow efficiency. Despite these advancements, significant limitations persist, including data heterogeneity, lack of standardized infrastructures, limited interpretability of algorithmic outputs, risks of bias, and evolving regulatory and ethical considerations. AI has the capacity to augment clinical decision-making, enhance workflow efficiency, and improve patient outcomes in the ICU. However, its real-world impact depends on addressing challenges related to data quality, transparency, fairness, regulatory oversight, and clinician training. With responsible implementation and continued interdisciplinary collaboration, AI is positioned to become an integral component of modern critical care practice.

Keywords: Artificial intelligence, İntensive care unit, Machine learning, Clinical decision support systems.

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Özet

Yapay zekâ (YZ), klinisyenlerin hızla gelişen büyük miktarda fizyolojik, laboratuvar ve görüntüleme verisini işlemesi gereken yoğun bakım ünitelerinde (YBÜ) dönüştürücü bir teknoloji olarak ortaya çıkmıştır. Bu derleme, kritik bakımda mevcut YZ uygulamalarını değerlendirmeyi, organ ve sendroma özgü kullanım durumlarını vurgulamayı, önemli uygulama zorluklarını belirlemeyi ve YZ'nin YBÜ uygulamasına güvenli ve etkili bir şekilde entegrasyonu için gerekli gelecekteki yönleri özetlemeyi amaçlamaktadır. Anlatısal bir derleme metodolojisi benimsenmiştir. İlgili literatür, PubMed ve başlıca kritik bakım dergilerinde sistematik olmayan bir arama yoluyla belirlenmiş olup, yakın tarihli klinik, hesaplamalı ve translasyonel çalışmalara odaklanılmıştır. Kanıtlar, tanı, risk sınıflandırması, prognostik modelleme, karar desteği ve görüntüleme analizi gibi fonksiyonel alanlar ve solunum yetmezliği, akut böbrek yetmezliği, kardiyovasküler disfonksiyon, sepsis, travma, beslenme ve deliryum gibi organa özgü uygulamalar genelinde sentezlenmiştir. Yapay zekâ destekli araçlar, klinik bozulmanın erken tespiti, sonuçların tahmin edilmesi, mekanik ventilasyonun optimizasyonu, akut böbrek yetmezliğinin belirlenmesi, kardiyovasküler izlemenin iyileştirilmesi ve sepsis ile travmatik yaralanmaların daha iyi tespit edilmesinde önemli bir potansiyel göstermiştir. PACS'e entegre olanlar da dahil olmak üzere yapay zekâ destekli görüntüleme sistemleri, tanısal doğruluk ve iş akışı verimliliğinde belirgin iyileşmeler göstermiştir. Bu gelişmelere rağmen, veri heterojenliği, standartlaştırılmış altyapıların eksikliği, algoritmik çıktıların sınırlı yorumlanabilirliği, önyargı riskleri ve gelişen düzenleyici ve etik hususlar da dahil olmak üzere önemli sınırlamalar devam etmektedir. Yapay zekâ, klinik karar verme süreçlerini destekleme, iş akışı verimliliğini artırma ve yoğun bakım ünitesinde hasta sonuçlarını iyileştirme kapasitesine sahiptir. Bununla birlikte, gerçek dünyadaki etkisi, veri kalitesi, şeffaflık, adalet, düzenleyici denetim ve klinisyen eğitimi ile ilgili zorlukların ele alınmasına bağlıdır. Sorumlu uygulama ve sürekli disiplinler arası işbirliği ile yapay zekâ, modern yoğun bakım uygulamasının ayrılmaz bir bileşeni haline gelmeye hazırdır.

Anahtar Kelimeler: Yapay zekâ, Yoğun bakım ünitesi, Makine öğrenmesi, Klinik karar destek sistemleri.

INTRODUCTION

Intensive care units (ICU) are critical environments designed to provide intensive, high-quality medical care and life-saving treatments for patients suffering from single or multiple organ dysfunctions, life-threatening illnesses, or high-risk conditions (Marshall et al., 2017). These units operate under high pressure, where clinicians must make timely decisions based on a continuous flow of patient data. The data generated includes vital signs, laboratory results, medical imaging, and clinical notes (Pinsky et al., 2024). These vast and complex datasets present a significant challenge for clinicians, as they must rapidly interpret and act upon this information. Artificial Intelligence (AI) offers the potential to overcome these challenges by enabling predictive analytics and supporting the development of clinical decision support systems (CDSS) to improve patient outcomes in ICU (Yoon et al., 2022).

AI has gained significant attention in recent years due to its ability to process and analyze large datasets, identify patterns, and assist in decision-making. Despite the promising potential of AI in intensive care, the technology is not without its challenges. This review will provide an overview of the main applications of AI in intensive care, examine the challenges in its implementation, and explore the future directions for AI in these critical care settings.

This narrative review synthesizes recent evidence on AI in the ICU, focusing on functional domains, diagnosis, risk prediction, decision support, imaging, data management, organ-specific applications, and discusses key implementation challenges and future directions. Relevant articles were identified through a non-systematic search of PubMed and major critical care journals, with emphasis on recent clinical and translational studies.

General Concepts and Functional Domains of AI in the ICU

Diagnosis and Early Warning Systems

AI has been widely utilized in early detection of critical conditions such as sepsis, acute respiratory distress syndrome (ARDS), and acute kidney injury (AKI) (Laino et al., 2022; Ozrazgat-Baslanti et al., 2021; Wang et al., 2021). By integrating real-time monitoring of vital signs and laboratory parameters, AI systems can detect early signs of deterioration, thus allowing for timely interventions and improving patient outcomes (Yang et al., 2023). Machine learning algorithms can analyze vast amounts of physiological data to predict deterioration, often before it is clinically apparent, providing clinicians with critical decision support. AI-based early warning systems are already deployed in several ICU, and ongoing research continues to improve their accuracy and responsiveness (Wang et al., 2021).

Risk Stratification and Prognostic Modeling

Accurate prediction of patient outcomes in ICU is essential for clinical decision-making and resource management (Lemeshow et al., 1995). Predictive models using AI, such as artificial neural networks, Targeted Real-time Early Warning System (TREWS), and deep learning algorithms, have shown greater efficacy in forecasting ICU mortality, length of stay, and recovery trajectories compared to traditional scoring systems like APACHE II, SAPS II, and SOFA (Adams R et al , 2022; Mirzakhani et al., 2022; Naqvi et al., 2016; Pimentel et al., 2021). These models are trained on historical patient data, including vital signs, laboratory tests, and demographic information, allowing them to identify patterns that may not be immediately apparent to clinicians. With higher accuracy rates, AI models have the potential to better inform decisions on resource allocation, help prioritize care, and guide clinicians in treatment planning.

Clinical Decision Support Systems

AI-based CDSS in ICU help clinicians make data-driven decisions regarding mechanical ventilation, arrhythmia management, fluid therapy, and antibiotic optimization (Moazemi et al., 2023). These systems are designed to assist, not replace, clinicians by offering insights, recommendations, and predictive analyses that improve patient care. The integration of AI in CDSS aims to enhance decision-making processes, making them more precise and timely. However, challenges such as the "black box" nature of AI systems and data bias can limit their practical adoption (Ribeiro et al., 2016). Ensuring transparency, interpretability, and addressing clinician concerns regarding the reliability of AI systems are essential for successful implementation.

Medical Imaging Analysis

AI's impact in medical imaging is particularly significant in the ICU. AI-driven diagnostic models can assist clinicians in analyzing chest X-rays, CT scans, and ultrasounds. For instance, in the case of COVID-19 pneumonia, AI has demonstrated its ability to rapidly detect patterns such as ground-glass opacities and consolidations on CT scans (Laino et al., 2022). In parallel, recent evidence suggests that the integration of AI into Picture Archiving and Communication Systems (PACS) has substantially transformed imaging workflows and diagnostic efficiency. A comprehensive review by Pérez-Sanpablo et al. reported that AI-enhanced PACS platforms improved diagnostic accuracy by up to 93.2% in certain modalities, particularly in early tumor detection and subtle anomaly identification, while reducing diagnostic turnaround times by as much as 90% for time-critical conditions such as intracranial hemorrhage. Convolutional neural networks incorporated into PACS demonstrated accuracy levels of 94% in segmentation tasks and effectively corrected motion artifacts, significantly enhancing image interpretability. Furthermore, natural language processing (NLP) tools embedded within PACS reduced radiology reporting times by 30–50%, increased standardization, and improved consistency in reporting (Pérez-Sanpablo et al., 2025). These innovations—coupled with cloud-based PACS solutions enabling real-time interdisciplinary collaboration—highlight the expanding potential of AI-based imaging systems to support rapid diagnostics, reduce human error, and harmonize interpretation standards within ICU workflows. Nevertheless, challenges remain, particularly regarding interoperability, data privacy, and regulatory compliance, underscoring the need for robust frameworks to safely integrate AI-powered imaging tools into critical care environments.

Data Quality and Accessibility

The efficacy of AI in the ICU is heavily dependent on the quality and consistency of data. Electronic health records (EHRs) are often heterogeneous, with varying formats and inconsistent data entries, which complicate the training and validation of AI models (Gutierrez, 2020). Furthermore, technical and legal barriers to data sharing, such as privacy concerns and hospital policies, limit the ability to build large, diverse datasets that are essential for training AI models. Ensuring data accuracy and completeness is crucial for the reliability of AI systems, and efforts to standardize EHRs and improve data accessibility are ongoing (Heaton, 2018).

Organ- and Syndrome-Specific Clinical Applications of AI

Respiratory System

AI has been increasingly adopted in the management of respiratory failure and mechanical ventilation, where timely and precise decision-making is central. Recent machine learning–based systems have demonstrated the ability to continuously analyze ventilator waveforms, estimate respiratory mechanics, and detect patient–ventilator asynchrony with high accuracy. For example, supervised models trained on flow and airway pressure data have achieved near-perfect prediction of real-time resistance–compliance values, supporting personalized ventilation strategies (Hezarjaribi et al., 2018). AI has also been used to optimize ventilator weaning. Multi-stage prediction models incorporating patient demographics, disease severity scores, and ventilator parameters have shown 65–84% accuracy in identifying optimal extubation timing (Liu et al., 2022). Moreover, AI-based latent class analyses have enabled subphenotyping of heterogeneous syndromes such as ARDS, identifying hyper-inflammatory and hypo-inflammatory clusters with distinct clinical profiles and outcomes (Sinha et al., 2020). Also during the COVID-19 pandemic, AI tools expanded rapidly to support diagnosis, risk stratification, and triage. Early triage algorithms such as CURIAL, using only routine laboratory tests available within one hour of admission, achieved AUCs between 0.86 and 0.88 for COVID-19 identification (Soltan et al., 2022). Deep learning systems interpreting chest X-rays or CT scans have reached diagnostic performances rivaling or exceeding radiologists, with some CT-based models achieving AUC values as high as 0.98 (Shamout et al., 2021). These advances demonstrate the potential of AI to support individualized respiratory management in ICU.

Renal System

AI applications in the renal domain have focused primarily on the early detection of AKI, which is a frequent and serious ICU complication. Deep learning models using diverse data types—including laboratory values, vital signs, medications, and EHR histories—have predicted AKI up to 48 hours before onset with AUC values above 0.92 (Tomašev et al., 2019). AI systems have also been developed to predict contrast-induced nephropathy with accuracies around 80% and to assist in stratifying patients at risk of progression to end-stage renal disease (Yin et al., 2017) Furthermore, computer-aided diagnostic algorithms have demonstrated capability in distinguishing benign from malignant renal lesions using radiologic features, and pilot systems have used AI to optimize anemia treatment dosing for chronic kidney disease patients (Yu et al., 2017) Collectively, these approaches enhance early recognition, guide therapeutic decisions, and support renal-protective strategies in the ICU.

Cardiovascular System

Cardiovascular applications of AI in ICU encompass early detection of heart failure, arrhythmia prediction, hemodynamic instability forecasting, and coronary disease risk stratification. Neural-network-based ECG interpretation systems have demonstrated superior performance in identifying left ventricular systolic dysfunction, including subclinical disease not detected by conventional metrics (Gharehchopogh & Khalifelu, 2011; Kashou et al., 2021). Advanced models such as FAST-PACE have predicted imminent cardiac arrest or respiratory failure up to six hours before occurrence, with AUROC values approaching 0.88 (Kim et al., 2019). AI-enabled echocardiography platforms (e.g., HeartModel) offer automated chamber quantification and ejection fraction assessment, improving workflow and reproducibility. Additionally, risk-prediction models using machine learning techniques have accurately estimated rehospitalization and mortality risk among heart-failure patients, outperforming traditional tools (Choi et al., 2020; Luo et al., 2017).

Sepsis

Sepsis remains one of the most time-sensitive conditions in critical care, making early detection and risk assessment ideal targets for AI. Machine learning algorithms such as the Artificial Intelligence Sepsis Expert have integrated vital signs, laboratory findings, and dynamic physiologic features to predict sepsis several hours before clinical recognition, achieving AUC values up to 0.85 (Nemati et al., 2018). Deep learning approaches trained on large ICU datasets have outperformed traditional statistical models by recognizing sepsis or impending septic shock nearly 20 hours earlier than Cox-based frameworks (Fagerström et al., 2019). Other studies using cytokine profiles and NLP clinician notes have produced highly accurate prognostic models with sensitivities exceeding 90% (Goh et al., 2021; Lukaszewski et al., 2008). Overall, evidence suggests AI-driven systems can markedly improve sepsis prediction, triage, and timely intervention.

Trauma

Trauma care frequently requires rapid radiologic interpretation, often under resource-limited circumstances. AI-driven fracture detection algorithms trained on appendicular skeletal radiographs have reached AUC values around 0.94, significantly aiding clinicians when radiology support is limited (Duron et al., 2021; Guly, 2001). In pediatric trauma, AI assistance has improved sensitivity by approximately 10% without sacrificing specificity, demonstrating value as a second-reader system (Nguyen et al., 2022). Although real-world performance and integration into busy trauma workflows require further study, current evidence suggests AI can reduce missed injuries and enhance diagnostic reliability in ICU.

Nutrition

Nutritional assessment in ICU is often subjective and prone to error. AI-assisted decision support systems have been shown to increase compliance with caloric and protein goals by more than 50% compared to standard care (Ettori et al., 2019). By identifying undernutrition earlier and guiding individualized interventions, AI systems may improve recovery trajectories, though their effect on mortality remains unclear.

Delirium

Delirium is common in ICU but frequently underdiagnosed. Machine-learning-based prediction models using patient demographics, comorbidities, and environmental factors have shown good performance in identifying patients at high risk for delirium (Ocagli et al., 2021). By improving recognition of this high-morbidity condition, AI tools may facilitate earlier interventions and reduce long-term cognitive complications.

AI and Treatment Outcomes

Predicting morbidity and mortality is essential in critical care. Machine-learning-based outcome models, including random forests, naïve Bayes, and adaptive resonance theory networks, have outperformed traditional scoring systems such as SOFA, SAPS, and APACHE II (Awad et al., 2017). Algorithms like AutoTriage, using as few as eight EHR parameters, have achieved AUROC values around 0.88 for mortality prediction (Calvert et al., 2016). These systems demonstrate the potential of AI to refine prognostic assessment and support complex decision-making.

Challenges in Implementing AI in Intensive Care

Despite the substantial progress made in the application of AI in ICU, significant challenges remain in its widespread adoption. One key obstacle is the issue of data quality: ICU data is often incomplete, inconsistent, or noisy, which can undermine the performance of AI models (Rieke et al., 2020). Additionally, algorithm transparency and the "black box" nature of AI systems create trust issues among clinicians (Yoon et al., 2022). The challenge of ensuring that AI algorithms are both fair and generalizable across diverse patient populations and clinical settings is also a significant hurdle (Obermeyer et al., 2019).

Moreover, ethical concerns surrounding the use of AI in ICU need to be addressed. These concerns include issues of bias in training datasets, data privacy, and the potential for AI systems to replace human judgment in decision-making (Pimentel et al., 2021). Lastly, the regulatory and legal frameworks necessary to ensure the safe and ethical deployment of AI in ICU are still developing (Singh et al., 2025).

Future Perspectives and Recommendations

The successful integration of AI into intensive care medicine will depend on strategic advancements across several interconnected domains. Addressing these areas holistically is essential for ensuring that AI systems become reliable, ethical, and clinically impactful tools:

Improving Data Sharing and Collaboration: High-performing and generalizable AI models require large-scale, diverse, and representative datasets. Facilitating secure data exchange between institutions-while adhering to privacy regulations-remains a major priority. Federated learning approaches, which enable decentralized model training across multiple centers without transferring sensitive patient-level data, represent a promising solution for overcoming current barriers. Expanding multicenter collaborations and establishing standardized ICU data infrastructures will markedly enhance algorithm robustness and external validity (Rieke et al., 2020).

Addressing Ethical and Legal Challenges: Ethical considerations must remain central to AI adoption. Key concerns include data privacy, informed consent, risk of algorithmic bias, and the potential amplification of health inequities if models are trained on non-representative datasets. Comprehensive legal frameworks are needed to govern data usage, define liability in AI-assisted decision-making, and safeguard patient rights. Ensuring fairness, transparency, and continuous auditing of AI systems will be essential for mitigating unintended harms and promoting equitable care delivery (Obermeyer et al., 2019).

Ensuring Algorithm Transparency and Accountability: As AI systems become increasingly embedded in clinical workflows, transparency becomes essential for clinician trust and patient safety. Developing interpretable and explainable AI models-capable of providing rationale for predictions will help clinicians critically evaluate system outputs rather than passively accepting them. (Ribeiro et al., 2016). Furthermore, regulatory agencies are actively working to establish safety, performance, and post-deployment monitoring requirements for AI-enabled clinical software, ensuring accountability throughout the model's lifecycle (Singh et al., 2025).

Clinical Training and Education: The clinical workforce must be adequately equipped to interpret and utilize AI outputs. This requires structured educational programs that teach clinicians the fundamental principles of AI, its limitations, sources of error, and best practices for integrating AI recommendations with clinical judgment. As ICU environments evolve, clinicians will increasingly serve as both end-users and stewards of AI technologies, underscoring the need for competency-based training modules at both undergraduate and postgraduate levels (Schneeberger et al., 2020).

By addressing these technical, ethical, and educational priorities in parallel, the field of intensive care medicine can move toward a future in which AI systems function not as replacements, but as reliable and ethically grounded partners that enhance clinical expertise and ultimately improve patient outcomes.

CONCLUSION

AI has the potential to transform intensive care medicine by enabling earlier detection of clinical deterioration, enhancing diagnostic precision, improving workflow efficiency, and supporting complex decision-making processes. As demonstrated across domains such as respiratory management, sepsis prediction, renal injury detection, cardiovascular monitoring, trauma imaging, nutritional assessment, and delirium surveillance, AI-driven tools can augment the capabilities of clinicians and meaningfully contribute to patient safety and outcomes. Nevertheless, realizing this potential requires systematic attention to key challenges, including the heterogeneity and reliability of ICU data, the need for transparent and explainable algorithmic outputs, mitigation of bias, and stringent ethical and regulatory oversight. Ensuring equitable, secure, and generalizable AI deployment depends on robust data governance frameworks, interdisciplinary collaboration, and continuous evaluation of model performance in real-world clinical environments.

Looking ahead, the integration of AI into critical care should be guided by principles of accountability, clinician empowerment, and patient-centeredness. Investment in clinician education, development of interoperable digital infrastructures, and adoption of standards for trustworthy AI will be essential. If implemented responsibly, AI systems will not replace human expertise but rather serve as sophisticated partners supporting intensivists in delivering timely, individualized, and high-quality care. Ultimately, the sustainable incorporation of AI into ICU practice has the potential to reshape critical care delivery and contribute to improved clinical outcomes on a global scale.

Limitations of the Study

This narrative review has several limitations. First, the study is non-systematic and therefore may not include all relevant publications on artificial intelligence applications in intensive care. Selection bias is possible due to reliance on available electronic databases and the authors' judgment during the screening process. Second, heterogeneity in the methodologies, datasets, and performance metrics of the included AI studies limits direct comparison across models and clinical domains. Third, many of the cited AI tools are derived from retrospective or single-center studies, which may reduce generalizability to broader ICU settings. Finally, rapid advancements in AI technologies may lead to emerging evidence that was not captured at the time of manuscript preparation.

Declaration of Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript. No conflicts of interest, whether financial, professional, or academic, are associated with the preparation, analysis, or submission of this study. The content of the manuscript reflects independent scientific evaluation without external influence.

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Ethical Approval

As this study is a narrative review based solely on previously published literature, it did not involve human participants, patient data, or animal subjects. Therefore, ethical approval was not required. All included studies were referenced appropriately, and the review adhered to principles of academic integrity and responsible scholarship.

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