USE OF AI IN THE ICU FOR MONITORING CRITICALLY ILL PATIENTS: A LITERATURE REVIEW

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ABSTRACT

INTRODUCTION: The advancement of artificial intelligence (AI) has revolutionized the management of critically ill patients, especially in Intensive Care Units (ICUs). Through predictive algorithms, AI enables real-time analysis of large volumes of data, helping to identify serious conditions early and personalize treatments. This has provided faster diagnoses and more accurate interventions, in addition to optimizing clinical decision-making. OBJECTIVE: With this in mind, the objective of this study was to analyze the impact of the main artificial intelligences for the optimization of intensive care. METHODOLOGY: The present work is an integrative literature review, in view of the need to agglutinate the main types of scientific works and analyze their impact related to the theme under discussion. The search was carried out in an exploratory manner in the main databases of the medical literature, such as PubMED, Cochrane, SciELO and Web of Science. RESULTS: The results obtained reinforce the importance of the use of artificial intelligence (AI) in monitoring, early diagnosis, and personalization of care in ICUs. Several studies highlight the positive impacts of AI, particularly in the continuous monitoring of vital signs and the early detection of critical conditions such as sepsis, organ failure, and other complications in critically ill patients. CONCLUSION: The use of AI in intensive care medicine has already demonstrated its value in improving clinical outcomes, reducing mortality, and personalizing the treatment of critically ill patients, as long as it continues to be implemented as a clinical decision support and not as a substitute for medical judgment.

Keywords: Artificial intelligence. Intensive Care Unit. Machine Learning. Monitoring. Personalized treatment.

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INTRODUCTION

The advancement of artificial intelligence (AI) has revolutionized the management of critically ill patients, especially in Intensive Care Units (ICUs). Through predictive algorithms, AI enables real-time analysis of large volumes of data, helping to identify serious conditions early and personalize treatments. This has provided faster diagnoses and more accurate interventions, in addition to optimizing clinical decision-making (DOE, J *et al*., 2022; WU, T *et al*., 2023; DOE, J *et al*., 2024).

Among the most important applications of AI is the early detection of sepsis, acute kidney injury, gastroenterology diagnoses, imperceptible findings on imaging exams and others, which enables the adequacy, anticipation of medical conducts, increasing the prognosis of patients and offering health professionals the opportunity to intervene before the appearance of clinical symptoms. Other studies, such as that of Alanazi *et al.,* 2022, confirm that AI systems applied to the monitoring of vital signs and some other studies demonstrate the use of this tool for treatment personalization, reinforcing the essential role of these technologies in critical care settings (SHAWWA, K *et al*., 2020; Kwak, G. H . *et al.,* 2020; WANG, X *et al*., 2023; GARCIA, H *et al*., 2023).

From this perspective, the personalization of treatment and support tools has been a promising area for AI in ICUs. Pelosi *et al*., 2021, reported that using algorithms to automatically adjust mechanical ventilation parameters resulted in a significant reduction in ventilation time, as well as minimizing respiratory complications. Some other studies bring the possibility of adjusting vasopressor medications, in the case of septic shock, for example, demonstrating that this personalization of care, adjusted in real time, demonstrates the ability of AI to improve clinical outcomes by individualizing treatments according to the needs of each patient (Otaguro T, *et al.,* 2021; Choi, H *et al.,* 2023; Huang, CY *et al*., 2023; Ates HC, *et al.,* 2024).

The search in the literature currently demonstrates several tools, from the use of machine learning, ChatGPT, XGBoost, Random Forest, Neural Circuits and several other data automation and predictive synthesis tools, all of which demonstrate the effectiveness of the tools when used as a complement to professional performance. Thus, this paper reviews the most recent contributions of AI in monitoring and personalizing the care of critically ill patients, analyzing the most relevant clinical outcomes and the impact of these innovations on the daily practice of ICUs (Li, X *et al*., 2020; Shashikumar SP, *et al*., 2021; Burns, J *et al.,* 2022; Hsu, CC *et al.,* 2023).

GENERAL OBJECTIVE

Analyze the impact of key artificial intelligences for critical care optimization.

SPECIFIC OBJECTIVES

- Analyze the impact of AI on the agility of early diagnosis of sepsis;
- To assess the effectiveness of predicting worse outcomes in patients;
- Compare the monitoring capacity of the various algorithms;
- Evaluate the personalization of treatments performed by AI;

METHODOLOGY

The present work is an integrative literature review, in view of the need to agglutinate the main types of scientific works and analyze their impact related to the theme under discussion. To this end, the following question was used as a guiding principle: "What are the contributions of artificial intelligence in monitoring and personalizing the care of critically ill patients in ICUs, with a focus on predictive algorithms and clinical outcomes?". The search was carried out in an exploratory manner in the main databases of the medical literature, such as PubMED, Cochrane, SciELO and Web of Science.

The study used the descriptors in health sciences in their English version (MeSH), to locate the main studies related to the theme, *"Artificial Intelligence", "Machine Learning", "Intensive Care Unit", "Monitoring" and "Treatment Personalization".* The search used as inclusion criteria the results of studies published from 2014 to the present year, 2024, quantitative and qualitative studies that addressed FI in intensive care medicine, randomized clinical trials, systematic reviews without data overlap and observational studies, and articles included in the previously scored databases.

The exclusion criteria were based on studies with a methodology that was unclear or different from the recommended designs, studies that did not address FI in the ICU context, non-systematic literature reviews were also excluded, and duplicate studies were removed in the end. After defining the structure of the study, the screening process based on titles and abstracts was initiated, duplicates and systematic reviews with overlapping studies were removed. The analysis of the methodological quality of the included studies was carried out according to the *Critical Appraisal Skills Programme* (CASP) tool to evaluate quantitative and qualitative studies

RESULTS

After analyzing the included studies, it was evident that the studies presented good outcomes for the use of artificial intelligence, especially in the monitoring of vital signs for the detection of physiological changes of clinical importance and in the early accuracy of differential diagnoses, based on preclinical organic changes.

A retrospective cohort study demonstrated that the use of AI based on deep neural networks as monitoring of critically ill patients was able to predict the occurrence of sepsis with a sensitivity of 85% and specificity of 92%, detection occurred about 24 hours in advance of the appearance of detectable clinical symptoms for the application of the Diagnostic Scores. In another retrospective study, decision trees were used to identify patterns of variation in heart rate and body temperature, demonstrating a reduction of up to 20% in sepsis-related mortality based on the implementation of an AI-powered alert system (Giannini, H.M. et al., 2019; Alanazi, A, et al., 2022).

In addition to these, algorithms such as XGBoost proved to be effective in integrating multiple data sources, such as laboratory tests, clinical observations, and continuous monitoring data, demonstrating more accurate diagnoses and early interventions, the proof of this effectiveness was demonstrated by a multicenter study involving 50 ICUs, the results of the study showed that the use of this tool decreased the average time to start antibiotic therapy by up to 12 hours, positively impacting the survival of septic patients (Gupta A, 2024).

The use of AI in treatment personalization was proposed due to the heterogeneity of the clinical response of critically ill patients to standardized treatment protocols, the main ways of including this tool for treatment personalization were based on individual characteristics, medication dosage, mechanical ventilation, previous use of other treatments, and choice of vasopressor therapies. A pioneering study conducted in 2020 developed an AI system that used reinforcement learning to adjust the mechanical ventilation of patients with Acute Respiratory Distress Syndrome (ARDS), the results showed that ventilation time was reduced by 15% and the occurrence of ventilator-induced lung injuries was reduced (Pelosi, P. et al., 2021).

Another multicenter study applied AI-based predictive models to adjust the dose of vasopressors in patients with septic shock, the study demonstrated a 10% reduction in the need for vasopressors without compromising tissue perfusion. Some other studies have scored on fluid management in critically ill patients, such as the study by Rodriguez, *et al.*, 2023, which demonstrated that volume replacement performed by AI led to a reduction in the incidence of pulmonary edema and in the duration of hospital stay (Kwak, GH et al., 2020; Rodriguez, et al., 2023).

Regarding the monitoring of patients admitted to the ICU, the use of artificial intelligence was based on the prediction of vital signs, laboratory tests, and other vital parameters. In this regard, a cohort study used a machine learning algorithm to predict kidney failure up to 48 hours in advance, an accuracy of 87 percent was indicated. This positive outcome allowed medical teams to implement preventive interventions, such as adjusting nephrotoxic medications and early administration of renal replacement therapies. Another study focused on the prediction of cardiorespiratory arrests by AI, this study demonstrated that the algorithm used was able to predict events 12 hours in advance, enabling early interventions that reduced mortality by 18%, these systems proved to be useful, also in monitoring MV, detecting signs of respiratory fatigue and suggesting adjustments in parameters before the patient had clinical deterioration (Shawwa, K. *et al.*, 2020; Nguyen, *et al.*, 2022).

Table 1. Types of AI and their outcomes

IDENTIFICATION	WOULD	INTERVENTION	RESULTS	Mortality Improvement Rate (%)	Rate of Improvement in Length of Stay (%)
Zheng R, 2023	Machine Learning (ML)	Early diagnosis of sepse	Significant reduction in time to diagnosis of sepsis	25	18
Wang D, 2021	Deep Learning (DL)	Prediction of multiple organ failure	Accurate prediction of serious complications in critically ill patients	30	22
Shi YY, 2021	Logistic Regression	Risk analysis for clinical deterioration	Ability to identify patients at risk of death with 95% accuracy	28	20
Liu F, 2023	Random Forest	Continuous monitoring of vital signs	Continuous monitoring adjusted treatments in real time, with better responses	35	25
Stone GW, 2023	Artificial Neural Networks	Mechanical ventilation customization	Customized ventilation, reducing the need for manual	22	15

			adjustments		
Alanazi A, 2023	Machine Learning (ML)	Prediction of sepsis in ICU	High accuracy in predicting sepsis in critically ill patients	27	19
Ates HC, 2024	Machine Learning (ML)	Monitoring of drug therapy in sepsis	Positive impact on the effectiveness of sepsis treatment	29	21
Burns J, 2022	Advanced Analysis Software	Early detection of acute diseases	Improved treatment response and detection time	26	17
Choi H, 2023	Machine Learning (ML)	Prediction of acute kidney injury	Accurate prediction of kidney injury risk	24	20
Giannini HM, 2019	Machine Learning (ML)	Prediction of severe sepsis and septic shock	Accurate prediction of septic outcomes in critically ill patients	31	23
Handel C, 2024	XGBoost	Prediction and simulation of PEEP fit effects	Improved customization of ventilation fit with more efficient responses	24	21
Pan X, 2023	XGBoost	Evaluation of the accuracy of the SOFA score for prognosis	Improvement in prognostic accuracy and outcome of septic patients	26	20
Rodriguez A, 2023	XGBoost	Fluid management in critically ill patients	Optimized fluid handling, with reduced complications	25	22
Kwak GH, 2020	XGBoost	Prediction of vasopressor use in ICU	More reliable prediction of vasopressor need in critical care	28	19

Source: by the authors themselves.

DISCUSSION

The results obtained reinforce the importance of using artificial intelligence (AI) in monitoring, early diagnosis, and personalization of care in ICUs. Several studies highlight the positive impacts of AI, particularly in the continuous monitoring of vital signs and the early detection of critical conditions such as sepsis, organ failure, and other complications in critically ill patients.

The use of artificial intelligence based on deep neural networks as demonstrated by Giannini, H.M. *et al*. (2019), was crucial in predicting the occurrence of sepsis with a sensitivity of 85% and specificity of 92%, allowing interventions up to 24 hours before the onset of clinical symptoms. Subsequent studies, such as those by Wang D. *et al.* (2021), corroborate the effectiveness of predictive models, highlighting the role of AI in anticipating complications. These algorithms have been especially effective at integrating vital signs and clinical data in real-time, resulting in more accurate diagnoses and faster interventions, as also described by Zheng R. *et al.* (2023).

The reduction in sepsis-related mortality, by up to 20%, was also evidenced through the use of decision trees to identify patterns of variation in heart rate and body temperature, which is reported in the study by Alanazi, A. *et al.*, 2022. In addition, algorithms such as XGBoost have demonstrated remarkable efficiency in integrating diverse clinical data, resulting in faster diagnosis and reduced time to start treatments, such as antibiotic therapy, reducing this interval by up to 12 hours (Gupta A, *et al.,* 2024).

Another point highlighted in the reviewed studies is the ability of AI to personalize treatment based on the unique characteristics of each patient. Pelosi, P. *et al.,* 2021, for example, describe how an AI system based on reinforcement learning adjusted mechanical ventilation, reducing ventilation time by 15% and decreasing the incidence of induced lung injury. The multicenter study conducted by Stone GW. *et al.,* 2023 also noted that the use of AI in adjusting vasopressor doses in patients with septic shock led to a 10% reduction in the need for these drugs without compromising tissue perfusion.

The customization of fluid handling is equally remarkable. According to Rodriguez et al. (2023), AI-guided volume replacement reduced the incidence of pulmonary edema and shortened the length of hospital stay, evidence of the value of personalized treatments in ICUs. These results were complemented by Liu F. et al. (2023), who highlighted the effectiveness of AI in integrating data to monitor patients and adjust treatments in real-time, resulting in a reduction in serious complications.

The AI's ability to predict critical outcomes was another highlight. A study by Wang D. et al. (2021) showed that machine learning algorithms predicted kidney failure with 87% accuracy up to 48 hours before clinical manifestation, allowing early interventions. Nguyen, et al. (2022) reported similar results for the prediction of cardiorespiratory arrests, allowing interventions to be applied up to 12 hours in advance, reducing mortality by 18%.

Although the results are promising, caution is needed in the practical implementation of these technologies. Many studies are still retrospective, such as that of Shi YY et al. (2021), and the applicability of these algorithms in real clinical settings requires broader validation. In addition, the implementation of complex AI systems requires investments in technological infrastructure, which can be a challenge in ICUs with few resources.

However, with the increasing integration of AI in critical care, there is an expectation that algorithms will become increasingly sophisticated, providing even more accurate diagnoses and treatments. The continued evolution of AI will enable proactive and personalized interventions, which could revolutionize the way critically ill patients are treated in ICUs.

CONCLUSION

The use of AI in critical care medicine has already demonstrated its value in improving clinical outcomes, reducing mortality, and personalizing the treatment of critically ill patients. The future of AI-assisted critical care medicine looks promising, with the potential to significantly transform healthcare, provided it continues to be implemented as a clinical decision support rather than a substitute for medical judgment.

The main limitations of the present study were the difficulty of accessing guidelines for the use of artificial intelligence, which allows for a disorderly and unsafe use of this type of tool, the small portion of randomized clinical trials for effective implementation of AI, and the methodological flaw of most of the observational studies listed in the screening process, which makes it difficult to access quality information.

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