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Human-AI Decision Support for Enhanced Healthcare Management: The Case of A New Sepsis Prediction and Treatment System

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Abstract

Sepsis is a severe medical condition caused by an abnormal response to infection, impacting overall patient safety and quality of care in healthcare management. Although early warning systems have been developed to identify patients at higher risk of sepsis, they often generate too many false positive alarms, causing digital fatigue and being ignored by healthcare providers. This problem escalated into late recognition of sepsis, as heavy workload and low staffing levels made completing the sepsis bundle within an hour challenging. To address this issue, the current study proposes a Human-AI Decision Support Framework (HADS) to identify high-risk patients and improve sepsis prevention and management. More specifically, we develop a prediction model that incorporates physicians' expert knowledge to identify at-risk patients for early recognition. This retrospective study used records from 74,567 patients in the Medical Information Mart for Intensive Care (MIMIC-IV). Second, mitigation strategies are recommended to enhance decisionmaking by leveraging a systems-thinking approach. The proposed framework, utilizing a Bayesian Belief Network, outperforms the existing alert system in terms of model performance and reduces false alarms by 48%. Results highlight that antibiotic prescription, initiating blood culture collection, oxygen saturation monitoring, and hourly observations are the critical interventions that significantly influence the onset and the management of sepsis. Our framework eliminates several processes in current sepsis pathways, reducing response time and improving outcomes by preventing deterioration during the critical golden hour. Future research directions and applications for healthcare management, based on the proposed framework, are discussed.

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Keywords: sepsis management, human-AI interaction, system thinking, artificial intelligence, healthcare operations, patient safety

Managerial relevance statement

Streamlining sepsis care is essential in improving patient outcomes and reducing mortality rates associated with this life-threatening condition. By implementing evidence-based protocols and leveraging technological advancements, a well-designed sepsis management system expedites recognition, diagnosis, and appropriate treatment. This system needs to meet the requirements, including standardized screening tools, clear communication pathways among healthcare providers, and the optimal use of antibiotics and fluids based on individual patient conditions within the first hour. The current study proposes a new sepsis management framework, the HumanAI Decision Support Framework (HADS), that combines clinical guidelines with expert knowledge embedded in an AI-based system. HADS integrates the experience of multiple experts and adapts to complex, personalized cases of sepsis. In practice, this framework is implemented by incorporating clinicians' user requirements during the design stage. It provides a faster realtime analysis and decision-making support than previous systems, particularly during the critical "golden hour” of sepsis, helping clinicians act more quickly and appropriately.

1. Introduction

Sepsis is a dysregulated inflammatory immune reaction to infections that causes multi-organ failure and remains one of the leading causes of death globally [1]. In the US, the average annual sepsis-related mortality rate is 50.2 per 100,000 population, with relatively stable trends over time [2]. Regarding this, promptly identifying sepsis symptoms is critical to the patient’s survival rate, though it may burden healthcare facilities with increased costs and required resources [3]. Sepsis

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was the most expensive condition and the third most frequent cause of hospitalizations, leading to 1,094,000 hospital admissions and a total of $20.3 billion in hospital costs [4]. In clinical settings, hospitals typically implement rapid response programs based on early warning scores (EWS) and systems as a standardized package to identify patients at risk of various health deteriorations [5]. Elevated risks are especially pronounced in individuals with severe infections or sepsis, which are responsible for over 50% of fatalities in hospitals [6].

In response to the need for prompt identification and treatment of sepsis, previous research has developed algorithms for early detection and prediction to enhance decision-making in sepsis [7]. Additionally, the use of Artificial Intelligence (AI) for decision support in sepsis has been highlighted, with applications in predicting, diagnosing, and managing sepsis [8]. Furthermore, implementing computerized surveillance algorithms and the Decision Support System (DSS) has shown potential to improve sepsis outcomes. However, it can be resource-intensive and challenging to sustain over time [9].

While different frameworks have been proposed, there is consensus that predicting and treating sepsis requires decision-support tools, adherence to time-based sepsis bundles, early recognition, and the implementation of protocols based on evidence-based guidelines [10]. Reflecting this theme, the most updated alert system for managing various symptoms, including sepsis, is the Electronic Health Records (EHR)-based EWS, which is widely practiced in hospitals. EWS calculates a patient's risk using the Modified Early Warning Score (MEWS) protocol. It is a tool applied to all patients, not just those with sepsis. Consequently, EWS often generates too many false-positive alarms because its users (i.e., healthcare providers) must attend to several patients with diverse medical issues [11].

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In this article, as an incremental contribution to the existing literature on digital symptom diagnosis and treatment programs, we propose a new sepsis management scheme, the Human-AI Decision Support Framework (HADS). This framework incorporates more timely and accurate sepsis predictions and guidelines to enable prompt, reliable treatment. Compared to the currently implemented EWS, our proposed HADS employs the Bayesian Belief Network (BBN) algorithm to predict and assess sepsis risk factors. The BBN algorithm plays a vital role in sepsis management. It provides a structured way to model probabilistic relationships among relevant variables, allowing healthcare managers to infer the likelihood of outcomes even with incomplete or uncertain information at a given point in time [12]. We compare our suggested HADS model with other Machine Learning (ML) algorithms (as a baseline) to prove that HADS is more reliable and robust in sepsis prediction and management. NLP is advancing.

More specifically, the contributions of the current study to the digital medical management system in relation to HADS are as follows: *First*, HADS is a two-stage model that highlights the importance of integrating systems-thinking principles into framework development. In the first stage, we build a predictive model to identify individuals at high risk of developing sepsis. Healthcare providers often struggle to identify such individuals because sepsis symptoms are not observed or may resemble those of other infections. Therefore, integrating expert knowledge into system design is vital, as it combines clinical expertise with advanced technology to create a robust, practical framework. In the second stage, based on the predictions from the first stage, HADS provides more accurate diagnoses and recommends mitigation strategies to improve decisionmaking.

Second, the supporting algorithm, BBN, can model uncertainty and complex dependencies between multiple risk factors. BBN can continuously monitor a patient's condition and alert

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healthcare providers to potential risks, allowing rapid intervention. Enabling early detection eventually reduces response time and helps prevent the onset of severe complications. Reducing response time is crucial in sepsis, as timely treatment significantly lowers mortality and long-term complications.

Third, previous research has identified the importance of potential cause (or feature) variables based on ML model outputs, attributing the impact of each feature on a particular prediction [13]. In the HADS model, we determine feature importance by combining expert knowledge (e.g., a physician's) during brainstorming sessions throughout the HADS process. This is a crucial contribution, as experts can help identify which features are most relevant to a prediction problem based on their domain experience, thereby helping to focus on and choose the most impactful variables. The previous study acknowledged diverse perspectives on sepsis management within sociotechnical healthcare systems, encompassing system design, people, organizations, environments, and risk factors [14].

Fourth, the penalized framework facilitates earlier diagnosis and treatment, empowering providers to develop targeted mitigation strategies that address specific patient vulnerabilities. Consequently, patients benefit from improved care pathways, reduced morbidity, and enhanced communication with healthcare providers, thus fostering a supportive environment that prioritizes patient-centered care. Furthermore, incorporating real-time data analytics enables continuous monitoring and adaptive management. This ensures that patient care evolves in response to changing clinical conditions, ultimately leading to an enhanced patient experience characterized by improved safety, satisfaction, and trust in the healthcare system.

The HADS framework is human-centred by design, developed to address the challenges faced by healthcare providers in decision-making, enhance interpretability, and ensure that AIgenerated

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outputs remain transparent, actionable, and supportive of, rather than substitutive for, clinical expertise.

The remaining parts of this paper are organized as follows: We provide a literature review on the EWS currently practiced in hospitals. We then introduce and discuss our proposed model, HADS, and the sepsis cohort data analyzed for this study. Following the comparison of the HADS model with other ML algorithms using performance metrics, we present robustness and sensitivity tests for our model. Finally, we conclude this paper by discussing the implications of our study, its limitations, and future directions.

2. Background

2.1 Sepsis Care Process

In the healthcare setting, the workflow begins with healthcare staff, typically nurses, regularly monitoring vital signs (e.g., respiratory rate, heart rate, systolic blood pressure, temperature, and level of consciousness). These values are logged in the EWS, either manually or automatically via connected devices. The MEWS algorithm then calculates a score based on those criteria. If the score exceeds a certain threshold, it triggers an alert that prompts closer observation, reassessment, or escalation to medical teams for intervention. This system aims to catch signs of physiological decline before the situation becomes critical, improving patient outcomes and potentially reducing mortality. A high MEWS score and sepsis-specific markers trigger an urgent alert to initiate a sepsis care bundle**,** including rapid antibiotic administration, fluid resuscitation, and further diagnostic tests.

False-positive alarms often plague current EWS implementations in healthcare settings. These systems are designed to err on the side of caution, alerting healthcare providers whenever vital signs deviate from predefined thresholds. However, this leads to frequent alarms, leaving

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clinicians, especially nurses, inundated with alerts that sometimes require urgent action. This phenomenon, alert or digital fatigue, diminishes the system's effectiveness. Additionally, managing constant alerts can increase cognitive load and stress, negatively impacting the overall workflow and quality of care [19].

The management of sepsis requires timely intervention to improve patient outcomes. Previous studies have shown improved compliance with procedures and enhanced nurses' clinical assessment skills [15]. Adequate clinical and technical governance structures are critical to ensuring high-quality patient care, safety, and continuous improvement in healthcare organizations [16]. These structures integrate policies, procedures, and systems that support the delivery of safe and effective clinical care, as well as the efficient and secure management of technical and information systems [17]. This initiative ensures that healthcare AI governance promotes transparency and interpretability, aligning with ethical principles and societal values.

2.2 Decision Support Systems (DSS) for Sepsis Management

2.2.1 Machine Learning based DSS in Sepsis Management

Risk stratification for disease is critical to enhancing patient safety by identifying high-risk individuals, facilitating early interventions, and enabling tailored preventive strategies and individualized care plans [18]. The DSS serves as a vital tool for healthcare providers in the documentation, surveillance, and clinical management of sepsis, providing a structured framework for early detection and standardized, evidence-based intervention protocols [14].

The integration of AI into DSS for sepsis management represents a significant advancement in healthcare, with the potential to improve diagnosis, treatment, and patient outcomes. For instance, a recent study [19] discusses the application of AI-driven DSS for sepsis management, emphasizing ML algorithms' ability to analyze complex interactions among multivariate risk

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factors. Another study [20] demonstrates a significant improvement in predictive performance by using unstructured data, such as clinical notes, and comparing Logistic Regression (LR), Naïve Bayes, Support Vector Machine (SVM), and Random Forest (RF).

2.2.2 Human-AI Decision Support Systems

Human-AI decision support systems aim to enhance clinical decision-making by combining AI's strengths with healthcare providers' expertise and judgment [21]. AI can rapidly analyze patient data, identify high-risk cases, and suggest evidence-based interventions. At the same time, clinicians contribute contextual understanding, ethical considerations, and real-time adjustments based on patient-specific factors [22]. Effective human-AI collaboration requires transparent and interpretable AI models that provide actionable insights, rather than just predictions, enabling clinicians to evaluate recommendations [23]. Additionally, these systems must integrate seamlessly into clinical workflows to support provider decision-making [24].

Integrating human expertise into DSS is essential for enhancing patient outcomes and ensuring that clinical decisions are both informed and empathetic [25]. With an understanding of human experts' perspectives on patient contexts and ethical considerations, healthcare systems can deliver personalized and effective care [26]. This aspect emphasizes the importance of usercentered design, ensuring that healthcare professionals can interact efficiently with systems without feeling overwhelmed or misled by data [27]. Furthermore, fostering an environment where healthcare professionals can easily access and interpret data while providing their expertise leads to more accurate diagnoses, tailored treatments, and improved patient safety [28].

Prior work on integrating clinician expertise with AI for sepsis has demonstrated promising results but remains limited by several critical gaps [29]. Many existing AI models focus primarily on predictive accuracy, often neglecting the dynamic, context-specific decision-making processes

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clinicians use at the bedside [30]. The proposed expert knowledge-AI DSS addresses these gaps by (1) integrating interpretable AI explanations with clinician expertise to enhance trust and usability and (2) embedding adaptability to align with hospital workflows and patient complexities. The framework aims to foster synergistic decision-making by bridging these gaps, ultimately improving sepsis outcomes through a more responsive and clinically grounded AI partnership.

3. Methods and Data

3.1 Human-AI Decision Support (HADS) Framework: The Proposed Model

Figure 1(a) compares the current MEWS-based EWS with the proposed HADS. The existing EWS often fails to ensure treatment within the critical *golden hour* due to uniform alert thresholds and inconsistent staff responses to sepsis notifications. These limitations delay activation of the Sepsis 1-Hour Bundle [1], which emphasizes immediate, evidence-based interventions. Although the alert system aims to prompt rapid action, its impact diminishes when caregivers do not respond promptly, undermining the central goal of improving sepsis outcomes.

Figure 1(b) illustrates the structure of the proposed HADS framework, which operates through two sequential stages. In Stage 1, the system identifies patients at high risk of sepsis through a structured data pipeline. It begins with preprocessing (handling missing data, removing outliers, and normalizing variables), followed by feature extraction and engineering based on key clinical indicators such as vital signs and laboratory results. Iterative consultations with physicians guided feature selection, Bayesian network design, and visualization of inference results to ensure alignment with clinical workflows. Class-balancing techniques addressed data imbalance, and datasets were divided into 80/20 training and testing sets to validate model performance. This

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process integrates systems-thinking principles by considering people, technology, organizational structures, and environmental factors within a sociotechnical context.

In Stage 2, HADS translates predictions into actionable recommendations by integrating clinical expertise with probabilistic modeling. It includes protocols for standardized sepsis screening, timely communication across care teams, and patient-specific antibiotic and fluid management within the first hour. By combining insights from EWS alerts and real-time analytics, HADS supports dynamic treatment adjustments and identifies potential workflow barriers.

Continuous professional training and protocol updates remain essential to ensure consistent practice. However, challenges persist across multiple system dimensions. From the *people's* perspective, staff availability, reliance on peer support, and resistance to new systems affect adoption. *Task-related* barriers include prescription delays, clinician workload, and inconsistent adherence to protocols. *Technological* issues, such as EHR integration and implementation costs, further hinder scalability. *Organizational* constraints, such as limited budgets, resource shortages, and hierarchical resistance, along with *environmental* pressures from fast-paced clinical settings, compound these challenges. Together, these factors underscore the complexity of embedding decision support systems like HADS into real-world healthcare environments.

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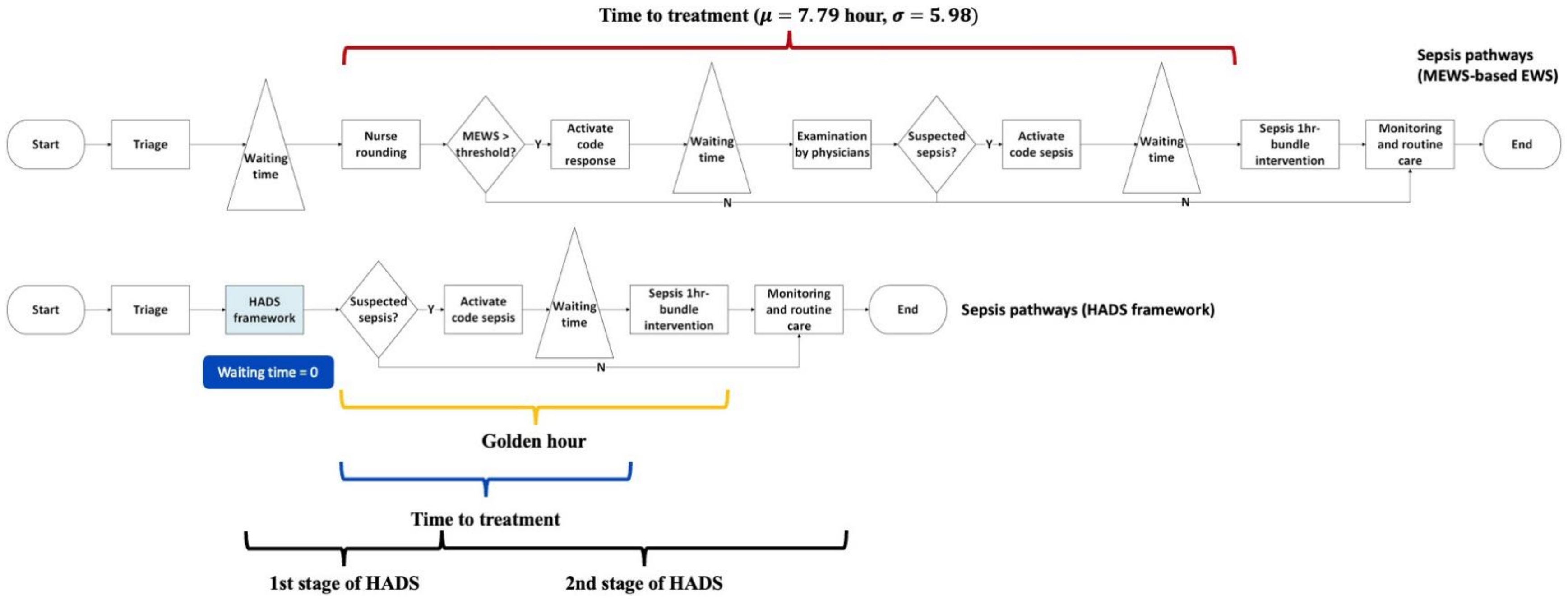
Figure 1. The current sepsis pathways and the proposed framework

a. The proposed HADS model compared to the currently used sepsis pathways model (EWS)



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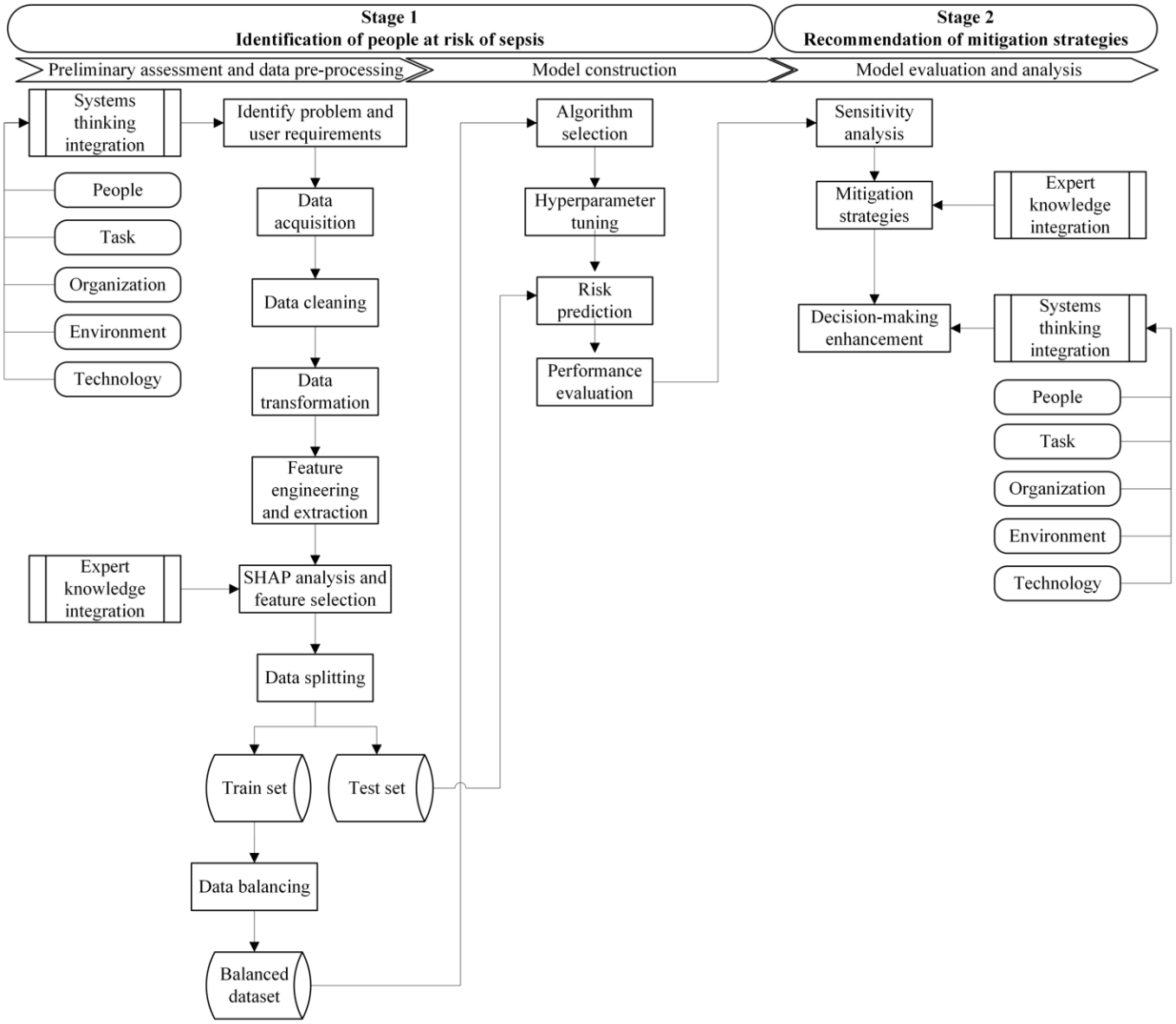
b. Two-stage Human-AI Decision Support (HADS) Framework



3.2 Dataset Characteristics

This study was designed using a retrospective cohort of patients with sepsis and non-sepsis admitted to the ICU. The data were obtained from the Medical Information Mart for Intensive Care (MIMIC-IV), a freely available database of ICU stays from 2008 to 2019, accessible via PhysioNet [31]. All patient data used in this study were de-identified in accordance with Health Insurance Portability and Accountability Act (HIPAA) guidelines [32] before analysis. Access to the MIMIC database is strictly controlled, requiring completion of a certified training program and approval

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of a data use agreement. Furthermore, for any potential deployment in clinical practice, compliance with institutional IRB policies would be ensured, along with the maintenance of secure audit trails for data usage. Variables were extracted based on their association with sepsis onset after brainstorming with healthcare providers, including physicians, nurses, and pharmacists.

The data included 21 variables: 3 demographic, 7 vital signs, 6 clinical, 2 sepsis bundlerelated, and 3 organizational. Data extracted from the EHR underwent several pre-processing steps before being formally analyzed and used for model development. The study focused on 74,567 patient records, including 2053 sepsis cases, for analysis to identify indicative features that can be used to train a BBN.

During brainstorming sessions, two physicians occasionally proposed differing views on the relevance of features. To resolve this, we employed analytical validation using Shapley Additive exPlanations (SHAP) values (Figure 2) and objectively assessed the suggested features. Since we used a public dataset to develop the model, we lack some variables that would guide us during data collection in the hospital for future work. The expert-driven feature importance is presented in Table 2 of the Supplementary Files I. The missing biomarkers, like ‘procalcitonin’ and ‘creatinine’, could partially be captured in the ‘comorbidity’ variable. The missing ‘white blood cell’ could be captured in rising ‘temperature’ often linked to infection, inflammation, and immune response. The missing ‘lactate’ marker could be captured in ‘lab_test_priority.’ Based on Table 2 in Supplementary 1, 78% of expert-driven features ranked highly in our feature importance analysis (as shown in Figure 2).

Handling imbalanced datasets is a critical challenge in ML, particularly in large-scale settings where one class or category substantially outnumbers the others. The data contains only 3% of sepsis cases, compared to 97% of non-sepsis cases. This imbalance can lead to biased models that favor the majority class and perform poorly on the minority class, as ML algorithms may

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struggle to learn effectively from the data. The Synthetic Minority Oversampling Technique (SMOTE) has gained recognition for addressing concerns related to imbalanced data [33]. By generating synthetic samples for the minority class, SMOTE helps balance the dataset and improves the model's ability to learn from the data effectively [34].

3.3 Bayesian Belief Networks

BBN is a valuable tool for modeling complex systems by representing probabilistic relationships between variables. It combines a Directed Acyclic Graph (DAG), which encodes conditional independence relationships, and Conditional Probability Tables (CPT), which quantify dependencies between nodes. Given a DAG with nodes $X_1, \dots, X_n$, the joint distribution factorizes as:

$$P(X_1, \dots, X_n) = \prod_{i=1}^{n} P(X_i | Parents(X_i)) \quad (1)$$

where $Parents(X_i)$ are the direct causes X_i in the graph. Each node is independent of its nondescendants given its parents according to the Markov property [37].

BBN uses probabilistic graphical models that integrate multifaceted clinical data from EHRs and lab results, enabling dynamic updates to sepsis risk probabilities. This method enables more precise prediction of sepsis onset than the hospital's existing EWS, facilitating early, targeted interventions. BBN approaches have been particularly effective in extracting meaningful insights from heterogeneous healthcare data, enabling the discovery of disease biomarkers and enhancing medical informatics applications [38]. Three notable learning approaches in BBN are Naive Bayes, Tree-Augmented Naive Bayes (TAN), and the Multivariate Information-based Inductive Causation (MIIC) [39]. This framework implemented the MIIC algorithm [40] to derive the DAG, chosen for its ability to (1) detect non-linear dependencies using mutual information $I(X, Y)$:

$$I(X, Y) = \sum_{x,y} P(x, y) \log \frac{P(x,y)}{P(x)P(y)} \quad (2)$$

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which the independence assumption of Naive Bayes fundamentally cannot capture. (2) MIIC enables robust causal discovery of clinically plausible pathways (for instance, identifying age as an upstream factor influencing blood pressure, which subsequently affects sepsis risk), while TAN's tree-structured dependencies impose artificial constraints on these relationships. (3) resolve edge orientation ambiguities via Bayesian Dirichlet equivalence (BDeu) scoring, which penalizes overly complex structures, thus avoiding overfitting:

$$BDeu(G, D) = \prod^{\$}{}_{\%\&!} \prod_{j=1}^{q_i} \frac{\Gamma(\alpha_{ij})}{\Gamma(\alpha_{ij}+N_{ij})} \prod_{k=1}^{r_i} \frac{\Gamma(\alpha_{ij}k+N_{ijk})}{\Gamma(\alpha_{ijk})} \quad (3)$$

This method is advantageous in scenarios where multiple models are plausible, as it systematically compares them based on their predictive performance [41]. Once the graph structure is learned, conditional probability tables (CPT) are estimated using maximum likelihood based on historical patient data. CPT was learned for robust parent configurations:

$$P(X_{\%} = x | Parents(\mathrm{X}_{\#}) = p) = \underline{\qquad\qquad} 567\$8567\$8(()9,9)) \quad (4)$$

After training, the BBN enables inference by updating probability distributions when new patient observations are made. Finally, the learned BBN is validated using test data, and adjustments are made to improve predictive accuracy.

4. Results

After outlining the proposed framework, the following section presents the evaluation results of the proposed approach. It starts with descriptive statistics and model interpretability through SHAP, continues with risk assessment using BBN, and concludes with robustness evaluation through sensitivity analysis.

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4.1 Descriptive statistics of the dataset and SHAP analysis

Descriptive statistics for the dataset are provided in the supplementary file. SHAP analysis was applied to identify the features that affect the prediction model. Figure 2 shows nine top features, including *drg_mortality, acuity, gender, systolic_blood_pressure, race, drg_severity, age, temperature_score, and transfer_to_ICU*. Each point represents an individual patient's data, with the horizontal axis indicating the SHAP value (i.e., the feature's impact on the model output) and the vertical axis listing the features in order of importance. Positive SHAP values indicate that the feature contributes to a higher risk of sepsis, while negative values suggest a lower predicted risk.

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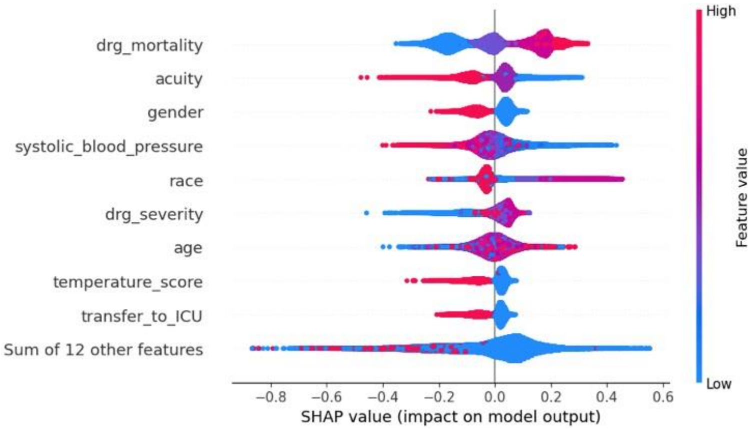
Figure 2. Interpretability of features importance by SHAP value



At the top, *drg_mortality, acuity,* and *gender* are the most influential predictors, indicating that mortality risk category, severity at admission, and patient sex are strongly associated with sepsis outcomes. The widespread points suggest significant variability in how these features impact predictions across patients. For example, higher acuity scores or mortality risk groups generally increase sepsis risk, while gender shows a mixed but noticeable effect. Vital signs and clinical measures, such as systolic blood pressure and temperature_score, also play crucial roles in sepsis prediction. The color gradient (red = high values, blue = low values) reveals how feature values influence the model. For instance, lower systolic blood pressure (blue) tends to shift predictions toward higher sepsis risk, consistent with hypotension being a key clinical sign of sepsis. Similarly, abnormal temperature scores (fever or hypothermia) have a substantial effect on predictions.

Demographic and care-related variables, such as age, race, and transfer_to_ICU, further influence the model’s decision-making. Older patients (red) are generally at higher risk, while ICU transfer status reflects the patient’s clinical trajectory, signaling more severe illness and a higher likelihood of sepsis. The “Sum of 12 other features” at the bottom aggregates additional variables with smaller but still meaningful contributions, reinforcing that sepsis prediction is multifactorial and benefits from incorporating diverse patient data.

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Collaborative discussions and brainstorming sessions with physicians are key to enhancing the predictive capabilities of models used in the HADS. By engaging in these dialogues, healthcare professionals can leverage their clinical expertise to identify and prioritize features to incorporate as predictors. These steps will guide the selection of suitable parameters for sepsis prediction before deploying a sepsis management system adapted to users' needs. It allows for the incorporation of expert knowledge and the updating of beliefs as new information becomes available, enhancing the system's adaptability and accuracy.

4.2 Risk prediction using Bayesian Belief Networks

The BBN in Figure 3 illustrates a probabilistic model that captures the relationships among several clinical variables related to sepsis outcomes. The nodes, represented by ovals, correspond to factors such as "antibiotic_prescription," "blood_culture," "comorbidity," "acuity," and "outcome," among others. The directed arrows between the nodes indicate conditional dependencies, showing how one variable influences another. For instance, "blood_culture," "lab_test_priority," and “comorbidity” have direct effects on "outcome." Similarly, "time_to_treatment" is influenced by multiple factors, such as "acuity" and "observation_per_hour." “acuity” is affected by "respiratory_rate_score," "o2saturation_score," and affects “transfer_to_ICU,” suggesting that these factors contribute to the severity of the condition and impact the overall prognosis. The "outcome" node appears to be the central variable, receiving inputs from various factors, including "blood_culture" and "diastolic_blood_pressure," suggesting it serves as the key predictor of patient prognosis. Additionally, operational decisions such as "time_to_treatment" affect "transfer_to_ICU," indicating that delays in administering appropriate antibiotics significantly increase the need for ICU transfer and mortality, underscoring the importance of timely, comprehensive care.

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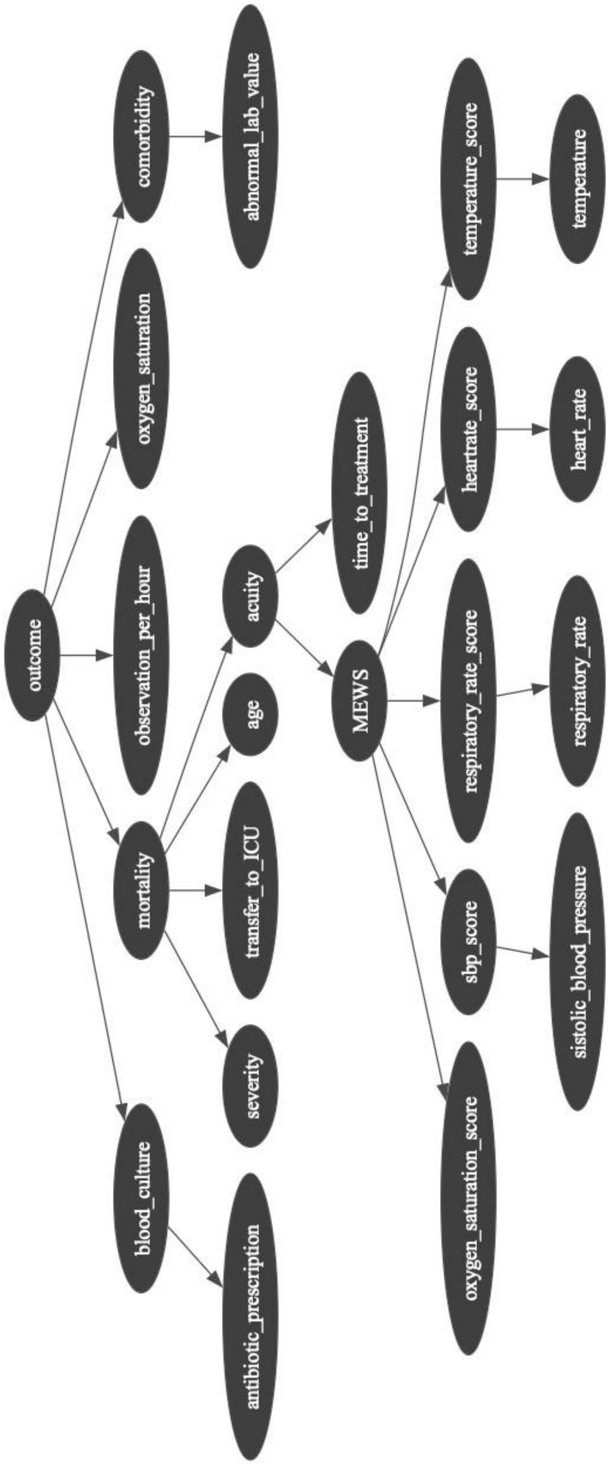
Figure 3. Bayesian Belief Networks of the proposed model



Bayesian inference refers to a method of statistical inference in which Bayes' theorem is used to update the probability estimate for a hypothesis as more evidence or information becomes available. It allows incorporating prior knowledge or beliefs into the analysis alongside the

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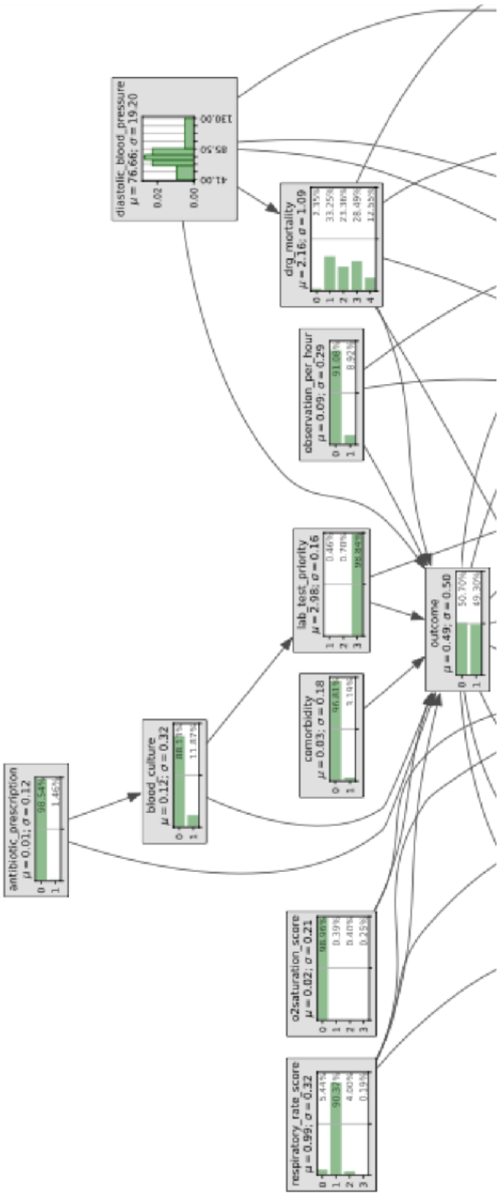
observed data. Figure 4 used Bayesian inference to assess the impact of predictors on sepsis outcome. This approach enables data analysis and parameter estimation, which are crucial for making informed decisions.

Figure 4. Bayesian inference of the proposed model (cont.)



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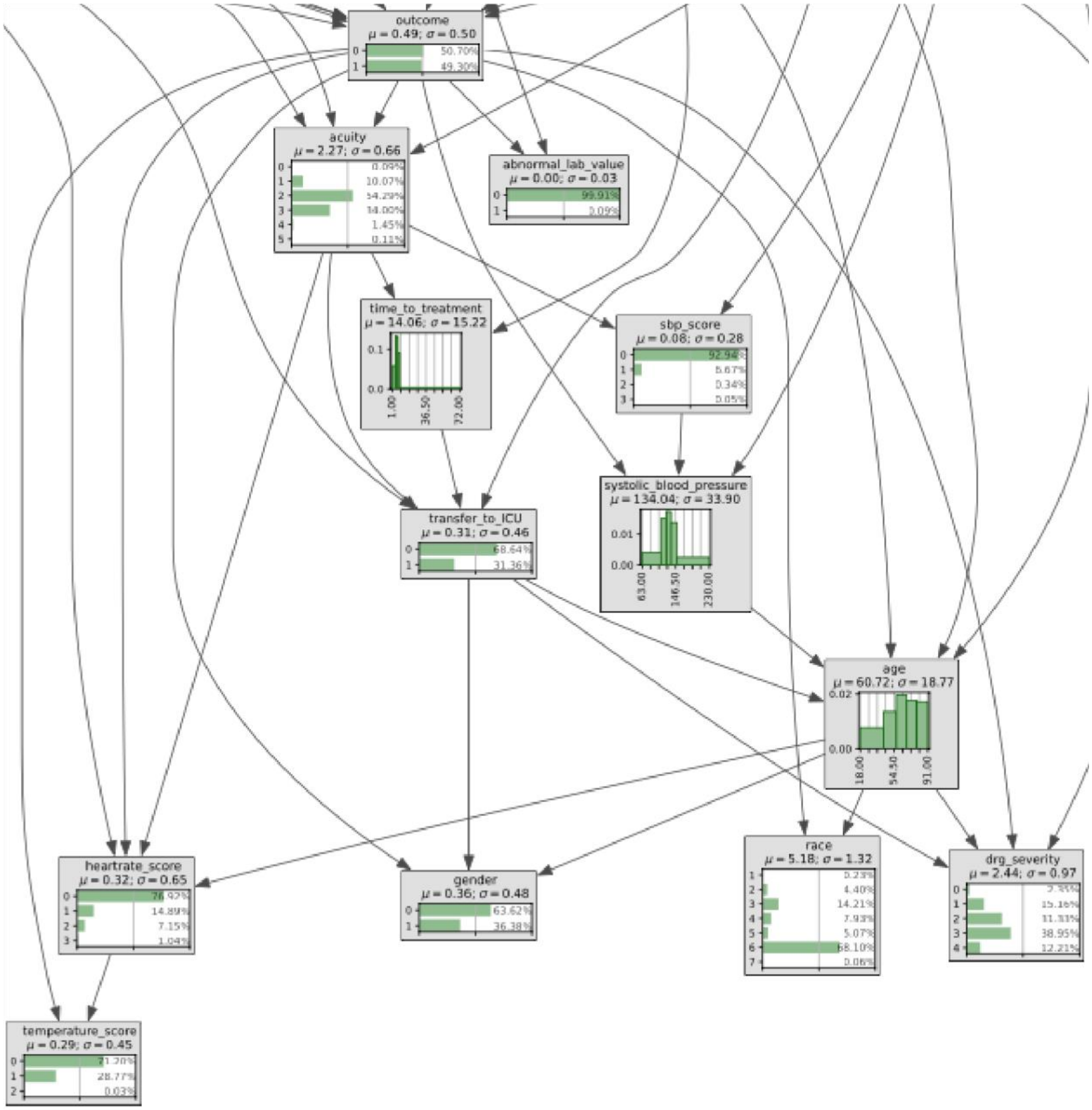

The Bayesian inference diagram in Figure 4 visualizes the probability distributions for each variable involved in predicting sepsis outcomes. Each box shows the probability of different states a variable can take and its mean (μ) and standard deviation (σ), quantifying the central tendency and variability. For example, the "antibiotic_prescription" variable has a mean of 0.01, which indicates a very low probability of antibiotics being prescribed in the dataset. However, it still has

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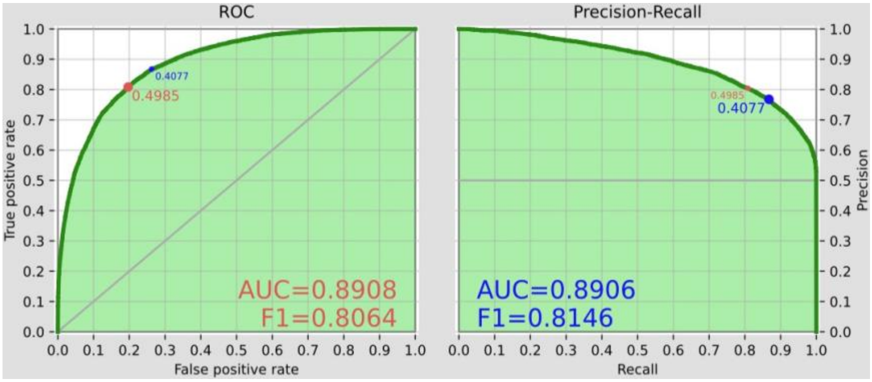
some variability, as shown by its standard deviation (σ = 0.12). This suggests that most patients in the model do not receive antibiotics, but the probability can vary under certain conditions.

Similarly, variables like "lab_test_priority" (μ = 2.98, σ = 0.16) and "blood_culture" (μ = 0.12, σ = 0.32) directly affect the "outcome," which is central to the model. The distribution for "outcome" shows the probability of different patient outcomes, ranging from recovery to worsening, based on influencing factors such as "comorbidity" (μ = 0.03), "observation_per_hour" (μ = 0.09), and "lab_test_priority" (μ = 2.98). The values in these variables indicate how each factor impacts the outcome and how probabilities shift depending on the patient's clinical profile.

The proposed model achieved an accuracy of 80.25% while its Area Under Curve (AUC) – Receiving Operating Characteristic (ROC) and AUC-Precision-Recall were 89%, as shown in Figure 5.

Figure 5. Performance metrics of the proposed model



We also applied several ML algorithms: Linear Regression (LR), decision tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), eXtreme Gradient Boosting (XGBoost), Random Forest (RF), and Gradient Boosted Decision Trees (GBDT) as a baseline to prove that the proposed model is better than the others. The comparison results for the other ML algorithms, the existing model, and the proposed HADS model are shown in Figure 6. The proposed BBN-based

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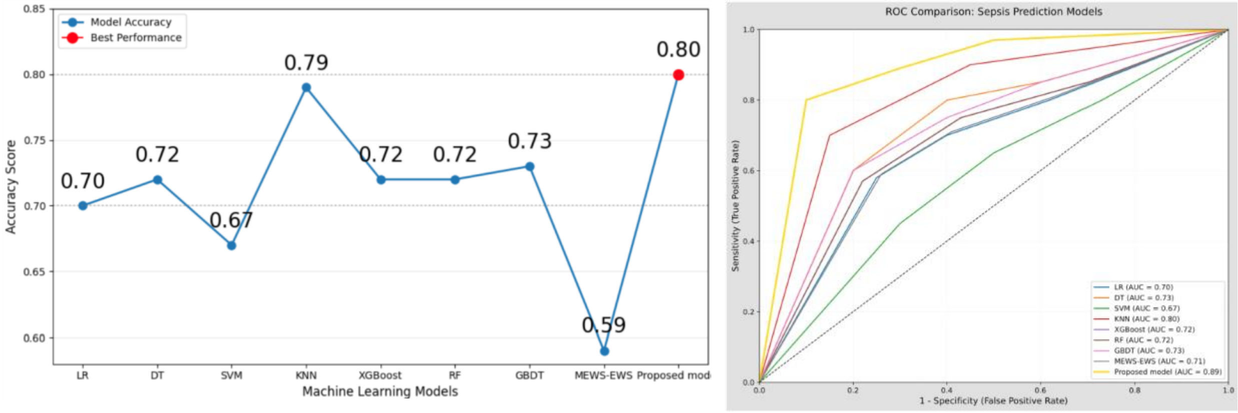
model achieves superior accuracy and ROC performance compared to traditional ML models, particularly in domains where probabilistic reasoning and uncertainty modeling are critical [42]. The proposed model outperformed the other algorithms, achieving the highest accuracy of 80% and an AUC-ROC of 89%. It explicitly captures dependencies and conditional probabilities among variables, making them highly interpretable and robust.

Figure 6. Performance metrics for the sepsis model



a. Model accuracy comparison

b. ROC comparison for sepsis prediction model

BBN excels at structured decision-making, incorporating prior knowledge and dynamically updating beliefs in light of new evidence, leading to more stable and reliable predictions [62]. Additionally, while tree-based models and SVMs may suffer from overfitting or require extensive hyperparameter tuning, BBN naturally balances complexity through probabilistic inference [45]. Their ability to model causal relationships rather than just associations allows them to generalize better, leading to improved ROC curves, especially in real-world scenarios with noisy or incomplete data [46].

A confusion matrix is a vital tool for evaluating the performance of classification models. It provides a detailed breakdown of how well a model's predictions align with actual outcomes, showing the counts of true positives, true negatives, false positives, and false negatives. As shown

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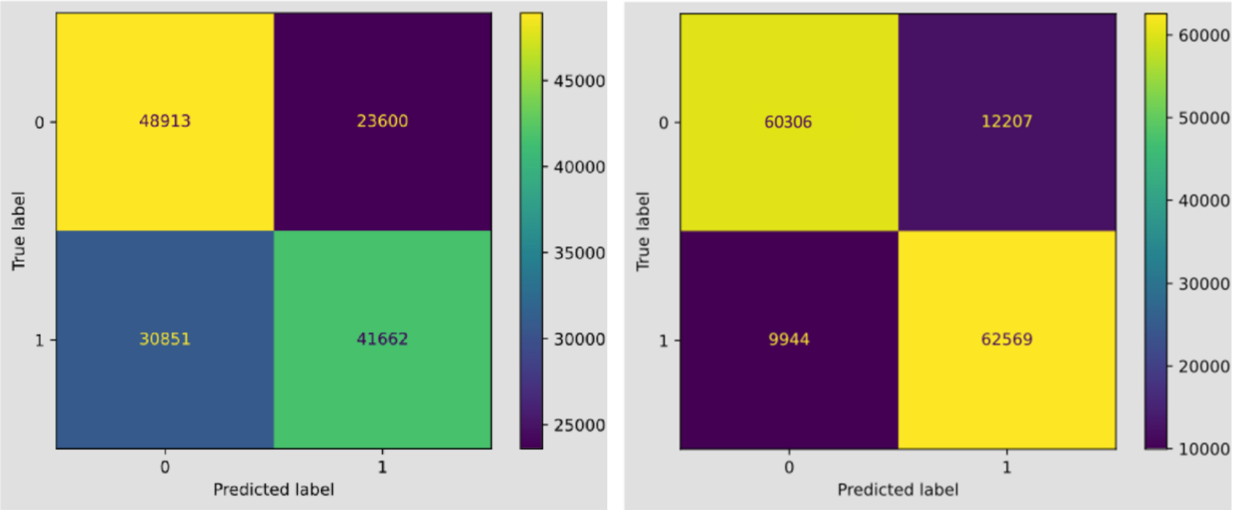
in Figure 7, the HADS model appears to outperform other models in overall classification performance. It has fewer false positives and false negatives than the MEWS-based EWS. This could indicate that the HADS model is better at identifying both classes and may provide a more balanced prediction across the dataset. The false-positive rate for the HADS framework is 12,207, a 78% decrease compared to the existing EWS, which generates 23,600 false positives.

Furthermore, the results show a 67% reduction in false negatives, from 30,851 to 9,944 alarms.

Figure 7. Confusion matrix of BBN



a. Confusion matrix of MEWS-based EWS b. Confusion matrix of HADS

If a sepsis patient is caused by a bacterial infection, every hour that passes before antibiotics are administered increases the risk of mortality by 8% [47]. Consequently, physicians often prescribe antibiotics preemptively, even before confirming the infection's cause, to mitigate potential risks. However, this practice can lead to unnecessary antibiotic administration when the infection is not bacterial, contributing to antibiotic resistance and increased healthcare costs. Based on our estimates, the reduction in the number of false positives is 11.393 patients, and the antibiotic cost is $42,67 [48] per dose per patient. The cost-reduction analysis of unnecessary antibiotic administration is $486,139.3.

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4.3 Sensitivity Analysis

Sensitivity analysis in sepsis risk prediction identifies which clinical variables most strongly influence sepsis likelihood, guiding clinicians to prioritize critical factors in diagnosis and treatment. Because sepsis is multifactorial, affected by age, comorbidities, infection type, and organ function, highlighting the most sensitive variables helps improve data accuracy and monitoring. This enhances model reliability, supports timely interventions, and optimizes resource allocation in critical care.

Table 1 presents the sensitivity analysis for key features, including antibiotic prescription, blood culture, oxygen saturation, and hourly observation. Age, race, and gender were fixed, as these variables influenced others but were not themselves affected. The sensitivity analysis evaluates deviations from a normalized baseline of 50% (representing a neutral reference point) to the observed outcome values in Figure 4. This baseline was chosen to standardize comparisons across variables and highlight relative trends.

Table 1. Sensitivity analysis under different clinical scenarios

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Scenario	Description	Effect on Sepsis Probability
1. Antibiotic prescription	Early antibiotics signal suspected infection; delays increase the likelihood of severe sepsis or septic shock.	Probability decreased from 50% to **21.2%** when antibiotics were prescribed promptly. Early intervention improves survival, but stewardship is essential to prevent overuse.
2. Blood culture collection	Detects pathogens in the bloodstream to confirm diagnosis and guide targeted therapy. Timely sampling ensures appropriate treatment initiation.	Probability decreased from 50% to **30.2%** when blood cultures were collected early. It enables faster diagnosis, while delays prolong empirical therapy and risk treatment mismatch.
saturation	Maintaining oxygen saturation ≥95% correlates with better outcomes. Levels below 92% may indicate respiratory compromise requiring urgent intervention.	Probability increased from 50% to **70.9%** when oxygen levels dropped. Rapid recognition and escalation of care, such as oxygen supplementation or mechanical ventilation, are critical to prevent organ failure.
4. Hourly Observation	Continuous or hourly monitoring allows early detection of clinical deterioration and rapid response.	Probability decreased from 50% to **20%** with consistent monitoring. Frequent assessment improves early recognition of sepsis progression and enhances timely decision-making.

5. Discussion and Conclusions

5.1 Contributions of the Study

Integrating human expertise with AI-driven tools is essential for optimizing sepsis management, as timely intervention directly affects patient survival [49]. While AI has demonstrated transformative potential across various industries and domains, its application in healthcare enables

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rapid analysis of large clinical datasets to identify early signs of sepsis and provide timely alerts to clinicians [50]. However, human oversight remains indispensable for contextualizing AI predictions, differentiating sepsis from similar conditions, and making ethically informed decisions [51]. This collaboration reduces diagnostic delays, limits false alarms, and supports sound clinical judgment in critical settings.

The HADS framework introduces a two-stage, systems-thinking approach to sepsis management that integrates expert clinical knowledge with advanced analytics. Using BBN to represent uncertainty and model complex risk interactions, HADS outperforms traditional MEWSbased systems in accuracy, ROC performance, and reductions in false alarms and clinician fatigue. By decreasing false positives and negatives, it facilitates earlier intervention, particularly through timely antibiotics, blood cultures, oxygen monitoring, and hourly patient assessments, all of which are vital to survival.

Sepsis management faces four significant uncertainties: clinical, data, modeling, and prognostic, which stem from patient variability, incomplete or noisy data, and ambiguous diagnoses [52]. BBN addresses these challenges by incorporating prior knowledge, estimating missing values, and dynamically updating probabilities as new data emerge. Sensitivity analysis highlights key variables such as oxygen saturation ≥95% as protective factors, while continuous updates enhance prognostic confidence and decision accuracy.

Results indicate the probability of developing sepsis decreases from 50% to 21.2% with antibiotics, to 30.2% with blood cultures, and to 20% with consistent monitoring. Conversely, it rises to 70.9% when oxygen saturation falls. These findings underscore how AI-assisted systems can guide targeted interventions, improving outcomes and optimizing resource allocation.

Beyond prediction, HADS promotes collaboration and learning. It integrates BBN-driven insights with clinicians' expertise, emphasizing communication across care teams and fostering

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systems-wide improvement [53]. Brainstorming sessions help refine predictive models and align them with clinical realities, reinforcing both accuracy and usability [54]. For healthcare leaders, implementing HADS enhances patient-specific, context-aware decision-making, strengthens adherence to clinical standards, and cultivates a culture of data-informed, compassionate care.

5.2 Implications for Theory and Practice

Developing a framework to enhance decision-making in sepsis management requires both theoretical and practical considerations. Table 2 compares EWS and HADS, highlights the limitations of static alert systems, and demonstrates how HADS provides adaptive, interpretable, and collaborative decision support. A future comparison between unaided clinical judgment and BBN-assisted decisions could further quantify their benefits. The key contribution here is introducing HADS as a system-level framework that augments human judgment and supports transparent, team-based decision-making in sepsis care.

Table 2. Comparison between the HADS Framework and MEWS-based EWS

Aspect	**Human-AI Decision Support (HADS) Framework**	**MEWS-based Early Warning System (EWS)**
Implementation	Requires alignment with organizational policies and workflow integration	Focuses on technical deployment without needing organizational changes [55]
User Training	Extensive training for staff across different roles	Training limited to system users, typically IT and healthcare professionals [56]
Interdisciplinary Collaboration	Involves collaboration among clinicians, administrators, IT staff, and data scientists	Primarily involves collaboration between IT staff and data scientists [57]
Adaptability	Can be adapted to specific organizational needs and practices	Adaptability depends on the system's flexibility and the ability to update algorithms [58]
Cost	Higher initial cost due to training, integration, and collaboration efforts across organizational level	Lower initial cost, mainly involving software and hardware [59]

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Data Integration	Integrates with multiple organizational data sources (EHR, lab systems, expert knowledge)	Relies on predefined data sources [60]
Decision-Making Support	Supports clinical decision-making within the context of organizational processes and protocols	Provides decision support based on data and algorithms, independent of organizational context [61]
User Acceptance	May face resistance from staff due to changes in workflow and responsibilities	Generally easier to accept by users as it does not affect the current workflow [62]
Outcome Measurement	Evaluated based on clinical outcomes and organizational impact	Evaluated primarily on technical performance metrics like accuracy and response time [63]

Streamlining sepsis care is essential to reducing mortality and improving patient outcomes. Clinical decisions typically depend on experience, protocols, and team coordination; HADS strengthens these by offering real-time, data-driven insights. Its predictive capabilities reduce false alerts, support early intervention, and generate patient-specific recommendations through Bayesian inference. With interpretable outputs, clinicians can integrate AI-generated evidence with human expertise, improving communication and shared understanding. Acting as both a decision-support and communication layer, HADS enhances collaboration without disrupting workflows. Moreover, by making AI reasoning transparent, it engages patients and families in care decisions, increasing satisfaction and trust.

Ongoing education is essential to ensure consistent adherence to sepsis protocols and effective use of the system. Maintaining model accuracy requires continuous data updates and validation informed by clinical feedback. Balancing automation with human oversight remains crucial. Table 3 outlines the managerial implications of HADS for both large and small hospitals across various domains, with corresponding KPI.

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Table 3. Managerial Implications of HADS for Big and Small Hospitals

Domain	Implications for Big Hospitals	Implications for Small Hospitals	KPI to track
Training and adoption	Role-based simulations (ED, ICU, wards); additional module inside EHR	Brief in-service training and silent deployment	Training completion, post-training alert handling time
Quality and safety programs	Incorporate HADS into sepsis quality dashboards reported to the executives	Use HADS as early screening to meet bundle compliance without adding staff	LOS, in-hospital mortality, 30-day readmissions
Financial	ROI from reduced false positives affecting fewer unnecessary lab order	Prioritize wards with highest sepsis incidence for phased rollout	Cost per sepsis case, antibioticcost reduction, cost saving from LOS reduction
Lab Operations	Ensure on-hand sepsis bundle kits and rapid antibiotics access	Provide a pre-package sepsis bundle kits to achieve the golden hour	Stock-outs, time-to-treatment
Risk and ethics	Maintain audit trails for every alert and action, document human rationale when overriding AI recommendations	Audit the alert → action → outcome in EHR notes	% alerts with documented rationale, external review findings
Change management	Hospital-wide implementation supported by EHR vendor	One-ward pilot, then hospital-wide	Adoption rate, resolution time, Plan-Do-Check-Action cycle

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Implementing HADS for sepsis management carries clear managerial implications across governance, workforce, operations, and quality domains. Leadership should form a multidisciplinary team to establish a human-in-the-loop escalation protocol and calibrate BBN thresholds to local risk profiles. Because HADS enhances accuracy and reduces false positives, managers can adopt *alert fatigue reduction* as a key performance indicator (KPI) and reallocate staff time from reactive alert handling to proactive patient care.

Further, training programs should focus on interpreting BBN-based explanations, preventing automation bias [64], and embedding rapid treatment workflows, such as early antibiotics, blood cultures, and hourly assessments, into standardized order sets. Operationally, reliable access to antibiotics and culture kits must be ensured through real-time inventory tracking and coordinated supply management. Incorporating antimicrobial stewardship within this process helps balance early empiric therapy with the long-term goal of minimizing resistance.

From a management perspective, implementing a live dashboard to track KPI, such as timeto-antibiotic, adherence to sepsis bundles, alert precision, ICU transfers, and mortality, enables accountability and continuous improvement. Finally, privacy, cybersecurity, and liability policies should be reviewed to align with AI deployment in clinical settings. Managed this way, HADS becomes a systems-thinking upgrade that enhances timeliness, safety, and trust while driving a measurable improvement in organizational performance and patient outcomes.

5.3 Limitations and Future Research

This study has several limitations. First, although potential implementation barriers such as financial costs, training needs, and staff resistance were discussed, they were not quantitatively analyzed, limiting the practical assessment of feasibility. Future research should measure these barriers, including economic, human resource, and adoption-related factors, to better evaluate implementation readiness.

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Second, the effectiveness of HADS depends on the quality and representativeness of its training data. AI models often rely on historical datasets that may not capture diverse patient populations, introducing bias and reducing accuracy for underrepresented groups [65]. Sepsis's dynamic progression also demands real-time data integration, yet delays in data processing remain a technical challenge. Ethical and privacy concerns further complicate deployment; without transparency, AI recommendations could undermine clinician–patient trust or autonomy. Addressing these risks requires secure data management, explainable outputs, and diverse training datasets to enhance fairness and accountability.

Future work should focus on algorithm optimization, data integration, and clinical applicability. Incorporating natural language processing (NLP) can improve the use of unstructured clinical notes, enriching model insights. Advancements in explainable AI (XAI) will also be critical for increasing clinician trust and for integrating XAI into workflows [66]. Enhancing interoperability through standardized data formats and communication protocols will support seamless adoption across health systems.

Continuous model validation across diverse datasets beyond the MIMIC-IV database will strengthen generalizability and robustness. Collaborative platforms for sharing AI models, clinical feedback, and best practices could accelerate large-scale deployment. Overall, ongoing interdisciplinary research and regulatory guidance are essential to ensure HADS remains transparent, reliable, and equitable across diverse healthcare settings.

Funding

Not applicable

References

[1] L. Evans *et al.*, "Surviving Sepsis Campaign: International Guidelines for Management of Sepsis and Septic Shock 2021," *Critical Care Medicine*, vol. 49, no. 11, pp. e1063–e1143, Nov. 2021, doi: 10.1097/CCM.0000000000005337.

[2] J. Prest, T. Nguyen, T. Rajah, A. B. Prest, M. Sathananthan, and N. Jeganathan, "Sepsis-

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Related Mortality Rates and Trends Based on Site of Infection," *Critical Care Explorations*, vol. 4, no. 10, p. e0775, Oct. 2022, doi: 10.1097/CCE.0000000000000775.

[3] J. X. Moore, J. P. Donnelly, R. Griffin, G. Howard, M. M. Safford, and H. E. Wang, "Defining Sepsis Mortality Clusters in the United States*," *Critical Care Medicine*, vol. 44, no. 7, pp. 1380–1387, July 2016, doi: 10.1097/CCM.0000000000001665.

[4] A. Pfuntner, L. M. Wier, and C. Steiner, "Costs for Hospital Stays in the United States, 2011," in *Healthcare Cost and Utilization Project (HCUP) Statistical Briefs*, Rockville (MD): Agency for Healthcare Research and Quality (US), 2006. Accessed: Sept. 27, 2024. [Online]. Available: http://www.ncbi.nlm.nih.gov/books/NBK179289/

[5] W. Augutis, T. Flenady, D. Le Lagadec, and E. Jefford, "How do nurses use early warning system vital signs observation charts in rural, remote and regional health care facilities: A scoping review," *Australian Journal of Rural Health*, vol. 31, no. 3, pp. 385–394, June 2023, doi: 10.1111/ajr.12971.

[6] V. Liu *et al.*, "Hospital Deaths in Patients With Sepsis From 2 Independent Cohorts," *The Journal of the American Medical Association*, vol. 312, no. 1, p. 90, July 2014, doi: 10.1001/jama.2014.5804.

[7] M. Ayvaci, Z. Mobini, and Ö. Özer, "To Catch A Killer: A Data-Driven Personalized and Compliance-Aware Sepsis Alert System," *SSRN Journal*, 2021, doi: 10.2139/ssrn.3805931.

[8] J. Ghossein, B. N. Hryciw, and K. Kyeremanteng, "Redefining sepsis management: The comprehensive impact of artificial intelligence," *Journal of Intensive Medicine*, vol. 5, no. 2, pp. 134–136, Apr. 2025, doi: 10.1016/j.jointm.2024.08.002.

[9] K. Katsaliaki and S. Kumar, "The Past, Present, and Future of the Healthcare Delivery System Through Digitalization," *IEEE Engineering Management Review.*, vol. 50, no. 4, pp. 21–33, Dec. 2022, doi: 10.1109/EMR.2022.3223112.

[10] A. Bennett and N. Kallus, "Proximal Reinforcement Learning: Efficient Off-Policy Evaluation in Partially Observed Markov Decision Processes," *Operations Research*, vol. 72, no. 3, pp. 1071–1086, May 2024, doi: 10.1287/opre.2021.0781.

[11] M. Holland and J. Kellett, "The United Kingdom's National Early Warning Score: should everyone use it? A narrative review," *Internal and Emergency Medicine*, vol. 18, no. 2, pp. 573–583, Mar. 2023, doi: 10.1007/s11739-022-03189-1.

[12] P. Barbrook-Johnson and A. S. Penn, "Bayesian Belief Networks," in *Systems Mapping*, Cham: Springer International Publishing, 2022, pp. 97–112. doi: 10.1007/978-3-03101919-7_7.

[13] Z. Noroozi, A. Orooji, and L. Erfannia, "Analyzing the impact of feature selection methods on machine learning algorithms for heart disease prediction," *Scientific Reports*, vol. 13, no. 1, p. 22588, Dec. 2023, doi: 10.1038/s41598-023-49962-w.

[14] D. F. Barbieri *et al.*, "Systems-based framework for clinical decision-support system integration for patient sepsis management: A theoretical application of the SEIPS model," *Human Factors in Healthcare*, vol. 7, p. 100098, June 2025, doi: 10.1016/j.hfh.2025.100098.

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[15] M. Rababa, D. Bani Hamad, and A. A. Hayajneh, "Sepsis assessment and management in critically Ill adults: A systematic review," *PLoS ONE*, vol. 17, no. 7, p. e0270711, July 2022, doi: 10.1371/journal.pone.0270711.

[16] R. Al-Nammari, M. C. E. Simsekler, A. F. Gabor, and A. Qazi, "Exploring Drivers of Staff Engagement in Healthcare Organizations Using Tree-Based Machine Learning Algorithms," *IEEE Transaction on Engineering Management*, vol. 70, no. 8, pp. 2988–2997, Aug. 2023, doi: 10.1109/TEM.2022.3209879.

[17] K. Katsaliaki, S. Kumar, and P. Galetsi, "Health Technology Assessment Framework for Certification of mHealth Apps," *IEEE Engineering Management Review*, pp. 1–21, 2025, doi: 10.1109/EMR.2025.3622048.

[18] 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, Sept. 2024, doi: 10.1016/j.jnlssr.2024.04.003.

[19] G. Wardi, R. Owens, C. Josef, A. Malhotra, C. Longhurst, and S. Nemati, "Bringing the Promise of Artificial Intelligence to Critical Care: What the Experience With Sepsis Analytics Can Teach Us," *Critical Care Medicine*, vol. 51, no. 8, pp. 985–991, Aug. 2023, doi: 10.1097/CCM.0000000000005894.

[20] Y. Yang *et al.*, "Research on the death risk prediction model for patients with sepsis based on machine learning," *Interdisciplinary Nursing Research*, vol. 4, no. 2, pp. 83–90, June 2025, doi: 10.1097/NR9.0000000000000092.

[21] L. Polster, V. Bilgram, and S. Görtz, "AI-Augmented Design Thinking: Potentials, Challenges, and Mitigation Strategies of Integrating Artificial Intelligence in HumanCentered Innovation Processes," *IEEE Engineering Management Review*, pp. 1–36, 2024, doi: 10.1109/EMR.2024.3512866.

[22] C. M. Van Leersum and C. Maathuis, "Human centred explainable AI decision-making in healthcare," *Journal of Responsible Technology*, vol. 21, p. 100108, Mar. 2025, doi: 10.1016/j.jrt.2025.100108.

[23] S. Zilker, S. Weinzierl, M. Kraus, P. Zschech, and M. Matzner, "A machine learning framework for interpretable predictions in patient pathways: The case of predicting ICU admission for patients with symptoms of sepsis," *Health Care Management Science*, vol. 27, no. 2, pp. 136–167, June 2024, doi: 10.1007/s10729-024-09673-8.

[24] B. Ruyobeza, S. S. Grobbelaar, and A. Botha, "Toward a Framework for Interweaving Adoption and Scaling Requirements Into Healthcare System Development and Project Management Processes," *IEEE Engineering Management Review*, vol. 53, no. 2, pp. 96–109, Apr. 2025, doi: 10.1109/EMR.2024.3412795.

[25] C. Y. Elgin and C. Elgin, "Ethical implications of AI-driven clinical decision support systems on healthcare resource allocation: a qualitative study of healthcare professionals' perspectives," *BMC Medical Ethics*, vol. 25, no. 1, p. 148, Dec. 2024, doi: 10.1186/s12910024-01151-8.

[26] L. Tomkins and A. Bristow, "Evidence-based practice and the ethics of care: 'What works' or 'what matters'?," *Human Relations*, vol. 76, no. 1, pp. 118–143, Jan. 2023, doi: 10.1177/00187267211044143.

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[27] B. Maqbool and S. Herold, “Potential effectiveness and efficiency issues in usability evaluation within digital health: A systematic literature review,” *Journal of Systems and Software*, vol. 208, p. 111881, Feb. 2024, doi: 10.1016/j.jss.2023.111881.

[28] X. Aizaga-Villon, K. Alarcon-Ballesteros, J. Cordova-Garcia, V. S. Padilla, and W. Velasquez, “FIWARE-Based Telemedicine Apps Modeling for Patients’ Data Management,” *IEEE Engineering Management Review*, vol. 50, no. 2, pp. 173–188, June 2022, doi: 10.1109/EMR.2022.3169991.

[29] A. Zhou, R. Beyah, and R. Kamaleswaran, “OnAI-Comp: An Online AI Experts Competing Framework for Early Sepsis Detection,” *IEEE/ACM Transaction on Computational Biology and Bioinformatics*, vol. 19, no. 6, pp. 3595–3603, Nov. 2022, doi: 10.1109/TCBB.2021.3122405.

[30] P. Papareddy *et al.*, “Transforming sepsis management: AI-driven innovations in early detection and tailored therapies,” *Critical Care*, vol. 29, no. 1, p. 366, Aug. 2025, doi: 10.1186/s13054-025-05588-0.

[31] A. Johnson, L. Bulgarelli, T. Pollard, S. Horng, L. A. Celi, and R. Mark, “MIMIC-IV.” PhysioNet. doi: 10.13026/6MM1-EK67.

[32] H. Subramanian, A. Sengupta, and Y. Xu, “Patient Health Record Protection Beyond the Health Insurance Portability and Accountability Act: Mixed Methods Study,” *Journal of Medical Internet Research*, vol. 26, p. e59674, Nov. 2024, doi: 10.2196/59674.

[33] R. Hassanzadeh, M. Farhadian, and H. Rafieemehr, “Hospital mortality prediction in traumatic injuries patients: comparing different SMOTE-based machine learning algorithms,” *BMC Medical Research Methodology*, vol. 23, no. 1, p. 101, Apr. 2023, doi: 10.1186/s12874-023-01920-w.

[34] Y. Feng, C. H. Roney, J. D. Bayer, S. A. Niederer, M. Hocini, and E. J. Vigmond, “Detection of focal source and arrhythmogenic substrate from body surface potentials to guide atrial fibrillation ablation,” *PLoS Computational Biology*, vol. 18, no. 3, p. e1009893, Mar. 2022, doi: 10.1371/journal.pcbi.1009893.

[35] P. Barbrook-Johnson and A. S. Penn, “Bayesian Belief Networks,” in *Systems Mapping*, Cham: Springer International Publishing, 2022, pp. 97–112. doi: 10.1007/978-3-03101919-7_7.

[36] S. Albreiki, M. C. E. Simsekler, A. Qazi, and A. Bouabid, “Assessment of the organizational factors in incident management practices in healthcare: A tree augmented Naive Bayes model,” *PLoS ONE*, vol. 19, no. 3, p. e0299485, Mar. 2024, doi: 10.1371/journal.pone.0299485.

[37] P. Fuster-Parra, A. M. Yañez, A. López-González, A. Aguiló, and M. Bennasar-Veny, “Identifying risk factors of developing type 2 diabetes from an adult population with initial prediabetes using a Bayesian network,” *Frontiers in Public Health*, vol. 10, p. 1035025, Jan. 2023, doi: 10.3389/fpubh.2022.1035025.

[38] R. J. Turner, K. Hagoort, R. J. Meijer, F. Coenen, and F. E. Scheepers, “Bayesian network analysis of antidepressant treatment trajectories,” *Scientific Reports*, vol. 13, no. 1, p. 8428, May 2023, doi: 10.1038/s41598-023-35508-7.

[39] Z. Ghahramani, “Probabilistic machine learning and artificial intelligence,” *Nature*, vol.

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521, no. 7553, pp. 452–459, May 2015, doi: 10.1038/nature14541.

[40] R. E. Neapolitan, "Learning Bayesian networks," in *Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining*, San Jose California USA: ACM, Aug. 2007, pp. 1–1. doi: 10.1145/1327942.1327961.

[41] L. Verny, N. Sella, S. Affeldt, P. P. Singh, and H. Isambert, "Learning causal networks with latent variables from multivariate information in genomic data," *PLoS Computational Biology*, vol. 13, no. 10, p. e1005662, Oct. 2017, doi: 10.1371/journal.pcbi.1005662.

[42] N. Kumaraswamy, T. Ekin, C. Park, M. K. Markey, J. C. Barner, and K. Rascati, "Using a Bayesian Belief Network to detect healthcare fraud," *Expert Systems with Applications*, vol. 238, p. 122241, Mar. 2024, doi: 10.1016/j.eswa.2023.122241.

[43] A. Al Nuairi, M. C. E. Simsekler, A. Qazi, and A. Sleptchenko, "A data-driven Bayesian belief network model for exploring patient experience drivers in healthcare sector," *Annals of Operations Research*, vol. 342, no. 3, pp. 1797–1817, Nov. 2024, doi: 10.1007/s10479023-05437-9.

[44] A. Qazi, M. C. E. Simsekler, and M. K. S. Al-Mhdawi, "Prioritizing Indicators for Rapid Response in Global Health Security: A Bayesian Network Approach," *International Journal of Disaster Risk Science*, vol. 15, no. 4, pp. 536–551, Aug. 2024, doi: 10.1007/s13753-024-00570-w.

[45] A. Qazi, M. C. E. Simsekler, and M. K. S. Al-Mhdawi, "Bayesian network and structural equation modeling of dependencies between country-level sustainability risks and logistics performance," *Annals of Operations Research*, Jan. 2024, doi: 10.1007/s10479-023-05723-6.

[46] A. Qazi, M. C. E. Simsekler, and S. Formaneck, "Supply chain risk network value at risk assessment using Bayesian belief networks and Monte Carlo simulation," *Annals of Operations Research*, vol. 322, no. 1, pp. 241–272, Mar. 2023, doi: 10.1007/s10479-02204598-3.

[47] S. Kc, "Management of sepsis in acute care," *Strategic Management Journal*, vol. 63, no. 1, pp. 5–9, Jan. 2022, doi: 10.11622/smedj.2022023.

[48] Enhance Health, "How Much Do Antibiotics Cost Without Insurance?" February 12. [Online]. Available: https://enhancehealth.com/blog/how-much-do-antibiotics-cost-withoutinsurance/

[49] C. Yin, P.-Y. Chen, B. Yao, D. Wang, J. Caterino, and P. Zhang, "SepsisLab: Early Sepsis Prediction with Uncertainty Quantification and Active Sensing," in *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, Barcelona Spain: ACM, Aug. 2024, pp. 6158–6168. doi: 10.1145/3637528.3671586.

[50] D. O'Reilly, J. McGrath, and I. Martin-Loeches, "Optimizing artificial intelligence in sepsis management: Opportunities in the present and looking closely to the future," *Journal of Intensive Medicine*, vol. 4, no. 1, pp. 34–45, Jan. 2024, doi: 10.1016/j.jointm.2023.10.001.

[51] M. T. Chua *et al.*, "The role of artificial intelligence in sepsis in the Emergency Department: a narrative review," *Annals of Translational Medicine*, vol. 13, no. 1, pp. 4–4, Feb. 2025, doi: 10.21037/atm-24-150.

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[52] R. K. Chakraborty and B. Burns, "Systemic Inflammatory Response Syndrome," in *StatPearls*, Treasure Island (FL): StatPearls Publishing, 2025. Accessed: Feb. 10, 2025. [Online]. Available: http://www.ncbi.nlm.nih.gov/books/NBK547669/

[53] D. La Torre, C. Colapinto, I. Durosini, and S. Triberti, "Team Formation for HumanArtificial Intelligence Collaboration in the Workplace: A Goal Programming Model to Foster Organizational Change," *IEEE Transactions on Engineering Management*, vol. 70, no. 5, pp. 1966–1976, May 2023, doi: 10.1109/TEM.2021.3077195.

[54] W. Glover, Q. Li, E. Naveh, and M. Gross, "Improving Quality of Care Through Integration in a Hospital Setting: A Human Systems Integration Approach," *IEEE Transactions on Engineering Management*, vol. 64, no. 3, pp. 365–376, Aug. 2017, doi: 10.1109/TEM.2017.2682267.

[55] G. J. Escobar *et al.*, "Piloting electronic medical record–based early detection of inpatient deterioration in community hospitals," *Journal of Hospital Medicine*, vol. 11, no. S1, Nov. 2016, doi: 10.1002/jhm.2652.

[56] S. Upadhyay and H.-F. Hu, "A Qualitative Analysis of the Impact of Electronic Health Records (EHR) on Healthcare Quality and Safety: Clinicians' Lived Experiences," *Health Serv Insights*, vol. 15, p. 11786329211070722, 2022, doi: 10.1177/11786329211070722.

[57] G. Bastian, G. H. Baker, and A. Limon, "Bridging the divide between data scientists and clinicians," *Intelligence-Based Medicine*, vol. 6, p. 100066, 2022, doi: 10.1016/j.ibmed.2022.100066.

[58] E. G. Desalegn, M. J. C. Guedes, J. F. Da Silva Gomes, and S. M. Tebeka, "Disentangling organizational agility from flexibility, adaptability, and versatility: a systematic review," *Futur Bus J*, vol. 10, no. 1, p. 117, Dec. 2024, doi: 10.1186/s43093-024-00405-6.

[59] T. Donovan, B. Abell, M. Fernando, S. M. McPhail, and H. E. Carter, "Implementation costs of hospital-based computerised decision support systems: a systematic review," *Implementation Sci*, vol. 18, no. 1, p. 7, Feb. 2023, doi: 10.1186/s13012-023-01261-8.

[60] D. An, M. Lim, and S. Lee, "Challenges for Data Quality in the Clinical Data Life Cycle: Systematic Review," *Journal of Medical Internet Research*, vol. 27, p. e60709, Apr. 2025, doi: 10.2196/60709.

[61] J. Brunner, E. Anderson, D. C. Mohr, A. Cohen-Bearak, and S. T. Rinne, "From 'Local Control' to 'Dependency': Transitions to Single-Vendor Integrated Electronic Health Record Systems and Their Implications for the EHR Workforce," *Journal of General Internal Medicine*, vol. 38, no. S4, pp. 1023–1030, Oct. 2023, doi: 10.1007/s11606-02308281-6.

[62] J. Luo *et al.*, "Role of perceived ease of use, usefulness, and financial strength on the adoption of health information systems: the moderating role of hospital size," *Humanities and Social Sciences Communications*, vol. 11, no. 1, p. 516, Apr. 2024, doi: 10.1057/s41599-024-02976-9.

[63] E. Ha *et al.*, "Evaluating the Usability, Technical Performance, and Accuracy of Artificial Intelligence Scribes for Primary Care: Competitive Analysis," *JMIR Human Factors*, vol. 12, pp. e71434–e71434, July 2025, doi: 10.2196/71434.

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[64] 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*, July 2024, doi: 10.1016/j.jnlssr.2024.06.001.
[65] M. Tatar, S. Farokhi, A. A. Foumani, E. Uzunlar, and O. M. Araz, “Application of Gemini in Public Health Amid the Artificial Intelligence Era,” *IEEE Engineering Management Review*, pp. 1–13, 2025, doi: 10.1109/EMR.2025.3577913.
[66] 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 Medical Informatics and Decision Making*, vol. 24, no. 1, p. 337, Nov. 2024, doi: 10.1186/s12911-024-02758-y.

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