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PERSPECTIVES

The Role of Artificial Intelligence in Managing Central Line-Associated Bloodstream Infection (CLABSI) for Patient Safety and Quality of Care

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Abstract: Central Line-Associated Bloodstream Infections (CLABSI) pose significant challenges in healthcare systems globally, contributing to increased morbidity, mortality, and healthcare costs. As healthcare organizations strive to improve patient safety and quality of care, Artificial Intelligence (AI) presents considerable promise in the prevention, detection, and management of CLABSI. This paper proposes a conceptual framework that integrates AI within healthcare systems, aligning technological innovations with human workflows, system design, and risk management strategies. By taking a systems approach, the framework supports the implementation of AI tools in ways that are compatible with the complexity of healthcare delivery. The paper explores the potential and significance of AI in enhancing healthcare through the prevention, early detection, and management of patient safety concerns, including CLABSI. It highlights how AI applications can predict infection risks, support timely interventions, and operate in tandem with standard infection control protocols to reduce the incidence of CLABSI. This integrated approach aims to promote safer, more efficient, and patient-centered care.

Keywords: CLABSI, central line-associated bloodstream infection, artificial intelligence, patient safety, risk management, quality of care

Introduction

Healthcare-associated infections (HAIs) encompass a wide range of infections that patients may acquire during the course of treatment for other conditions within a healthcare setting, often due to factors such as invasive procedures, compromised immunity, prolonged hospital stays, or the use of medical devices like central lines, ventilators, and urinary catheters.[1] Central line-associated bloodstream infection (CLABSI), ventilator-associated pneumonia (VAP), and catheter-associated urinary tract infection (CAUTI) are a few examples of HAIs that cause a significant burden on patient health and healthcare systems. In the United States (US) alone, 1 in 31 patients develop HAIs daily, leading to an annual death toll of 72,000. In addition, Meta-analyses have estimated the annual cost of HAIs in the US to be almost $10 billion.[2]

Among the HAIs, CLABSI stands out for its significant implications for morbidity, mortality and economic impact. It is associated with mortality rates ranging from 12% to 25% and an estimated cost of approximately $45,000 per case, largely driven by prolonged hospitalization and intensive medical care 3. Recently, the COVID19 pandemic exacerbated the situation, causing a 47% increase in CLABSI standardized infection ratios (SIRs) in the US between 2019 and 2020.[3] This increase was attributed to factors such as decreased frequency of patient contact, longer durations of hospitalization, and staffing changes. While central lines are commonly used for administering certain medications, fluids, and obtaining blood samples, particularly in intensive care settings or for patients requiring long-term intravenous access,[4] they are not universally required for all such interventions. Therefore, it is crucial to implement stringent infection control practices in

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the care and maintenance of central lines (eg, maximal sterile barrier precautions during insertion[5] and standardized care bundles[6]) to minimize the risk of associated infections.

Traditional initiatives like the CLABSI Prevention Registered Nurse (PRN) program at a private teaching hospital in Denver, Colorado, US, have shown promise in addressing CLABSI challenges by emphasizing education, standardized care, and patient-centered outcomes.[3] The program provided 24 hours of focused training on central line care and maintenance to create a specialized nurse role, significantly reducing CLABSI rates. Despite its success, the high costs and time required for training, and the risk of system bottlenecks or reliance on a few specialized individuals, could potentially create single points of failure in the infection control process.

Despite the serious consequences of CLABSIs and the considerable efforts to reduce their occurrence, including financial penalties by the Centers for Medicare and Medicaid Services, an estimated 30,100 CLABSI cases still occur annually in the US.[7] This ongoing challenge highlights the urgent need for innovative, patient-centered solutions, with Artificial Intelligence (AI) offering a promising approach to address the issue. Integrating multidisciplinary frameworks and advanced risk assessment tools has shown significant potential in improving safety in critical care settings.[8]

The role of AI in healthcare has grown rapidly in recent years with the availability of large-scale multimodal data and advancements in computational models and algorithms.[9] AI techniques offer promising potential in managing complex HAIs, such as CLABSI. By leveraging AI, healthcare providers (HCPs) can potentially identify high-risk patients, optimize prevention strategies, and enhance monitoring and response to CLABSI occurrences.

This paper explores the role of AI in managing CLABSI, with a focus on its potential to enhance patient safety and healthcare quality. It begins with a review of recent literature on AI applications in the prediction, detection, and prevention of CLABSI. Building on this foundation, the paper introduces a systems-based methodology for designing an AI-driven decision support framework that emphasizes the integration of people, systems, design principles, and risk management strategies. A comprehensive framework is then proposed for implementing AI across the CLABSI care continuum, addressing key deployment challenges and identifying opportunities for future research. The paper concludes by synthesizing the contributions of the framework and underscoring the importance of adaptable, ethically grounded AI solutions to improve outcomes in intensive care settings.

Literature Review

An earlier study explored the role of supervised machine learning and deep learning approaches in predicting CLABSI and mortality rates in patients admitted to intensive care units (ICU).[7] The authors employed the common Multiparameter Intelligent Monitoring in Intensive Care (MIMIC) III database that contains the medical records of more than 46,500 admitted cases in the US. Comparisons among algorithms, including logistic regression, gradient boosted trees, and deep learning, highlight the efficacy of deep learning in predicting mortality and central line placement, while logistic regression emerges as the most effective for predicting CLABSI among ICU patients. The findings reveal a mortality rate of 10.1% among ICU patients, with 38.4% receiving central line placement. Deep learning classifiers exhibited superior performance, achieving high area under the curve (AUC) scores for mortality prediction (0.885) and central line placement (0.816). These findings hold significant implications for decision-makers by showing that AI-based tools can enhance prediction accuracy while improving the quality of services and reducing operational costs.

Pai et al gathered data from a cohort of 5199 patients admitted to the ICU, among whom 1647 individuals developed CLABSI, while the remainder developed non-bloodstream infections.[10] The data was collected at Taichung Veterans General Hospital from 2015 to 2019. The study employed five different machine-learning models to predict CLABSI cases. The findings suggested that alkaline phosphatase (ALKP) and central venous catheter (CVC) period as key predictors and indicators for bloodstream infections. In addition, the findings highlighted that the random forests model produced the highest prediction accuracy with an area under the receiver operating characteristic (AUROC) curve of 0.855 and 0.851 for the validation and testing datasets, respectively. Moreover, the study provided information on the appropriate cut-off laboratory values for bloodstream infection diagnostics and how varying these cut-off thresholds would affect the model accuracy. The authors argued that leveraging AI tools to manage CLABSI would result in better predictions, enabling timely and more efficient treatments.

In a recent article, researchers sought to predict impending CLABSIs in hospitalized cardiac patients.[11] Using a machine-learning model, specifically a random forest classification, researchers aimed to predict which patients admitted to the cardiac ICU or cardiac ward at Boston Children's Hospital would develop a CLABSI within 24 hours of admission. Data collection spanning January 2010 to August 2020 included variables related to infection occurrence from patients with CVCs admitted to specified units, excluding those with bacterial endocarditis. The study encompassed 104,035 patient-days and 139,662 line-days from 7468 unique patients, with 399 positive blood cultures, predominantly *Staphylococcus aureus* as the pathogen. Key predictors of CLABSI included prior infection history, elevated heart rate and temperature, increased C-reactive protein levels, parenteral nutrition exposure, and alteplase use for CVC clearance. The predictive model successfully identified 25% of positive cultures with a false-positive rate (FPR) of 0.11% and AUC of 0.82. This study represents an initial step toward developing a CLABSI alert system to enhance current practices, potentially improving patient outcomes and contributing to cost savings.

A recent systematic review aimed to thoroughly evaluate evidence-based interventions designed to prevent and reduce the incidence of CLABSIs in adult intensive care settings.[12] The review concentrates on attaining a zero-incidence rate of CLABSIs, with a focus on applying positive displacement needleless connectors. The scope of the analysis includes research published from January 2016 through June 2020, with a specific emphasis on adult ICU environments. The review's findings highlight the practicality of achieving a zero-incidence rate of CLABSIs through the strategic implementation of positive displacement needleless connectors, with a suite of supplementary interventions. These additional measures encompass the deployment of checklists and vigilant monitoring of the central line care bundle, the introduction of silver-impregnated dressings, the continuous education of ICU staff, bedside monitoring in real-time, and the compulsory reporting of CLABSI occurrences. While the systematic review did not focus on AI interventions, its findings hold crucial implications for nursing practice and policy. They emphasize the importance of strict adherence to infection control standards and evidence-based practices to lower CLABSI rates, ultimately reducing healthcare expenditures. Moreover, the review stresses the critical need to integrate CLABSI prevention protocols into nursing curricula to bolster the knowledge and clinical expertise in the domain of infection prevention and control.

Further, researchers, in another study, developed a machine learning algorithm (MLA) aimed at predicting the likelihood of CLABSI development before central line placement during a patient's hospital stay.[13] This MLA utilizes electronic health record (EHR) data, minimizing disruption to clinical workflows. The study employed three supervised machine learning classifiers: XGBoost (XGB), logistic regression, and decision tree models. These classifiers retrospectively analyzed EHR data from 27,619 patient encounters. XGBoost emerged as the top performer, achieving an AUROC curve of 0.762 for CLABSI risk prediction 48 hours post-central line placement. By identifying at-risk patients, improving monitoring, modifying treatments, and reducing infection rates, this approach ultimately leads to enhanced patient outcomes and cost savings. These models offer early indicators of patient susceptibility to CLABSI post-central line placement, aiding clinical decision-making through risk-based patient stratification. This process addresses the lack of tools for CLABSI risk stratification and facilitates proactive management and prevention of CLABSIs in clinical settings. The gaps and limitations of the study include further validation in live clinical settings and the tuning of machine learning algorithm parameters to individual hospitals.

Moreover, Beeler et al emphasized the pivotal role of real-time monitoring and prediction in reducing hospital stay time and costs associated with CLABSI.[14] Therefore, the authors utilized the data from three tertiary hospitals in the US to develop various random forest models to predict CLABSI. The best-performing model was found to produce an AUROC curve of 0.82. These models support decision-makers in efficiently allocating resources for CLABSI prevention by identifying high-risk patients who would benefit from timely interventions most. This approach can enhance patient care quality and mitigate healthcare costs.

Another previous investigation presented a comprehensive exploration of the application of AI in HAI surveillance.[15] The study aims to enhance surveillance, improve laboratory diagnosis, and educate on hand hygiene within the realm of infection prevention and control (IPC). Through the evaluation of AI tools such as OpenAI's ChatGPT Plus (GPT-4) and the Mixtral 8×7b-based local model, the research shows the potential of AI in accurately identifying HAIs, particularly CLABSI and CAUTI. Findings reveal that while AI demonstrates proficiency in detecting HAIs with clear prompts, challenges arise with ambiguous inputs, highlighting the necessity of clear communication and human oversight.

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Furthermore, the study elucidates AI's role in epidemiology, laboratory diagnosis, and hand hygiene education, emphasizing the need for prospective evaluation in real-world clinical settings and close collaboration with IPC experts to ensure clinical relevance. The implications of AI in HAI surveillance extend to healthcare efficiency, quality improvement, resource allocation, and educational value, suggesting its potential to significantly enhance healthcare outcomes and operational efficiency when integrated judiciously into IPC measures.

A prior study conducted between 2015 and 2017 in two adult tertiary care hospitals in the US aimed to implement and sustain evidence-based behaviors and practices to reduce annual CLABSI.[16] Employing an agile implementation model, the authors systematically identified areas for potential enhancement and thoroughly reviewed the literature to identify the most effective evidence-based practices in mitigating the problem. Moreover, the model utilizes AI tools to identify non-value-added activities and problems that result in wasting resources. This methodological approach highlights the healthcare system within the hospital as a Complex Adaptive System (CAS), facilitating a better understanding of the hospital's capacity to adjust to dynamic environments. The study reported a significant reduction in CLABSI rate from 1.76 to 1.24 per 1000 days, resulting in higher quality and more efficient healthcare services. Table 1 summarizes the range of challenges and AI solutions aimed at addressing CLABSI, as outlined in the reviewed literature.

The table showcases a diversity of predictive models and systematic interventions employed to mitigate the risks and impacts of CLABSIs. Notable among these are the use of deep learning, logistic regression, and random forests, which have demonstrated high predictive accuracies for CLABSI occurrences and patient outcomes in ICUs. These models

Table 1 Comparative Analysis of AI Solutions for Predicting and Preventing CLABSI

Objective	Contribution	Limitation	Ref
Predicting CLABSI in ICU patients	Deep learning and logistic regression models for mortality and central line placement	Used International Classification of Diseases, 9th Revision (ICD-9) codes for identifying CLABSI, introducing potential coding errors, and relied on retrospective data from the MIMIC III database, which may contain errors	[7]
Predicting CLABSI in ICU patients	Random forests model using clinical data achieved high prediction accuracy	Relied on a slightly imbalanced dataset from a single medical center. Analysis excludes ICU stays under 96 hours.	[10]
Early detection of CLABSI in cardiac patients	Random forest classification model to predict CLABSI occurrence within 24 hours of admission; potential for CLABSI alert system development	Retrospective, single-center study, susceptible to practice evolutions over time.	[11]
Prevention of CLABSIs in adult ICU settings	Evidence-based interventions including positive displacement needleless connectors, education, and monitoring	Does not focus on AI interventions, lacked randomized controlled trials.	[12]
Early prediction of CLABSI risk prior to central line placement	Machine learning algorithms (XGB, logistic regression, decision tree) analyzing EHR data; XGB showed highest prediction accuracy	Relied on ICD codes with poor sensitivity for CLABSI detection, used retrospective data	[13]
Efficient allocation of resources for CLABSI prevention	Random forest models to predict CLABSI; real-time monitoring to identify high-risk patients	Uses line-days which may inflate risk values, learning based on NHSN definitions may not reflect true infection rates.	[14]
Improvement in HAI surveillance, including CLABSI	Use of Large Language Models (LLMs) (including GPT-4) for enhanced HAI detection and surveillance, emphasizing the need for clear communication and human oversight	Relied on fictitious scenarios instead of real medical records.	[15]
Reducing CLABSI rates in hospitals	AI model using CAS framework and behavioral economics for system optimization and tailored intervention.	Conducted at a single academic institution limiting generalizability.	[16]

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leverage large-scale databases and patient records to enhance prediction and treatment protocols. Systematic interventions highlighted in the table include the implementation of the AI model employing the CAS framework to identify non-value-added activities and tailor evidence-based solutions to the unique environment of healthcare settings. However, the limitations outlined indicate potential biases from retrospective data, reliance on ICD coding, which may lack sensitivity, and challenges in generalizing findings across different healthcare settings. Ultimately, these studies showcase the potential of integrating AI and machine learning into healthcare practices to improve predictive accuracy, optimize resource allocation, and enhance patient outcomes in the fight against CLABSIs.

Methodology: A Systems Approach

The design and development of an AI-driven decision support framework for CLABSI management necessitates a comprehensive and systematic approach to ensure effectiveness, safety, and adherence to ethical standards. The systems approach offers a robust methodology for addressing complex problems such as CLABSI by considering the entire ecosystem in which these problems exist.[17] This approach is characterized by four key components: people, systems, design, and risk, as visualized in Figure 1.[18] Each component plays a vital role in the framework's development and operationalization:

1) People: Identifies who will use the AI system within CLABSI management, including HCPs, patients, and administrative personnel. It locates the system within various healthcare environments where it will be deployed and situates it within the complex dynamics of healthcare interactions.
2) Systems: Understands the roles of different stakeholders interacting with the system. It organizes the technological and organizational infrastructures, including data management systems and existing healthcare IT infrastructure, and integrates these components to ensure seamless interaction between the systems and the AI tools.
3) Design: Explores the specific needs of the end-users of the AI system in the context of CLABSI management. It creates not only the technical aspects of the system, such as algorithms and models, but also the user interface and experience design, ensuring usability, accessibility, and efficacy.
4) Risk: Examines the current procedures in CLABSI management, assesses the potential risk factors, and proposes improvements to mitigate these risks.

Adopting a systems approach ensures a holistic consideration of the complex interdependencies within healthcare settings.[19] It aids in the creation of a decision support framework that is not only technologically advanced but also socially acceptable and institutionally integrable. This methodology section will delve deeper into each of these

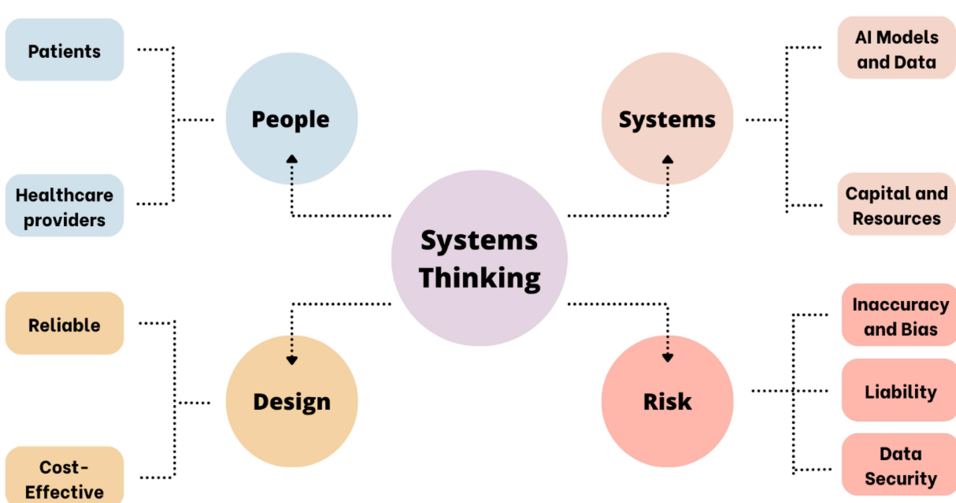

Figure 1 Conceptual framework of the systems approach.

components, detailing how they contribute to the development of a comprehensive, effective, and ethically sound AI-driven framework for managing CLABSI.

People

In addressing the people aspect of the systems approach, it is crucial to identify the key stakeholders who will interact with and utilize the AI system within CLABSI management. These stakeholders include patients, HCPs such as physicians, nurses, administrative personnel, and infection control specialists, who are responsible for diagnosing, treating, and preventing CLABSI cases. HCPs rely on AI tools to enhance decision-making processes, optimize treatment plans, and improve patient outcomes. Patients, on the other hand, as the recipients of care, may benefit from AI-driven interventions that facilitate early detection and prevention of CLABSI. Their engagement in the prevention and management process is essential for the successful implementation of AI-driven solutions. Additionally, administrative personnel, such as hospital administrators and information technology staff, are responsible for overseeing the integration of AI technologies into existing healthcare systems, ensuring smooth operation, and monitoring outcomes.

The AI system is situated within various healthcare environments, such as hospitals, and long-term care facilities, where CLABSI management is a critical concern. As the system is deployed in these settings, it is essential to consider the complex dynamics of healthcare interactions, including interdisciplinary collaboration, communication, and decision-making processes. Understanding the roles and responsibilities of each stakeholder group, as well as the barriers and facilitators affecting their ability to use the AI system, is crucial for its successful implementation. Further, factors such as organizational culture, workflow processes, resource availability, and stakeholder engagement influence how the AI system is utilized and integrated into the overall healthcare framework. By addressing the questions of who will use the system, where the system will be deployed, and the factors affecting the system, we can ensure that the AI-driven solution for CLABSI management is tailored to the unique needs and challenges of the healthcare sector, ultimately improving patient outcomes and reducing the burden of CLABSI on healthcare systems.

Systems

This part of the systems approach deals with organizing and integrating various entities, including people, Information Technology (IT), and data warehouses, to ensure seamless interaction among them. In this context, one major step is considering the stakeholders of the proposed system and understanding their needs, notions, and requirements.[20] In our system, the main stakeholders are the patients, HCPs, staff, and management. Moving to other elements of the system that need to be addressed and understood and to highlight the importance of identifying the elements of the decision-making process, a study was conducted to review system elements affecting the disposition decision-making in the emergency room.[21]

In the proposed model, different elements need to be considered collectively in a holistic view. For instance, budgetary constraints, the procurement of medical equipment and devices, training and workshops for the HCPs are all elements that should be considered in the system. Finally, in this step, a deep understanding of the interactions between the previously discussed stakeholders and elements must occur. The integrated system description must abide by the output of previous steps by utilizing the components and elements of the system to achieve the intended outcomes. The representation of the interactions among the system's elements is crucial for understanding system behavior, dependencies, and relationships. For instance, the hospital management will be concerned with different medical equipment, data, and budgetary constraints. Also, resistance to change will be faced by patients, staff, and HCPs. Training and culture adoption will have to be presented by physicians and care providers. The mechanism of how the system performs should be communicated in various ways, including graphical representation. Flowcharts, Unified Language Modeling (UFL), Entity-Relationships Diagrams (ERD), and Network Diagrams are effective tools for communicating how systems work. The role of graphical representation is essential in discovering and communicating value by understanding the current state, and stakeholders' prospects.[22]

Design

The third section of the system thinking framework is design. This section mainly explores the needs and requirements for framework development and investigates how these needs are met and how well they are met. The examined literature expressed the urgent need for a more efficient and patient-centric approach to managing CLABSI.[9] This will reduce the risk associated with confirmed CLABSI cases. In addition, Scardoni et al emphasized that it is pivotal for HCPs to develop a more cost-effective approach for dealing with and managing CLABSI.[2] Accomplishing that allows for better understanding of CLABSI and the complexities associated with preventing and managing it. To accomplish these needs, there is a need for a better understanding of the role of AI in managing CLABSI, developing tailored AI algorithms for predicting and detecting CLABSI and integrating AI with clinical expertise to make better data-driven decisions. Lastly, assessing how well the needs are met is a crucial part of the design phase in the system thinking approach. Therefore, there is a need to develop specific, measurable metrics and criteria such as the time needed to identify a CLABSI case, the percentage of reduction in CLABSI cases, the mortality rate associated with CLABSI, the cost of managing a CLABSI case from detection to full recovery. Additionally, the implemented AI models and algorithms must be refined and updated regularly to boost their accuracy and performance.

Risk

CLABSI management encompasses prevention, detection, and resolution, involving rigorous infection control protocols, such as strict hand hygiene, barrier precautions during catheter insertion, and continuous surveillance. Integrating AI into such critical healthcare processes aims to enhance efficiency and efficacy but also introduces significant challenges. These include issues related to data quality, model accuracy, and system integration that must be constantly monitored.

AI models may inaccurately predict potential CLABSI cases, which can result in bypassed prevention protocols or misdiagnoses. In critical healthcare settings like the ICU, such errors could delay necessary interventions, worsening patient conditions and possibly resulting in fatal outcomes. The lack of generalization in datasets is a glaring limitation of the discussed literature. Models trained on retrospective data from single clinics may not perform well universally due to dataset shifts, a phenomenon where models underperform post-deployment due to discrepancies between training environments and real-world application contexts.[23] Furthermore, data breaches could expose sensitive patient information to unauthorized individuals or malicious actors, undermining trust, and compliance with privacy laws. Moreover, legal and ethical challenges arise when AI-driven decisions result in patient harm, complicating the determination of liability, especially with the lack of patient consent. Finally, integration risks include resistance from healthcare staff, inadequate training on new systems, and the potential for increased workload due to dual management systems.

To mitigate these risks, it is essential to validate and enhance the AI models using diverse, multi-site datasets and clinical trials to improve generalization. These models must also continually adapt to new data and clinical advances. Strengthening cybersecurity measures is critical to protect patient data, while maintaining clinical oversight ensures that AI supports, rather than replaces, professional judgment. Addressing ethical concerns involves clear guidelines for transparency and accountability. Effective integration of AI requires comprehensive training for all end-users and fostering a culture that values both technological advancements and traditional healthcare principles. By implementing these strategies, the potential of AI to enhance CLABSI management can be realized while ensuring safety, efficacy, and ethical compliance.

Proposed Framework

The proposed framework starts with explaining the role of AI in managing CLABSI and how AI can be integrated with clinical expertise to provide a more efficient and patient-centric healthcare system. This framework consists of three primary stages: prevention, detection, and management. In the prevention stage, patients are classified based on their probability of developing CLABSI. This allows HCPs to take proactive early measures to prevent infection. The detection stage focuses on patients who were not initially predicted to be at risk but later exhibit clinical indicators suggestive of CLABSI such as fever, chills, hypotension, or abnormal laboratory results (eg, elevated white blood cell count, positive blood cultures).[24] These symptoms and signs are typically documented through routine clinical observations, diagnostic tests, and EHR inputs. AI tools are employed to identify CLABSI and provide the necessary information to allow physicians to make a data-informed decision. Lastly, the management stage identifies high-risk patients, allowing for better resource allocation and prioritization and developing personalized treatment plans. Figure 2 provides a clear illustration of the developed framework.

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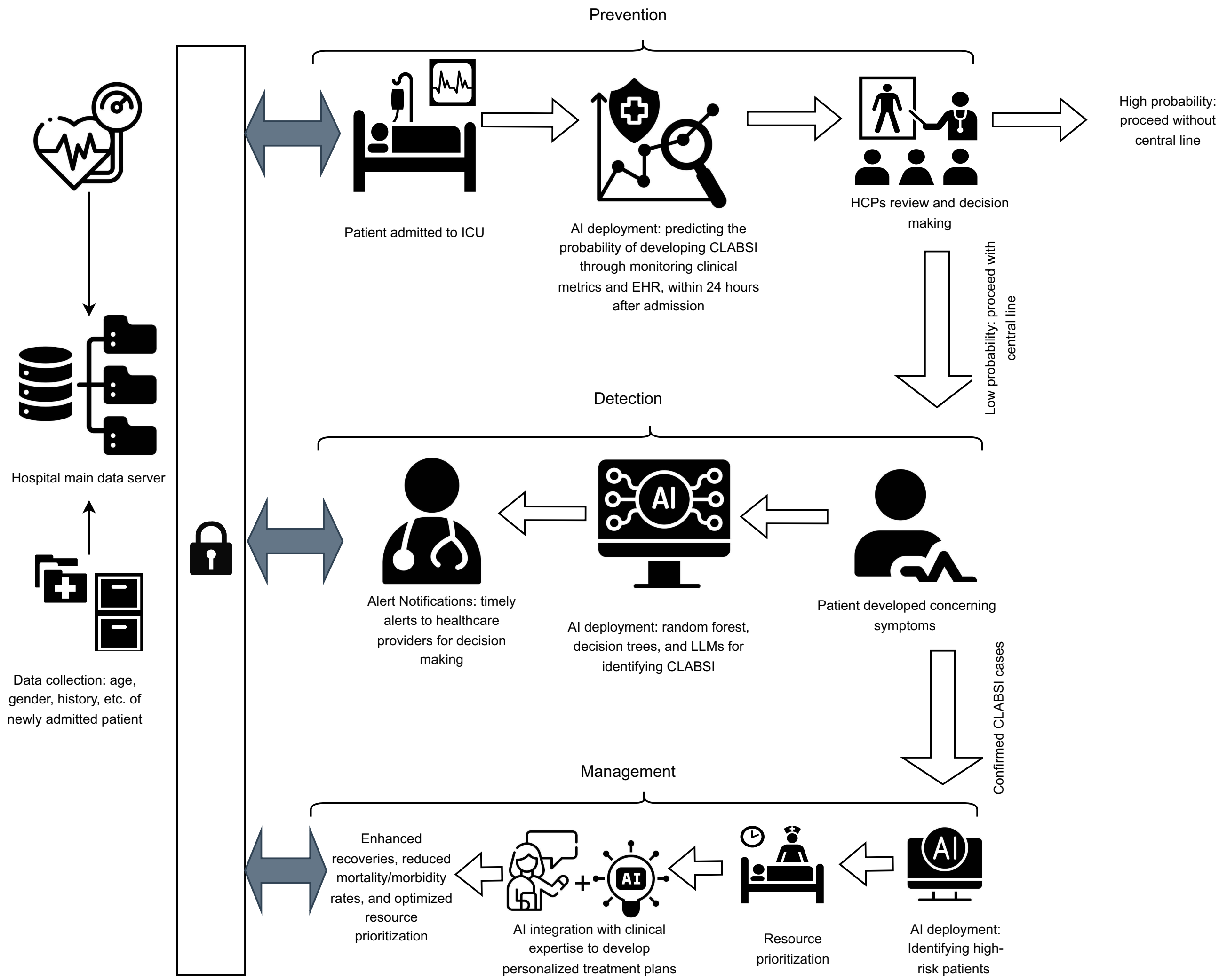

Figure 2 Proposed framework for the role of AI in managing CLABSI.

Prevention

The prevention stage of our proposed AI-driven solution framework focuses on proactive measures to mitigate the risk of CLABSI in newly admitted ICU patients who are scheduled for central line placement. Utilizing historical EHR alongside real-time ICU monitoring data, our framework employs deep learning, logistic regression, and random forest models discussed in the literature review[7,11,13] to predict the likelihood of CLABSI development. These models integrate data securely stored in the hospital's data systems, ensuring robust data protection.

The system of joint models assesses the probability of developing CLABSI within 24 hours of admission to the ICU and classifies cases as high risk when they exceed a predetermined probability threshold. When a high risk of infection is predicted, the system generates real-time alerts via the HER system or clinical communication platforms. These alerts are directed not only to attending physicians but also to the broader clinical care team, including nurse practitioners (NPs), physician assistants (PAs), and covering providers, based on the current assignment and availability of care team members. The alerts include relevant clinical data points such as elevated temperature, white blood cell count, catheter placement time, and vital sign trends. This ensures timely awareness and action, even in situations where the primary physician is off-duty or care has been transitioned to another provider, thus, maintaining a crucial human element in the decision loop to counteract potential risks associated with automation reliance and model inaccuracies in practical applications. This stage not only anticipates CLABSI occurrence but also empowers HCPs with actionable insights, significantly enhancing patient safety and care efficiency.

Detection

The detection stage of our proposed AI-driven solution framework is critical for the early identification of CLABSI as they occur. This stage begins when a patient who passes the prevention stage exhibits the symptoms, previously discussed, that could indicate an infection. Employing AI tools to analyze real-time data streams from clinical monitoring systems and laboratory results, our framework uses a combination of random forests, decision trees, and LLMs, as highlighted in our literature review.[10,15] These models not only accurately predict but also provide a level of explainability, aiding HCPs in their diagnostic processes with crucial insights. Upon detecting potential signs of CLABSI, the AI system promptly alerts clinical teams (infectious disease specialists, infection prevention practitioners, or critical care physicians) to further assess the situation. This prompt detection is vital as it allows for the immediate allocation of specialized personnel to confirm the presence of CLABSI, ensuring swift intervention. Should a CLABSI case be confirmed, it signals a transition to the management stage; however, it also indicates a miss in our prevention stage, marking the incident as a false negative. This instance is subsequently fed back into the hospital's secure database. Such cases are invaluable for retraining our prediction models, enhancing their accuracy, and adapting to dataset shifts.

Integrating human verification into this process is critical for managing accountability and reducing automation bias. Moreover, rapid AI-driven detection and preliminary diagnosis save valuable time for HCPs, making this approach cost-effective. It expedites the diagnosis process, allowing for quicker responses that can potentially reduce the duration of infection and associated healthcare costs. The detection stage not only improves patient outcomes by enabling timely interventions but also contributes to the overall cost-effectiveness of managing healthcare resources in a high-stake environment, such as ICU.

Management

The management phase starts after determining confirmed CLABSI cases. During this phase, supervised machine learning and deep learning algorithms are deployed to categorize the confirmed cases into various risk levels. This categorization helps differentiate patients based on their risk of developing CLABSI, classifying them as high-risk, medium-risk, or low risk patients. Consequently, the decision makers can strategically allocate and prioritize resources such as computational capacity, medical devices, and HCPs, leading to enhanced effectiveness, efficiency, and cost-effectiveness in patient care delivery. During continuous monitoring of confirmed CLABSI cases, real-time data is fed back to the hospital's main data server. This significantly increases the amount of data on the hospital's server, which can be utilized to develop more accurate and efficient models. Moreover, a major aim of the management phase is to employ interdisciplinary collaboration among AI algorithms and clinical expertise to develop personalized treatment plans for infected patients. In fact, personalized treatment plans have been proven effective in treating a wide range of diseases.[25,26] Despite their effectiveness, the examined literature showed no evidence that such plans have ever been developed for CLABSI patients. Therefore, this paper fills this gap by recognizing the role of personalized treatment plans in enhancing healthcare quality and safety for CLABSI patients. In addition, they contribute to reducing the hospital's CLABSI management costs, which in turn results in higher profits and better allocation of resources.

Deployment Challenges

The deployment of an AI-driven solution framework for the prevention, detection, and management of CLABSI in ICU environments introduces several challenges that are both technical and organizational in nature. These challenges include issues related to system integration, human oversight, stakeholder resistance, and the need for adaptability in complex clinical settings. As highlighted in the proposed framework (Figure 2), the interaction between multiple system components demands seamless integration with EHR systems and clinical monitoring tools. However, many healthcare institutions still face data silos and interoperability barriers, which may limit the effectiveness of AI models designed to predict or detect CLABSI. Addressing these limitations requires the development of standardized data pipelines and secure, real-time interfaces between clinical databases and AI modules. Future research should focus on creating robust architectures that allow these integrations to occur with minimal disruption to existing workflows.

Another major challenge is the human factor, particularly trust, acceptance, and competence in engaging with AI tools.[27] While top-level management may resist implementation due to concerns about high initial investment and uncertain return on investment, frontline HCPs may express skepticism over model accuracy, fear of deskilling, or apprehension about being replaced. These concerns, if unaddressed, could result in low adherence to AI-generated alerts, especially in critical infection control scenarios such as CLABSI management. Patients, too, may hesitate to consent to treatment plans perceived as overly dependent on automated decision-making, particularly if transparency in how AI supports clinical judgment is lacking. To address these challenges, a targeted communication strategy must be implemented for each stakeholder group, outlining the system's objectives, implementation timeline, and safeguards in place to ensure human oversight and accountability. Additionally, training programs that involve clinicians in the development and testing phases can foster a sense of ownership and build trust in the technology.

Equally important is the development of personalized treatment strategies based on AI insights. While our framework emphasizes such plans in the management stage, current literature lacks examples of their application to CLABSI specifically. Future research should explore how supervised learning models can inform individualized care pathways for infected patients, potentially improving outcomes while optimizing ICU resource allocation. Real-time data captured during ongoing CLABSI cases could be used not only for monitoring but also for continuously retraining and improving prediction models, making the system more adaptive to clinical and environmental shifts. The integration of wearable biosensors and mobile monitoring technologies represents another promising direction for enhancing early detection and patient-specific intervention.

Finally, from a financial and policy standpoint, administrative hesitation often stems from uncertainty about cost-effectiveness. A well-documented cost-benefit analysis demonstrating reductions in CLABSI-related complications, ICU stays, and antibiotic use can provide the necessary justification for investment. Exploring funding models and regulatory incentives to support AI integration in infection control efforts will be critical to broader adoption. In sum, while deploying AI in the fight against CLABSI presents a range of challenges, each of these obstacles can be mitigated through focused stakeholder engagement, targeted training, interdisciplinary collaboration, and continued research into adaptive, personalized, and scalable AI solutions. Figure 3 provides a visual representation of the interconnections among these components and highlights the importance of addressing them as a cohesive system.

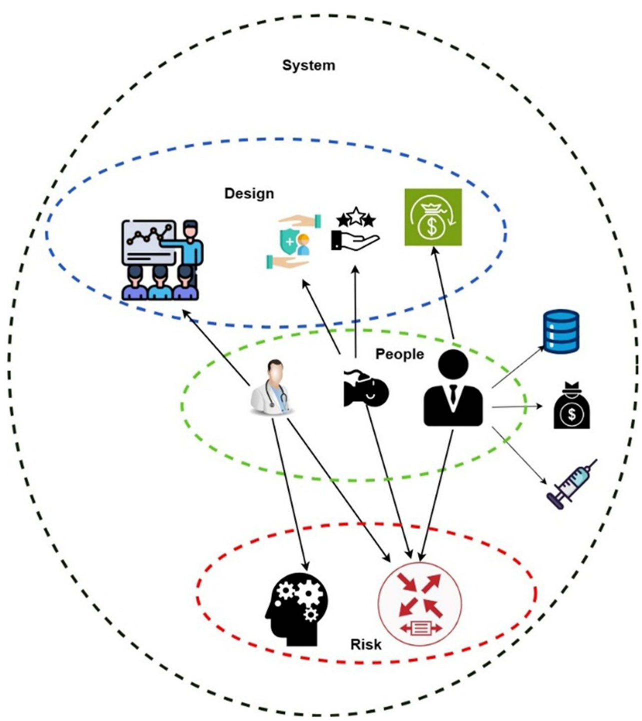

Figure 3 Deployment challenges and interactions in the proposed framework.

To refine the proposed framework, future research should investigate adaptive learning models capable of updating in near-real-time as new CLABSI cases emerge. Another promising area involves integrating AI with bio-sensing wearables for earlier symptom detection. Furthermore, evaluating the impact of personalized AI-driven treatment plans, currently underexplored in CLABSI literature, should be a priority. Cross-institutional collaborations could validate model generalizability across diverse ICU settings.

Addressing these deployment challenges in a targeted and evidence-based manner is essential for realizing the full potential of AI in reducing CLABSI incidence, enhancing patient outcomes, and optimizing ICU resource allocation.

Conclusion

The development of an AI-driven decision support framework for CLABSI management requires a comprehensive and systematic approach to ensure effectiveness, safety, and ethical alignment within clinical environments. Leveraging a systems approach allows for addressing the multi-dimensional nature of CLABSI by considering the interconnected components (clinical workflows, data infrastructure, human actors, and institutional policies) that influence both infection risk and treatment outcomes. Our proposed framework incorporates four core components: People, Systems, Design, and Risk, each of which plays a crucial role in enabling the successful implementation and sustainability of the solution.

The framework is structured into three primary stages: prevention, detection, and management, each addressing distinct needs in the CLABSI care continuum. In the prevention stage, AI functions to stratify patients based on their individual risk profiles, using historical and real-time data to anticipate CLABSI onset and prompt timely clinical intervention. In the detection stage, AI analyzes dynamic clinical indicators such as vital signs, lab results, and patient symptoms to identify potential infections, providing alerts and interpretability that support swift diagnostic confirmation. During the management stage, AI assists in classifying confirmed CLABSI cases into severity levels, enabling better resource prioritization and the formulation of personalized treatment strategies, an area currently underrepresented in CLABSI care literature.

Despite its potential, deploying AI for CLABSI management faces several domain-specific challenges. These include the need for accurate and interoperable data inputs that reflect the nuances of infection patterns in ICU settings, clinician trust in AI predictions particularly when dealing with critical infections, and resistance from stakeholders wary of over-reliance on technology. Additionally, the rarity and variability of CLABSI cases create challenges in model generalizability and necessitate ongoing data collection and model retraining. Future AI systems must therefore be adaptable, transparent, and integrated within clinician workflows to be truly effective.

By applying a systems approach and addressing the clinical, technical, and organizational complexities unique to CLABSI, this framework provides a pathway toward safer, more responsive, and cost-effective care. It emphasizes the role of AI not as a replacement, but as a complement to clinical expertise, supporting early intervention, accelerating accurate diagnosis, and guiding personalized treatment decisions. Ultimately, this contributes to improved patient outcomes, reduced healthcare costs, and enhanced quality of care in intensive care environments where every second matters.

Disclosure

The authors report no conflicts of interest in this work.

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