Published in final edited form as:
Curr Opin Infect Dis. 2024 August 01; 37(4): 290–295. doi:10.1097/QCO.0000000000001028.

Navigating the Future: Machine Learning's Role in Revolutionizing Antimicrobial Stewardship and Infection Prevention and Control

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Abstract

Purpose of review: This review examines the current state and future prospects of machine learning (ML) in infection prevention and control (IPC) and antimicrobial stewardship (ASP), highlighting its potential to transform healthcare practices by enhancing the precision, efficiency, and effectiveness of interventions against infections and antimicrobial resistance.

Recent findings: ML has shown promise in improving surveillance and detection of infections, predicting infection risk, and optimizing antimicrobial use through the development of predictive analytics, natural language processing, and personalized medicine approaches. However, challenges remain, including issues related to data quality, model interpretability, ethical considerations, and integration into clinical workflows.

Summary: Despite these challenges, the future of ML in IPC and ASP is promising, with interdisciplinary collaboration identified as a key factor in overcoming existing barriers. ML's role in advancing personalized medicine, real-time disease monitoring, and effective IPC and ASP strategies signifies a pivotal shift towards safer, more efficient healthcare environments and improved patient care in the face of global antimicrobial resistance challenges.

Keywords

Machine Learning; Artificial Intelligence; Antimicrobial Stewardship; Infection Prevention and Control

Introduction:

From enhancing the efficiency of prospective audit and feedback programs [1–3] to improving the prediction of antimicrobial resistance (AMR) [4], machine learning (ML) is poised to disrupt infection prevention and control (IPC) and antimicrobial stewardship

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Conflicts of interest
There are no conflicts of interest.

(ASP) practices. This review seeks to discuss the current applications of ML within IPC and ASP practices, exploring its potential in refining the precision, efficiency, and effectiveness of surveillance programs, managing infections, and combating AMR. We also highlight the potential of an integrated future state, where the combination of clinical insight with cutting-edge computational techniques become paramount in devising innovative strategies to address the critical challenges faced by IPC and ASP in modern healthcare delivery systems.

Current State of Machine Learning in Infection Prevention and Antimicrobial Stewardship

To contextualize the applications of ML within IPC and ASP, it is essential to first discuss what ML entails. At its core, ML is a subset of artificial intelligence (AI) that enables computers to learn from and make decisions based on data, without being explicitly programmed for specific tasks. This is achieved through algorithms that iteratively learn from data, allowing the system to find hidden insights without being explicitly directed where to look. ML can be broadly categorized into three types: supervised learning, where the model is trained on a labeled dataset; unsupervised learning, where the model learns from an unlabeled dataset to identify patterns; and reinforcement learning, where an algorithm learns to make decisions through trial and error to achieve a certain goal [5].

In healthcare, ML is applied to various data types, including but not limited to clinical data, genomic data, and imaging data. For clinical data, ML models are trained to predict clinical events by learning from historical health records and patient data [6]. When applied to genomic data, ML aids in understanding the genetic factors of diseases and antimicrobial resistance (AMR), enabling the development of targeted therapies and the prediction of AMR patterns [7]. Furthermore, in medical imaging, ML algorithms are trained to automatically detect and classify abnormalities [8].

One of ML's first applications, the MYCIN system [9], was created in the 1970s, and served as a computer-based consultation to aid in the diagnosis and treatment of bacteremia. Decades later, many of the recent changes in the ML field have revolved around increased computational power and novel algorithms and methods. Simultaneously, a paradigm shift in how data are used and analyzed for clinical decision-making has created a synergistic platform for advancement in IPC and ASP. With the capability to process and learn from vast amounts of data far beyond human capacity, ML algorithms have shown potential in enhancing diagnostic accuracy [10], predicting patient outcomes [11], and personalizing treatment options [12,13]. This shift towards data-driven decision-making promises to improve IPC and ASP by identifying patterns and trends that are not immediately apparent, enabling a more proactive and targeted approach to managing infections and antimicrobial use.

Infection Surveillance—The recent examples of integrating ML into infection surveillance and detection marks a significant leap forward in the identification and control of healthcare-associated infections (HAIs). Through the analysis of extensive datasets from electronic health records (EHRs), ML can identify patterns and correlations that might go unnoticed by conventional epidemiological methods [14]. Despite a higher rate of false positives, an ML model using EHR data to generate daily risk for hospital-onset *Clostridiodes difficile* (C. difficile) infection identified the same number of cases as pre-onset swab-based surveillance providing opportunity for early intervention and prevention [15]. Prior to clinical suspicion, an ML-based model facilitated the early detection of ventilator-associated pneumonia (VAP) due to prediction of an impending VAP event [16].

At the public health level, natural language processing (NLP) techniques including sentiment analysis and topic modeling on social media data have gleaned insights into emerging outbreaks [17–21]. Several ML models have used clinical data to develop Hepatitis B virus (HBV) risk assessment models but remain in the pre-clinical deployment phase [22]. From using weather and air pollution as inputs to models that predict infection, recovery, and mortality rates for COVID-19 [23], to integrating multiple modeling techniques to enhance understanding of Mpox spread [24], ML techniques have the potential to inform policy making.

Infection risk factors, diagnosis, and prognosis prediction—ML has also demonstrated significant potential in infection stages prediction and risk assessment, offering tools for early identification of patients at risk of developing healthcare associated infections. This can tailor preventive measures, optimize patient management, and improve clinical outcomes. ML models have been developed to predict the risk factors and occurrence of surgical site infections (SSIs) by analyzing preoperative and intraoperative data, surpassing the performance of traditional risk stratification techniques [25, 26]. Similarly, ML models derived from administrative and EHR text data achieved high performance in the detection of SSIs holding the potential of automating the detection of complex SSIs [27].

ML has been employed to forecast the occurrence of bloodstream infections caused by Gram-positive and Gram-negative bacteria, facilitating early and appropriate antimicrobial therapy [28]. ML has also been shown to identify secondary bacterial infections in COVID-19 patients, enabling preemptive interventions to mitigate the severity of these complications [29].

Antimicrobial Resistance: ML has emerged as an important tool in the battle against AMR. Both supervised and unsupervised ML techniques have been used to predict the presence of antibiotic resistance, including the identification of risk factors for a *vancomycin-resistant Enterococci* (VRE) carrier state [30].

Newer ML techniques used for the prediction of antimicrobial resistance directly from the mass spectra, of matrix-assisted laser desorption/ionization–time of flight (MALDI-TOF) clinical isolate profiles, offer the potential for rapid and precise detection of resistant microorganisms prior to traditional laboratory resistance testing [31]. Utilizing data from whole-genome sequencing, scientists have leveraged traditional ML strategies to predict minimum inhibitory concentrations of thirteen different antimicrobials to *Acinetobacter baumannii* isolates [32]. Additionally, the introduction of a unique phylogeny-related parallelism score, which assesses the correlation of specific features with the population structure of sample sets, enhanced the effectiveness of ML in predicting antibiotic resistance to *Mycobacterium tuberculosis* [33].

Antimicrobial Stewardship: Integrating ML models into clinical practice enables healthcare providers to benefit from a more nuanced understanding of infection risk factors, promoting personalized patient care and more judicious use of antimicrobial agents. This approach not only supports antimicrobial stewardship efforts by reducing unnecessary antibiotic use but also contributes to the overall goal of enhancing patient safety and quality in healthcare settings.

To support this goal, ML models have been developed to optimize the use of antimicrobials in healthcare settings, inform stewardship interventions, and offer insights into antibiotic prescribing patterns and resistance trends [34]. ML algorithms have facilitated intravenous to oral antibiotic switches, and improved patient outcomes while minimizing the risk of the development of resistance [12].

Challenges and Limitations:

Despite the promising advancements ML offers in the realms of IPC and ASP, significant challenges and limitations remain in data quality, model generalizability, model transparency, workflow integration, and ethical considerations.

Data Quality and Model Generalizability and Interpretability—One of the primary hurdles of ML development is the quality and heterogeneity of data. ML models rely on the availability of large, high-quality datasets. However, in the context of healthcare, data are frequently fragmented across different systems and often lack standardization [35]. This variability can limit the generalizability of models across different healthcare settings. Additionally, mimicking the distribution of problems in ASP and IPC, the majority of datasets used to train ML models for ASP and IPC are imbalanced datasets, where some classes have significantly more samples than others, leading to a skewed distribution of data, which adds another layer of complexity that necessitates the utilization of sampling methods [36].

Federated learning offers a promising approach by allowing multiple institutions to collaboratively train a machine learning (ML) model without sharing raw data. This method addresses the limitations of centralized training models and can maintain performance even with imbalanced datasets. However, the adoption of federated learning in healthcare is still in its early stages and demands significant coordination among various institutions throughout each phase of the process [37].

Another significant challenge is the interpretability and transparency of ML models. The “black box” nature of some advanced ML algorithms can make it difficult for clinicians to understand how predictions are made, which in turn can hinder their trust and willingness to rely on these systems for decision-making [38]. In addition to ensuring that ML models are transparent and interpretable, resources are frequently needed to monitor deployed models in healthcare environments, and procedures for continued model surveillance are still nascent [39].

Workflow Integration and Ethical Considerations—Integrating ML algorithms into clinical workflows goes beyond technological implementation and involves alignment with the workflow, culture, and practices of healthcare professionals. From the early stages of ML development, it is crucial to consider these factors, as training models at various points of care can yield different prediction metrics and address different questions [40]. Resistance to change and concerns about automation replacing human judgment can also be significant barriers to adoption [41].

Furthermore, ethical considerations, including privacy concerns and algorithmic bias, are paramount. ML models can perpetuate or even exacerbate biases present in the training data, leading to disparities in patient care. Ensuring that models are fair, equitable, and respectful of patient privacy is essential for their ethical application in healthcare [42].

While ML presents a transformative opportunity for IPC and ASP, addressing these challenges is essential for realizing its full potential. Overcoming these challenges are paramount and highlight the importance of dually trained clinical informaticists and infectious diseases clinicians and providers. Their role in facilitating collaboration between data scientists, clinicians, and operational leaders is vital to navigating these challenges, and ensures that ML tools are dependable, interpretable, and seamlessly integrated into healthcare delivery.

Future Directions

Despite existing challenges, the future of ML in IPC and ASP holds vast potential for progress, innovation, and improvement. Leveraging ML's capabilities offers a bright future where healthcare providers can make well-informed decisions, ensuring antibiotics are used wisely and effectively. This strategy not only contributes to combating antimicrobial resistance but also supports broader public health objectives by enhancing patient safety and promoting the responsible use of essential medical resources.

Furthermore, the integration of genomics, natural language processing, and ML is set to transform how transmission events are identified, assist in evaluating outbreak responses, and lay the groundwork for automated infection detection strategies. With technological advancements, incorporating these tools into healthcare protocols is expected to significantly enhance the accuracy and efficiency of IPC and ASP efforts.

Enhanced infection screening and prediction: ML systems not only have the potential to enhance the accuracy and promptness of infection detection but also alleviate the workload on infection control teams by automating routine surveillance tasks [14]. Furthermore, ML models can assimilate various data sources, including microbiological reports, patient demographics, and clinical outcomes, to provide an all-encompassing view of infection risks. This comprehensive approach can improve healthcare facilities' capability to implement focused prevention strategies, ultimately leading to lower transmission rates of HAIs and better patient outcomes.

The employment of ML in infection surveillance and detection signifies an exciting advancement in IPC and ASP, offering novel tools to address the ongoing challenges posed by infectious diseases in healthcare settings.

Technological Innovations and Integration: Global deployment of technologies like the prediction of AMR through genomic data, not only offers a faster and more accurate alternative to traditional culture-based methods but allows for timelier and more targeted antimicrobial therapy [31]. Furthermore, a future where the wide use of explainable AI models demystify ML predictions for clinicians, will foster trust and facilitate its adoption in clinical decision-making [34].

NLP techniques and large language models extract valuable information from clinical notes, laboratory reports, and other unstructured data sources, offering a richer context for training and development of ML models to identify risk factors, automate abstraction of infection cases, and track outbreaks in real time.

Enhancing Personalized Medicine and Real-Time Monitoring: The growth of personalized medicine, supported by machine learning, promises to tailor treatment plans to the unique data of each patient, potentially minimizing adverse drug reactions and enhancing therapeutic outcomes. Additionally, techniques and algorithms for predictive model development are becoming more sophisticated, allowing for the improved forecasting of infectious disease outbreaks. These advancements enable public health responses to be dynamically adjusted and mitigate the impact on communities. The ongoing commitment of researchers, clinicians, and policymakers will be essential for transforming IPC and ASP practices for the betterment of global health.

Conclusion:

Machine learning has emerged as a transformative force in the fields of IPC and ASP, promising to enhance the precision, efficiency, and effectiveness of healthcare interventions. As this review highlights, the integration of ML in these domains offers innovative solutions for surveillance, detection, prediction, and management of infections and antimicrobial resistance. However, realizing the full potential of ML requires addressing challenges related to data quality, model interpretability, ethical considerations, and integration into clinical workflows. The continued evolution of ML technologies presents an exciting avenue for advancements in personalized medicine, real-time disease monitoring, and the development of more effective IPC and ASP strategies. Collaborative efforts across various disciplines will be key to overcoming existing barriers and leveraging ML to improve patient outcomes, optimize antibiotic use, and combat the global threat of antimicrobial resistance. The journey ahead is promising, with ML poised to play a pivotal role in shaping the future of infection prevention and antimicrobial stewardship.

Financial support and sponsorship

RJM reports funding from the Centers for Disease Control and Prevention (U01CK000590), the National Institutes of Health (1R01AI178121), and the Texas Health Resources Clinical Scholars Program.

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Key Points:

1. Predictive analytics, large language models, and natural language processing, are key areas for future machine learning development in IPC and ASP.
2. Data quality, model interpretability, ethical considerations, and clinical integration are significant barriers to machine learning's full potential in ASP and IPC.
3. Cross-disciplinary effort and training are crucial for overcoming the barriers in machine learning implementation in ASP and IPC.