Health Science Reports

Health Science Reports Open Access

NARRATIVE REVIEW OPEN ACCESS

Enhancing Infection Control in ICUS Through AI: A Literature Review

Aditya Amit Godbole[1] | Paras[2] | Maanya Mehra[3] | Sumitaksha Banerjee[4] | Poulami Roy[5] | Novonil Deb[5] | Sarang Jagtap[6]

[1]Department of surgery, Bharati Vidyapeeth (Deemed to University) Medical College, Pune, India | [2]Department of surgery, Government Medical College, Patiala, India | [3]Department of surgery, University College of Medical Sciences and G.T.B. Hospital, Delhi, India | [4]Department of surgery, Burdwan Medical College and Hospital, Barddhaman, India | [5]Department of surgery, North Bengal Medical College and Hospital, Siliguri, India | [6]Department of surgery, Jalal-Abad State Medical University, Jalal-Abad, Kyrgyzstan

Correspondence: Sarang Jagtap (sarangjagtap2148@gmail.com)

Received: 15 January 2024 | **Revised:** 22 September 2024 | **Accepted:** 23 November 2024

Funding: The authors received no specific funding for this work.

Keywords: artificial intellegence | hospital acquired infections | intensive care units | machine learning | surgical site infections | ventilator-associated pneumonia

ABSTRACT

Introduction: Infection control in intensive care units (ICUs) is crucial due to the high risk of healthcare-associated infections (HAIs), which can increase patient morbidity, mortality, and costs. Effective measures such as hand hygiene, use of personal protective equipment (PPE), patient isolation, and environmental cleaning are vital to minimize these risks. The integration of artificial intelligence (AI) offers new opportunities to enhance infection control, from predicting outbreaks to optimizing antimicrobial use, ultimately improving patient safety and care in ICUs.

Objectives: The primary objectives are to explore AI's impact on predicting HAIs, real-time monitoring, automated sterilization, resource optimization, and personalized infection control plans.

Methodology: A comprehensive search of PubMed and Scopus was conducted for relevant articles up to January 2024, including case series, reports, and cohort studies. Animal studies and irrelevant articles were excluded, with a focus on those considered to have significant clinical relevance.

Discussion: The review highlights AI's prowess in predicting HAIs, surpassing conventional methods. Existing evidence demonstrates AI's efficacy in accurately predicting and mitigating HAIs. Real-time patient monitoring and alert systems powered by AI are shown to enhance infection detection and patient outcomes. The paper also addresses AI's role in automating sterilization and disinfection, with studies affirming its effectiveness in reducing infections. AI's resource optimization capabilities are exemplified in ICU settings, showcasing its potential to improve resource allocation efficiency. Furthermore, the review emphasizes AI's personalized approach to infection control post-procedures, elucidating its ability to analyze patient data and create tailored control plans.

Abbreviations: ABHR, alcohol-based hand rubs; AI, artificial intelligence; AIDBOT, artificial intelligence disinfection roBOT; ANN, artificial neural network; ARDS, acute respiratory distress syndrome; ATP, adenosine triphosphate; AUROC, area under ROC curve; CAUTI, catheter-associated urinary tract infections; CDI, clostridioides difficile infections; CHF, congestive heart failure; CLABSI, central line-associated bloodstream infections; EHR, electronic health records; FAP, false alarm probability; FDA, U.S. Food and Drug Administration; HAI, healthcare-associated infections; ICU, intensive care units; IPC, infection prevention and control; IT, information technologies; LR, logistic regression; ML, machine learning; NLP, natural language processing; PPE, personal protective equipment; qSOFA, quick sequential organ failure assessment; RGB-D, red green blue-depth; SIRS, systemic inflammatory response syndrome; SLAM, simulation localization and mapping; SSI, surgical site infections; SSSI, single-sensor-single-indication; SVM, support vector machine; VAP, ventilator-associated pneumonia; XGB, extreme gradient boosting.

1 | Introduction

The significance of infection control within intensive care units (ICUs) has been inextricably intertwined with offering better, state-of-the-art care in today's rapidly evolving healthcare landscape [1]. Healthcare institutions face a substantial problem due to the prevalence of healthcare-associated infections (HAIs), which stands at 7% [2]. These infections not only jeopardize patient safety but also put a strain on available resources, lengthen hospital stays, and increase healthcare expenses. It is therefore becoming more crucial for ICUs to have efficient infection control procedures as healthcare providers work to improve patient safety and give the best care possible [3].

Healthcare facilities must navigate a challenging and varied management of HAI. The enclosed nature of ICUs, with their high patient density, weakened immune systems, and invasive interventions, provide a conducive environment for infection transmission.

Additionally, the emergence of drug-resistant pathogens makes infection control techniques much more challenging. Despite concerted efforts to implement customary infection prevention measures, healthcare institutions often find themselves grappling with persistent HAIs, necessitating the need for a more novel and data-driven strategy.

In this setting, artificial intelligence (AI) emerges as an intriguing option that has the potential to completely overhaul ICU infection control [4]. AI has the potential to revolutionize infection prevention by analyzing immense quantities of data, spotting patterns, and forecasting results. Healthcare practitioners can track hygiene procedures, identify early indicators of infection outbreaks, and optimize the use of antibiotics by utilizing AI-driven solutions. AI's incorporation into infection control ushers in a new era of proactive and individualized patient care while also enabling healthcare teams to make informed decisions.

2 | Methodology

We conducted a comprehensive search of the Pubmed and Scopus databases to identify all the relevant articles for this study, reviewing all relevant articles like case series, case reports, cohort studies, editorials, and brief reports for up until January 2024. The search terms included "artificial intellegence," "hospital acquired infection," "CLABSI," "clostridium difficle infection," "sepsis" and "models" with appropriate use of boolean operators AND, OR, NOT. Individual AI models and infections were also searched to avoid missing any relevant articles. We manually searched the reference lists of the included studies as well as previous reviews to ensure that our search strategy did not overlook any potentially relevant studies. No language restriction was used and commentaries or studies conducted solely in animal models were excluded. Additionally, articles that were not related to our study were also excluded. The articles considered in this review were selected with a particular emphasis on those that were deemed to hold significant clinical and medical relevance.

3 | Predicting the Risk of HAIs for Patients Using AI

Healthcare-associated infections (HAIs) are a critical concern in the healthcare industry, posing a significant threat to patient safety and a substantial burden on both clinical and financial aspects. These infections occur during the process of care and encompass a range of conditions, including central line-associated bloodstream infections (CLABSI), ventilator-associated pneumonia (VAP), surgical site infections (SSI), Clostridioides difficile infections (CDI), and catheter-associated urinary tract infections (CAUTI) [5]. The gravity of the situation is evident in Europe, where over 2.6 million new cases of HAIs are estimated annually, surpassing the cumulative burden of all other reported infectious diseases [6, 7]. Similarly, the impact has been alarming in South East Asia and Africa [8, 9]. In the United States, HAIs contribute to 72,000 deaths per year, emphasizing the urgent need for effective surveillance and prevention strategies [10].

HAI surveillance is the cornerstone for organizing, implementing, and maintaining infection prevention and control programs. The objectives of surveillance include quantifying infection rates, facilitating comparisons within and between healthcare facilities, encouraging clinical teams to adopt best practices, and identifying priority areas for resource allocation [11]. Traditional surveillance methods encompass continuous, active/passive, prevalence surveys, and alert-based surveillance, each presenting challenges in terms of labor intensity, cost, and time consumption [12]. However, the evolution of information technologies (IT) and the digitalization of health data offer a promising avenue for the automation of HAI surveillance [13]. This digital transformation can operate on three levels: enhancing surveillance practices' reliability, efficiency, and standardization; reducing costs and saving time; and enabling real-time analysis and action [14, 15].

The integration of AI and machine learning (ML) into HAI surveillance introduces a new paradigm that holds great potential. Traditionally, HAI surveillance systems relied on fixed and predefined classification algorithms or simple rule-based decision trees. However, recent evidence suggests that AI and ML, encompassing a range of statistical and computational techniques, can revolutionize the development of HAI surveillance algorithms [13]. At its core, ML involves iterative optimization of mathematical models to fit available data with increasing accuracy. Applied to infection prevention and control, ML can yield an improved understanding of HAI risk factors, enhanced patient risk stratification, identification of transmission pathways, and timely detection and infection control.

The potential of AI and ML in HAI surveillance is underscored by their ability to harness the power of diverse electronic health data sources. These sources include electronic health records (EHRs), patient vitals, laboratory results, medication information, and more. By analyzing these data points holistically, AI algorithms can unveil hidden correlations and patterns that contribute to HAI risk [15]. One of the most promising applications is the development of early warning systems in ICUs. By leveraging predictive algorithms, they can detect deviations from normal ranges in a patient's vital signs that might signal the onset of an infection. This allows healthcare providers to take immediate action, mitigating the infection's progression [3]. Moreover, AI and ML enable patient risk stratification that tailors interventions to individual patients based on their unique risk factors. By analyzing a patient's medical history, comorbidities, age, and other pertinent data, AI models offer a refined approach to prioritizing resources and interventions [6]. This personalized approach enhances the efficiency and effectiveness of infection prevention measures.

AI's potential extends to pathogen detection and identification. By analyzing microbial data, AI algorithms can rapidly detect and identify the specific pathogens causing infections, including their antibiotic resistance profiles. This information empowers healthcare professionals to implement targeted and effective treatment strategies, improving patient outcomes [7]. Another remarkable application of AI in HAI surveillance is through predictive modeling. These models estimate the likelihood of patients developing a specific type of HAI based on their clinical characteristics and the ICU environment. This predictive capability assists healthcare providers in allocating resources efficiently and implementing pre-emptive measures [8]. Natural language processing (NLP), a subset of AI, adds yet another dimension to HAI surveillance. NLP can analyze unstructured clinical notes and reports, extracting valuable insights about patient conditions, symptoms, and treatments. By incorporating these insights into risk assessment, healthcare teams gain a more comprehensive understanding of HAI risk factors [9]. Real-time surveillance and alerts represent a critical component of AI-powered HAI surveillance. These systems continuously monitor patient data, promptly triggering alerts when specific criteria indicative of a potential HAI are met. This real-time intervention empowers healthcare providers to take swift action, potentially preventing the escalation of infections [16].

Despite the promising potential of AI and ML, their successful implementation in ICU settings necessitates rigorous validation, integration with existing workflows, and careful consideration of ethical and privacy concerns. While AI-driven HAI surveillance offers unprecedented advantages, the effectiveness of these methods hinges on the quality and quantity of available data, the complexity of the ICU environment, and the specific infections being targeted.

The integration of ML based models into the surveillance and prediction of healthcare-associated infections (HAIs) marks a significant advancement in the field, offering a potentially transformative approach to enhancing patient safety and infection control. The emergence of ML-based techniques has opened new avenues for the detection, control, and prevention of HAIs, revolutionizing the way healthcare professionals approach these critical challenges.(Table 1)

Focusing on CLABSI surveillance, researchers have embarked on studies that illuminate the power of ML algorithms in this context. Beeler et al. [17] embarked on a comparative analysis, pitting an ML-random forest model against a traditional non-ML logistic regression model. Impressively, the ML model showcased superior performance, boasting an impressive AUROC of 0.87 as opposed to the logistic regression model's 0.79. This accomplishment underscores the potential of ML to outperform traditional methods. Furthermore, this study extended its implications by validating the most successful ML model for personalized daily CLABSI risk assessment, showcasing its adaptability and real-time applicability. Parreco et al. [18] took a similar route by assessing different ML-based models for CLABSI surveillance. Their findings crowned the Gradient boosted trees-ML model as the leader in accuracy, precision, sensitivity, and negative predictive value. This comparison indicated the potential of ML in offering heightened real-time identification and risk prediction for CLABSI, underscoring its potential as a valuable tool in the fight against HAIs (Table 1).

Expanding the scope to sepsis surveillance, researchers have begun unraveling the potential of ML in this critical domain. Desautels et al. [19] engineered an ML-based classification system that, when put to the test against traditional scoring systems, emerged as the clear victor in sepsis detection. Its superior accuracy, illustrated by an AUROC of 0.88, even in the presence of data gaps, demonstrates ML's ability to revolutionize early sepsis identification. Shimabukuro et al. [20] took this exploration further by delving into the clinical implications of ML-based sepsis detection. Their experimental study revealed a significant reduction in hospital length of stay and mortality rates, positioning ML as a potential catalyst for improved clinical outcomes in sepsis management (Table 1).

The application of ML in predicting Clostridium difficile infection (CDI) has also been a subject of study. Oh et al. [21] challenged the static non-ML prediction models for CDI by advocating for a dynamic ML-based approach. Their model yielded impressive performance measures, including AUROCs of 0.82 and 0.75 at different institutions. The demonstrated ability to customize ML-based risk models for specific settings underscores the potential for earlier and more accurate CDI risk identification, presenting a significant advancement in infection prevention strategies. However, Escobar et al. [22] tempered these results by revealing the limited scope of ML models in predicting recurrent CDI, showcasing the complexity of CDI prediction (Table 1).

Turning attention to surgical site infections (SSI), a multitude of studies have embarked on harnessing ML-based models to predict, control, and evaluate these infections. The landscape here is diverse, encompassing various algorithms such as Bayesian network classifiers, artificial neural networks (ANN), and natural language processing (NLP). The results have been mixed, with some studies reporting promising outcomes in predicting SSI risk and identifying risk factors. Notably, the application of ANN algorithms demonstrated remarkable potential in predicting SSI in the context of neurosurgery and head and neck surgery [24], underlining the adaptability of ML-based techniques to different surgical settings.

Expanding the purview to general HAI surveillance, numerous studies have ventured into exploring ML-based models for identifying determinants, risk factors, and predictive outcomes. Swedish data [21] revealed that gradient-boosted trees exhibited heightened recall and precision, solidifying their place as a powerful tool for HAI surveillance. Cohen et al. [25–27] delved into the efficacy of one-class support vector machines (SVMs), unveiling their potential to tackle data imbalance and deliver superior sensitivity, specificity, and accuracy in HAI detection. These findings accentuate the versatility of ML in addressing the multifaceted challenges of HAIs.

TABLE 1 | Characteristics of studies highlighting role of AI in predicting the role of HAI.

Study	Country	Study setting	Study population	Study design	Objective	Infection type
Beeler, 2018 [17]	USA	Hospital	Neonatal and pediatric patients	Retrospective design	Assess and validate a machine learning model to accurately predict the risk of Central Line-Associated Bloodstream Infections (CLABSI) in real-time.	CLABSI
Parreco, 2018 [18]	USA	ICU	Inpatients	Retrospective cohort	Compare machine learning techniques for predicting central line-associated bloodstream infection (CLABSI)	CLABSI
Desautels, 2016 [19]	USA	ICU	> 15 y ICU patients	Retrospective cohort	Compare machine learning-based sepsis prediction models with traditional sepsis scoring systems.	Sepsis
Shimabukuro, 2017 [20]	USA	ICU	Medical-surgical ICU patients	Prospective cohort	Prediction of sepsis	Sepsis
Oh, 2018 [21]	USA	Hospital	Adult impatients	Retrospective cohort	Assess the applicability of a generalizable machine learning approach using structured EHR data to create a CDI risk stratification model tailored to specific patient populations and facilities.	CDI
Escobar, 2017 [22]	USA	Hospital	Adult impatients	Retrospective cohort	Development and validation of CDI predictive models in a large, representative adult population.	CDI
Ehrentraut, 2018 [23]	Sweden, Finland	Hospital	All impatients	Retrospective cohort	Application of support vector machines and gradient tree boosting to identify patient records with hospital-acquired infections.	HAI
Kuo, 2018 [24]	Taiwan	Surgery	Head & neck surgery patients	Retrospective cohort	Comparison of artificial neural networks (ANN) and logistic regression models for predicting surgical site infections (SSI).	SSI
Cohen, 2004 [25]	Switzerland	Hospital	Hospitalized impatients	Retrospective cohort	Utilize data mining techniques to identify nosocomial infections.	HAI
Cohen, 2006 [26]	Switzerland	Hospital	Hospitalized impatients	Retrospective cohort	Identifying patients at high risk for acquiring nosocomial infections by evaluating the performance of a support vector machine algorithm.	HAI
Cohen, 2008 [27]	Switzerland	Hospital	Hospitalized impatients	Retrospective cohort	Use data mining techniques to identify nosocomial infections.	HAI

While the results from these studies paint a promising picture of the potential of ML in HAI surveillance, it is crucial to acknowledge the contextual nuances and challenges inherent in this field. Sensitivity, specificity, accuracy, and AUROCs exhibited significant variability across different studies, reflecting the complexity and heterogeneity of HAIs. As the healthcare landscape evolves, it becomes imperative to embark on further research, validation, and standardization efforts to fully harness the transformative capabilities of AI and ML in the ongoing battle against HAIs.

4 | Real-Time Monitoring and Alert Systems

4.1 | Limitations of Conventional Monitoring and Alert Systems in ICU

Continuous monitoring of patient vitals and alert systems are the key to an efficient ICU and have recently gained increasing attention due to the COVID-19 pandemic. Physiologic monitoring screens first appeared in the ICU in the 1970s, these screens were designed using a single-sensor-single-indication layout, which shows only one indication for each patient-attached sensor. While the traditional monitors have since undergone significant improvements, there are numerous obstacles still to be overcome.

A Survey Study conducted by Poncette et al. in Germany highlighted the difficulties faced by the ICU staff with the current monitoring systems [28], including-

1. Alarm Fatigue: There are concerns for patient safety when doctors fail to respond to clinically important alarms because of the high volume of alarms, which has been linked to many unfavorable physician responses like disabling or silencing critical alarms and setting inappropriate alarm parameters. Studies show that 80%–90% of warnings are erroneous, yet these gadgets are created with a "better safe than sorry" mentality. In 2010, for instance, the FDA received >2500 complaints of adverse events connected to the use of ventilators, and of those, roughly a third indicated a problem with the alarm system [29].
2. Heavy workload: Critical care medicine requires highly competent and experienced doctors and nurses, as a result, there is a shortage of manpower and the clinicians are often in a state of exhaustion with high occupational pressure. This may lead to delayed treatment and reduced work quality.
3. Inadequate infection control practices: The intensive care unit (ICU) is a breeding ground for superbugs because of the close quarters and lack of Infection Prevention and Control (IPC) training among the nursing staff.
4. Lack of interoperability: Nurses often need to integrate vitals from multiple devices to assess the patient's condition, thus, automatic exchange of information between devices would save valuable time in case of emergencies.
5. Too many sensor cables: Entanglement of cables is a problem not just in the ICU but also in wards and Operation Theaters. noninvasive wireless sensors are an easy solution to this issue.
6. Lack of staff training and standard operating procedure: According to a study done in Germany, mortality rates in the control group (where SOP was not implemented) were 57%, whereas, in the intervention group (where SOP was implemented), mortality rates were just 38.5%.

Considering these shortcomings, we aim to evaluate the potential benefits of implementing AI in Intensive Care Units.

5 | Use of Artificial Intelligence in the Enhancement of Real-Time Monitoring of Patients

AI in healthcare refers to the application of ML algorithms, AI software, and other forms of digital intelligence to healthcare data to emulate human intelligence and improve its interpretability, assessment, and understanding. AI may now be combined with critical care medicine, allowing for the creation of Intelligent ICUs and Smart Wards thanks to advancements in computer power and medical technology. There is experimental evidence that AI can be used to drastically cut down on the number of alerts caregivers receive—by as much as 99.3% [30]. This significantly reduces alarm fatigue associated with conventional monitoring systems which has long been considered a health hazard in the ICU setting due to sensory overload and desensitization among clinicians [31]. AI determines if a group of caregivers should be alerted and whether or not to include a false alarm probability (FAP) label in the message. Apart from this, AI has the potential to decrease workload by enabling remote patient monitoring.

Other applications of AI in monitoring critical patients include:

1. Its superior text and picture processing capabilities provide a more accurate diagnosis. Semi-supervised ML using a variational autoencoder may be used to quantify pulmonary edema caused by congestive heart failure (CHF), and a ML model can distinguish the existence of CHF from other causes of lung illness. Myocardial infarction may be detected in real-time with the help of AI, reducing the need for invasive procedures like angioplasty and stenting as a result.
2. Prediction of disease progression using random forest models: The ability to forecast outcomes in the intensive care unit via the application of an algorithm. The system relies on a group of interconnected decision trees that may learn from experience and adjust to new information as it arrives. Yoon et al. demonstrated that a dynamic model based on random forest classification could accurately foretell the onset of cardiorespiratory instability 90 min in advance of its actual occurrence [32].
3. Personalized medical care: AI may aid by finding unique patterns within complicated data and identifying distinct phenotypes or endotypes that represent the vital condition of the individual, allowing for more individualized therapy.
4. Guiding Clinical Decisions: AI's potential therapeutic value would be most evident in resource-limited settings

with few treatment alternatives, such as emergencies in rural places where physicians are few and patient transport is impossible.

5. Length of stay, ICU readmission and death rates, and the risk of acquiring medical problems or illnesses like sepsis and ARDS have all been predicted by certain models using huge population datasets.

6 | Use of AI in Early Detection and Control of Infections

McCoy et al. implemented an algorithm for early detection of sepsis based on ML wherein the post-implementation period saw a reduction of 60.24% in the in-hospital death rate, 9.5% in the duration of stay, and 50.1% in the risk of readmission within 30 days due to sepsis [33]. Thus, AI has revolutionized the management of Infection and sepsis in the ICU through its systematic approach to Infection Prevention and Control-

Predicting Infection with Improved Diagnostic Accuracy and Patient Surveillance: ML algorithms trained on regularly gathered healthcare data (medical history, clinical parameters, biochemistry findings, etc.) in retrospective databases are used to estimate future risk in forecasting models. They are founded on the assumption that if a doctor is forewarned of a negative outcome, that outcome may be changed. The risk of hospital-acquired infections can also be determined based on compliance with the hand hygiene protocols of patients and physicians, personal protective equipment used by medical professionals, and adherence to hospital protocols among ICU staff members. To reduce the likelihood of CLABSI, the AI model may make predictions such as when to replace or remove catheters proactively. Rapid diagnosis of infectious patients may be facilitated by AI-enhanced laboratory microscopy. Over 90% accuracy has been achieved when using a convolutional neural network (based on visual data processing) to classify bacteria in blood culture specimens at the gram stain stage [34].

Antimicrobial Therapy: AI has been utilized to improve the existing phenotypic and genotypic methodologies used in pathogen and resistance detection. Ho et al. showed that when Raman optical spectroscopy is integrated with deep learning, it can correctly identify 30 common bacterial infections with an average isolate-level accuracy of more than 82% and an antibiotic treatment identification accuracy greater than $97.0\% \pm 0.3\%$ [35].

Thus, AI can identify pathogens and assess antibiotic susceptibility in diagnostic samples like blood, urine, and sputum without culturing the organism and saves valuable time in complicated cases.

7 | Current Examples of AI-Based Alert Systems and Their Potential Benefits in Preventing Adverse Outcomes

Research shows that ICU staff is often eager to learn new technology to improve patient outcomes and reduce workload. This may be in the form of wireless sensors and remote patient monitoring as well as clinical decision support through AI [28]. Some of the AI-based algorithms developed to improve real-time patient monitoring and treatment outcomes include-

1. Early management and prevention of sepsis: Intending to recognize sepsis within the first hour of admission, Mollura et al. have created a unique AI-based method for early diagnosis of sepsis using physiological waveforms. Data from the MIMIC-III database is used to inform the model, which then proposes that sophisticated multivariate modeling of vital sign waveforms and continuous monitoring are crucial for diagnosing sepsis [36]. Komorowski et al. demonstrate how reinforcement learning could be applied to suggest individualized and clinically interpretable treatment strategies for sepsis. In an independent cohort, the patients who received the treatment regimen as suggested by the AI Clinician had the lowest mortality rate [37].

2. Mortality Prediction: Most standard severity of disease scoring methods used to assess mortality risk in the intensive care unit were developed using logistic regression (LR). Probabilistic graphical models and Extreme Gradient Boosting (XGB) are two examples of ML models that have been shown to increase prediction accuracy in patient outcomes. A Spanish investigation showed that the XGB was able to reach a sensitivity of 0.831 and a specificity of 0.86, guaranteeing an acceptable precision (0.528), whereas traditional systems could only manage values substantially lower than these [38].

3. Reduce alarm fatigue and associated implications: The software was developed in Java and used RabbitMQ to send warnings to a broker, which in turn transmits them to a consumer app, which represents the real reception of these alerts by the healthcare team. The study assumed that (a) healthcare practitioners should not be notified more than once within the Minimum Notification Interval about the same sort of anomaly for the same patient, and (b) the application of the reasoning algorithm over how to notify should not compromise patient safety [31].

4. Adverse outcomes prediction and prevention: Yoon et al designed a model that used a normalized dynamic risk score trajectory with a random forest model to predict tachycardia 75 min before it developed and reported an accuracy of 0.81 and AUC of 0.87 [39]. Deep learning was developed to capture CT scan prognosis information and provide an AI severity score for prognosis severe evolution for COVID-19 hospitalized patients. AI provides Good reproducibility, quantification of disease extent, imaging biomarkers, and visual inspection of images along with reducing the burden on radiologists [40].

5. Autonomous Patient Monitoring Using Pervasive Sensing and Deep Learning: It uses a gadget driven by AI that can detect and recognize faces, analyze facial expressions, determine body position, and track the movement of limbs. Assessing critically ill patients' affect and emotions, allows us to provide comprehensive care and can even be applied in autonomous detection of delirium [41].

AI algorithms for critical care have been rapidly evolving in recent years, allowing for improved real-time monitoring that benefits both patients and intensive care unit (ICU) doctors. However, our knowledge of AI's potential in emergency medicine is currently somewhat sketchy. In addition, AI has several obstacles to clear before it can be used routinely in hospitals.

7.1 | Automated Sterilization and Disinfection Protocols

Healthcare-acquired infections (HAIs) are a big problem in a healthcare setting. These infections mainly result from an interplay of host factors (severe disease, comorbidities, low immunity) and pathogen factors (virulence, antibiotic resistance). The factors that affect this interplay are preventive measures and disinfection protocols implemented by healthcare professionals [42]. Thus, a possible solution to reduce the incidence of HAIs is the implementation of infection prevention strategies and disinfection protocols. Infection control is achieved by proper hygiene and the introduction of barriers at appropriate locations. Contact transmission can be avoided by using personal protective equipment like gloves and gowns. Droplet transmission can be prevented by using masks, appropriate ventilation systems, and isolation. Airborne transmission can be prevented using isolation rooms and recirculation of air via filters [43]. Hand Hygiene has played a key role in improving infection control with plenty of evidence indicating that it reduces infection rates [44]. All the methods mentioned above are the conventional methods that have been implemented to reduce the incidence of HAIs. But in today's era, AI offers a promising potential to reduce the risk of HAIs. Although culture and behavior change is necessary to improve infection control practices, AI has proved to be a fast, consistent, and reliable tool for developing surveillance, diagnosis, and hand hygiene monitoring models [45]. In this review, we explore different avenues demonstrating the potential application of AI in infection prevention and control in an ICU setting. After a thorough review of the existing literature, we found that although there are articles on the implementation of AI in sterilization and infection control, very few articles are based on an intensive care setting.

7.2 | Use of AI-Based Robots in Disinfection

Hong H. et al. (2021) developed a UVD robot with RGB-D cameras, laser sensors, and UV-C lights called Artificial Intelligence Disinfection roBOT (AIDBOT). It uses the Simulation Localization and Mapping (SLAM) module for navigation and the YOLOv4 model for object detection. It also consists of a real-time obstacle avoidance algorithm. To prevent UV-C exposure, it has a warning sound to alert humans who come within its 10 m radius. It also automatically shuts down the harmful light if a human comes within a 5 m radius. This robot has displayed some remarkable results. It identified objects like buttons, handles, desks, and chairs with an accuracy of 90%, 93.3%, and 90%. It was able to able to identify humans with an accuracy of 100%. The UV-C light achieved a 99.9% sterilization effect within 11 s for *S. aureus*, 15 s for *P. aeruginosa*, and 19 s for *E. coli*. Current methods of sterilization consist of fixed or manual transport-dependent sterilization equipment. These robots can replace this existing equipment to sterilize the environment more efficiently [46].

7.3 | Hand Hygiene

Many articles discuss applications developed using AI to improve hand hygiene practices. Although these articles are not ICU-focused, we discuss those that potentially could be used in an ICU setting.

Ghosh et al. (2013) developed SureWash, an AI-based system that assessed hand hygiene techniques and the effectiveness of an automated training system. It had an interrater reliability (IIR) of 80% compared to that of human reviewers (88%). It also studied the poses missed and the impact of feedback on technique (+2.23%), duration (+11%), and participation (+113%) [47]. This system was then used in their study by Higgins A. et al. (2013) along with an adenosine triphosphate (ATP) monitoring system to measure hand washing technique. Hand-washing compliance increased and the technique implemented by participants improved during the span of this study [48]. The SureWash system was also used by Thirkell G. et al. along with MEG: A tablet-based clinical support tool and GOJO: a SmartLink activity monitoring system. MEG was responsible for hand hygiene auditing while GOJO analysed events and opportunities to monitor and measure hand hygiene performance. This system was implemented in an oncology unit. Their pilot study displayed a positive reaction from healthcare workers and patients [49]. Singh et al. (2020) developed a Convolutional neural network-based machine-learning algorithm to detect hand hygiene dispensers used in a hospital setting. This algorithm had a sensitivity and specificity of 92.1% and 98.3% respectively [50]. Awwad S. et al. (2019) developed a model to detect the use of alcohol-based hand rubs (ABHR), their use, and the doctor-patient physical contact. It was able to detect that the hand hygiene technique was good (sensitivity 83%, specificity 88%). It also was able to determine that the ABHR was dispensed and there was doctor-patient physical contact with perfect accuracy (sensitivity 100%, specificity 100%) [51].

These studies highlight the potential AI holds in improving hand hygiene in healthcare settings. These algorithms need to be further evaluated in ICU settings to test their accuracy and efficiency.

7.4 | Challenges

AI has provided a boost in improving infection prevention and control (IPC) practices. But on a personalized level, behavioral and cultural changes are necessary to improve these practices. AI depends on the quality of the data and the high level of reference standards used to train it. These standards are difficult to match in IPC. Efficient algorithms should be developed to prevent under-fitting or over-fitting of data [45].

7.5 | Opportunities

After an extensive literature review, the authors noticed a lack of articles on the application of AI in ICU settings. Although there are algorithms and models for improving IPC, their application in ICU settings is yet to be studied.

Recent years have seen a significant rise in the development of AI algorithms related to critical care with the ability to optimize real-time monitoring that is beneficial to both patients and ICU clinicians. However, our understanding of AI's potential in critical care is still limited. Additionally, there are challenges that AI must overcome before becoming a routine part of clinical practice.

8 | Post Procedure/Operation Infection Prediction and Management Using Patient-Specific AI-Based Control Plans

The management of postprocedure infection or sepsis is a difficult and diverse task that is still best left to highly qualified and talented human experts. However, as more and more AI applications are made for medical purposes, it is becoming clear that some of these choices may soon be made by what we would call "intelligent" computers, which would improve clinical practice and patient outcomes [52]. In fact, the vast majority of the tasks required in the clinical management of sepsis (early detection, selection of antibiotic therapy, hemodynamic optimization, etc.) might be carried out independently or optimized by specialized algorithms.

First of all, it appears that automated algorithms are capable of identifying patients who are at risk for sepsis, either immediately ("sepsis detection") or in the future ("sepsis prediction") [53]. This can be accomplished using a variety of supervised learning techniques that have been tested on a data set of both positive and negative sepsis cases. For instance, using simple vital signs many hours before onset, a model based on gradient tree boosting demonstrated good accuracy for predicting sepsis and septic shock [54]. Even more basic rule-based algorithms can identify patients who are at risk, for instance by looking for end-organ damage, the nonspecific Systemic Inflammatory Response Syndrome (SIRS), quick Sequential Organ Failure Assessment (qSOFA), or SOFA scores [55]. The small study by Shimabukuro et al. was notable for being one of the few to show improved outcomes with an algorithm from a randomized trial, which is a crucial lesson: successful implementation and clinician acceptance are much more crucial than an algorithm's inherent complexity [56].

The next set of methods is unsupervised learning, which is used to isolate subgroups of sepsis patients. Sepsis is arguably a very generic syndrome. Applying clustering algorithms to categorize patients based on their clinical, biological, or omics data has been suggested by a number of teams [57, 58].

Even though the majority of this study is still exploratory and hypothesis-generating, it now seems conceivable to imagine actual application. Antclife showed through the use of transcriptome data that a segment of patients had worse results when given steroids, which may have future clinical applications [58].

To this day, optimizing the blood volume in circulation using intravenous fluids and/or vasopressors remains the cornerstone of hemodynamic therapy of sepsis. Reinforcement learning may be able to aid in the difficult process of administering these medications at the proper time and dosage [59]. Reinforcement learning models the disease process of septic patients into several health states, after which the judgments made by human practitioners are examined and their worth is determined [58]. The final step is to identify the choices that are more likely to increase organ function and/or survival. By calculating the relative risk of death for various timing possibilities, a different strategy could be used to determine the ideal moment to begin vasopressors [60].

It is difficult to accurately predict what would have occurred to the patient when the algorithm and clinicians disagree. This makes evaluating the worth of new judgments in a purely retrospective manner tough. Retrospective validation is based on an expert appraisal of the model behavior, sensitivity analysis to verify its robustness, and a class of statistical methods known as "of-policy evaluation" to quantify the value of the algorithm's judgments, all of which have drawbacks [59, 61].

9 | Challenges and Limitations of AI Implementation

As the journey towards integrating AI into healthcare gains momentum, it becomes evident that the path is not without its share of challenges and limitations. Ethical considerations loom large in the discourse surrounding AI in healthcare, particularly in the realms of data privacy, algorithmic transparency, and the mitigation of biases. The convergence of sensitive patient data and advanced algorithms necessitates a vigilant approach to safeguarding privacy while ensuring that decision-making processes remain transparent and free from discriminatory biases. Moreover, as healthcare systems pivot towards AI-driven approaches, a fundamental cultural shift within healthcare settings becomes imperative. This transition entails not only the adoption of new technological tools but also the cultivation of a mindset that values data-driven insights as integral to patient care. Accompanying this cultural evolution is the crucial need for comprehensive training of healthcare personnel, equipping them with the skills and knowledge to effectively harness the potential of AI and integrate it seamlessly into their clinical practices.

The introduction of AI also brings about the challenge of navigating the complexities of technological infrastructure and investment. While the promise of AI in revolutionizing healthcare is tantalizing, the initial financial commitment required for technology acquisition, software development, and system integration can pose a formidable barrier, particularly for resource-constrained healthcare facilities. Furthermore, the reliability and interpretability of AI systems remain subjects of scrutiny. Ensuring that AI-driven decisions can be understood, validated, and trusted by healthcare professionals is paramount. The intricate interplay of these challenges underscores the necessity of an all-encompassing approach that addresses not only the technical aspects of AI integration but also the ethical, social, and organizational dimensions, fostering a holistic ecosystem wherein AI aligns seamlessly with the overarching goals of healthcare.

10 | Broader Impact of AI on Healthcare and Infection Control Strategies

The transformative potential of AI radiates far beyond the boundaries of ICUs, casting a profound influence over the entire healthcare landscape. The successful implementation of AI-driven infection control practices in ICUs can serve as a vanguard for reshaping infection control strategies across

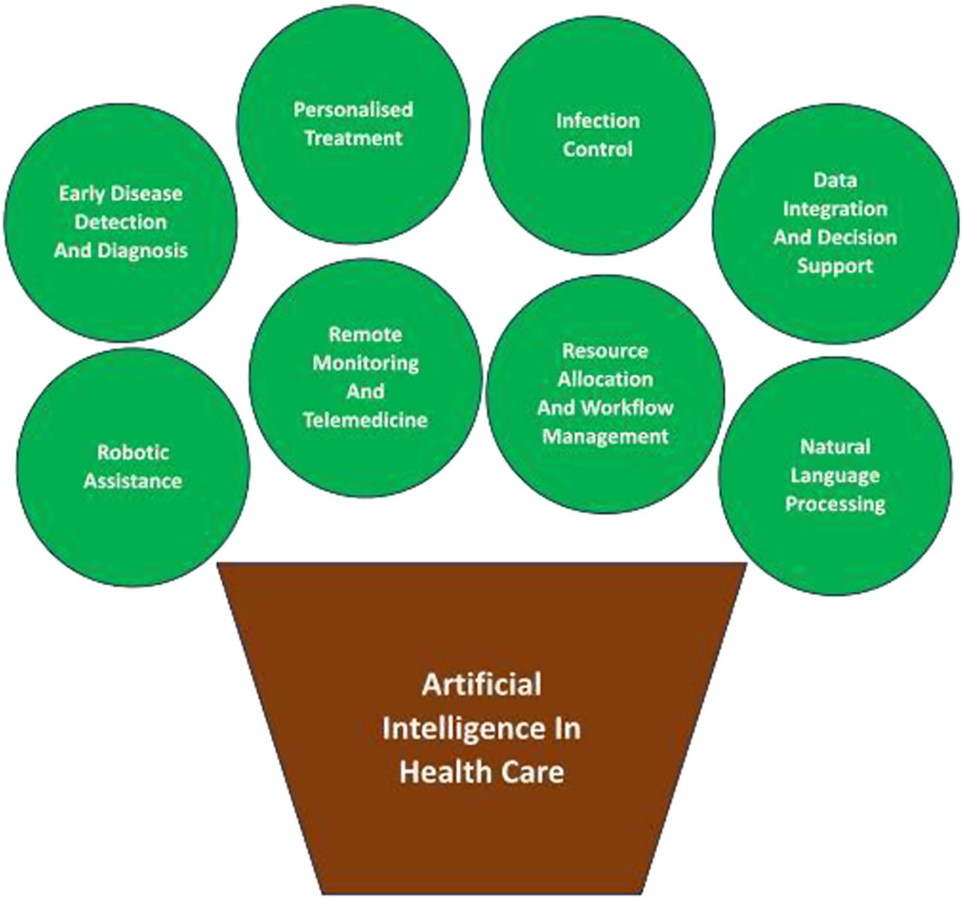

FIGURE 1 | The various arenas where artificial intelligence can be implemented in healthcare.

diverse healthcare settings. By harnessing AI's predictive capabilities to mitigate HAIs, healthcare facilities stand to significantly enhance patient outcomes throughout the continuum of care. The ripple effect of this transformation is evident in the creation of a healthcare ecosystem characterized by heightened proactivity, personalization, and efficiency.

AI's predictive prowess holds the potential to recalibrate healthcare into a realm where interventions are not only timely but also precisely tailored to individual patients. The infusion of data-driven insights, facilitated by AI integration, has the power to revolutionize evidence-based policy-making. Healthcare facilities, armed with a wealth of information extracted from AI-analyzed data, can make well-informed decisions about resource allocation, infection control strategies, and patient care protocols. This paradigm shift not only optimizes healthcare operations but also empowers policymakers to craft strategies that are rooted in real-world evidence and dynamic patient needs.

In conclusion, the impact of AI on infection control extends well beyond the confines of ICUs, resonating across the entire healthcare spectrum. While challenges may abound, the promise of AI to elevate healthcare to new levels of effectiveness, personalization, and evidence-based decision-making remains undeniable. As the healthcare landscape continues to evolve, embracing AI's transformative potential stands as a pivotal step towards a future where technology and human expertize harmoniously unite to ensure optimal patient well-being and pave the way for a new era of healthcare excellence.

11 | Resources Optimization Using AI

Managing resources in ICUs is a multifaceted endeavor according to patient acuity, clinical needs, and logistical hurdles. Efficiently allocating resources such as ICU beds and personal protective equipment (PPE) involves intricate decision-making processes. This section elucidates the challenges inherent in managing these resources, explores how AI can optimize their allocation through predictive modeling and demand forecasting and offers real-world examples that underscore the practical efficacy of AI-driven resource optimization strategies.

12 | Challenges in Managing ICU Resources

ICU bed availability poses an ongoing challenge due to the fluctuating demand arising from emergent medical conditions, surgical procedures, and infectious disease outbreaks. This often leads to bottlenecks and compromises patient care. Furthermore, the COVID-19 pandemic exacerbated these challenges, putting immense strain on healthcare systems' capacity to provide adequate ICU beds and specialized care.

Simultaneously, ensuring the timely availability and appropriate utilization of PPE is crucial for safeguarding both patients and healthcare providers. The need to balance patient care requirements with supply chain complexities adds layers of intricacy to resource management.

13 | AI-Driven Resource Optimization

AI's predictive capabilities have proven instrumental in optimizing ICU resources. Predictive modeling harnesses historical data and ML algorithms to forecast future trends. In the context of ICU resource allocation, AI can analyze variables like patient demographics, disease prevalence, severity, and seasonal factors to predict ICU bed demand over various timeframes. By identifying patterns and correlations, AI aids healthcare administrators in preemptively adjusting resource allocation to meet demand.

Demand forecasting, a subset of predictive modeling, is particularly relevant for PPE allocation. AI can integrate variables such as infection rates, patient volume, and PPE usage patterns to generate real-time predictions. These insights guide procurement and distribution decisions, ensuring optimal PPE availability while minimizing waste and shortages.

Effectively managing ICU resources is an intricate task that requires balancing patient care needs with logistical constraints. AI-driven predictive modeling and demand forecasting emerge as formidable tools to tackle this challenge. Real-world examples exemplify AI's transformative impact on resource allocation, bed availability, PPE management, and capacity planning. As healthcare systems continue to evolve, integrating AI into resource management strategies holds immense promise for enhancing patient care, optimizing operational efficiency, and fostering resilient healthcare systems (Figure 1).

14 | Conclusion

In conclusion, the fusion of AI with infection control practices in ICUs offers a glimpse into a future where patient safety and care are elevated to unprecedented levels. The multi-faceted approach outlined in this paper, spanning risk prediction, real-time monitoring, automation, resource optimization, and personalized care plans, embodies the potential of AI to address the complex challenges of infection prevention. While challenges and ethical considerations lie ahead, the remarkable progress made in this arena cannot be ignored. As healthcare professionals and policymakers navigate the evolving landscape, embracing AI's transformative potential can lead to safer, more efficient ICUs, setting the stage for a future where technology and human expertize converge for optimal patient care. Further research and collaborative efforts are needed to refine AI-driven infection control strategies and unlock their full potential in the pursuit of patient well-being and healthcare excellence.

Author Contributions

N.D. and A.A.G. were involved in the ideation and planning of the manuscript. All authors contributed to writing, editing and reviewing of the manuscript.

Acknowledgments

The authors received no specific funding for this work.

Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare that they have no competing interests.

Data Availability Statement

The authors confirm that the data supporting the findings of this study are available within the article.

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