
Hospital-Acquired Infection Management with Artificial Intelligence: A Comprehensive Review

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Abstract

Hospital-acquired infections (HAIs) remain a major contributor to patient morbidity, mortality, and healthcare costs. This review examines how artificial intelligence (AI) enhances HAI detection, surveillance, and management through models such as support vector machines, decision trees, and natural language processing. These techniques enable real-time risk prediction and support clinical decision-making. Key challenges including data privacy, system integration, and model interpretability are also discussed. The review highlights the need for ethical, interdisciplinary approaches and concludes that AI offers a promising shift from reactive to proactive infection control in modern healthcare systems.

Keywords: Hospital-Acquired Infections, Nosocomial Infections, Artificial Intelligence, Machine Learning, Intelligent Surveillance, Predictive Modelling, Clinical Decision Support.

1 Introduction

Hospital-acquired infections (HAIs), also referred to as nosocomial infections, pose a persistent challenge to healthcare systems worldwide due to their significant impact on patient morbidity, mortality, and resource utilisation. These infections—such as urinary tract infections (UTIs), surgical site infections (SSIs), bloodstream infections, and ventilator-associated pneumonia—typically arise during hospitalisation and are not present or incubating at the time of admission [1]. They are often linked to invasive procedures, medical devices, or surgical interventions, and are caused by a wide range of pathogens, including bacteria, viruses, fungi, and parasites [2]. Traditional HAI surveillance methods, including manual chart reviews and laboratory reports, are limited by delays, subjectivity, and underreporting. Variability in clinical decision-making further complicates infection control efforts. The COVID-19 pandemic intensified these issues by introducing new transmission risks and straining healthcare infrastructure. In response, artificial intelligence (AI) has emerged as a transformative approach to infection surveillance and management. AI models—including support vector machines (SVMs), decision trees, neural networks, and natural language processing (NLP)—can process large-scale healthcare data in real time, enabling early identification of infection risks, predicting outbreak trends, and optimizing clinical resources. Notably, recent studies have reported AUROC values exceeding 90% for AI-based HAI prediction models [3], highlighting their potential for real-world deployment. Furthermore, AI-based training and monitoring systems (AITMS) have improved adherence to infection control protocols, such as the use of personal protective equipment (PPE), through continuous surveillance and feedback [4]. These systems can uncover patterns in complex datasets that may elude conventional analytical approaches, thereby facilitating personalised and proactive interventions. A comparative summary of conventional versus AI-based methods for HAI surveillance is presented in Table 1. A broader conceptual framework for AI-driven infection management, covering technologies, data sources, and stakeholders, is illustrated in Figure 1.

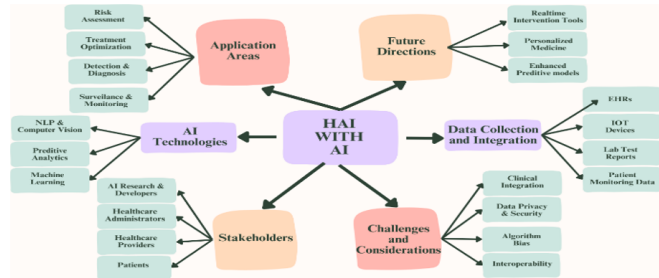


Figure 1 Overview of the study: Conceptual framework outlining AI applications for HAI management, including key stakeholders, technologies, data sources, and future directions.

Table 1 Comparison of traditional and AI-based methods for HAI surveillance

| Aspect | Traditional Methods | AI-based Methods |
|-------------------|--|---|
| Performance | Variability in sensitivity and specificity; generally modest detection rates | Higher sensitivity and specificity in identifying HAIs; demonstrated superior performance in some clinical settings [5] |
| Data Requirements | Manual data entry; prone to incompleteness and underreporting | Capable of processing large, complex datasets; reliant on quality of digitised records [6] |
| Timeliness | Often delayed due to retrospective review | Near real-time detection and intervention possibilities |

2 Methodology

This review investigates the application of artificial intelligence (AI) models in predicting and managing hospital-acquired infections (HAIs) across healthcare environments. A structured literature review approach was adopted to ensure the inclusion of relevant and high-quality studies.

Inclusion Criteria

Peer-reviewed articles published from 2010 onwards were considered if they:

- Employed empirical methods for HAI prediction or management,
- Implemented AI or machine learning (ML) algorithms, and
- Reported model performance metrics such as accuracy, precision, recall, F1-score, or AUROC.

Exclusion Criteria

The following were excluded from the review:

- Non-empirical works (e.g., opinion pieces, editorials),
- Non-English publications, and
- Studies not explicitly addressing HAIs.

Research Objectives

The review aimed to answer the following research questions:

- **RQ1:** How effective are AI models in predicting HAIs across clinical settings?
- **RQ2:** Which AI techniques yield the best results, and under what conditions?
- **RQ3:** What are the key challenges in deploying AI models for HAI surveillance in real-world hospitals?

Search Strategy and Screening

Relevant literature was identified through keyword-based searches in PubMed, IEEE Xplore, Scopus, and Google Scholar. Search terms included combinations of “hospital-acquired infections,” “nosocomial infections,” “machine learning,” “artificial intelligence,” and “predictive modelling.” Titles and abstracts were screened for relevance, followed by full-text reviews of selected articles. Data were extracted on algorithms used, datasets, evaluation metrics, and implementation context.

Scope of the Review

The review focuses on AI-enabled monitoring and infection control systems within hospital settings. Emphasis is placed on model performance, interpretability, and practical feasibility. Studies involving structured (e.g., electronic health records) and unstructured data (e.g., clinical notes) were included to capture the diversity of AI techniques in use.

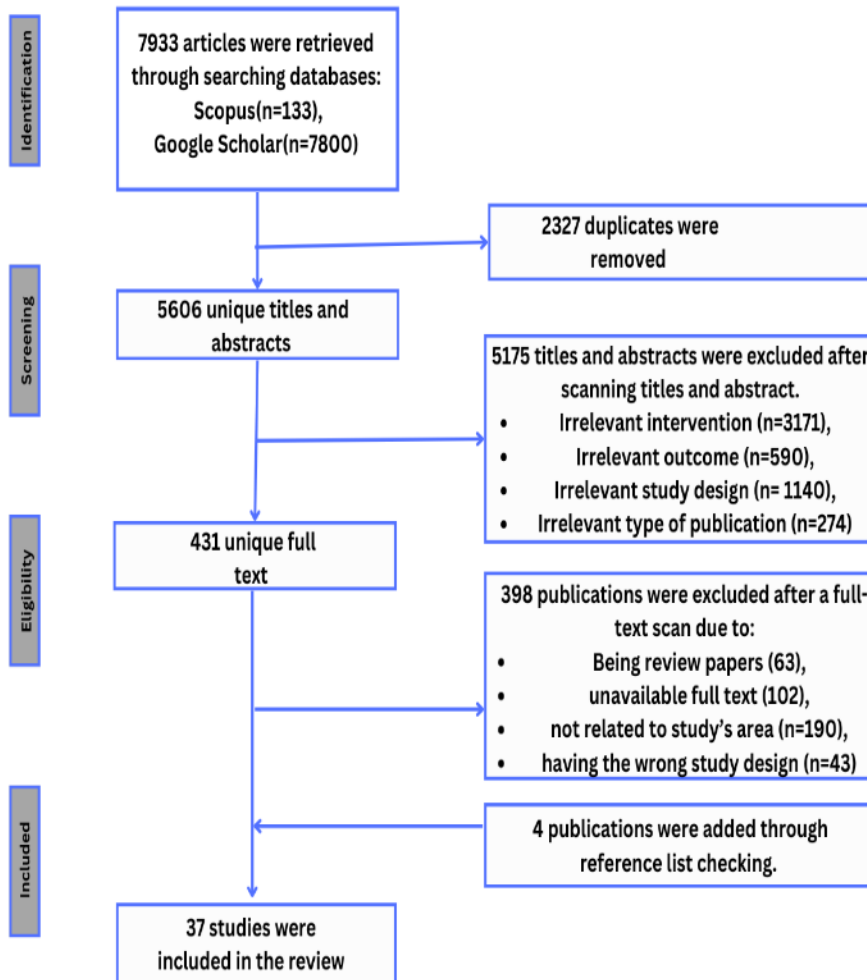


Figure 2 Systematic review methodology applied for literature selection

3 Results and Discussion

This section synthesises findings from selected studies on AI applications for the prediction, surveillance, and control of hospital-acquired infections (HAIs). The discussion is structured around the research questions outlined in the methodology.

RQ1: Efficiency of AI Models in Predicting HAIs

Numerous studies report that AI models outperform conventional approaches in HAI prediction. Ferreira et al. [7] employed random forest algorithms using over 200 NHSN-based features, achieving superior accuracy across diverse hospital datasets. Similarly, Ehrentraut et al. [5] demonstrated that gradient tree boosting achieved a recall of 93.7% and an F1-score of 85.7%, significantly surpassing traditional surveillance scores such as SAPS II. Support vector machines (SVMs) and ensemble techniques have been particularly effective in modelling nonlinear risk factors. For instance, Barchitta et al. [8] showed improved HAI identification using ICU admission data, while Branch-Elliman et al. [9] successfully applied natural language processing (NLP) to detect urinary tract infections from clinical narratives. These findings collectively affirm the high predictive capability of AI in clinical infection control.

RQ2: Effective AI Techniques and Their Contexts

Among the evaluated methods, SVMs with radial basis function (RBF) kernels, random forests, XGBoost, and decision trees emerged as consistent top performers. Ensemble methods, in particular, showed robustness across varied datasets—including structured EHRs, microbiological results, and clinical notes. Savin et al. [10] noted that XGBoost handled imbalanced and noisy datasets effectively. Moreover, studies emphasise the role of model optimisation: Ehrentraut et al. [5] demonstrated that simple preprocessing and hyperparameter tuning significantly enhanced model precision and recall, suggesting the importance of calibration over algorithm choice alone.

Table 2 Mapping of infection types to AI approaches and data characteristics

| Infection Type | Key Data Features | Suitable AI Approaches |
|---------------------------------|---|---|
| Urinary tract infections (UTIs) | Demographics, urinalysis, catheter use | Logistic regression, decision trees, ensemble models (random forest, XGBoost) |
| Surgical site infections (SSIs) | Surgical history, culture reports, wound classification | NLP on clinical notes + structured data via ensemble models |
| Ventriculitis and meningitis | CSF analysis, imaging, neurological markers | Tree-based models (random forest, XGBoost) |
| Catheter-associated infections | Insertion/removal logs, nursing notes, microbial tests | RNNs, LSTM for temporal data; Bayesian networks + NLP |

Table 2 summarises key infection types with corresponding data characteristics and AI models. These mappings indicate that no universal model exists for all HAIs; model selection must align with clinical context and data availability.

RQ3: Challenges in Real-World Implementation

Despite strong performance in controlled studies, several barriers hinder AI integration in clinical environments. Matheny et al. [11] and Jiang et al. [12] highlight challenges such as data heterogeneity, lack of generalisability, and the “black box” nature of complex models, which limit interpretability and clinician trust. Privacy and data governance are critical concerns, particularly in deep learning applications where model logic is difficult to audit [13]. Integration with existing hospital information systems also presents technical challenges, requiring robust interoperability and cross-disciplinary collaboration [14]. Nonetheless, promising real-world use cases exist. Dos Santos et al. [3] applied a multilayer perceptron model that successfully identified 67 of 73 HAI cases in deployment, achieving high sensitivity. Their findings underscore the potential of AI for early detection, provided continuous model validation and clinical oversight are ensured.

4 Conclusion

This review highlights the growing relevance of artificial intelligence (AI) in hospital-acquired infection (HAI) prediction, surveillance, and control. Across various infection types and healthcare settings, AI models—including support vector machines (SVMs), decision trees, ensemble methods such as random forest and XGBoost, and deep learning techniques—have consistently outperformed traditional statistical approaches. These models effectively process structured data, clinical biomarkers, and unstructured notes to provide early, accurate risk identification and support evidence-based decision-making. However, several implementation challenges remain, including data fragmentation, limited model interpretability, and interoperability with hospital systems. Ethical concerns surrounding patient privacy and algorithmic transparency further complicate adoption. Future progress will depend on developing explainable AI systems, integrating predictive models into real-time hospital workflows, and designing unified frameworks capable of managing multiple HAI types through multi-modal learning.

Cross-disciplinary collaboration and continuous model validation are essential to ensure safe, effective, and sustainable deployment. With appropriate governance and clinical engagement, AI can transform infection control into a proactive, data-driven domain that improves patient outcomes and enhances healthcare efficiency.

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Biography



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