Enhance Patient Safety through AI-driven Decision Support Systems for Sepsis Management: A review and future research agenda

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Abstract

Background: Sepsis is a life-threatening condition where the body's reaction to infection leads to organ dysfunction. It is a significant patient safety concern, requiring prompt diagnosis and treatment to prevent complications or death. For such prevention, an AI-driven Decision Support System (DSS) may play a vital role in managing sepsis through early detection, alerting clinicians to potential cases, and facilitating prompt interventions.

Objective: This paper reviews the existing AI-driven DSS applications in sepsis diagnosis and provides initial intervention and suitable treatment recommendations. All original literature (qualitative and quantitative) was reviewed to understand the current scope of DSS for sepsis management and to analyze existing methods used to evaluate and report the systems.

Methods: A literature review, guided by PRISMA 2020 and supported by bibliometric analysis, was conducted in June 2024. The search utilized two electronic databases, SCOPUS and PubMed, and included articles focused on using DSS for diagnosing and managing sepsis.

Results: The search strategy identified 3,470 articles, with 37 meeting the inclusion criteria. The publications spanned from 2010 to 2024, with 57% conducted in the United States. The studies primarily explored the use of AI-driven DSS for diagnosing sepsis in adults and managing its progression. Various data types, such as electronic health records, expert-derived knowledge, and clinical notes, were utilized to determine risk factors linked to sepsis.

Conclusions: Current research needs more evidence on the tangible impact of DSS in aiding healthcare providers with sepsis-related decision-making. Additional studies are required to refine the design and implementation of clinical DSS, assess their effects on clinical practices, identify barriers to adoption, and explore innovative strategies for advancing sepsis management. Improving these systems' accuracy, reliability, and usability could enhance sepsis detection, optimize treatment decisions, and ultimately save more lives in combating this deadly condition.

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Original Manuscript

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Keywords: sepsis, patient safety, artificial intelligence, machine learning, decision support tool, decision support system

1. Introduction

Sepsis is a critical patient condition where organ malfunction occurs due to an uncontrolled immune response triggered by infection [1,2]. The high number of deaths and illnesses caused by sepsis, along with its significant impact on the economy, makes it a central issue of global public health [3]. Sepsis leads to major risks to patient safety and global health, prompting a heightened focus on prevention, early diagnosis, and clinical management [4]. Approximately 48.9 million cases of sepsis and 11.0 million fatalities associated with sepsis were documented across the globe in 2017, accounting for roughly 20% of the total worldwide deaths [5]. Sepsis also holds substantial importance within the intensive care unit (ICU), impacting around 30% of patients [6]. Sepsis can arise as a result of infections acquired from Healthcare-Associated Infection (HAI), which can largely be avoided by implementing suitable measures for Infection Prevention and Control (IPC) [7]. Significant findings indicate that implementing comprehensive IPC measures can remarkably decrease hospital-acquired (HA) sepsis incidents, potentially preventing as much as 55% of all HAI [8].

Sepsis management continues to be a significant challenge for healthcare systems worldwide. Research conducted on hospital admissions in the United States revealed a yearly rise of 8.7% in the occurrence of sepsis among patients receiving hospital care [9]. Moreover, sepsis is responsible for over 50% of fatalities that occur within hospitals, and the likelihood of death rises significantly as the severity of the condition worsens [10]. Specifically, the mortality rates are estimated at 10-20% for sepsis, 20-40% for severe sepsis, and 40-80% for septic shock [11]. Moreover, the unintended adverse effects on patients resulting from state interventions have been recorded, which include unnecessary antibiotics administration to uninfected patients [12], the emergence of antibiotic resistance [13], diversion of attention from other medical conditions and essential bedside tasks [14], and exhaustion from following protocols and metrics [15].

Developing and implementing decision support systems (DSS) for sepsis management have shown promise in improving early detection and treatment outcomes [16]. These systems leverage advanced algorithms and data integration to provide healthcare providers with timely alerts and actionable insights [17]. Integrating machine learning (ML) and artificial intelligence (AI) into these systems is crucial, aiming to enhance accuracy and reduce false alarms. Earlier research showcased the application of a sepsis bundle that effectively identified sepsis and provided instructions for initial treatment, reducing sepsis mortality [18]. The sepsis bundle's components with specific care delivery goals within the first hour of sepsis detection are associated with improved outcomes [19].

The widespread integration of digital healthcare support systems has become possible due to the extensive adoption of data-rich electronic health records in healthcare institutions [20]. Specifically, integrating DSS within hospital systems holds the promise of aiding in the prompt and precise identification of sepsis at an early stage. These systems can include built-in tools that warn healthcare professionals about patients at risk of developing sepsis [21][22], reducing the physical and mental workload associated with manual patient monitoring [20].

However, challenges in real-world deployment persist, with issues such as user acceptance and the complexity of human-AI collaboration. Studies also underscore the importance of user-centered design in AI-based DSS, identifying barriers to implementation and emphasizing the need for tools that align with the workflow of healthcare professionals [23].

2. Methodology

2.1. Systematic review

The methodology framework for this review followed the Preferred Reporting Items for a Systematic Review and Meta-analysis of Diagnostic Test Accuracy Studies (PRISMA-DTA) guidelines [24], shown in Figure 1.

2.1.1. Search strategy

Primary literature studies were reviewed through online article databases, emphasizing research in medicine, computer science, and systems engineering. For this study, two bibliographic databases were utilized:

- Scopus
- PubMed

The online search was conducted on June 17, 2024. Additionally, a manual review of reference lists from all potentially eligible studies was performed to supplement the findings.

2.1.2. Keywords identification

The subsequent search terms were formulated by employing synonymous expressions and relevant phrases related to the implementation of AI-driven Decision Support Systems (DSS) in the early detection of sepsis and its initial treatment, as seen in Table 1.

Table 1. Search terms for AI-driven DSS

Source	Search terms
Scopus	sepsis AND (decision support system OR DSS OR decision support tool OR DST OR decision support framework OR DSF) AND artificial intelligence OR machine learning AND timely treatment AND personalized medicine AND golden hour AND biomarker AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "English"))

PubMed	sepsis AND bundle OR golden hour AND decision* OR dss OR cds OR cdss AND artificial intelligence OR machine learning OR deep learning AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "English"))

2.1.3. Eligibility criteria

This review includes publications meeting the following criteria: (1) studies involving decision support systems (DSS) for sepsis prediction and management; and (2) articles published in English. Studies were excluded if they met any of the following conditions: (1) they were reviews, opinion pieces, editorials, debate papers, dissertations, or abstracts; (2) they used pediatric, neonatal, or maternal data; (3) they lacked explicit algorithms; (4) they were conference abstracts or did not have full-text availability; or (5) they lacked clearly defined outcomes.

The exclusion criteria were designed to eliminate studies outside the review's scope, such as those not focused on DSS for sepsis prediction and management. This review specifically targeted sepsis in adult patients, leading to the exclusion of studies addressing pediatric, neonatal, or maternal sepsis.

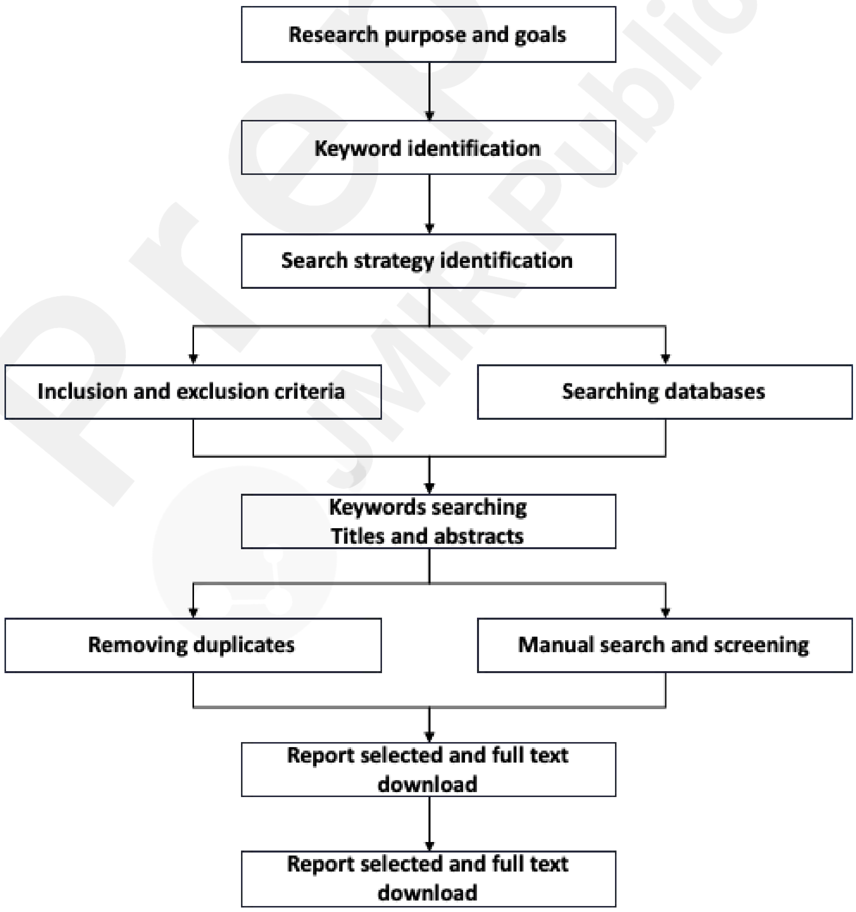

Figure 1. The flowchart in the literature review

2.1.4. Selection method

The selection method is a critical step in systematic reviews, ensuring that only studies relevant to the research objectives are included in the analysis. In the context provided, the selection method was implemented as follows:

- Initial Screening: titles and abstracts of all retrieved publications were analyzed using predefined eligibility criteria. This step aimed to quickly identify studies likely to meet the review's focus, excluding those that did not, such as irrelevant topics, ineligible populations, or non-research articles (e.g., reviews and opinion pieces).
- Full-Text Retrieval: for publications deemed potentially eligible after the initial screening, the full text of each study was obtained. This ensured a more detailed evaluation of their content against the eligibility criteria.
- Independent Review: the reviewer independently assessed each full text to minimize bias and ensure consistency.
- Conflict Resolution: if disagreements arose over the inclusion of a study, a discussion was held, focusing on the full text to resolve differences. This collaborative step ensured that all decisions were well-informed and justified.

Importance of the selection method to minimize bias by using predefined criteria and independent reviewers, the selection process ensures objectivity and reduces personal or procedural biases. A structured method ensures that all relevant studies are considered and irrelevant ones are excluded systematically. The process can be documented step-by-step, clarifying how studies were chosen or excluded, critical for reproducibility and accountability in systematic reviews.

2.1.5 Data extraction

A systematic process of gathering specific and relevant information from the selected articles to ensure consistency and enable comprehensive analysis. In the context of the above passage, data extraction involved identifying and recording the following details from each publication:

- Title: The article's name provides insight into the primary focus of the study.
- Authors: The researchers who conducted the study, allowing an evaluation of their expertise and contribution to the field.
- Publication Date: The year the study was published is vital for assessing its recency and relevance.
- Country: The geographical context or origin of the study, which can help analyze regional trends and perspectives in research.
- Objectives: The main goals or research questions the study aimed to address, clarifying its

purpose.

- Datasets: The data sources or repositories used in the study, crucial for understanding the validity and generalizability of the results.
- Sample Size: The number of participants, records, or data points included in the study, which affects its statistical power and reliability.
- DSS Approach: The specific methods, frameworks, or algorithms used for decision support systems are central to evaluating the study’s innovation and applicability.
- Outcomes Reported: The key findings or results relevant to sepsis prediction and management are essential for assessing the study's impact on the field.

This structured approach to data extraction ensures that all necessary information is captured systematically, allowing for accurate comparisons and synthesis across studies. It also helps maintain transparency and replicability in the review process.

2.2 Bibliometric review

Bibliometric review analysis is a study that evaluates research work published in scientific journals by assessing specific measures. It assists in identifying the most popular and referenced authors or institutions, the top relevant articles, and the frequently cited keywords within a specific study area. Additionally, it enables the analysis of a publication’s influence and resonance among specialists and proves the author’s popularity. When combined with other methodologies, bibliometrics could be a prescient tool as it aids in identifying trends [25].

VOSviewer software was used to draw graphical bibliometric maps. This software focuses on the visual display of bibliometric mapping, and its feature is notably beneficial for presenting large bibliometric maps in an easy-to-understand format [26].

3. Results

The database search totaled 3,470 studies, from which 37 were selected for inclusion in this review after thorough screening and evaluation. These studies were assessed according to criteria outlined for DSS, aligned with sepsis guidelines and expert knowledge frameworks. The selected studies span the publication period from 2010 to 2024. Figure 2 illustrates the study selection process using a PRISMA diagram, detailing the progression from the initial search to the final set of analyzed studies.

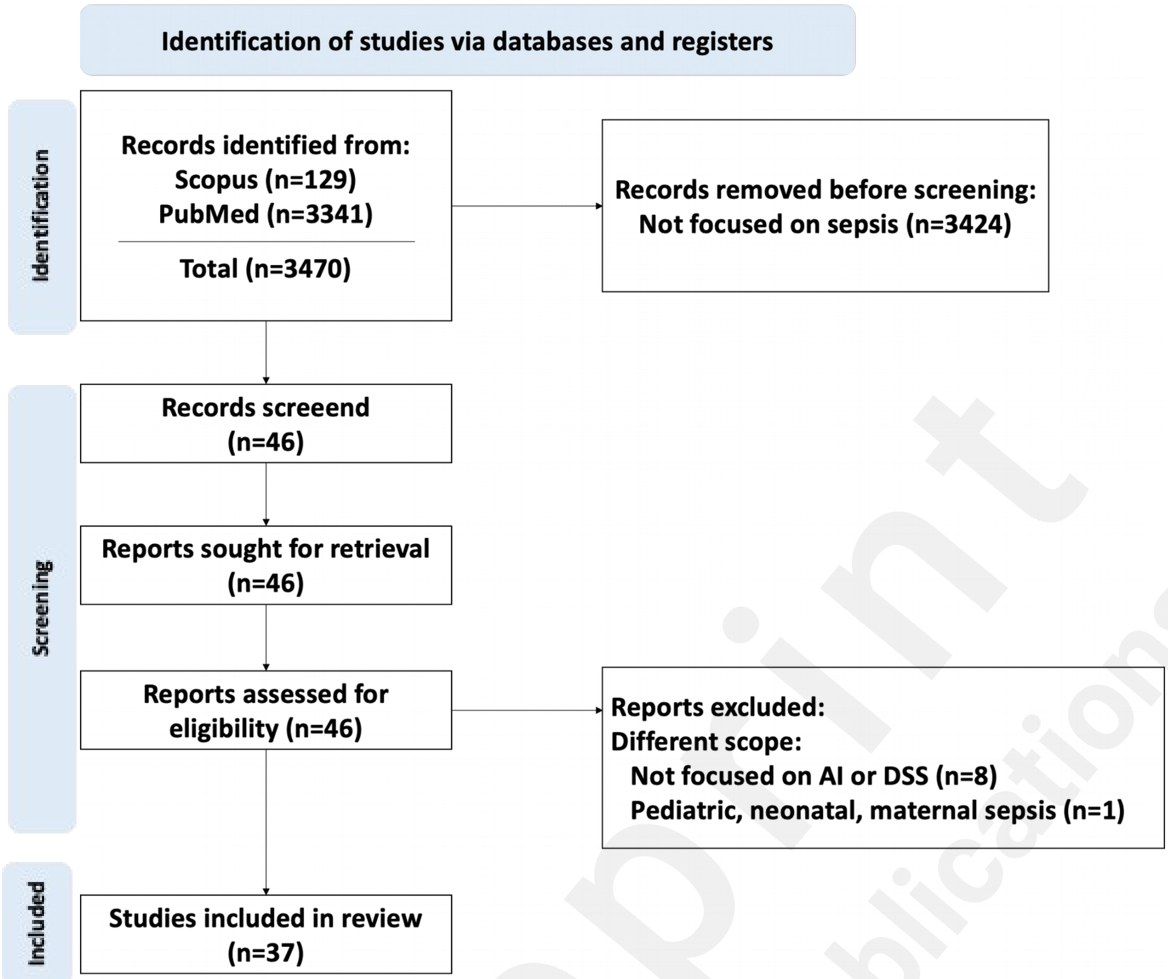

Figure 2. PRISMA flow diagram

4. Analysis and findings

Upon removing 3,470 academic papers before the initial screening phase of our research process, we identified 46 papers that appeared relevant to our investigation. However, 9 of these papers were excluded from our analysis as they needed to adhere to the inclusion criteria that we had set. The rationale behind the exclusion was their insufficient emphasis on the application of DSS, as they failed to provide any valuable insights that could facilitate appropriate intervention and treatment strategies. Furthermore, any studies concerning DSS, specifically within pediatric, neonatal, and maternal populations, were excluded from our review, as the central focus of this paper was explicitly directed toward adult cases and their unique circumstances. In conclusion, we were left with 37 papers that met all the necessary criteria and were thus included in the final study. The comprehensive analysis of these selected papers will contribute significantly to understanding DSS applications in adult populations, particularly in healthcare intervention and treatment options.

4.1. Decision Support Systems

4.1.1. Publication output and growth trend

The number of published articles is an essential indicator of a scientific study discipline' or subject's development trend. The studies covered in the study spanned the years 2010 to 2023, as shown in Figure 3, with 2 from 2010, 1 from 2014, 2 from 2015, 3 from 2016, 3 from 2017, 5 from 2019, 5 from 2020, 6 from 2021, 3 from 2022, 4 from 2023, and 3 from 2024. Those studies came from various countries around the globe, with 21 from the United States, 3 from Canada, 3 from China, 1 from Germany, 2 from Italy, 1 from the Netherlands, 1 from South Korea, 1 from Sweden, 1 from Switzerland, and 1 from Thailand, as shown in Figure 4.

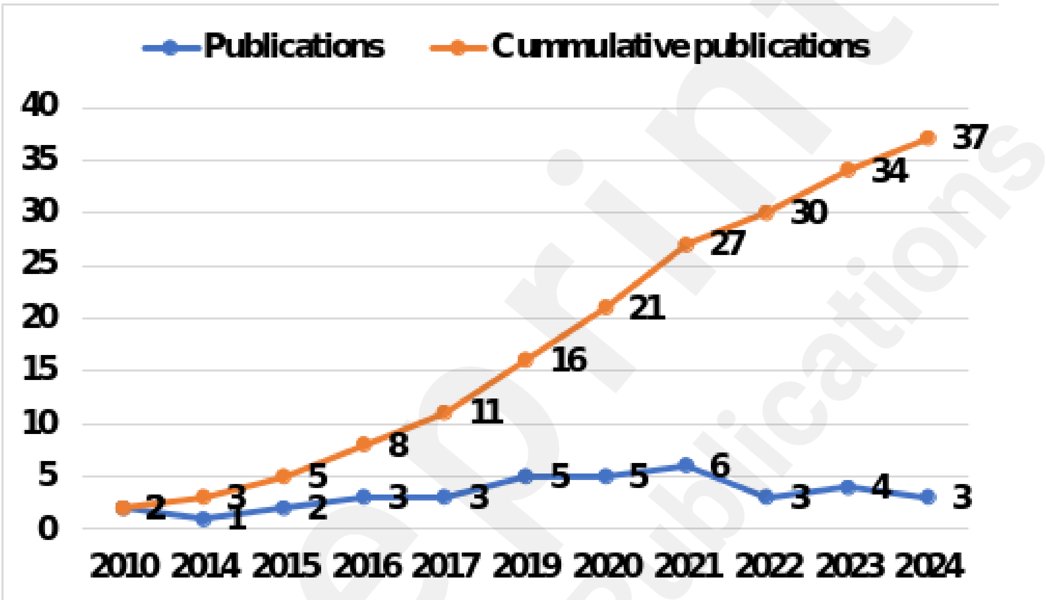

Figure 3. Count of scholarly articles and the cumulative total of articles published annually

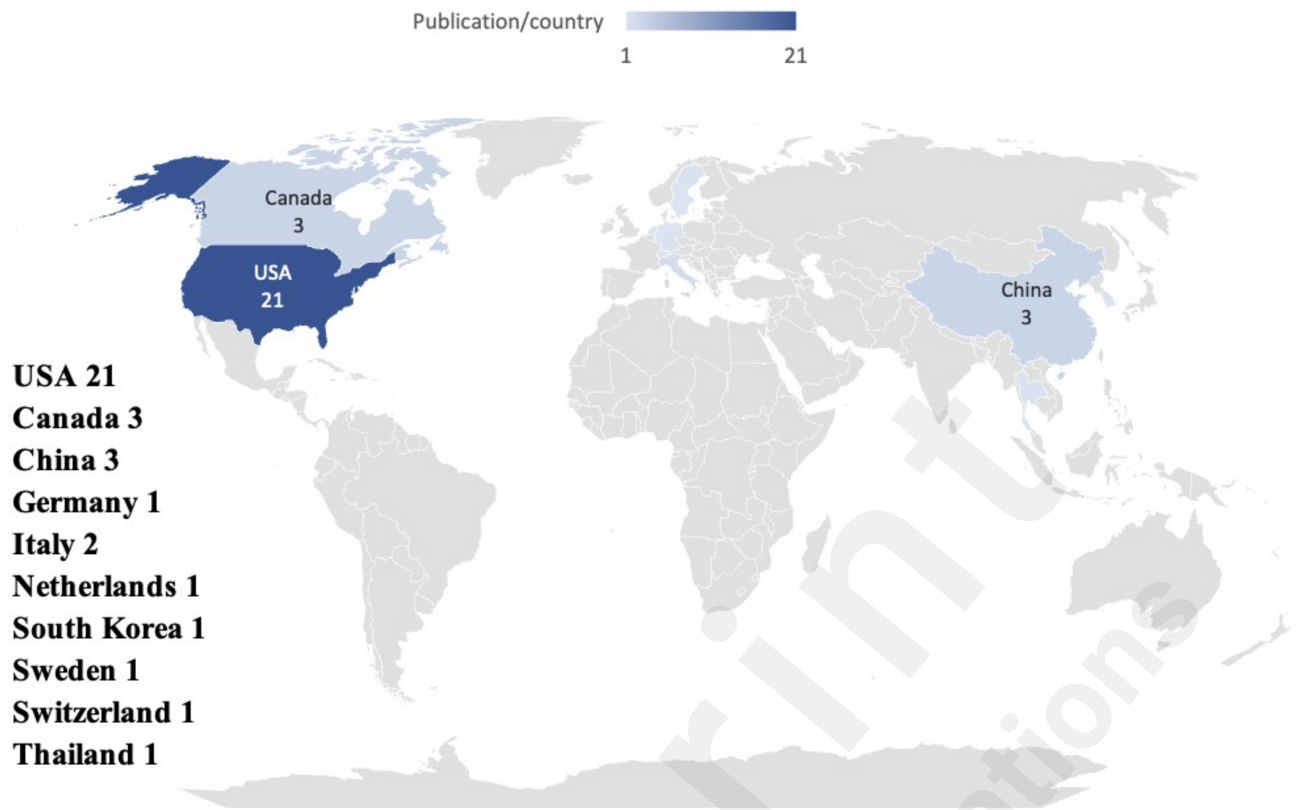

Figure 4. Number of publications per country

4.1.2. Keywords and Citation Analysis

An in-depth examination of the specific keywords employed within the scholarly articles discussing DSS to predict sepsis will likely uncover significant themes and evolving research trajectories currently shaping this particular domain of study. The analytical process of these keywords was meticulously conducted and subsequently visualized utilizing VOSviewer, which is explicitly illustrated in Figure 5. This figure effectively portrays how the keywords associated with the articles on sepsis prediction tend to cluster cohesively while concurrently providing a visual representation of the diverse Decision Support Systems that are being utilized to ascertain the presence of sepsis, to implement initial interventions and management strategies, as well as to adhere to established clinical practice guidelines.

Moreover, Table 1 presents a comprehensive citation analysis that elucidates the frequency with which the sepsis Decision Support System framework has been referenced in various other scholarly publications while identifying the most prominent publisher and author who has made significant contributions to this field of research.

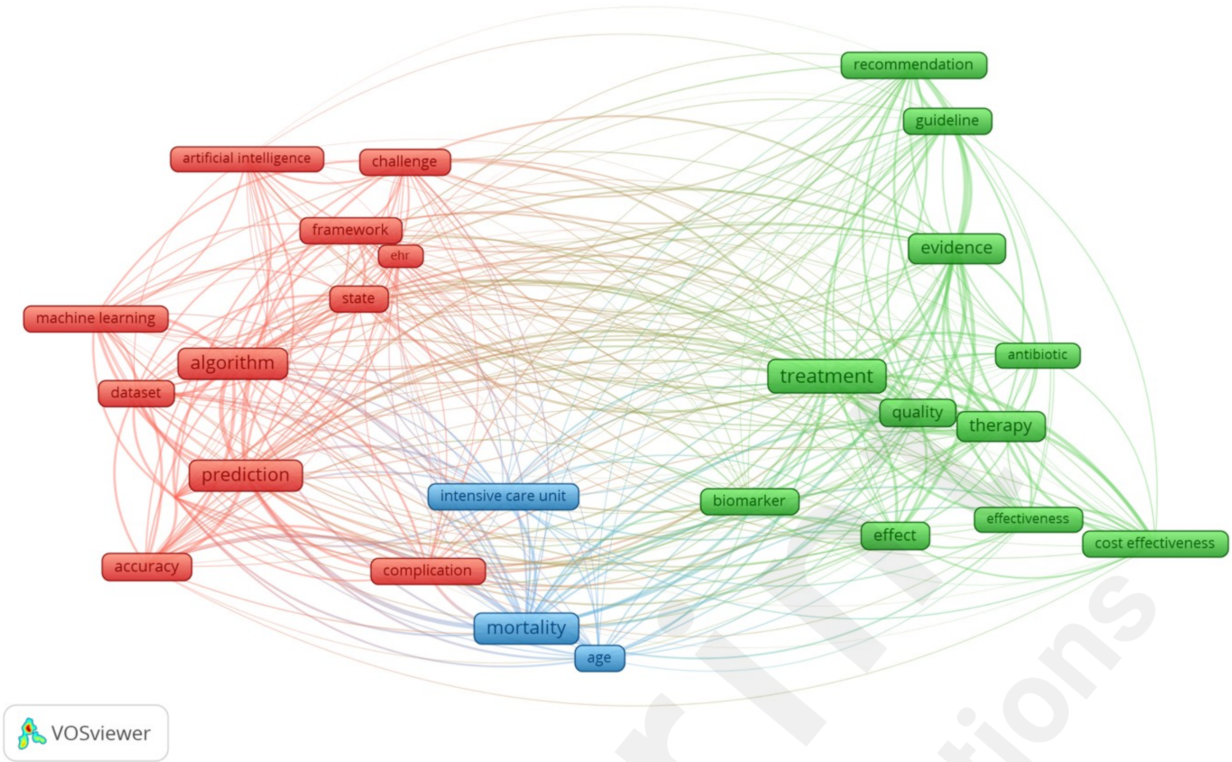

Figure 5. Keywords analysis of publications

Table 2. The list of most cited publications in the study

Article	Year of publication	Country	Affiliation	Publisher	Number of Citations
[27]	2017	USA	-University of California San Francisco -University of California Berkeley -Dascena	BMJ Open Respiratory Research	330
[28]	2017	USA	-Harvard Medical School -Massachusetts Institute of Technology -Google -New York University	PLoS ONE	294
[29]	2016	USA	-Dascena -University of California San Francisco	Computers in Biology and Medicine	262
[30]	2014	USA	University of California	Journal of the American Medical Informatics Association	218
[31]	2022	USA	-Johns Hopkins University -Johns Hopkins Hospital -University of California -Howard County General Hospital	Nature	145

4.1.3. Sepsis diagnosis criteria and risk factors

The criteria for diagnosing sepsis have evolved over time, and several scoring systems have been developed to aid clinicians in assessment and early intervention. Key criteria include the SIRS (Systemic Inflammatory Response Syndrome) [32], MEWS (Modified Early Warning Score) [33], SOFA (Sequential Organ Failure Assessment) [34], and qSOFA (quick SOFA) [35]. Although widely used, the SIRS criteria have limitations in specificity and can occur in various hospitalized patients beyond those with sepsis [36]. Therefore, a comprehensive approach that considers a combination of clinical indicators, inflammatory markers, and organ dysfunction is crucial for an accurate diagnosis of sepsis. The Sepsis-3 criteria, introduced by the Sepsis Definition Task Force in 2016, emphasize the importance of assessing the severity of illness through criteria like an acute change in the total SOFA score of ≥ 2 points consequent to infection [1]. This change in the SOFA score is indicative of organ dysfunction, a key feature in sepsis diagnosis [37]. Additionally, the qSOFA score, which includes altered mental status, respiratory rate, and systolic blood pressure, has been introduced to help diagnose sepsis [38]. The study showed that MEWS had the highest overall accuracy, outperforming qSOFA and SIRS [39].

Several risk factors contribute to developing sepsis, including demographic factors, underlying health conditions, and organ dysfunction, as summarized in Table 3. Figure 6 plots diagnosing criteria and risk factors that affect sepsis development to better analyze the existing studies included in this paper. Understanding these interrelated factors is vital for healthcare providers to recognize potential sepsis cases and initiate prompt treatment for at-risk individuals.

Table 3. Identified risk factors for sepsis according to studies included in the review

Risk factor	Description	Studies in the review
Demographic	Certain demographic characteristics help identify populations that may be more vulnerable to developing this serious illness, such as older age [40] and male gender [41].	[27][28][29][31][33][42][43][44][45][46][47][48][49][50][51][52][53]
Comorbidity	Comorbidity refers to the presence of one or more additional diseases or disorders that occur alongside a primary disease or condition in the same individual [54].	[43][44][43][44][45][58][59][60][61]
Organ dysfunction	Organ dysfunction is a significant risk factor for the development of sepsis, as it impairs the body's ability to respond effectively to infections [62].	[59][63][64][65][66][67][68]

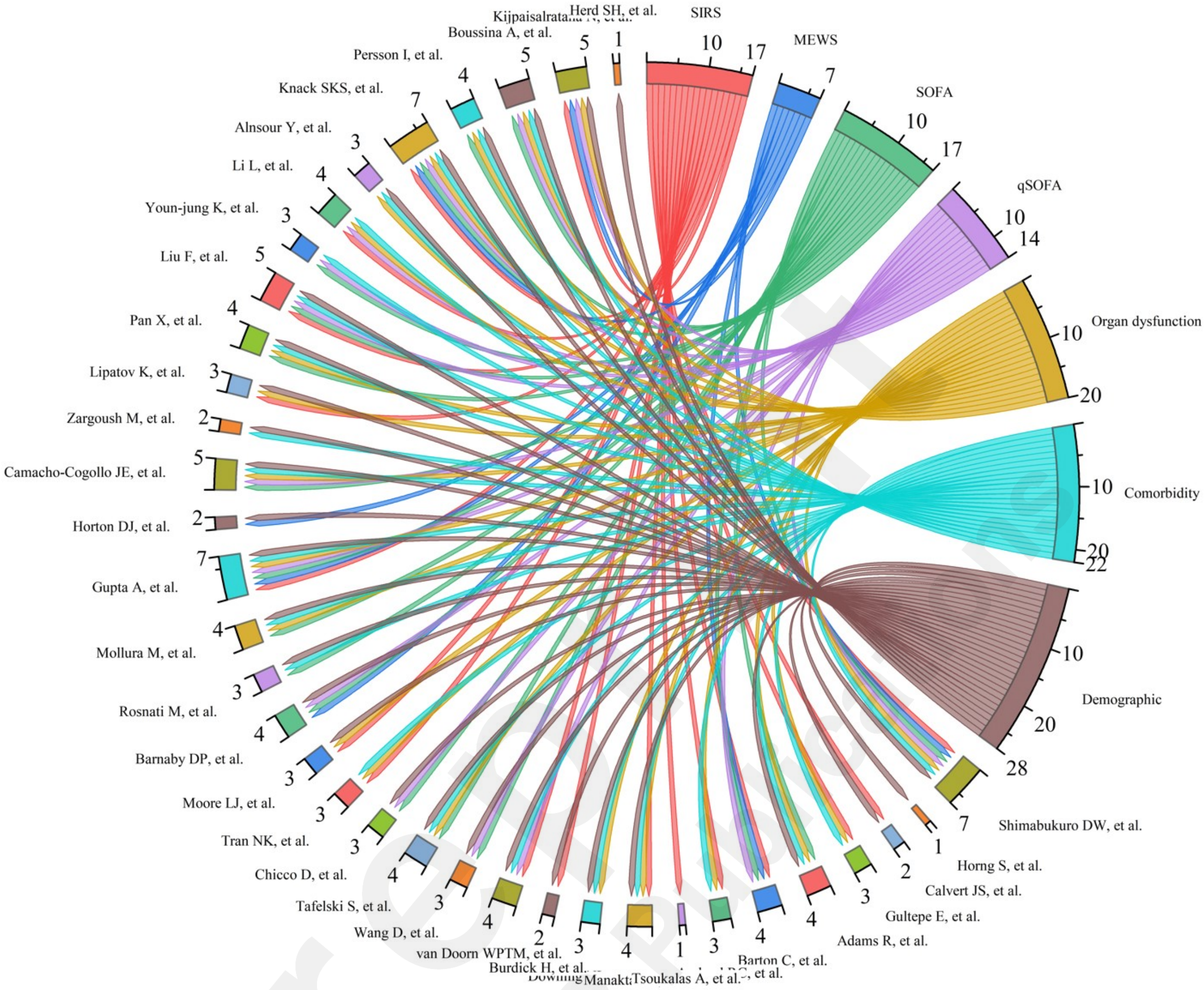

Figure 6. Criteria and risk factors for sepsis diagnosis for studies included in the review

Sepsis remains a critical health issue with profound implications for patient outcomes, including mortality rates, length of hospital stays, and the potential for readmission. Despite significant advancements in medical management and the implementation of sepsis protocols, achieving timely intervention remains a key challenge, and mortality continues to be a pressing concern. The length of hospital stay for patients diagnosed with sepsis is another critical outcome that has significant healthcare implications. This prolonged hospitalization not only strains healthcare resources but also increases the risk of hospital-acquired infections and other complications, which can further complicate recovery. The burden of prolonged hospitalization highlights the importance of effective sepsis interventions to reduce the duration of care and improve overall patient outcomes. Moreover, readmission rates following a sepsis episode indicate a need for enhanced post-discharge strategies and follow-up care. These high readmission rates impact patient quality of life and increase healthcare costs and resource utilization.

4.1.4. Data extraction

The subsequent Tables 5 through 9 meticulously described and analyzed data from various studies about DSS, which specifically focus on the implications, efficacy, and contributions of such systems in the context of sepsis research. Encompassing the diverse algorithms employed within these DSS frameworks, the specific types of input data that have been utilized, the particular settings and criteria, as well as the outcomes achieved and the initial management strategies employed in sepsis studies. Collectively, these tables serve as a thorough overview that includes empirical results, methodological approaches, data input specifications, environmental contexts, and strategic management interventions that are essential for understanding the full impact of DSS on sepsis studies. In doing so, they provide invaluable insights that are crucial for researchers, clinicians, and stakeholders who are engaged in the ongoing efforts to enhance patient outcomes in the face of this challenging medical condition.

Table 4. Characteristics of sepsis studies based on literature

Study	Year	Publication	Country	Study type	Main objectives
[45]	2023	Journal	Australia	Retrospective	Compare clinician documentation against a formal sepsis pathway and assess appropriateness of initial antibiotic prescription in the ED.
[17]	2022	Journal	United States	Retrospective	Compare sepsis care protocols before and after the introduction of a sepsis monitoring system integrated with DSS.
[68]	2021	Journal	South Korea	Prospective	Develop a qSOFA-based clinical DSS to facilitate quicker sepsis detection and treatment.
[33]	2020	Journal	United States	Prospective	Assess the clinical and financial impact of mEWS-based clinical DSS.
[69]	2020	Journal	United States	Retrospective	Develop clinical DSS to predict sepsis using tree augmented naïve Bayesian network.
[47]	2019	Journal	United States	Prospective	Determine whether EHR-based clinical DSS improves the treatment and patient outcomes with severe sepsis.
[65]	2019	Journal	Australia	Retrospective	Evaluate sepsis alert rule to assess the performance of DSS in detecting sepsis and patient deterioration.
[28]	2017	Journal	United States	Retrospective	Demonstrate the benefit of using free text data in addition to vital sign and demographic data to identify patients with suspected sepsis.
[46]	2017	Journal	United States	Prospective	Create a system using a triad of change management, electronic surveillance, decision support to the point of care using a mobile application.
[70]	2016	Journal	United States	Retrospective	Accelerate diagnostic and therapeutic interventions to avert serious complications like organ failure.
[71]	2016	Journal	United States	Prospective	Evaluate DSS impact and identify indicators that may influence outcomes for quality improvement.
[63]	2015	Journal	United States	Retrospective	Develop data-driven-based DSS framework to suggest favorable actions, predict mortality, and LOS.
[64]	2015	Journal	United States	Prospective	Examine the diagnostic accuracy of a two-stage clinical decision support system for early recognition and stratification of patients with sepsis.
[30]	2014	Journal	United States	Prospective	Develop a DSS to identify patients at high risk for hyperlactatemia based upon routinely measured vital signs and laboratory studies.
[51]	2010	Journal	Germany	Prospective	Investigate the influence of DSS on infection management of severe sepsis and septic shock.
[53]	2010	Journal	United States	Prospective	DSS to support management of surgical sepsis to improve abdominal sepsis mortality.

The following Tables 5, 6, 7, 8, and 9 present the extracted data from DSS-related studies, including the result and contribution of DSS on sepsis studies, algorithms used in the DSS of sepsis studies, input data used in the DSS of sepsis studies, setting and criteria used in the DSS of sepsis studies, outcomes and initial management used in the DSS of sepsis studies. Together, these tables provide a comprehensive overview of the multifaceted landscape of DSS within sepsis studies, encompassing results, methodologies, data inputs, contextual settings, and management strategies.

Table 5. Result and contribution of DSS on sepsis studies

Study	Time span	Sample characteristics	Results	Contribution
[45]	23 Feb – 9 May 2018	219 patients	The use of a formal sepsis pathway improves the screening and early diagnosis of sepsis for antibiotic prescribing guidance in the ED.	Antibiotic prescription decision support tools to minimize delays in a busy clinical environment.
[17]	9 April 2011 – 5 Jan 2018	1.950 patients	The performance of sepsis alert: Sensitivity 79.9%, specificity 80%, PPV 27.9%, NPV 97.2%.	Higher rates of bundle completion, fluid bolus, antibiotic administration in the post-intervention period.
[68]	1 July – 31 Dec 2016	306 patients	-Prediction accuracy is 86.6%. -Bundle compliance rate in ED was higher (57.4%) after implementation of DSS.	Age and body temperature were associated with bundle compliance.
[33]	1 Nov 2014 – 31 Oct 2015 & 1 March 2016 – 28 Feb 2017	3.664 patients	The intervention was associated with a decrease in direct cost by 23% and hospital LOS by 0.63 days. No significant change in mortality.	-Display real-time MEWS scores in the EHR patient dashboard. -Send alerts to taskforce when a patient's MEWS reached a threshold of 5.
[69]	-	16.909 patients	AUROC is 0.84, outperformed the existing diagnostic criteria like SIRS (0.59), qSOFA (0.65), MEWS (0.75), SOFA (0.80).	Capture the interaction among clinical variables and identify the optimal set of biomarkers affecting sepsis prediction.
[47]	Nov 2014 – March 2015	1.123 patients	Comparison between intervention and control groups: -Percentage of patient with new antibiotic orders (35% vs 37%). -No difference in-hospital mortality at 30 days, LOS greater than 72 hours, rate of transfer to ICU within 48 hours of alert, or proportion of patients receiving at least 30 mL/kg of intravenous fluids.	There was no significant difference between the intervention and control groups
[65]	Dec 2014 – June 2016	28.957 patients	Four revised versions of an electronic sepsis alert had higher sensitivity but lower specificity than original rule.	Develop algorithms to evaluate the performance of sepsis alert to improve patient outcomes.

[28]	17 Dec 2008 – 17 Feb 2013	230.936 patients	The best performance in predicting sepsis made use of all of the free text as input data.	Demonstrate the significant improvement in prediction result using unstructured data such as clinical notes.
[46]	1 Jan 2011 – 30 Sep 2013	3.562 patients	Combination of change management, computerized surveillance, and mobile based point of care alerting decreased sepsis mortality by 53%.	The DSS delivered to the point of care resulted in significant reduction in mortality of sepsis.
[70]	2012-2013	6.200 patients	Median time from arrival to DSS activation was 3.5 hours and system activation to diagnostic collect was 8.6 hours.	Determine the performance of a DSS, understand the epidemiology of sepsis, and identify opportunities for quality improvement.
[71]	2014-2015	16.527 patients	-Risk of adverse outcome improved 30% after sepsis program go-live. -97% patients detected by the cloud-based sepsis DSS were screened and stratified by providers.	A multidisciplinary sepsis program enabled by a 2-stage sepsis DSS expedites accurate detection, stratification of patients with sepsis and intervention.
[63]	1 Jan 2010 – 31 Dec 2010	1.492 patients	-Data-derived antibiotic administration led to a favorable patient outcome in 49% of the cases. -25.9% of the patients had 90% of their transitions to better states. Mortality was predicted with an AUC (0.7) and accuracy (0.82).	Model was able to suggest favorable actions, predict mortality and LOS with high accuracy.
[64]	2014	2.620 patients	-A sepsis alert activated on 16% of adult patients. -The patient population characteristics showed 72% sensitivity and 73% PPV. -Post-alert screening achieved 81% sensitivity and 94% PPV.	DSS binary alarm system with cross checking functionality improves early recognition and facilitates stratification of patients with sepsis.
[30]	1 Jan 2010 – 31 Dec 2010	741 patients	-Prediction of lactate level with accuracy 99%. -Mortality prediction with accuracy 73% and AUC 73% using 3 features: median of lactate levels, mean arterial pressure, and median absolute deviation of the respiratory rate.	Introduced a prediction model of lactate levels and mortality risk from patient vital signs and WBC to drive the appropriate response by clinical staff.
[51]	2006-2007	1.158 patients	-Adherence of SOP was significantly increased to 87.2%. -Daily antibiotic usage was reduced to 1.3 agents/day. -The mean ± SD time from onset of severe sepsis and septic shock until antibiotic administration was 1.9 ± 2.5 hours. -Mortality rate did not reach statistical significance.	DSS improved the mean conformity to recommendations, antibiotic adherence, therapy patterns, and diagnostic procedures.
[53]	1 Sept 2007 – 30 Sept 2009	87 patients	-Increased compliance of sepsis bundles to 79%. -Sepsis mortality has declined to 27%.	DSS results in significantly improved survival in patients with intra-abdominal surgical sepsis.

Table 6. Algorithms or methods used in the DSS for sepsis

Study	Logistic Regression	Linear Regression	TAN Bayesian	Markov Model	Naïve bayes	Support Vector Machines	Gaussian Mixture Models	Random Forest	Partially Markov Process	Observable Decision	Randomized trial	control
[45]		✓										
[17]		✓										
[68]	✓											
[33]		✓										
[69]			✓									
[47]											✓	
[65]		✓										
[28]	✓				✓	✓		✓				
[46]											✓	
[70]		✓										
[71]		✓										
[63]				✓		✓			✓			
[64]		✓										
[30]				✓	✓	✓	✓					
[51]											✓	
[53]		✓										

Table 7. Input data included in the sepsis studies

Study	Patient Demographics	Symptoms and risk of infections	Clinical documentation	Major Comorbidities	Laboratory results	Procedure / surgery	Medication Data	Biomarkers	Clinical notes
[45]	✓	✓	✓	X	X	✓	X	X	X
[17]	✓	✓	✓	✓	X	X	X	X	X
[68]	✓	✓	✓	✓	X	X	✓	X	X
[33]	✓	✓	✓	✓	X	X	X	X	X
[69]	✓	✓	✓	X	✓	✓	✓	✓	X
[47]	✓	✓	✓	X	✓	✓	X	X	X
[65]	✓	✓	✓	✓	✓	X	X	✓	X
[28]	✓	✓	✓	X	X	X	X	X	✓
[46]	✓	✓	✓	✓	✓	X	✓	X	X
[70]	✓	✓	✓	X	✓	X	✓	X	X
[71]	✓	✓	✓	X	✓	X	✓	✓	X
[63]	✓	✓	✓	X	✓	X	✓	✓	X
[64]	✓	✓	✓	X	✓	X	✓	X	X
[30]	✓	✓	✓	X	✓	X	✓	✓	X
[51]	✓	✓	✓	✓	X	✓	✓	X	X
[53]	✓	✓	✓	X	✓	✓	X	✓	X

Table 8. Setting and criteria used in the DSS of sepsis studies

Study	Setting	Data source	Task force use	DSS criteria	Sepsis bundle compliance (of all cases)	Time to first antibiotic
[45]	ED	Collected data	X	SIRS and sepsis-3 definitions	63.7%	-Sepsis = 117 min -Septic shock = 95 min
[17]	ICU and ED	Collected data	X	SIRS and sepsis-2 definitions	96%	Within 3 hours
[68]	ED	Collected data	✓	Sepsis, septic shock, qSOFA	57.4%	-Sepsis = 151 min -Septic shock = 108 min
[33]	ICU	Collected data	✓	SIRS, mEWS	56%	Within 24 hours
[69]	-	Cerner Corporations HIPAA-compliant Health Facts database	X	Biomarkers, SIRS, qSOFA, MEWS, SOFA	-	Within 72 hours after blood culture
[47]	Inpatient wards (ICU excluded)	Collected data	✓	SIRS, SOFA	37%	3 hours
[65]	ICU	Collected data	✓	SIRS	-	-
[28]	ED	Collected data	X	Vital signs and demographics	-	-
[46]	Respiratory	Collected data	✓	Sepsis 3h and 6h	-	3 hours

	and General Medicine Units			bundles		
[70]	ED, ICU	Collected data	X	SIRS	-	-
[71]	ED, Medicine, Critical Care, Surgery (ICU excluded)	Collected data	X	SIRS	-	-
[63]	ICU	Collected data	X	SOFA	-	-
[64]	ICU	Collected data	✓	SIRS	91%	-
[30]	ICU	Collected data	X	SIRS	-	-
[51]	ICU	Collected data	✓	SOFA	-	3 hours
[53]	ICU	Collected data	X	SIRS	79%	6 hours

Table 9. Outcomes and initial management used in the DSS of sepsis studies

Study	Data	Source of infection	Outcomes	Reference for interventions	Alert delivery
[45]	Paper-based scanned to a digital medical record	HA sepsis	Sepsis identification	Clinical expert	Patient dashboard
[17]	EHR	CA and HA sepsis	Sepsis identification, LOS, mortality	Manual chart review	EHR dashboard, email feedback
[68]	EHR	HA sepsis	Sepsis identification	Clinical protocol	Patient dashboard, bundle checklists, SOFA calculator
[33]	EHR	HA sepsis	Sepsis identification, LOS, mortality, ward to ICU transfer, readmission, total cost	Clinical protocol	mEWS dashboard, patient dashboard
[69]	EHR	HA sepsis	Sepsis identification	Clinical expert	EHR dashboard
[47]	EHR	HA sepsis	Sepsis identification, LOS, mortality, rate of patient transfer to ICU	Clinical expert	EHR dashboard, pager
[65]	EHR	HA sepsis	Sepsis identification, total number of alerts, mortality	Clinical expert	EHR dashboard
[28]	EHR	HA sepsis	Sepsis identification	-	EHR dashboard
[46]	EHR	HA sepsis	Sepsis identification, mortality	Sepsis order set and clinical protocol	Mobile alert
[70]	EHR	CA and HA sepsis	Sepsis identification, LOS		EHR dashboard
[71]	EHR	HA sepsis	Sepsis identification	Cloud-based clinical protocol	EHR dashboard
[63]	EHR	HA sepsis	LOS, ICU stay, mortality	Clinical protocol	EHR dashboard
[64]	EHR	HA sepsis	Sepsis identification, LOS	Clinical protocol	Binary alarm
[30]	EHR	HA sepsis	Sepsis identification, mortality,	-	-

			lactate levels		
[51]	Paper-based medical notes	HA sepsis	Sepsis identification, LOS, mortality	Clinical protocol	Web-based interface
[53]	EHR	HA sepsis	Sepsis identification, mortality, bundle compliance	Clinical protocol	-
[72]	PROWESS	HA sepsis	Serious bleeding, intracranial hemorrhage (ICH), acute myocardial infarction (AMI), acute renal failure, mortality	-	-

5. Discussion

In this review, we identified 37 scholarly articles that focused on deploying DSS-related algorithms for the early detection and preliminary management of sepsis. Most of the contributions originated from the United States, Canada, China, and Italy, highlighting a significant lack of representation from other geographical regions. Many articles utilized data extracted from hospital electronic health records (EHR) to substantiate the assertion that a proactive approach does not impose an additional burden on healthcare practitioners.

Many healthcare institutions have implemented automated alert systems to improve the timely diagnosis and treatment of sepsis. It is designed to predict and detect patient deterioration by monitoring real-time vital signs and risk indicators, ideally triggering timely interventions that improve patient outcomes. However, integrating these systems into existing workflows is complex, often requiring advanced infrastructure, consistent training, and substantial buy-in from healthcare staff. One major issue is the need for interoperability between Early Warning Score (EWS) technologies and current EHR systems, which restrict the seamless sharing of critical patient information across departments. Inadequate integration can result in more complete data, thereby reducing the effectiveness of EWS in providing accurate alerts.

Risk assessment [73] for disease enhances patient safety by identifying individuals at higher risk, enabling early interventions, tailored preventive measures, and personalized care plans to reduce the likelihood of complications and improve health outcomes. The DSS serves as an instrumental resource for healthcare practitioners in the documentation, surveillance, and management of sepsis by furnishing a framework for identifying sepsis and standardizing the intervention protocols grounded in evidence-based adaptive knowledge. The DSS evaluates patient data, encompassing vital signs, laboratory findings, and medical histories, to identify early indicators of sepsis, frequently before its clinical onset. It utilizes data analytics, machine learning methodologies, and predictive modeling techniques to augment clinical decision-making processes and enhance patient outcomes. This capacity for early detection facilitates prompt intervention, which may lead to a reduction in mortality rates and an enhancement of patient prognosis.

The adherence of the sepsis bundle was evaluated based on documented suspected sites of infection during sepsis management and was compared to established therapeutic or local guideline recommendations. A failure to accurately assess sepsis or septic shock is anticipated to result in antibiotic administration delays, which increase the mortality rate among septic patients.

5.2 Gaps and opportunities for DSS in sepsis studies

After reviewing all publications in this study, DSS has proven invaluable in healthcare, aiding clinicians in making well-informed decisions for their patients. A critical advantage of AI-based DSS in sepsis management is the ability to adaptively learn from diverse datasets across different healthcare environments, making predictions more accurate and personalized. These systems often employ ML techniques to process large volumes of multidimensional data to generate real-time, patient-specific recommendations [74]. Some DSS can suggest optimal treatment pathways, including antibiotic selection and fluid resuscitation plans, tailored to individual patients' risk factors and physiological markers. However, notable gaps and limitations still need to be addressed despite their benefits. One key challenge is seamlessly integrating DSS systems into existing healthcare workflows. By integrating with EHR, DSS provides clinicians with information at the point of care, streamlining workflow and reducing cognitive load during critical decision-making. Lack of interoperability and standardization across different EHR systems hinders the widespread adoption and effectiveness of DSS.

Another barrier is the resistance from healthcare professionals who may be wary of increased automation bias in clinical decision-making [75]. Many clinicians are hesitant to rely on automated alerts for decisions traditionally based on their expertise. Without proper customization and training, DSS may generate false positives or unnecessary alerts, overwhelm staff, and reduce confidence in the system. Financial constraints further limit DSS adoption, as the cost of implementing, maintaining, and upgrading these systems can be prohibitive for hospitals operating on tight budgets, especially those in rural or underserved areas. Effective

DSS implementation requires ongoing investment in staff education and technical support. Yet, many hospitals lack the financial resources for these needs, leading to inconsistent utilization and a preference for manual monitoring.

Cultural factors within hospitals also play a role in the limited adoption of DSS. Hospitals with hierarchical structures may struggle to encourage the collaborative culture needed for DSS to be effectively used across multidisciplinary teams. To function optimally, there must be coordinated communication between doctors, nurses, and support staff who interpret alerts and respond promptly. In environments where collaboration is not emphasized or team members are not encouraged to report patient concerns, alerts may be ignored or insufficiently acted upon, limiting their potential to improve patient outcomes. Additionally, the lack of standardized protocols for interpreting and responding to alerts often causes discrepancies in how different departments and practitioners handle early warnings, leading to inconsistencies in patient care. Without uniform adoption and clear guidelines, DSS cannot fulfill their intended purpose of early intervention, thus remaining an underutilized tool in hospital settings.

Additionally, DSS systems often rely on retrospective data, limiting their ability to adapt to dynamic patient needs and real-time changes. Another crucial aspect is the need for accurate and up-to-date clinical knowledge as outdated guidelines and incomplete evidence can lead to suboptimal recommendations and potential harm. Finally, the issue of alert fatigue arises when DSS systems generate excessive alerts, overwhelming clinicians and reducing their trust in the system. To maximize the utility of DSS, addressing these gaps and limitations is essential, necessitating advancements in interoperability, data quality, knowledge management, and the development of personalized DSS algorithms, as shown in Table 10.

Table 10. Gaps and opportunities for AI-driven DSS models in sepsis applications

	Data	Model Structure	Model Implementation
Gaps	**Data representation:** insufficient high-quality data for training robust models **Dynamic and heterogeneous data:** handling dynamic and heterogeneous data sources **Noisy or incomplete data:** noise and missing values may mislead the optimization process and hinder the discovery of high-quality solutions	**Personalized risk prediction:** limited focus on personalized risk prediction **Real-Time decision support:** challenges in providing real-time decision support **Integration of biomarkers:** limited integration of emerging biomarkers into decision support systems	**Clinical Workflow Integration:** limited incorporation of DSS into existing clinical workflows **Personalized medicine approach:** lack of personalized treatment recommendations based on patient-specific factors **User-centered design:** insufficient emphasis on user-centered design in the development of decision support systems
Opportunities	Promote standardized data formats and explore techniques to enhance dataset quality. Integrate diverse data types and consider real-time data for dynamic updates. Applying data imputation to fill in missing values. Consider outlier detection and removal to mitigate the impact of noise.	Employ personalized models that consider medical history for more accurate risk assessments. Develop algorithms to analyze data in real-time, ensuring timely alerts and interventions. Incorporate novel biomarkers in early diagnosis and monitoring.	Explore strategies for seamless integration of DSS into EHR to ensure user adoption. Tailor DSS considering patient specific features and organizational data for more effective treatment Collaborate with healthcare professionals to create user-friendly interfaces that align with clinicians preferences.

6. Conclusion

The study presents a PRISMA-based review that employed an innovative methodology to highlight the implementation of DSS across diverse data categories, including EHR, expert knowledge, and clinical documentation. DSS provides empirical evidence substantiating their efficacy and capacity to enhance healthcare delivery. This methodology elevates the standards of healthcare and hospital experiences for patients suffering from sepsis, concurrently contributing to the mitigation of occupational burnout among healthcare professionals.

After thoroughly analyzing numerous studies, it has become evident that DSS implementation can significantly enhance clinical decision-making and improve patient outcomes. By integrating clinical knowledge, patient-specific data, and evidence-based guidelines, DSS systems provide timely and relevant information at the point of care. DSS systems enhance healthcare delivery quality, safety, and efficiency through alerts, reminders, and suggestions. They offer valuable insights like drug interaction alerts, diagnostic support, treatment recommendations, and risk assessments. These systems empower clinicians with evidence-based guidelines and protocols, enabling them to deliver personalized and effective care. By aggregating and analyzing patient data, DSS systems generate actionable insights, supporting clinicians in providing accurate diagnoses and tailored treatment plans. Ultimately, DSS is crucial in improving patient outcomes and driving advancements in healthcare practice.

CRediT authorship contribution statement

FR and MS: Conceptualization, Data curation, Writing – original draft; FR: Writing – review & editing, Visualization, Investigation, Formal analysis, Methodology; FR, MS, MO, SA, AA: Writing – review & editing, Methodology; MS and SA: Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] M. Singer *et al.*, “The Third International Consensus Definitions for Sepsis and Septic Shock (Sepsis-3),” *JAMA*, vol. 315, no. 8, pp. 801–810, Feb. 2016, doi: 10.1001/jama.2016.0287.

[2] M. Sartelli *et al.*, “Raising concerns about the Sepsis-3 definitions,” *World J Emerg Surg*, vol. 13, p. 6, 2018, doi: 10.1186/s13017-018-0165-6.

[3] K. Reinhart, R. Daniels, N. Kissoon, F. R. Machado, R. D. Schachter, and S. Finfer, “Recognizing Sepsis as a Global Health Priority — A WHO Resolution,” *N Engl J Med*, vol. 377, no. 5, pp. 414–417, Aug. 2017, doi: 10.1056/NEJMp1707170.

[4] “Improving the prevention, diagnosis and clinical management of sepsis.” Accessed: Jun. 11, 2023. [Online]. Available: https://www.who.int/servicedeliverysafety/areas/sepsis/en/

[5] K. E. Rudd *et al.*, “Global, regional, and national sepsis incidence and mortality, 1990–2017: analysis for the Global Burden of Disease Study,” *The Lancet*, vol. 395, no. 10219, pp. 200–211, Jan. 2020, doi: 10.1016/S0140-6736(19)32989-7.

[6] Y. Sakr *et al.*, “Sepsis in Intensive Care Unit Patients: Worldwide Data From the Intensive Care over Nations Audit,” *Open Forum Infectious Diseases*, vol. 5, no. 12, p. ofy313, Dec. 2018, doi: 10.1093/ofid/ofy313.

[7] H. Saito, C. Kilpatrick, and D. Pittet, “The 2018 World Health Organization SAVE LIVES: Clean Your Hands Campaign targets sepsis in health care,” *Intensive Care Med*, vol. 44, no. 4, pp. 499–501, Apr. 2018, doi: 10.1007/s00134-018-5097-9.

[8] P. W. Schreiber, H. Sax, A. Wolfensberger, L. Clack, S. P. Kuster, and Swissnoso, “The preventable proportion of healthcare-associated infections 2005–2016: Systematic review and meta-analysis,” *Infect. Control Hosp. Epidemiol.*, vol. 39, no. 11, pp. 1277–1295, Nov. 2018, doi: 10.1017/ice.2018.183.

[9] G. S. Martin, D. M. Mannino, S. Eaton, and M. Moss, “The Epidemiology of Sepsis in the United States from 1979 through 2000,” *N Engl J Med*, vol. 348, no. 16, pp. 1546–1554, Apr. 2003, doi: 10.1056/NEJMoa022139.

[10] V. Liu *et al.*, “Hospital deaths in patients with sepsis from 2 independent cohorts,” *JAMA*, vol. 312, no. 1, pp. 90–92, Jul. 2014, doi: 10.1001/jama.2014.5804.

[11] G. S. Martin, “Sepsis, severe sepsis and septic shock: changes in incidence, pathogens and outcomes,” *Expert Rev Anti Infect Ther*, vol. 10, no. 6, pp. 701–706, Jun. 2012, doi: 10.1586/eri.12.50.

[12] L. Durairaj and G. A. Schmidt, “Fluid Therapy in Resuscitated Sepsis,” *Chest*, vol. 133, no. 1, pp. 252–263, Jan. 2008, doi: 10.1378/chest.07-1496.

[13] M. H. Legese *et al.*, “Sepsis: emerging pathogens and antimicrobial resistance in Ethiopian referral hospitals,” *Antimicrob Resist Infect Control*, vol. 11, no. 1, p. 83, Dec. 2022, doi: 10.1186/s13756-022-01122-x.

[14] R. M. Werner and D. A. Asch, “The unintended consequences of publicly reporting quality information,” *JAMA*, vol. 293, no. 10, pp. 1239–1244, Mar. 2005, doi: 10.1001/jama.293.10.1239.

[15] S. Westaby, “Publishing individual surgeons’ death rates prompts risk averse behaviour,” *BMJ*, vol. 349, no. aug12 10, pp. g5026–g5026, Aug. 2014, doi: 10.1136/bmj.g5026.

[16] K. M. Toffaha, M. C. E. Simsekler, and M. A. Omar, “Leveraging artificial intelligence and decision support systems in hospital-acquired pressure injuries prediction: A comprehensive review,” *Artificial Intelligence in Medicine*, vol. 141, p. 102560, Jul. 2023, doi: 10.1016/j.artmed.2023.102560.

[17] K. Lipatov *et al.*, “Implementation and evaluation of sepsis surveillance and decision

support in medical ICU and emergency department," *The American Journal of Emergency Medicine*, vol. 51, pp. 378–383, Jan. 2022, doi: 10.1016/j.ajem.2021.09.086.

[18] M. M. Levy *et al.*, "Mortality Changes Associated with Mandated Public Reporting for Sepsis. The Results of the New York State Initiative," *Am J Respir Crit Care Med*, vol. 198, no. 11, pp. 1406–1412, Dec. 2018, doi: 10.1164/rccm.201712-2545OC.

[19] M. M. Levy *et al.*, "Surviving Sepsis Campaign: Association Between Performance Metrics and Outcomes in a 7.5-Year Study," *Critical Care Medicine*, vol. 43, no. 1, pp. 3–12, Jan. 2015, doi: 10.1097/CCM.0000000000000723.

[20] A. Wulff, S. Montag, M. Marschollek, and T. Jack, "Clinical Decision-Support Systems for Detection of Systemic Inflammatory Response Syndrome, Sepsis, and Septic Shock in Critically Ill Patients: A Systematic Review," *Methods Inf Med*, vol. 58, no. S 02, pp. e43–e57, Dec. 2019, doi: 10.1055/s-0039-1695717.

[21] M. Joshi, H. Ashrafian, S. Arora, S. Khan, G. Cooke, and A. Darzi, "Digital Alerting and Outcomes in Patients With Sepsis: Systematic Review and Meta-Analysis," *J Med Internet Res*, vol. 21, no. 12, p. e15166, Dec. 2019, doi: 10.2196/15166.

[22] A. N. Makam, O. K. Nguyen, and A. D. Auerbach, "Diagnostic accuracy and effectiveness of automated electronic sepsis alert systems: A systematic review," *J Hosp Med*, vol. 10, no. 6, pp. 396–402, Jun. 2015, doi: 10.1002/jhm.2347.

[23] P. Festor, Y. Jia, A. C. Gordon, A. A. Faisal, I. Habli, and M. Komorowski, "Assuring the safety of AI-based clinical decision support systems: a case study of the AI Clinician for sepsis treatment," *BMJ Health Care Inform*, vol. 29, no. 1, p. e100549, Jul. 2022, doi: 10.1136/bmjhci-2022-100549.

[24] M. J. Page *et al.*, "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," MetaArXiv, preprint, Sep. 2020. doi: 10.31222/osf.io/v7gm2.

[25] N. Donthu, S. Kumar, D. Mukherjee, N. Pandey, and W. M. Lim, "How to conduct a bibliometric analysis: An overview and guidelines," *Journal of Business Research*, vol. 133, pp. 285–296, Sep. 2021, doi: 10.1016/j.jbusres.2021.04.070.

[26] N. J. Van Eck and L. Waltman, "Software survey: VOSviewer, a computer program for bibliometric mapping," *Scientometrics*, vol. 84, no. 2, pp. 523–538, Aug. 2010, doi: 10.1007/s11192-009-0146-3.

[27] D. W. Shimabukuro, C. W. Barton, M. D. Feldman, S. J. Mataraso, and R. Das, "Effect of a machine learning-based severe sepsis prediction algorithm on patient survival and hospital length of stay: a randomised clinical trial," *BMJ Open Respir Res*, vol. 4, no. 1, p. e000234, 2017, doi: 10.1136/bmjresp-2017-000234.

[28] S. Horng, D. A. Sontag, Y. Halpern, Y. Jernite, N. I. Shapiro, and L. A. Nathanson, "Creating an automated trigger for sepsis clinical decision support at emergency department triage using machine learning," *PLoS ONE*, vol. 12, no. 4, p. e0174708, Apr. 2017, doi: 10.1371/journal.pone.0174708.

[29] J. S. Calvert *et al.*, "A computational approach to early sepsis detection," *Computers in Biology and Medicine*, vol. 74, pp. 69–73, Jul. 2016, doi: 10.1016/j.compbiomed.2016.05.003.

[30] E. Gultepe, J. P. Green, H. Nguyen, J. Adams, T. Albertson, and I. Tagkopoulos, "From vital signs to clinical outcomes for patients with sepsis: a machine learning basis for a clinical decision support system," *J Am Med Inform Assoc*, vol. 21, no. 2, pp. 315–325, Mar. 2014, doi: 10.1136/amiajnl-2013-001815.

[31] R. Adams *et al.*, "Prospective, multi-site study of patient outcomes after implementation

of the TREWS machine learning-based early warning system for sepsis," *Nat Med*, vol. 28, no. 7, pp. 1455–1460, Jul. 2022, doi: 10.1038/s41591-022-01894-0.

[32] K.-M. Kaukonen, M. Bailey, D. Pilcher, D. J. Cooper, and R. Bellomo, "Systemic Inflammatory Response Syndrome Criteria in Defining Severe Sepsis," *N Engl J Med*, vol. 372, no. 17, pp. 1629–1638, Apr. 2015, doi: 10.1056/NEJMoa1415236.

[33] D. J. Horton *et al.*, "Modified early warning score-based clinical decision support: cost impact and clinical outcomes in sepsis," *JAMIA Open*, vol. 3, no. 2, pp. 261–268, Jul. 2020, doi: 10.1093/jamiaopen/ooaa014.

[34] S. Lambden, P. F. Laterre, M. M. Levy, and B. Francois, "The SOFA score-development, utility and challenges of accurate assessment in clinical trials," *Crit Care*, vol. 23, no. 1, p. 374, Nov. 2019, doi: 10.1186/s13054-019-2663-7.

[35] R. Sarkar, "A combined qSOFA-lactate model for sepsis-related mortality prediction: a small step towards an elusive answer?," *The Lancet Global Health*, vol. 10, no. 9, pp. e1214–e1215, Sep. 2022, doi: 10.1016/S2214-109X(22)00304-7.

[36] M. Svendsen, S. A. Steindal, M. Hamilton Larsen, and M. Trygg Solberg, "Comparison of the systematic Inflammatory response syndrome and the quick sequential organ failure assessment for prognostic accuracy in detecting sepsis in the emergency department: A systematic review," *International Emergency Nursing*, vol. 66, p. 101242, Jan. 2023, doi: 10.1016/j.ienj.2022.101242.

[37] Y. Zhang, H. Luo, H. Wang, Z. Zheng, and O. C. Ooi, "Validation of prognostic accuracy of the SOFA score, SIRS criteria, and qSOFA score for in-hospital mortality among cardiac-, thoracic-, and vascular-surgery patients admitted to a cardiothoracic intensive care unit," *J Card Surg*, vol. 35, no. 1, pp. 118–127, Jan. 2020, doi: 10.1111/jocs.14331.

[38] P. Herrod, M. Cox, H. Keevil, K. Smith, and J. Lund, "NICE guidance on sepsis is of limited value in postoperative colorectal patients: the scores that cry 'wolf!,'" *annals*, vol. 100, no. 4, pp. 275–278, Apr. 2018, doi: 10.1308/rcsann.2017.0227.

[39] B. Joveš, D. Obradovic, J. Matijasevic, S. Sovilj-Gmizic, and I. Vujovic, "Recognizing the high-risk patients with sepsis on time: MEWS, qSOFA or SIRS?," in *Acute critical care*, European Respiratory Society, Sep. 2019, p. PA4008. doi: 10.1183/13993003.congress-2019.PA4008.

[40] M. Ibarz, L. E. M. Haas, A. Ceccato, and A. Artigas, "The critically ill older patient with sepsis: a narrative review," *Ann. Intensive Care*, vol. 14, no. 1, p. 6, Jan. 2024, doi: 10.1186/s13613-023-01233-7.

[41] Y. Sakr *et al.*, "The influence of gender on the epidemiology of and outcome from severe sepsis," *Crit Care*, vol. 17, no. 2, p. R50, 2013, doi: 10.1186/cc12570.

[42] D. P. Barnaby, S. M. Fernando, C. L. Herry, N. B. Scales, E. J. Gallagher, and A. J. E. Seely, "Heart Rate Variability, Clinical and Laboratory Measures to Predict Future Deterioration in Patients Presenting With Sepsis," *Shock*, vol. 51, no. 4, pp. 416–422, Apr. 2019, doi: 10.1097/SHK.0000000000001192.

[43] M. Zargoush, A. Sameh, M. Javadi, S. Shabani, S. Ghazalbash, and D. Perri, "The impact of recency and adequacy of historical information on sepsis predictions using machine learning," *Sci Rep*, vol. 11, no. 1, p. 20869, Oct. 2021, doi: 10.1038/s41598-021-00220-x.

[44] F. Liu, J. Yao, C. Liu, and S. Shou, "Construction and validation of machine learning models for sepsis prediction in patients with acute pancreatitis," *BMC Surg*, vol. 23, no. 1, p. 267, Sep. 2023, doi: 10.1186/s12893-023-02151-y.

[45] S. H. Herd, P. L. Allen, L. J. Reed, J. A. O'Hern, J. Fraser, and K. L. Flanagan, "Time to

embrace sepsis pathways and antibiotic prescribing decision support in the emergency department: Observations from a retrospective single site clinical audit," *Emerg Medicine Australasia*, pp. 1742-6723.14206, Apr. 2023, doi: 10.1111/1742-6723.14206.
[46] S. Manaktala and S. R. Claypool, "Evaluating the impact of a computerized surveillance algorithm and decision support system on sepsis mortality," *Journal of the American Medical Informatics Association*, vol. 24, no. 1, pp. 88–95, Jan. 2017, doi: 10.1093/jamia/ocw056.
[47] N. L. Downing *et al.*, "Electronic health record-based clinical decision support alert for severe sepsis: a randomised evaluation," *BMJ Qual Saf*, vol. 28, no. 9, pp. 762–768, Sep. 2019, doi: 10.1136/bmjqs-2018-008765.
[48] H. Burdick *et al.*, "Effect of a sepsis prediction algorithm on patient mortality, length of stay and readmission: a prospective multicentre clinical outcomes evaluation of real-world patient data from US hospitals," *BMJ Health Care Inform*, vol. 27, no. 1, p. e100109, Apr. 2020, doi: 10.1136/bmjhci-2019-100109.
[49] W. P. T. M. van Doorn *et al.*, "A comparison of machine learning models versus clinical evaluation for mortality prediction in patients with sepsis," *PLoS One*, vol. 16, no. 1, p. e0245157, 2021, doi: 10.1371/journal.pone.0245157.
[50] D. Wang *et al.*, "A Machine Learning Model for Accurate Prediction of Sepsis in ICU Patients," *Front Public Health*, vol. 9, p. 754348, 2021, doi: 10.3389/fpubh.2021.754348.
[51] S. Tafelski *et al.*, "Computer-assisted decision support for changing practice in severe sepsis and septic shock," *J Int Med Res*, vol. 38, no. 5, pp. 1605–1616, 2010, doi: 10.1177/147323001003800505.
[52] D. Chicco and G. Jurman, "Survival prediction of patients with sepsis from age, sex, and septic episode number alone," *Sci Rep*, vol. 10, no. 1, p. 17156, Oct. 2020, doi: 10.1038/s41598-020-73558-3.
[53] L. J. Moore, K. L. Turner, S. R. Todd, B. McKinley, and F. A. Moore, "Computerized clinical decision support improves mortality in intra abdominal surgical sepsis," *Am J Surg*, vol. 200, no. 6, pp. 839–843; discussion 843-844, Dec. 2010, doi: 10.1016/j.amjsurg.2010.07.036.
[54] D. Sinapidis *et al.*, "Progression into sepsis: an individualized process varying by the interaction of comorbidities with the underlying infection," *BMC Infect Dis*, vol. 18, no. 1, p. 242, Dec. 2018, doi: 10.1186/s12879-018-3156-z.
[55] M. Rosnati and V. Fortuin, "MGP-AttTCN: An interpretable machine learning model for the prediction of sepsis," *PLoS ONE*, vol. 16, no. 5, p. e0251248, May 2021, doi: 10.1371/journal.pone.0251248.
[56] M. Mollura, L.-W. H. Lehman, R. G. Mark, and R. Barbieri, "A novel artificial intelligence based intensive care unit monitoring system: using physiological waveforms to identify sepsis," *Philos Trans A Math Phys Eng Sci*, vol. 379, no. 2212, p. 20200252, Dec. 2021, doi: 10.1098/rsta.2020.0252.
[57] A. Alanazi, L. Aldakhil, M. Aldhoayan, and B. Aldosari, "Machine Learning for Early Prediction of Sepsis in Intensive Care Unit (ICU) Patients," *Medicina (Kaunas)*, vol. 59, no. 7, p. 1276, Jul. 2023, doi: 10.3390/medicina59071276.
[58] X. Pan *et al.*, "Evaluate prognostic accuracy of SOFA component score for mortality among adults with sepsis by machine learning method," *BMC Infect Dis*, vol. 23, no. 1, p. 76, Feb. 2023, doi: 10.1186/s12879-023-08045-x.
[59] Y. Alnsour, R. Hadidi, and N. Singh, "Using Data Analytics to Predict Hospital Mortality

in Sepsis Patients:," *International Journal of Healthcare Information Systems and Informatics*, vol. 14, no. 3, pp. 40–57, Jul. 2019, doi: 10.4018/IJHISI.2019070104.
[60] I. Persson, A. Macura, D. Becedas, and F. Sjövall, "Early prediction of sepsis in intensive care patients using the machine learning algorithm NAVOY® Sepsis, a prospective randomized clinical validation study," *J Crit Care*, vol. 80, p. 154400, Apr. 2024, doi: 10.1016/j.jcrc.2023.154400.
[61] A. Boussina, G. Wardi, S. P. Shashikumar, A. Malhotra, K. Zheng, and S. Nemati, "Representation Learning and Spectral Clustering for the Development and External Validation of Dynamic Sepsis Phenotypes: Observational Cohort Study," *J Med Internet Res*, vol. 25, p. e45614, Jun. 2023, doi: 10.2196/45614.
[62] R. Pool, H. Gomez, and J. A. Kellum, "Mechanisms of Organ Dysfunction in Sepsis," *Crit Care Clin*, vol. 34, no. 1, pp. 63–80, Jan. 2018, doi: 10.1016/j.ccc.2017.08.003.
[63] A. Tsoukalas, T. Albertson, and I. Tagkopoulos, "From Data to Optimal Decision Making: A Data-Driven, Probabilistic Machine Learning Approach to Decision Support for Patients With Sepsis," *JMIR Med Inform*, vol. 3, no. 1, p. e11, Feb. 2015, doi: 10.2196/medinform.3445.
[64] R. C. Amland, J. J. Lyons, T. L. Greene, and J. M. Haley, "A two-stage clinical decision support system for early recognition and stratification of patients with sepsis: an observational cohort study," *JRSM Open*, vol. 6, no. 10, p. 2054270415609004, Oct. 2015, doi: 10.1177/2054270415609004.
[65] L. Li *et al.*, "Improving the Performance of Clinical Decision Support for Early Detection of Sepsis: A Retrospective Observational Cohort Study," *Stud Health Technol Inform*, vol. 264, pp. 679–683, Aug. 2019, doi: 10.3233/SHTI190309.
[66] N. Kijpaisalratana, J. Saoraya, P. Nhuboonkaew, K. Vongkulbhisan, and K. Musikatavorn, "Real-time machine learning-assisted sepsis alert enhances the timeliness of antibiotic administration and diagnostic accuracy in emergency department patients with sepsis: a cluster-randomized trial," *Intern Emerg Med*, Feb. 2024, doi: 10.1007/s11739-024-03535-5.
[67] N. K. Tran *et al.*, "Novel application of an automated-machine learning development tool for predicting burn sepsis: proof of concept," *Sci Rep*, vol. 10, no. 1, p. 12354, Jul. 2020, doi: 10.1038/s41598-020-69433-w.
[68] "Use of quick sequential organ failure assessment score-based sepsis clinical decision support system may be helpful to predict sepsis development," *SV*, 2021, doi: 10.22514/sv.2021.082.
[69] A. Gupta, T. Liu, and S. Shepherd, "Clinical decision support system to assess the risk of sepsis using Tree Augmented Bayesian networks and electronic medical record data," *Health Informatics J*, vol. 26, no. 2, pp. 841–861, Jun. 2020, doi: 10.1177/1460458219852872.
[70] R. C. Amland and K. E. Hahn-Cover, "Clinical Decision Support for Early Recognition of Sepsis," *Am J Med Qual*, vol. 31, no. 2, pp. 103–110, Mar. 2016, doi: 10.1177/1062860614557636.
[71] R. C. Amland, J. M. Haley, and J. J. Lyons, "A Multidisciplinary Sepsis Program Enabled by a Two-Stage Clinical Decision Support System: Factors That Influence Patient Outcomes," *Am J Med Qual*, vol. 31, no. 6, pp. 501–508, Nov. 2016, doi: 10.1177/1062860615606801.
[72] D. P. Schauer, A. C. Leonard, R. W. Hornung, J. A. Johnston, and M. H. Eckman, "Patient-specific decision modeling to guide the use of drotrecogin alpha (activated) in patients with severe sepsis," *J Crit Care*, vol. 23, no. 4, pp. 484–492, Dec. 2008, doi:

10.1016/j.jcrc.2007.12.016.
[73] A. Saad *et al.*, “An integrative risk assessment approach to enhancing patient safety in Continuous Renal Replacement Therapy (CRRT),” *Journal of Safety Science and Resilience*, vol. 5, no. 3, pp. 344–354, Sep. 2024, doi: 10.1016/j.jnlssr.2024.04.003.
[74] D. T. Al-Absi, M. C. E. Simsekler, M. A. Omar, and S. Anwar, “Exploring the role of Artificial Intelligence in Acute Kidney Injury management: a comprehensive review and future research agenda,” *BMC Med Inform Decis Mak*, vol. 24, no. 1, p. 337, Nov. 2024, doi: 10.1186/s12911-024-02758-y.
[75] M. Abdelwanis, H. K. Alarafati, M. M. S. Tammam, and M. C. E. Simsekler, “Exploring the risks of automation bias in healthcare artificial intelligence applications: A Bowtie analysis,” *Journal of Safety Science and Resilience*, vol. 5, no. 4, pp. 460–469, Dec. 2024, doi: 10.1016/j.jnlssr.2024.06.001.

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