Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 58 Issue: 09:2025
DOI: 10.5281/zenodo.17084836

ARTIFICIAL INTELLIGENCE APPLICATIONS IN INTENSIVE AND CRITICAL CARE: A SYSTEMATIC REVIEW OF PREDICTIVE, DIAGNOSTIC, AND EDUCATIONAL OUTCOMES

OMAR RAYYAN OMAR BARAYYAN
Emergency Medicine and Critical Care Medicine Consultant, Adult Critical Care Department, Ministry of Health, Riyadh Third Health Cluster, Diriyah Hospital, Riyadh, Saudi Arabia.

OSAMAH MOHAMMED BIN BAKHEET
Emergency Consultant, Emergency Department, First Health Cluster, Riyadh, Saudi Arabia.

AWN ABDULKHALIQ ALQARNI
Saudi and Jordanian Board Emergency Medicine, Emergency Department, First Health Cluster, Riyadh, Saudi Arabia.

MUATH AHMED AWAD ALAHAMDI
Internal Medicine and ICU Consultant, ICU Department, Ministry of Health, Riyadh Third Health Cluster, Diriyah Hospital, Riyadh, Saudi Arabia.

FARHAN HAMAD ALANAZI
Emergency Medicine and Critical Care Medicine Consultant, Adult Critical Care Department, Ministry of Health, Second Health Cluster, PMAH, Riyadh, Saudi Arabia.

BANDAR MOHAMMED ALANAZY
General Practice, FMC, Second Health Cluster, Riyadh, Saudi Arabia.

WADHA SALEM ALMARRI
Pharmacist, Pharmacy Department, King Fahd Military Medical Complex (KFMMC), Dhahran, Saudi Arabia.

RUQAYYAH ABDULLAH ALI ALMUSA
Nurse, MOTC Transplant, King Fahad Hospital, Dammam, Saudi Arabia.

Abstract

Background: Artificial intelligence (AI) is increasingly being explored in intensive and critical care for prediction, diagnosis, workflow optimization, and clinical training. With the rapid growth of machine learning applications in high-stakes environments such as intensive care units (ICUs) and emergency departments, evaluating their clinical utility and limitations is essential. Methods: A systematic search of PubMed, Scopus, Web of Science, and Embase was conducted for studies published between January 2020 and February 2025. Eligible studies included randomized trials, observational cohorts, and post hoc analyses that applied AI methods in critical care or emergency settings. Data on study design, patient population, AI methodology, and outcomes were extracted and synthesized narratively. Results: Ten studies were included, representing diverse settings such as ICUs, emergency departments, stroke centers, and oncology clinics. Populations ranged from critically ill patients with sepsis, hyperglycemic crises, trauma, and post–cardiac arrest to healthcare providers undergoing AI-assisted training. AI methods included random forest, multilayer perceptrons, artificial neural networks, extreme gradient boosting, and proprietary clinical decision support platforms. Findings demonstrated improvements in prediction accuracy (AUCs ranging from 0.79 to 0.97), workflow efficiency (e.g., 11.2-minute reduction in thrombectomy initiation), enhanced adherence to guidelines, and educational benefits. However, functional outcomes were inconsistently improved, and most studies highlighted challenges related to validation, methodological rigor, and real-world applicability. Conclusion: AI applications show significant promise in enhancing predictive accuracy, clinical efficiency, and provider education in intensive and critical care. Despite these advances, widespread clinical adoption is hindered by concerns over external validation, methodological transparency, and integration into healthcare systems. Future research should prioritize rigorous validation and standardized reporting to ensure safe and effective translation into practice.

Keywords: Artificial Intelligence, Machine Learning, Intensive Care Unit, Emergency Medicine, Prediction, Workflow Optimization, Clinical Decision Support.

INTRODUCTION

Artificial intelligence (AI) has emerged as one of the most transformative technologies in modern healthcare, offering powerful tools for prediction, diagnosis, and decision support. Within critical care and perioperative medicine, the integration of AI and machine learning (ML) has accelerated due to the increasing availability of large datasets and computational capacity. These technologies are capable of analyzing complex, high-dimensional data from electronic medical records, imaging, and monitoring systems to assist clinicians in time-sensitive and high-stakes environments. As a result, AI has gained particular relevance in intensive care units (ICUs) and operating rooms (ORs), where rapid and accurate decision-making can directly influence patient outcomes (Bellini et al., 2024).

The potential of AI in perioperative and OR management has been demonstrated across applications such as surgical duration prediction, post-anesthesia care unit resource allocation, and reduction of case cancellations. Advanced ML algorithms, including random forests and XGBoost, have consistently shown improved predictive performance compared with conventional approaches, underscoring their capacity to optimize efficiency and patient flow (Bellini et al., 2024). At the same time, in the field of medical imaging, deep learning models—particularly convolutional neural networks—have been widely investigated for diagnostic tasks. However, a systematic review highlighted that despite claims of AI models performing as well as or better than clinicians, most studies suffered from methodological limitations, inadequate reporting, and high risk of bias, raising concerns about translation into routine clinical use (Nagendran et al., 2020).

Beyond workflow optimization and diagnostics, AI has also been applied to improve the monitoring of critically ill patients. A recent clinical evaluation demonstrated that AI-assisted muscle ultrasound in ICU patients enhanced reproducibility, reduced scan time, and minimized interobserver variability in assessing muscle wasting. By automating rectus femoris cross-sectional area measurements, AI supported less experienced operators and improved the reliability of monitoring functional decline in critically ill patients (Nhat et al., 2024). Similarly, in the educational domain, AI-guided simulation has been explored for bronchoscopy training in critical-care physicians. A randomized controlled trial revealed that AI-based augmented reality training systems resulted in faster and more efficient bronchoscopy performance compared to expert tutor instruction, suggesting the potential for AI to enhance skill acquisition in clinical training (Agbontaen et al., 2025).

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 58 Issue: 09:2025
DOI: 10.5281/zenodo.17084836

The urgency of the COVID-19 pandemic further highlighted both the promise and pitfalls of AI adoption in emergency and ICU settings. While AI applications were rapidly developed to support diagnosis, prognostication, and resource optimization during the pandemic, most studies were at high risk of bias and demonstrated insufficient validation, limiting their readiness for clinical deployment. This reflects a broader challenge in AI research, where innovation often outpaces methodological rigor and real-world applicability (Chee et al., 2021). This systematic review therefore aims to synthesize current evidence on AI applications in critical care and related fields, evaluating their performance, clinical utility, and limitations to better understand their role in transforming patient outcomes and healthcare delivery.

METHODOLOGY

Search Strategy

A comprehensive literature search was performed to identify studies that evaluated the use of artificial intelligence (AI) applications in critical care and emergency medicine. Electronic databases including PubMed, Scopus, Web of Science, and Embase were searched from January 2020 to February 2025. The search strategy combined terms related to artificial intelligence and machine learning ("artificial intelligence," "machine learning," "deep learning," "neural networks") with clinical contexts ("intensive care," "critical care," "emergency department," "ICU," "sepsis," "stroke," "trauma," "delirium"). The search was supplemented by hand-screening the reference lists of relevant articles to ensure that no eligible studies were missed.

Eligibility Criteria

Studies were included if they were original research articles; involved adult or pediatric populations in critical care or emergency settings; applied AI or machine learning tools for diagnosis, prediction, workflow optimization, or clinical decision support, and; reported clinical, process-related, or educational outcomes. Both randomized controlled trials and observational studies were considered eligible. Studies were excluded if they were reviews, conference abstracts, case reports, editorials, or if they lacked sufficient detail about the AI method or study outcomes.

Study Selection

Two independent reviewers screened titles and abstracts to assess eligibility, followed by full-text review of potentially relevant articles. Disagreements were resolved by consensus or consultation with a third reviewer. A total of ten studies met the inclusion criteria and were included in this review. These studies comprised randomized clinical trials, cluster randomized designs, retrospective cohorts, and post hoc analyses of clinical trial datasets.

Data Extraction

Data were independently extracted by two reviewers using a standardized form. Extracted information included study citation, design, setting, sample size, patient or participant

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 58 Issue: 09:2025
DOI: 10.5281/zenodo.17084836

demographics, type of AI intervention, comparator (if applicable), primary and secondary outcomes, and main findings. Particular attention was paid to the AI methodologies used (random forest, neural networks, gradient boosting, proprietary clinical decision support systems) and to whether models were validated internally or externally.

Data Synthesis

Given the heterogeneity in AI applications, clinical populations, and reported outcomes, a quantitative meta-analysis was not feasible. Instead, results were synthesized narratively and tabulated according to study design, population, AI method used, main findings, and reported outcomes. Where possible, outcomes were grouped into predictive accuracy (sensitivity, specificity, AUC), workflow improvements (time to treatment, adherence rates), and clinical endpoints (mortality, neurological recovery, end-of-life care engagement).

RESULTS

A total of ten studies published between 2020 and 2025 were included in this review. The designs varied from randomized controlled trials and cluster randomized stepped-wedge trials to retrospective cohort analyses and post hoc evaluations of existing datasets. Sample sizes ranged widely, from small pilot investigations of twenty critically ill patients to large multicenter studies involving more than twenty thousand participants. The included studies were conducted across diverse clinical settings such as intensive care units, emergency departments, stroke centers, and oncology clinics, reflecting the broad applicability of artificial intelligence (AI) technologies in acute and critical care.

The populations studied were equally heterogeneous. Several trials focused on ICU patients at risk of sepsis or experiencing delirium, while others evaluated emergency department patients presenting with hyperglycemic crises or stroke. Post–cardiac arrest patients admitted to intensive care and trauma patients with life-threatening injuries were also represented. In addition, two studies assessed healthcare providers rather than patients, investigating the impact of AI systems on nurses’ adherence to delirium guidelines and physicians’ acquisition of bronchoscopy skills.

This diversity in both populations and settings demonstrates the wide range of clinical domains where AI is being tested. A variety of AI methods were applied across the included studies. Machine learning algorithms such as random forest, extreme gradient boosting, multilayer perceptrons, and artificial neural networks were employed to predict clinical outcomes including sepsis, mortality, and neurological recovery.

Proprietary platforms such as NAVOY® Sepsis and AI-AntiDelirium were developed as decision support tools within ICU workflows. Other approaches involved real-time imaging interpretation, such as automated large vessel occlusion detection on CT angiography and AI-assisted ultrasound for muscle wasting assessment.

Finally, augmented reality combined with AI guidance was tested as a training tool for bronchoscopy in critical-care physicians. These varied approaches highlight the rapid

ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 58 Issue: 09:2025
DOI: 10.5281/zenodo.17084836

expansion of AI beyond prediction tasks into workflow optimization, education, and real-time clinical decision support. The findings indicated that AI can enhance either predictive performance or process efficiency. Automated stroke triage systems reduced door-to-groin times for thrombectomy initiation by over eleven minutes, while machine learning-triggered behavioral nudges in oncology care increased the frequency of serious illness conversations and improved end-of-life planning.

In the ICU, the AI-AntiDelirium platform significantly increased nurses' adherence to guideline-based interventions and reduced extraneous cognitive load. Sepsis prediction models demonstrated strong prognostic performance, with the NAVOY® Sepsis algorithm anticipating onset up to three hours in advance and a random forest model achieving an area under the curve of 0.91.

An MLP-based model integrated into hospital information systems predicted adverse outcomes in hyperglycemic crises more accurately than conventional risk scores. In post–cardiac arrest care, artificial neural networks predicted long-term neurological recovery with superior accuracy compared to logistic regression. AI-assisted ultrasound shortened scan times by half and improved reproducibility in monitoring muscle wasting.

In the educational domain, AI-guided bronchoscopy training resulted in faster and more efficient performance than expert tutor instruction. Finally, in trauma care, an eXGBM algorithm predicted 30-day mortality with exceptional accuracy and was successfully deployed as an accessible web-based clinical tool.

Table 1: characteristics of included studies

Citation	Study Design	Sample Size	Method	AI Method Used	Main Findings	Outcomes
Martinez-Gutierrez et al., 2023 (JAMA Neurology)	Cluster randomized stepped-wedge clinical trial	443 screened, 243 included	AI-enabled automated LVO detection from CT angiogram + secure group messaging	AI algorithm for LVO detection	Reduced door-to-groin time by 11.2 minutes; improved workflow efficiency	Faster EVT initiation, no significant functional outcome differences
Manz et al., 2023 (JAMA Oncol)	Stepped-wedge randomized clinical trial	20,506 patients (41,021 encounters)	Behavioral nudges triggered by ML mortality prediction	Machine learning algorithm predicting 6-month mortality	Increased serious illness conversations (13.5% vs 3.4%)	Improved end-of-life care engagement, hospice enrollment impact
Zhang et al., 2025 (Intensive Crit Care Nurs)	Cluster randomized controlled trial	80 ICU nurses	AI-AntiDelirium system for adherence	AI-driven CDSS tailoring delirium prevention	Higher adherence (75% vs 58%), reduced	Improved guideline adherence, reduced extraneous

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 58 Issue: 09:2025
DOI: 10.5281/zenodo.17084836

			to delirium guidelines		cognitive load	cognitive load
Persson et al., 2024 (J Crit Care)	Prospective randomized validation study	304 ICU patients	NAVOY® Sepsis prediction with 4h routine clinical data	Machine learning algorithm (NAVOY Sepsis)	Predicted sepsis 3h before onset with high accuracy (0.79)	Validated accuracy, sensitivity 0.80, specificity 0.78
Hsu et al., 2023 (BMC Endocr Disord)	Retrospective cohort with AI integration	2666 ED patients with hyperglycemic crises	AI model using 22 EMR features integrated into HIS	Multilayer perceptron (MLP) vs RF, SVM, KNN, LightGBM	MLP best (AUC 0.852 sepsis, 0.743 ICU, 0.796 mortality)	Better than PHD score, real-time integration feasible
Johnsson et al., 2020 (Crit Care)	Post- hoc analysis of TTM trial cohort	932 OHCA patients	ANN applied to TTM trial dataset	Artificial neural network (ANN)	AUC 0.891, superior to logistic regression (p=0.029)	Improved prognostication, ANN stratified risk subgroups
Nhat et al., 2024 (Sci Rep)	Randomized sequential allocation (pilot)	20 ICU patients (59 scans)	AI-assisted ultrasound for rectus femoris CSA	AI image recognition and measurement tool	Reduced scan time (19.6→9.4 min), ICC 0.999 vs 0.982	Increased reproducibility, improved efficiency
Agbontaen et al., 2025 (Crit Care Med)	Randomized controlled trial (simulation)	40 critical-care physicians	AI vs expert tutor for bronchoscopy training	AI augmented reality (Ambu Broncho Simulator)	AI improved MIT, PT, and fewer revisits	Better training efficiency, promising for education
Wang et al., 2021 (Front Public Health)	Secondary analysis of retrospective observational cohort	4449 ICU infected patients	55 EMR features with random forest	Random forest ML	AUC 0.91, sensitivity 87%, specificity 89%	Strong predictive ability for sepsis in ICU patients
Han et al., 2024 (Int J Med Inform)	Model development and external validation	2662 trauma ICU patients + 131 external validation	AI mortality prediction mobile app	Extreme gradient boosting (eXGBM) vs RF, NN, SVM, DT	eXGBM best (AUC 0.974, accuracy 91.5%)	Validated, deployed as web-based tool for clinicians

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 58 Issue: 09:2025
DOI: 10.5281/zenodo.17084836

Table 2: Demographics, Findings, Outcomes

Citation	Sample Size / Demographics	Main Findings	Outcomes
Martinez-Gutierrez et al., 2023 (JAMA Neurology)	443 screened, 243 included	Reduced door-to-groin time by 11.2 minutes; improved workflow efficiency	Faster EVT initiation, no significant functional outcome differences
Manz et al., 2023 (JAMA Oncol)	20,506 patients (41,021 encounters)	Increased serious illness conversations (13.5% vs 3.4%)	Improved end-of-life care engagement, hospice enrollment impact
Zhang et al., 2025 (Intensive Crit Care Nurs)	80 ICU nurses	Higher adherence (75% vs 58%), reduced cognitive load	Improved guideline adherence, reduced extraneous cognitive load
Persson et al., 2024 (J Crit Care)	304 ICU patients	Predicted sepsis 3h before onset with high accuracy (0.79)	Validated accuracy, sensitivity 0.80, specificity 0.78
Hsu et al., 2023 (BMC Endocr Disord)	2666 ED patients with hyperglycemic crises	MLP best (AUC 0.852 sepsis, 0.743 ICU, 0.796 mortality)	Better than PHD score, real-time integration feasible
Johnsson et al., 2020 (Crit Care)	932 OHCA patients	AUC 0.891, superior to logistic regression (p=0.029)	Improved prognostication, ANN stratified risk subgroups
Nhat et al., 2024 (Sci Rep)	20 ICU patients (59 scans)	Reduced scan time (19.6→9.4 min), ICC 0.999 vs 0.982	Increased reproducibility, improved efficiency
Agbontaen et al., 2025 (Crit Care Med)	40 critical-care physicians	AI improved MIT, PT, and fewer revisits	Better training efficiency, promising for education
Wang et al., 2021 (Front Public Health)	4449 ICU infected patients	AUC 0.91, sensitivity 87%, specificity 89%	Strong predictive ability for sepsis in ICU patients
Han et al., 2024 (Int J Med Inform)	2662 trauma ICU patients + 131 external validation	eXGBM best (AUC 0.974, accuracy 91.5%)	Validated, deployed as web-based tool for clinicians

DISCUSSION

This systematic review highlights the expanding role of artificial intelligence (AI) in intensive and critical care. AI-based models demonstrated enhanced diagnostic accuracy, superior predictive performance, and workflow efficiency compared with traditional clinical approaches. These findings underscore the potential of AI to transform critical care delivery, while also emphasizing the need for methodological rigor and careful implementation. Several studies have compared the diagnostic performance of AI with that of clinicians. A review of deep learning models applied to medical imaging reported that, although many studies claimed comparable or superior performance to human experts, most were limited by high risk of bias, small comparator groups, and poor adherence to reporting standards (Nagendran et al., 2020). Similar concerns were

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 58 Issue: 09:2025
DOI: 10.5281/zenodo.17084836

echoed in a systematic review of barriers to AI implementation in healthcare, which identified ethical, technological, regulatory, and workforce-related obstacles as major challenges to translation into practice (Ahmed et al., 2023). Together, these findings highlight that the technical promise of AI must be matched with transparent reporting and robust clinical validation. Mortality prediction emerged as a key application area. In the cardiac intensive care unit (CICU), conventional severity scores such as APACHE and SOFA have shown inconsistent performance, whereas AI-based electrocardiographic models provided more dynamic and accurate risk stratification (Rafie et al., 2022). A meta-analysis of AI for sepsis detection demonstrated strong diagnostic performance, with pooled AUC values approaching 0.87, although heterogeneity across studies limited generalizability (Ji et al., 2024). In the neonatal intensive care setting, AI models trained on electronic medical record data successfully predicted outcomes such as sepsis, bronchopulmonary dysplasia, and mortality, frequently outperforming traditional statistical methods (McAdams et al., 2022). Collectively, these findings suggest that AI-based prognostic models may offer superior predictive accuracy across diverse ICU populations.

AI holds promise in diagnosis and clinical workflow optimization. A systematic review of AI applications in emergency and critical care diagnostics reported high precision in identifying acute conditions including cardiac arrest, sepsis, and gastrointestinal tumors (Sreedharan et al., 2024). Likewise, during the COVID-19 pandemic, AI models were rapidly developed for diagnosis and prognostication in acute care. Most were limited by methodological weaknesses and poor validation, underscoring the gap between rapid innovation and safe clinical adoption (Chee et al., 2021). These findings highlight a recurring pattern: AI demonstrates technical potential but often falls short of readiness for deployment in real-world acute care environments. AI is increasingly being applied to perioperative and nursing practice. A systematic review in cancer nursing demonstrated that predictive models improved identification of health problems and guided patient management, although most were developed in silico and not tested in clinical practice (O’Connor et al., 2024). In perioperative medicine, machine learning algorithms such as XGBoost and random forest were shown to improve prediction of surgical case duration, resource allocation in the post-anesthesia care unit, and identification of high-risk cancellations (Bellini et al., 2024). These findings suggest important implications for workforce efficiency and healthcare system optimization, although clinical integration remains limited.

CONCLUSION

This systematic review demonstrates that artificial intelligence has the potential to enhance predictive accuracy, streamline workflows, and improve educational outcomes in intensive and critical care. Across diverse clinical contexts, AI models outperformed conventional approaches in sepsis prediction, mortality prognostication, and resource optimization, while also supporting guideline adherence and skill acquisition. Despite these encouraging findings, translation into routine practice is limited. Key barriers include insufficient external validation, variability in study quality, and lack of standardized reporting, all of which reduce confidence in widespread implementation.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 58 Issue: 09:2025
DOI: 10.5281/zenodo.17084836

References

1) Agbontaen KO, Cold KM, Woods D, Grover V, Aboumarie HS, Kaul S, et al. Artificial Intelligence-Guided Bronchoscopy is Superior to Human Expert Instruction for the Performance of Critical-Care Physicians: A Randomized Controlled Trial. *Crit Care Med*. 2025;53(5): e1105–13. doi:10.1097/CCM.0000000000006629

2) Ahmed MI, Spooner B, Isherwood J, Lane M, Orrock E, Dennison A. A systematic review of the barriers to the implementation of artificial intelligence in healthcare. Cureus. 2023;15(10): e46454. doi: 10.7759/cureus.46454

3) Bellini V, Russo M, Domenichetti T, Panizzi M, Allai S, Bignami EG. Artificial Intelligence in Operating Room Management. *J Med Syst*. 2024;48(1):19. doi:10.1007/s10916-024-02038-2

4) Chee ML, Ong MEH, Siddiqui FJ, Zhang Z, Lim SL, Ho AFW, et al. Artificial Intelligence Applications for COVID-19 in Intensive Care and Emergency Settings: A Systematic Review. *Int J Environ Res Public Health*. 2021;18(9):4749. doi:10.3390/ijerph18094749

5) Han T, Xiong F, Sun B, Zhong L, Han Z, Lei M. Development and validation of an artificial intelligence mobile application for predicting 30-day mortality in critically ill patients with orthopaedic trauma. Int J Med Inform. 2024; 184:105383. doi: 10.1016/j.ijmedinf.2024.105383

6) Hsu CC, Kao Y, Hsu CC, Chen CJ, Hsu SL, Liu TL, et al. Using artificial intelligence to predict adverse outcomes in emergency department patients with hyperglycemic crises in real time. *BMC Endocr Disord*. 2023; 23:234. doi:10.1186/s12902-023-01437-9

7) Ji X, Huo H, Dong L. Early detection of sepsis using artificial intelligence in intensive care units: a systematic review and meta-analysis. J Intensive Care Med. 2025;40(3): e1372499. doi: 10.1177/08850666251372499

8) Johnsson J, Björnsson O, Andersson P, Jakobsson A, Cronberg T, Lilja G, et al. Artificial neural networks improve early outcome prediction and risk classification in out-of-hospital cardiac arrest patients admitted to intensive care. *Crit Care*. 2020; 24:474. doi:10.1186/s13054-020-03103-1

9) Manz CR, Zhang Y, Chen K, Long Q, Small DS, Evans CN, et al. Long-term effect of machine learning–triggered behavioral nudges on serious illness conversations and end-of-life outcomes among patients with cancer: a randomized clinical trial. JAMA Oncol. 2023;9(3):414-8.
Doi: 10.1001/jamaoncol.2022.6303

10) Martinez-Gutierrez JC, Kim Y, Salazar-Marioni S, Tariq MB, Abdelkhaleq R, Niktabe A, et al. Automated large vessel occlusion detection software and thrombectomy treatment times: a cluster randomized clinical trial. JAMA Netw Open. 2023;6(9): e2331550.
Doi: 10.1001/jamanetworkopen.2023.31550

11) McAdams RM, Kaur R, Sun Y, Bindra H, Cho SJ, Singh H. Predicting clinical outcomes using artificial intelligence and machine learning in neonatal intensive care units: a systematic review. *J Perinatol*. 2022;42(12):1561–75. doi:10.1038/s41372-022-01392-8

12) Nagendran M, Chen Y, Lovejoy CA, Gordon AC, Komorowski M, Harvey H, et al. Artificial intelligence versus clinicians: systematic review of design, reporting standards, and claims of deep learning studies. *BMJ*. 2020;368:m689. doi:10.1136/bmj.m689

13) Nhat PTH, Hao NV, Yen LM, Anh NH, Khiem DP, Kerdegari H, et al. Clinical evaluation of AI-assisted muscle ultrasound for monitoring muscle wasting in ICU patients. *Sci Rep*. 2024; 14:14798. doi:10.1038/s41598-024-64564-w

14) O'Connor S, Vercell A, Wong D, Yorke J, Fallatah FA, Cave L, et al. The application and use of artificial intelligence in cancer nursing: A systematic review. *Eur J Oncol Nurs*. 2024; 64:102510. doi: 10.1016/j.ejon.2024.102510

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 58 Issue: 09:2025
DOI: 10.5281/zenodo.17084836

15) Persson I, Macura A, Becedas D, Sjövall F. Early prediction of sepsis in intensive care patients using the machine learning algorithm NAVOY® Sepsis: a prospective randomized clinical validation study. J Crit Care. 2024; 80:154400. doi: 10.1016/j.jcrc.2023.154400

16) Rafie N, Jentzer JC, Noseworthy PA, Kashou AH. Mortality Prediction in Cardiac Intensive Care Unit Patients: A Systematic Review of Existing and Artificial Intelligence Augmented Approaches. *Front Artif Intell*. 2022; 5:876007. doi:10.3389/frai.2022.876007

17) Sreedharan JK, Saleh F, Alqahtani A, Albalawi IA, Gopalakrishnan GK, Alahmed HA, et al. Applications of artificial intelligence in emergency and critical care diagnostics: a systematic review and meta-analysis. Front Artif Intell. 2024; 7:1422551. Doi: 10.3389/frai.2024.1422551

18) Wang D, Li J, Sun Y, Ding X, Zhang X, Liu S, et al. A machine learning model for accurate prediction of sepsis in ICU patients. Front Public Health. 2021; 9:754348. Doi: 10.3389/fpubh.2021.754348

19) Zhang S, Ding S, Cui W, Li X, Wei J, Wu Y. Evaluating the effectiveness of a clinical decision support system (AI-AntiDelirium) to improve nurses' adherence to delirium guidelines in the intensive care unit. Intensive Crit Care Nurs. 2025; 87:103933. Doi: 10.1016/j.iccn.2024.103933