



REVIEW

Mapping Artificial Intelligence Research Trends in Critical Care Nursing: A Bibliometric Analysis

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Background: Recent development in AI-driven predictive analytics have demonstrated potential to enhance critical care workflows, particularly in three areas, including continuous vital sign monitoring in the ICU, intelligent nursing process management, AI-powered early risk stratification.

Objective: This bibliometric study analyzes trends of artificial intelligence research in critical care nursing between 2013 and 2023 and provides future research directions.

Results: The 1,346 relevant articles revealed a clear upward trajectory in research output related to AI in critical care nursing. The largest number of articles originated from the United States, followed by China, and the United Kingdom. Harvard University was the leading contributing institution, followed by the University of California and the Massachusetts Institute of Technology. Keyword clustering analysis generated seven representative cluster labels. Machine learning, AI, and deep learning were the major tools utilized during scholarly investigations of AI-driven research in critical care nursing.

Discussion: Our findings shed light on the opportunities for AI to transform critical care nursing practice, particularly in optimizing ICU workflow efficiency, precision patient monitoring, and evidence-based decision acceleration.

Conclusion: We advocate for the expansion of this type of research, the facilitation of collaboration among research institutions, and further development of international research collaborations.

Keywords: critical care nursing, artificial intelligence, visualization, CiteSpace

The rapid integration of information technology and modern medicine has positioned artificial intelligence (AI) as a transformative tool in healthcare, particularly in disease diagnosis, model prediction, data analysis, risk warning, and decision-making support. As a branch of computer science and fundamental to the fourth industrial revolution, AI leverages advanced algorithms, computational models, and systems to replicate and enhance human cognitive functions, leading to the development of intelligent robots that mimic many aspects of human thinking and behavior.² By facilitating the comprehensive analysis of vast medical datasets, AI allows clinical practitioners and researchers to explore nuanced disease patterns and interdependencies that pose great challenges in both clinical practice and research.³ In the nursing field, AI applications have gained traction in critical care settings, particularly for vital sign monitoring in the ICU, streamlined nursing process management, and early risk warning. For example, in China's large healthcare institutions, AI has been introduced into clinical nursing workflows, either as an independent tool or to assist nurses in emergency triage, medication reminders, resource allocation, data collection, and other tasks. In Japan, AI-powered robots have been introduced to hospitals to assist daily living activities and care of the elderly patients.⁵ Research on German nurses' perception of AI indicates that while there is a lack of understanding of AI knowledge, nurses generally believe that AI holds potential in bringing relief and support to nurses.⁶ During COVID19 pandemic in UK, AI was also found to be useful in helping identifying predict COIVD19 patients and optimizing resources that increase patient survival. Common challenges include resistance to adoption, accuracy issues in predictive models, data privacy and security, and ethics.

The above overview indicates that AI is becoming transformative in healthcare, with applications ranging from health service to health management. While existing studies have documented AI's potential in medicine, such as medical communications, initial diagnosis of complicated diseases, and health education, the integration of AI into nursing, particularly in critical care nursing, remains underexplored. Current literature on AI in nursing skews toward data accuracy, standardization, practice, and ethics, leaving gaps in understanding how AI innovations are adopted, adapted, or contested in diverse global contexts. This warrants a systematic examination of the geographic and institutional trends within nursing-specific AI research. Thus, the current study addresses these gaps through a bibliometric analysis of AI research trends in critical care nursing. Unlike prior reviews focused on clinical outcomes or AI functionalities, this analysis maps the evolution of AI in critical care nursing research themes and collaboration networks over time, while also highlighting the development of AI related research in critical care nursing in the global community.

This study aims to systematically analyze the growth trajectory, thematic evolution, and interdisciplinary intersections of AI research in critical care nursing, to identify geographic and institutional disparities in research output and collaboration, providing insights into AI research in critical care nursing globally and proposing a roadmap for future research, policy, and practice. Specifically, this study adopted bibliometric analysis using CiteSpace 6.22 software and the Web of Science (WOS) Core Collection database to map research trends and hotspots in AI applications in critical care nursing. Based on visual analysis of research trends, contributing authors and institutions, countries and regions, keywords, emerging terminology, and terminology clustering, the study identified key research hotspots and development trends in AI application in critical care nursing across China and worldwide.

Methodology

Data Collection

Data were extracted from the WOS Core Collection in August 2023 based on the following search strings: ((TS=(care or nurse or education or management)) AND TS=((ICU) OR (intensive care unit) OR (intensive care) OR (critical care)) AND TI=((artificial intelligence) OR (computational intelligence) OR (machine intelligence) OR (machine learning) OR (computer reasoning) OR (deep learning) OR (natural language processing)). The search dates were set to between 2013 and 2023, which led to the initial retrieval of 1,779 relevant articles. During the screening phase, English language publications consisting of empirical research or review articles on the topic of AI in critical care nursing in peer reviewed journals between 2013 and 2023 were included. Non-peer reviewed journal publications including conference papers, newspaper news, and were excluded.

Data Processing

The retrieved data (full record and cited references) were exported in plain text format and the file was renamed to download_xxx.txt. The "Remove Duplicates" function in CiteSpace software was used to filter and clean the data. Following a two-step manual screening process to exclude duplicates and irrelevant publications, a final cohort of 1,346 articles meeting the eligibility criteria was processed in CiteSpace for analysis (see Figure 1).

Analytical Methods

Bibliometric Analysis

The following results were summarized using the statistical analysis tool built into the WOS database: (1) number of annual publications; (2) top 10 authors and their publication volumes (h-indexes); (3) top 10 countries and their publication volumes; (4) top 10 research directions and their publication volumes. Common bibliometric indicators included annual publication volume, total citation count, average citation count per paper, and h-index.

Data Visualization

CiteSpace 6.2.2 software was used to perform a visual analysis of the imported 1,346 articles. The parameters for CiteSpace software were as follows: time slicing, 2013–2023; years per slice, 1; association strength algorithm, cosine; selection criteria (node threshold selection criteria), g-index; pruning algorithm, pathfinder; and clustering algorithm, log-likelihood ratio.

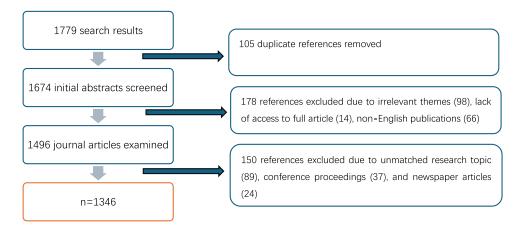


Figure I Procedure for screening and selecting the documents.

Results

Publication Trends

The number of international publications covering AI in critical care patient nursing research generally showed an upward trend. Beginning in 2017, the annual number of publications increased in an approximately linear manner, with a peak of 409 publications in 2022. The steady growth in the number of AI publications in the field of critical care nursing reflects the increased attention of researchers worldwide, such that a further increase can be expected. The number of publications related to the application of AI in critical care patient nursing and the identified trends are presented in Figure 2.

Author and Institutional Analyses

All of the top 10 authors had > 8 publications. The h-indexes of Celi LA (38), Liu Y (112), Lee J (27), and Rashidi P (25) reflect the substantial academic impacts of their research and corresponding recognition by the academic community (Table 1). This body of research primarily focuses on critical care data analysis, the development of predictive models,

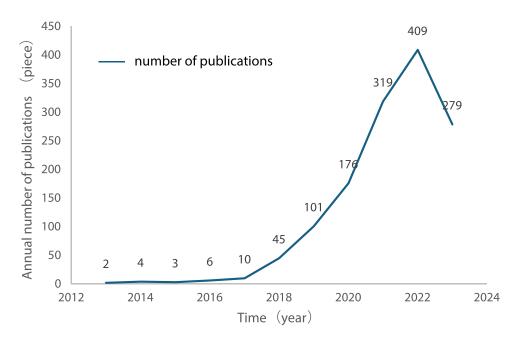


Figure 2 Trend of Research Publications on Artificial Intelligence in the Field of Critical Care Nursing from 2013 to 2023.

Table 1 Top 10 Authors in the Field of Artificial Intelligence (AI) in Critical Care Nursing Based on the Number of Publications

No.	Author	Publications	Percentage	h-index	No.	Author	Publications	Percentage	h-index
1	Celi LA	17	1.263	38	6	Rashidi P	9	0.669	25
2	Bihorac A	11	0.817	18	7	Wang H	9	0.669	5
3	Li L	П	0.817	3	8	Lee J	8	0.594	27
4	Liu C	9	0.669	3	9	Li J	8	0.594	7
5	Liu Y	9	0.669	112	10	Ozrazgat-baslanti T	8	0.594	20

decision analysis, and machine learning. The top three institutions were Harvard University (139), University of California (63), and Massachusetts Institute of Technology (40), all in the United States; they were responsible for 17.98% of the total number of publications. This finding points out that the top ranking institutions are all located in the United States, demonstrating that the United States holds a dominant position in scientific output within the field of artificial intelligence (AI)-based critical care patient research. Major research areas at US universities primarily focus on the application of AI and machine learning (ML) in healthcare, including clinical decision support, disease prediction, medical imaging analysis, and patient health management. Specific applications of AI technology include ICU sepsis prediction, postoperative complication monitoring, and cancer diagnosis and treatment. ⁸⁻¹⁰ This is mainly due to the fact that major US universities possess abundant research resources and funding support, coupled with their well-established environments for interdisciplinary collaboration, which fosters the advancement of AI technology in healthcare applications.

National/Regional Analyses

The 1,346 articles included in this study originated from 86 countries/regions. Table 2 lists the top 10 countries/regions. The top five countries/regions were the United States (521 articles), China (272), the United Kingdom (101), Canada (84), and South Korea (65). The United States had the highest number of articles, but its centrality was only 0.05. Germany had 63 articles, with a centrality of 0.23, and Spain had 43 articles, with a centrality of 0.31. The United States, leveraging its world-leading research institutions and robust scientific foundations, has become the country publishing the most papers in this field. These studies explore how advancements in data technologies and statistics can enhance the prediction of patient-centered outcomes, identify new treatment decision-making protocols linked to improved results, and enable real-time learning of these protocols, highlighting its dominance in the application of artificial intelligence to critical care research. China has significantly increased its investments in AI and healthcare in recent years, driving the production of high-quality research. However, its low level participation in international research collaborations, with a primary reliance on domestic research capacity, has limited its influence within the global academic community. 12

Table 2 Ranking of the Top 10 Countries in Publication Volume Concerning Research on Al in Critical Care Nursing

No.	Country	Publications	Percentage	Centrality	
ı	United States	521	0.387	0.05	
2	China	272	0.202	0.00	
3	United Kingdom	101	0.075	0.03	
4	Canada	84	0.062	0.09	
5	South Korea	65	0.048	0.00	
6	Germany	63	0.047	0.23	
7	Italy	62	0.046	0.04	
8	Taiwan China	59	0.044	0.00	
9	Australia	58	0.043	0.07	
10	Spain	43	0.032	0.31	

While Germany and Spain produce relatively fewer publications, they hold notable positions in AI-driven critical care research. Their high involvement in global collaboration networks highlights their important role in international cooperation. By actively engaging in transnational research activities, both countries have established extensive and robust partnerships with other nations, significantly enhancing the global reach and impact of their research. Thus, although the United States was a major producer of research into AI applications in critical care, Germany and Spain had a higher level of cooperation with the international community despite their limited published scholarship. China ranked second globally in terms of the number of articles, but its centrality was zero; this reflected a lack of international cooperation and the need to strengthen future cooperative efforts.

Keyword Analysis

Co-Occurrence Analysis of Keywords

A keyword, representing the topic of the article, is used to guide a generalized search and its subsequent refinement. The intermediary centrality of a keyword reflects its importance as a network node. Along with word frequency, keywords reflect common concerns and research hotspots. CiteSpace keyword clustering can clearly indicate the focus of a research field. In the present study, similar keywords were merged, including "intensive care" with "intensive care unit", "critical care" with "intensive care unit", and "ICU" with "intensive care unit". The top 10 keywords from 2013 to 2023 are listed in Table 3. Among the top 10 high-frequency words, "machine learning", "artificial intelligence", "mortality", and "outcome" showed high centrality, indicating their predominance in research applications concerning AI in critical care nursing.

Keyword Clustering Analysis

The log-likelihood ratio algorithm was utilized to cluster keywords; each cluster was marked and ranked to determine the research scope. A keyword clustering analysis of literature in the WOS from the past 10 years resulted in 456 nodes, 902 edges, and a network density of 0.0087, forming seven clusters: #0 cluster septic shock, #1 cluster predictive models, #2 cluster deep learning, #3 cluster machine learning, #4 cluster electronic health records, #5 cluster big data, and #6 cluster acute kidney injury (AKI) (Figure 3).

Keyword Time Period Analysis

The time period map derived from keyword clustering shows both the development of AI in the field of critical care research and the literature with significant influence during a certain time period. The first year of publication of articles classified in #3 cluster machine learning and #4 cluster electronic health records was 2013 and 2014, respectively; the most recent publications were classified in the #1 cluster random forest [previous paragraph says "#1 cluster predictive models"] and the #6 cluster AKI (Figure 4).

Keyword Emergence Analysis

CiteSpace includes a burst detection function to detect significant changes in the citation number during a certain period. Figure 5 shows the top 8 emergent words in terms of burst strength (ie, research hotspots in the field of AI in critical care nursing over the past decade). The red band in the figure represents a rapid increase in citation number during the corresponding period.

Table 3 Top 10 Keywords

Keywords	Frequency	Centrality	No.	Keywords	Frequency	Centrality
Machine learning	582	0.14	6	Model	142	0.07
Artificial intelligence	333	0.10	7	Risk	117	0.03
Intensive care unit	312	0.06	8	Prediction	114	0.06
Deep learning	178	0.04	9	Classification	99	0.00
Mortality	145	0.11	10	Outcome	94	0.22
	Machine learning Artificial intelligence Intensive care unit Deep learning	Machine learning 582 Artificial intelligence 333 Intensive care unit 312 Deep learning 178	Machine learning 582 0.14 Artificial intelligence 333 0.10 Intensive care unit 312 0.06 Deep learning 178 0.04	Machine learning 582 0.14 6 Artificial intelligence 333 0.10 7 Intensive care unit 312 0.06 8 Deep learning 178 0.04 9	Machine learning 582 0.14 6 Model Artificial intelligence 333 0.10 7 Risk Intensive care unit 312 0.06 8 Prediction Deep learning 178 0.04 9 Classification	Machine learning 582 0.14 6 Model 142 Artificial intelligence 333 0.10 7 Risk 117 Intensive care unit 312 0.06 8 Prediction 114 Deep learning 178 0.04 9 Classification 99

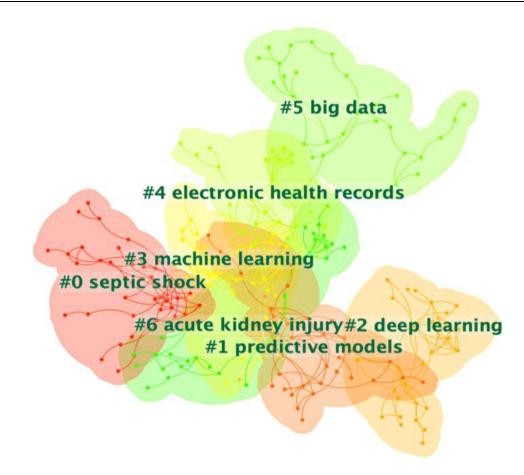


Figure 3 Keyword Clustering Diagram.

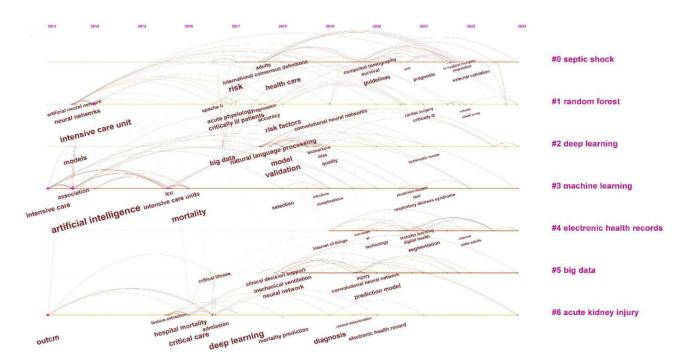


Figure 4 Time Zone Map.

Top 8 Keywords with the Strongest Citation Bursts

Keywords	Year Str	ength Begin	End	2013 - 2023
electronic medical record	2015	2.58 2015	2021	
neural network	2014	4.1 2014	2019	
artificial neural network	2014	2.62 2014	2019	
admission	2017	3.99 2017	2020	
classification	2017	4.64 2017	2019	
system	2018	3.02 2018	2019	
unit	2019	2.99 2019	2020	
predictive modeling	2018	2.61 2018	2019	

Figure 5 Keyword Emergence.

Discussion

Trends and Current Status of AI in the Field of Critical Care Research Publication Trends

This study examined 1,346 articles concerning the use of AI in the care of critically ill patients, based on a search of the WOS core collection database from 2013 to 2023. The slow upward trend in the number of articles on this topic published from 2013 to 2017 indicated that during this period, the use of AI in the critical care nursing field was in its initial stage. Common applications were the use of machine learning to predict or infer prognosis, hospitalization time, and mortality. However, beginning in 2018, the number of articles published showed a rapid upward trend: 319 articles were published in 2021, and 409 were published in 2022. Considering the rapid development of AI, its applications in the care of critically ill patients mainly involved analyses of electronic medical records (EMRs), risk model prediction, decision support, and nursing management. Overall, publication trends over the past 10 years demonstrate increasing interest in AI in the care of critically ill patients. More in-depth research regarding AI applications in critical care nursing can be expected, accompanied by an increased number of articles published in this field.

Authors and Institutions

Among the top 10 authors (> 8 papers) in the field of AI in critical care nursing, 4 were from the United States, 4 were from China, and the remaining 2 were from Canada and Germany, respectively. Based on the number of published papers, it can be inferred that there is a correlation between a country's AI development and its economic growth. Notably, China's rapid economic and technological advancement is reflected in its academic contributions, with four of the top 10 authors originating from Chinese institutions. Among these authors, 8 were affiliated with universities, while 2 represented hospital-based research teams. The top three institutions in terms of publications were Harvard University (139 papers), University of California (63 papers), and Massachusetts Institute of Technology (40 papers), highlighting the United States' historical and ongoing leadership in AI research. We believe this is mostly due to its foundational role in AI development and its research-intensive universities' AI knowledge production. Research by hospital nursing staff is limited due to time and energy constraints. Collaborations between university researchers and hospital clinical nursing workers can expand the research opportunities of hospital nursing staff concerning AI in critical care nursing.

Characteristics of National/Regional Publications

The top five countries/regions in terms of publication number were the United States (521), China (272), the United Kingdom (101), Canada (84), and South Korea (65). The number of publications from the United States far exceeded the numbers from other countries, reflecting the advanced stage of research concerning AI applications in critical care. However, the limited centrality of the United States (0.05) indicated the country's relatively low level of international cooperation, possibly due to extensive internal cooperation among its many research institutions. In contrast, Germany and Spain had fewer publications but relatively high centrality, based on their close cooperation with multinational companies and good cooperative relationships internationally. Although China was second only to the United States in

terms of the number of publications, its centrality was zero, indicating a lack of international cooperation, perhaps related to China's geographical location and cultural background. This finding suggests that China can benefit from greater research cooperation with institutions in European countries and the United States, which will promote the use of AI in critical care nursing within its hospitals.

Analysis of Hotspots and Trends in the Field of AI in Critical Care Research Analysis of Research Hotspots

Keywords reflect the core and essence of a body of literature because their frequency is directly proportional to research trends in a given field.¹⁵ The high centrality of the top 10 keywords from 2013 to 2023, including "machine learning", "artificial intelligence", "mortality", and "outcome", represents the focus of research. Analysis of the clustering results showed that applications of AI in critical care included patient monitoring, clinical decision support, and disease prediction. ¹⁶ González-Nóvoa et al¹⁷ used interpretable machine learning methods combined with patient vital sign data and previously triggered alarm data in an automated analysis to improve the accuracy of ICU alarm systems and reduce false alarms. Their method was validated using the MIMIC-III ICU patient research database. The method's ability to identify the most important factors in setting thresholds that will trigger alarms, thereby improving ICU alarm systems, was demonstrated. Youn et al¹⁸ designed and developed a low blood pressure alarm prediction system based on machine learning methods, then validated it through a randomized controlled trial. Most hypotension cases could be predicted, allowing alarms to be triggered 1 h before an occurrence. During the continuous monitoring of critically ill patients, a reliable and highly sensitive alarm system can reduce alarm fatigue among medical staff, increase medical staff trust in the alarm system, and ensure patient safety.

The rapid adoption of EMRs has generated large-scale data. Predictive modeling using those data in conjunction with AI and machine learning algorithms can facilitate disease prediction, optimize nursing processes, support nursing decisions, ¹⁹ and thus provide a crucial clinical decision-making support system in the ICU. In recent years, predictive models for use in the critical care setting have received considerable research attention worldwide.

Wickramaratne and Mahmud²⁰ developed a deep learning model (specifically, an integrated model based on bidirectional gated recurrent units) for the early detection of sepsis. Their aim was to allow early intervention by medical staff, which would improve critical care and enhance the patient survival rate. Researchers at Xiangya Hospital developed a CatBoost model to predict mortality in sepsis (S)-AKI patients based on machine learning. The model was validated using the intensive care data of 16,154 S-AKI patients to predict patient mortality. The results showed that the model was applicable in different regions and for different populations.²¹ To reduce the incidence of complications in critically ill patients, researchers use machine learning and deep learning methods along with EMR data to predict the risks of acute renal failure, bleeding, anemia, and stress injuries. 22-24 Dynamic models for predicting stress injury risks with data analysis and machine learning have also been described;²⁵ various machine learning methods (eg. classification algorithms, feature engineering, and model training) have also been used to develop stress injury prediction models.²⁶ The capabilities of these approaches include predicting the risks of stress injuries so that preventive measures can be taken, improving skin care in critically ill patients, and reducing the incidence of stress injuries. The coronavirus disease 2019 (COVID-19) pandemic demonstrated the irreplaceable role of AI in managing diseases caused by unknown pathogens. The rapid onset of the COVID-19 pandemic severely strained medical resources. Hospitals used AI-based strategies to cope with the severe shortage of ICU nurses, 27 which was vital during the early stages of the pandemic. For example, American researchers developed a risk prediction model based on machine learning to identify patients requiring ICU transfer within 24 h, ²⁸ thereby reducing workload and infection risk among ICU nurses.

Evolution Trend Analysis (Timeline)

The evolution of AI research in the field of critical care can be divided into three stages. In the initial period of 2013-2015, research focused on machine learning and EMRs. Inferences made based on machine learning algorithms combined with EMR data were utilized to assist ICU nurses with the early identification of changes in patient conditions, thereby enhancing decision-making. In the rapid development stage of 2015–2018, the research focus comprised big data and deep learning. The availability of EMRs rapidly increased the amount of accessible clinical medical data and laid

a foundation for the development of big data-based AI prediction models. Parallel advancements in computers enabled researchers to use deep learning technology to rapidly and effectively process big data, further improving the accuracy and effectiveness of prediction results. In 2018–2023, the direction of research gradually shifted towards the construction of prediction models, such as approaches to predict the timing and risk of various events; such predictions allowed nurses to take preventive measures and conduct very early assessments. These tools have improved the safety of critically ill patients and the quality of critical care. In early 2020, the global outbreak of COVID-19 placed substantial pressure on medical resources, and some pressure was alleviated using AI.

Keyword Emergence Analysis

The keyword analysis revealed that EMRs, neural grids, and artificial neural networks were early research hotspots. Neural networks and artificial neural networks, as keywords, suddenly increased in citation frequency beginning in 2014. Neural networks and artificial neural networks constitute a subset of machine learning; ²⁹ both remained research hotspots until 2019, with emerging strengths of 4.1 and 2.62, respectively. However, after 2019, the emerging strengths of these keywords began to weaken, suggesting their replacement with new research directions and hotspots, such as classification systems and prediction models. To improve the care of critically ill patients, researchers have used machine learning to develop a classification system for critically ill adult patients in the ICU according to their illness severity and nursing needs. The classification system can be applied to similar patient groups³⁰ and used to optimize the allocation of human resources. Elsewhere, researchers have used Bayesian artificial neural network prediction models to predict hypotensive events, which often occur in critically ill patients.³¹ These systems provide nursing teams early warnings before potential hypotensive events occur, along with prompts to conduct more intensive monitoring and evaluation, thereby reducing the incidence of hypotensive events. Delirium is also common in ICU patients, with incidences of 60-80% in mechanically ventilated ICU patients and 20-50% in non-mechanically ventilated patients.^{32,33} To prevent the occurrence of delirium, delirium prediction models,³⁴ early delirium prediction models,³⁵ ICU delirium prediction models and neurosurgical critical patient delirium prediction models³⁶ have been constructed. Chen Xiangping et al³⁷ performed a meta-analysis of various delirium prediction models to identify the most suitable model for use in clinical critical care, considering its capacity to allow very early intervention. For critically ill patients, unplanned extubation can have particularly detrimental effects on safety. A prediction model for the unplanned extubation of ICU patients, based on machine learning combined with EMR data, has been developed and validated.³⁸ The model enables the early detection and prevention of unplanned extubation; it has improved the quality of care for critically ill patients.

In contrast, there is a lack of investment in and clinical attention to patient mental health management, as well as a shortage of mental health workers. A prediction model able to identify high-risk groups would help address this shortage.³⁹ Critically ill patients often experience anxiety, depression, and post-traumatic stress disorder.⁴⁰ Prediction models are needed to identify patients at risk of post-intensive care syndrome and related mental disorders; however, such models are lacking, and further research is needed. These examples in Table 4 clearly demonstrate the utility of prediction models in the management of critically ill patients and efforts to improve the quality of care. It is likely that prediction models will continue to serve as both a research hotspot and a research trend in the field of AI applications to the care of critically ill patients.

Table 4 Al Application in ICU

Application Area Al Technology Used		Description	Potential Benefits	
Patient monitoring Machine learning methods		Combined with patient vital sign data and previously triggered alarm data	Improving ICU alarm systems	
Clinical decision support	Machine learning methods	Risk prediction model	Reduce workload and infection risk	
Disease prediction	Machine learning, deep learning methods	Develop integrated model, CatBoost model, dynamic model	Reduce the incidence of complications, predict the risks of acute renal failure, bleeding, anemia, and stress injuries, predict patient mortality	

Early Risk Warning System

Currently many ICUs have implemented rule-based early warning systems to monitor patients' vital signs and trigger alerts when patient deteriorations occur. By utilizing deep learning algorithms such as Long Short-Term Memory (LSTM) networks, patient deteriorations can be predicted with greater precision, enabling earlier identification of critical risk factors like sepsis and acute kidney injury (AKI). The integration of multi-source data (eg, physiological parameters, laboratory results, and imaging data) facilitates more comprehensive and accurate early warning capabilities.

Individualized Treatment

Traditional treatment protocols, which is typically based on population averages, often fail to address the unique needs of patients. By analyzing genomic profiles, medical histories, and real-time monitoring data, AI can assist in developing individualized treatment plans to optimize therapeutic outcomes. Furthermore, AI systems dynamically adjust medication dosages and therapeutic interventions based on real-time patient feedback and disease progression, ensuring optimal efficacy throughout the treatment process.

Automatic Diagnose and Policy Support

Traditionally physicians rely on manual data entry and experiential knowledge for diagnosis and decision-making. By employing Natural Language Processing (NLP), key information can be automatically extracted from Electronic Health Records (EHRs), enabling clinicians to accelerate diagnostic workflows and enhance decision accuracy, ¹⁹ leveraging big data and machine learning algorithms to deliver real-time treatment recommendations and risk assessments, reducing human errors while enhancing operational efficiency.

ICU Resource Management

The efficient allocation of ICU resources, including beds, equipment, and medical staff, is a challenge. Reinforcement learning algorithms can optimize healthcare workforce scheduling to ensure adequate staffing coverage across all shifts. For example, Internet of Things (IoT) technology combined with AI enables real-time monitoring of equipment status, rational allocation, and proactive maintenance to minimize resource waste.

Remote Monitor and Virtual Nursing Practice

Current remote monitoring systems predominantly rely on stationary devices with limited data transmission capabilities. Developing lightweight and comfortable wearable devices to continuously monitor patients' vital signs and enable real-time data transmission to the cloud would empower clinicians to access critical information on demand. Using AI-powered virtual assistants to interact with patients provide daily care guidance and alert healthcare providers to emergencies when necessary. 41

Data Analysis and Research Support

Vast amounts of clinical data remain underutilized due to inadequate analytical tools. Establishing a unified big data platform to integrate multi-source datasets would provide researchers with enriched data. For instance, studies demonstrate ways that deep ML assists healthcare professionals in deciphering complex datasets, uncovering latent patterns and correlations, and translating these insights into actionable preventive pathways for ICU-AW, thereby accelerating advancements in medical research.⁴²

Patients Experience and Family Participation

Patients and their families often experience unfamiliarity and anxiety in ICU environments, coupled with limited access to transparent information channels. Peschel et al demonstrated that AI-generated ICU diaries save time and labor compared to handwritten versions. However, ethical and professional considerations, particularly regarding AI's role in supplementing or replacing nurses in diary documentation require careful scrutiny to ensure patient-centered care integrity.⁴³

Limitations

The limitations of this study include the following. First, the study was based on an analysis of literature in the WOS Core Collection database only, which could potentially yield findings that are not representative enough. Second, some prediction models were developed solely based on retrospective studies at single centers and have not been externally validated. Datasets reflecting prospective evaluation and validation would be valuable sources of information. Moreover, considering the continuous increases in intensive care data and the introduction of new types of data, ethical and privacy issues must be adequately addressed; in addition, continuous monitoring of studies in the area of AI in critical care nursing is needed to reflect a more accurate depiction of the latest research trend.

Summary

In this study, CiteSpace software was used to analyze literature regarding AI in critical care from the WOS Core Collection database, with the goal of identifying research trends and hotspots in this field. The results showed an increase in the number of related publications, as well as minimal cooperation among countries and regions. Through clustering analysis, we found the application value of these technologies in improving the accuracy of ICU alarm systems, developing hypotension alarm prediction systems, and optimizing electronic health record (EHR) data utilization. The advancement of AI in critical care has shifted from machine learning combined with EHR data to more efficient data processing methods, with the construction of predictive models becoming mainstream, aiming to provide early warnings for various clinical events, optimize care workflows, and enhance critical care quality. In light of the findings, this study highlights the following implications. First, we believe that technological innovation is crucial for advancing clinical practice, this is exemplified by the adoption of precision medicine and automated diagnosis/decision-support systems. Second, strengthening international collaboration and data sharing accelerates knowledge dissemination and technology translation. In addition, prioritizing patient mental health management requires developing effective psychological risk prediction models to promote comprehensive health management in critically ill patients. Lastly, policy support and ethical considerations are indispensable, in particular, governments should implement policies to ensure the safe application of AI technologies and establish robust data privacy protection mechanisms.

Therefore, future efforts should focus on strengthening international exchanges and cooperation. Future research may also consider prioritizing human-centered AI design tailored to the unique demands of critical care nursing. This involves co-developing AI tools with nurses to ensure smooth integration into clinical work and to enhance, rather than undermine, clinical judgment. Research is also needed to address AI errors accountability, ethical issues in data-driven care, and mitigation of algorithmic biases. Additionally, future research will benefit from comparative analyses based on larger domestic and foreign literature databases to identify research hotspots and trends concerning AI applications in the field of critical care. Finally, policy research is encouraged to explore the mechanisms of using AI in critical care nursing that prioritizes patient safety, equity, and the value of human care in an increasingly AI mediated healthcare profession.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Disclosure

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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