Journal of Clinical and Nursing Research, 2026, Volume 10, Issue 4
http://ojs.bbwpublisher.com/index.php/JCNR
Online ISSN: 2208-3693
Print ISSN: 2208-3685

Research Progress on Nurse-Driven Warning Tools for Early Recognition of ICU Sepsis

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Abstract: Sepsis is the primary cause of deterioration and death in patients in the intensive care unit (ICU). Early identification and timely intervention are crucial for improving prognosis. Nurses, as frontline personnel providing bedside continuous monitoring, play a pivotal role in the early recognition of sepsis. This article systematically reviews the evolution, research progress, current challenges and shortcomings of nurse-driven early warning tools for sepsis in the ICU, and looks forward to future development directions, aiming to provide a reference for related research and clinical practice.

Keywords: Sepsis; Early recognition; Intensive care; Nurse-driven; Warning tools; Review

Online publication: Apr 30, 2026

1. Introduction

As a global healthcare challenge, sepsis and septic shock are the main causes of death for patients in the ICU [1]. According to the 2020 Global Burden of Disease Study, there were 48.9 million cases of sepsis worldwide in 2017, resulting in 11 million deaths and accounting for nearly 20% of all global deaths that year [2]. A multicenter cross-sectional study conducted in Asia revealed that patients with sepsis accounted for 22.4% of all ICU admissions, with a 90-day mortality rate of 36.6%. The study further revealed the critical effect of the "golden 3-hour" treatment time window, highlighting that early identification and timely intervention are the key to improving the prognosis of sepsis patients [3]. Nurses, as the frontline personnel who have the closest contact with patients and conduct continuous observation in the ICU, play an irreplaceable core role in the early identification of sepsis. This review aims to systematically explore the research progress and application status of such tools in the early identification of sepsis in the ICU, providing theoretical support and practical references for promoting the early identification of sepsis and nursing intervention, and thereby optimizing the management of sepsis in the ICU.

2.The core role and strategies of nurses in the early identification of sepsis

2.1. The challenges of sepsis in the ICU and the importance of early identification

Sepsis is a life-threatening organ dysfunction caused by the dysregulated response of the host to infection [4]. As a clinical unit dedicated to the treatment of critically ill patients, the intensive care unit (ICU) serves as both a key setting for infection prevention and control and a setting with a high prevalence of sepsis. Studies indicate that approximately 20%–30% of deaths among ICU patients are attributed to sepsis or septic shock placing infected patients admitted to the ICU at extremely high risk of developing sepsis [5].

Kumar et al. reported in 2004 that each hour of delay in antibiotic administration was associated with an approximately 7.6% decrease in survival, underscoring the critical importance of time-dependent treatment [6]. In 2018, the Surviving Sepsis Campaign (SSC) Guidelines based on the Sepsis-3.0 definition underwent key updates, integrating the original 3-hour and 6-hour treatment targets into “1-hour bundled treatment”, emphasizing the urgency of immediately initiating standardized intervention after the identification of sepsis [7]. In October 2021, SSC issued the latest version of the guidelines, providing new guidance and opinions for the management of sepsis [8].

Therefore, establishing an early-warning system that can accurately and promptly identify the risk of sepsis holds significant clinical importance for optimizing clinical practice and improving patient outcomes.

2.2. The core role of nurses in the early identification of sepsis

ICU nurses, as the core practitioners of 24-hour continuous monitoring of patients, are responsible for critical tasks such as dynamic monitoring of vital signs, real-time recording, and clinical status assessment. Studies have shown that through continuous close contact with patients, nurses can detect subtle fluctuations in vital signs. This experience-based assessment can detect abnormalities at an early stage and often precedes machine alerts. Moreover, this “contextual awareness” ability based on practice is something that current automated monitoring systems cannot fully replace [9]. The literature further indicates that nurse-led screening is often more sensitive than purely electronic alert systems. The nurse-driven model not only means that screening tasks are carried out by nurses, but also emphasizes granting nurses the power and responsibility to initiate subsequent diagnostic and treatment procedures, thereby shortening the time from detection to intervention and securing the critical window for improving patient outcomes [10].

3. The evolution and current status of the early warning tools driven by ICU sepsis nurses

3.1. Evolution of traditional identification tools and scoring systems for ICU sepsis

3.1.1. Identification model based on the comprehensive systemic inflammatory response (SIRS)

In the era when sepsis was defined primarily as a systemic inflammatory response triggered by infection, identification tools were largely constructed based on the criteria for systemic inflammatory response syndrome (SIRS). As the cornerstone of early screening, the identification of SIRS relied on the abnormal physiological parameters such as body temperature, heart rate, respiratory rate, and white blood cell count to indicate potential severe infection and inflammatory conditions. However, this model has limitations. Studies have shown that while SIRS is highly sensitive for sepsis screening, its specificity is extremely low, often leading to misdiagnosis of non-infectious inflammation. Moreover, it fails to directly reflect organ dysfunction or patient prognosis, resulting in limited warning value in high-risk settings such as the ICU [11].

3.1.2. The era of SOFA and qSOFA under the definition of Sepsis-3

With the release of the "International Consensus on the Definition of Sepsis-3" in 2016, sepsis was redefined as "life-threatening organ dysfunction caused by infection". This fundamental change gave rise to the second-generation identification tools centered around the Sequential Organ Failure Assessment (SOFA) and its rapid bedside version, the Quick Sequential Organ Failure Assessment (qSOFA). The SOFA score quantifies the severity of organ dysfunction through an objective assessment of six organ systems: respiratory, renal, liver, cardiovascular, hematological, and nervous. The qSOFA, based on criteria such as changes in consciousness, systolic blood pressure ≤ 100 mmHg, respiratory rate ≥ 22 breaths per minute, and Glasgow Coma Scale (GCS) < 15 points, rapidly identifies high-risk patients with suspected sepsis [4]. The design of these tools shifted from "searching for inflammation" to "evaluating organ function", significantly enhancing the specificity of early warnings and the ability to predict mortality risk.

3.1.3. The widespread application of early warning score (EWS)

The clinical application of SOFA is limited by its reliance on laboratory results, which precludes rapid use in critical situations [12]. In contrast, qSOFA serves as a convenient screening tool outside intensive care settings, but its sensitivity may be insufficient for early detection of all critically ill patient, particularly those in the ICU requiring immediate intervention, where reliance on qSOFA alone could lead to missed diagnoses [13]. To address these limitations, the screening strategy has further evolved to comprehensively integrate and optimize various early warning scores (EWS), and to link them with standardized response processes. Current tools, such as NEWS, MEWS, and their infection-adapted versions, are widely used to identify patients at risk of deterioration and offer higher sensitivity and practicality in early detection [14].

3.2. Current development status and tool types

3.2.1. Paper-based screening scale and flowchart

This stage is characterized by the introduction and promotion of a standardized screening model centered on structured assessment tools. Core forms include the qSOFA scorecard, NEWS/MEWS record sheets, and accompanying clinical decision flowcharts. Nursing staff perform bedside vital sign monitoring and manual data entry, calculate scores based on preset algorithms, determine risk categories using standardized flowcharts, and activate the corresponding tiered reporting mechanisms. This approach offers advantages such as low cost and simple training requirements [15]. However, this highly manual characteristic also leads to efficiency bottlenecks, with problems such as record delays and calculation errors, making it difficult to meet the extremely high requirements for timeliness in critical illness early warning.

3.2.2. The deep integration of early warning tools with electronic health record systems

In the context of the accelerated informatization process of medical institutions, the clinical decision support system (CDSS) integrates electronic health records (EHR) with Internet of Things (IoT) technology to achieve real-time automatic capture and dynamic calculation of vital signs, laboratory indicators, and imaging data. This system automates the calculation of core scores such as SOFA and NEWS. When parameters reach preset thresholds, it triggers graded warning responses through pop-up windows, audio-visual alerts, or mobile terminal task push notifications [16]. Empirical studies have shown that the automated warning system significantly shortens the time for clinical decision-making. Research indicates that the early warning system (EWS) can reduce the antibiotic administration time by approximately 30% and significantly lower the incidence of complications; however, alarm fatigue is the core challenge of current ICU informatization. In an ICU environment with dense monitoring equipment, healthcare workers need to handle up to 700 alerts daily, with 80% of them being false alarms, resulting in an increase of approximately 18% in the response delay rate of critical alerts [17].

3.2.3. Nurse-driven standardized bundled intervention protocol

The core of this approach is to closely integrate the early warning score with the evidence-based medical-based sepsis bundle response protocol [18,19]. For instance, when the system identifies a combination of indicators that meet the criteria for “suspected sepsis”, it will simultaneously trigger a task set with time constraints, such as completing blood culture, lactate measurement, and antibiotic administration within one hour. Under this framework, the role of nurses shifts from traditional screening executors to multidisciplinary coordinators, treatment drivers, and process supervisors. For example, after Ferguson et al. introduced the “Sepsis Care Bundle”, the 3-hour bundle treatment compliance rate in the medical institution increased from 40.5% to 73.7%, and the rate of drug administration within one hour also significantly improved [20].

3.2.4. Development and application of an intelligent early warning model based on machine learning

Traditional rule-based scoring systems can only identify existing physiological disorders, while machine learning models, by analyzing patient data, can predict more subtle changes before the onset of the disease [21]. For example, the TREWScore model, developed using the MIMIC-II database, can provide early warnings approximately 28 hours before the clinical diagnosis of septic shock, with validated discriminative performance [22]. This technological evolution introduces new demands on the role of nurses, who are no longer merely data entry personnel but are now expected to integrate AI-derived risk predictions with clinical presentations to formulate comprehensive assessments.

4. The integration and application of innovative technologies

4.1. Clinical applications of artificial intelligence and machine learning

With its powerful data analysis and pattern recognition capabilities, AI and machine learning technologies are driving a revolutionary transformation in early warning tools for sepsis. Li et al. pointed out in their review that artificial intelligence has the potential for transformation in the management of sepsis, especially in the aspects of early identification and prognosis prediction [23]. By analyzing complex clinical data, machine learning and deep learning models can capture subtle pattern. This significantly improves the timeliness of early intervention and helps reduce mortality rates. Hu et al. based on the MIMIC-IV database and using the XGBoost algorithm, constructed an early prognosis prediction model for sepsis [24]. This study also emphasized the importance of interpretable machine learning methods (such as SHAP), which helps clinicians understand the key features behind the model’s predictions. It not only proved the superiority of artificial intelligence in prediction performance but also demonstrated its practical value in clinical decision support. The systematic review by Islam et al. further evaluated the application of machine learning in the prediction of sepsis, indicating that artificial intelligence models have significant advantages in integrating multi-source heterogeneous data and can achieve high-precision early warning in various clinical scenarios such as emergency departments and intensive care units [25].

Currently, such systems have been put into practical use in several top medical centers in North America, such as the “Sepsis Watch” developed by Duke University Hospital and the similar system implemented by Johns Hopkins Hospital. Both achieve early warning for sepsis through real-time analysis of electronic health record data [26]. These practical applications have preliminarily indicated that AI-based early warning tools are expected to further improve patient prognosis by enhancing the early recognition rate and timeliness of intervention for sepsis.

4.2. The application of the internet of things (IoT) and wearable devices

Traditionally, ICU nurses spent a lot of time manually measuring, recording and transcribing vital signs. However, the system based on the Internet of Things integrates wearable biological sensors and intelligent connected bedside monitoring equipment, achieving automatic, high-frequency and continuous collection of patients’ vital signs [27]. This transformation not only reduces the repetitive labor of nurses, but also provides data density and dynamic trend information far superior to the traditional intermittent measurement methods, thereby laying a more comprehensive and real-time data foundation for AI prediction models.

Further research has further verified the potential of this technology: A study by Johns Hopkins University demonstrated that combining wearable biosensors with machine learning models can capture subtle physiological signals that traditional monitoring systems might miss, thereby enhancing the early identification of sepsis and creating conditions for earlier intervention [28]. Bignami et al. pointed out in their review that the integration of the Internet of Things monitoring system is conducive to continuous data collection and analysis, thereby reducing human errors and improving the accuracy of clinical decision-making [27]. A prospective observational study conducted by Garbern et al. continuously recorded heart rate, respiratory rate, and body temperature measurements using wearable biosensors and compared them with intermittent manual collection of vital signs [29]. This study confirmed that wearable biosensor devices can provide accurate continuous monitoring of heart rate and respiratory rate.

5. The existing limitations and challenges of nurse-driven early warning tools in the early identification of sepsis in the ICU

5.1. Alarm fatigue and the crisis of clinical disbelief

One of the most common and severe challenges faced by electronic warning systems in clinical applications is the clinical trust crisis caused by alarm fatigue. Numerous studies have confirmed that the majority of the alarms issued by ICU monitoring systems are ineffective. Statistical data show that up to 85% to 99% of the alarms are caused by improper equipment settings, normal physiological fluctuations of patients, or interference factors, and do not require immediate clinical intervention. Due to these high-frequency ineffective alarms, nurses in actual work have developed a “numb” state towards alarms, resulting in approximately 60% of the alarms being ignored or delayed responses, and approximately 85% of the nurses admitting to experiencing great psychological and work pressure due to the frequent alarms. The research further indicates that this noisy environment not only increases the risk of medical errors but also may cause patients’ sleep quality to decline due to frequent ringing sounds, thereby affecting recovery [30].

5.2. Data quality and core technical bottlenecks

Clinical data often suffer from issues such as scattered sources, inconsistent standards, and discontinuous collection. Moreover, the insufficient data interoperability among various internal information systems within hospitals makes it difficult to construct high-quality, integrated, and standardized data sets. This situation severely hinders the development and performance optimization of advanced early warning models. Additionally, a qualitative study indicates that many advanced artificial intelligence models, especially deep learning algorithms, with their decision-making logic lacking transparency and clinical interpretability. This directly affects the trust and acceptance of medical staff in the system's outputs [31].

5.3. The human factors of the nurses themselves

Research indicates that some nurses have insufficient understanding of the latest definition of sepsis, its pathophysiological mechanisms, early identification criteria, and treatment guidelines. They also experience lag in knowledge update and fragmented understanding. Multiple studies have found that the cognitive level of nurses regarding the "Guidelines for Treating Sepsis and Septic Shock" is generally low, with scores typically ranging from 10 to 18, and they are not precise in identifying high-risk groups such as the elderly [32]. The lack of systematic and continuous training further hinders nurses from accurately grasping the warning logic when using early warning tools and integrating system prompts with specific clinical situations effectively, thereby affecting the effective transformation of knowledge into practice. Additionally, ICU nurses generally face high workloads, continuous physical and mental stress, and an unbalanced ratio of nurses to patients [33].

5.4. Resource and cost constraints

Health economics analysis indicates that the total life cycle cost of clinical decision support systems is high. Their development, integration and continuous optimization impose continuous pressure on the financial and operational resources of medical institutions, which poses a real economic burden for many hospitals [34].

6. Conclusion

The nurse-driven early warning tools have significant clinical value in the management of sepsis in the ICU. Their development reflects the trend of evolving from rule-based scoring systems to data-driven intelligent prediction models. The core role of nurses in early identification cannot be replaced. Future research should focus on conducting high-quality clinical validation, developing assessment tools that are intelligent, interpretable, and clinically applicable, and deepening the integration of emerging technologies and nursing processes, thereby constructing a nurse-centered, human-machine collaborative sepsis management loop, and improving patient prognosis.

Funding

Zhejiang Provincial Medical and Health Science and Technology (Project No.: 2023KY956); Hangzhou Biomedicine and Health Industry Development Support Science and Technology Special Project (6th Phase) (Project No.: 2022WIC025); 2025 Hangzhou Normal University Teaching Construction and Reform, Construction of Digital-Enabled Clinical Teaching Case Database for Rehabilitation Nursing (Project No.: JG2025320)

Disclosure s tatement

The authors declare no conflict of interest.

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