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CURRENT STATUS OF ARTIFICIAL INTELLIGENCE IN ANTIMICROBIAL STEWARDSHIP: A COMPREHENSIVE LITERATURE REVIEW

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ABSTRACT

Antimicrobial Resistance (AMR) is a rising global problem and is a major challenge for modern healthcare systems. To prevent AMR, Antimicrobial Stewardship Programs (AMS) were introduced, and their implementation has led to significant changes in the regulation, surveillance, and usage of antimicrobial drugs with a primary goal to prevent the transmission of multidrug-resistant pathogens. However, several factors, such as the delay in microbiological diagnosis and the variability in each individual's pharmacokinetics, constrain these efforts. This phenomenon leads to irrational prescription of broad-spectrum antibiotics, thereby leading to higher rates of resistance. Artificial intelligence (AI), from advanced machine‑learning algorithms to natural language processing and autonomous systems, is increasingly being integrated into healthcare, offering a transformative, data‑driven way to support clinical decision‑making. This comprehensive literature review explores how AI is currently being used in antimicrobial stewardship and provides an in‑depth look at key performance metrics that highlight how algorithmic models can outperform traditional methods in choosing empirical therapies and improving diagnostic accuracy. The review also looks into how machine learning tools are helping to improve pharmacokinetic and pharmacodynamic dosing. Finally, the study addresses major social and technical challenges such as algorithmic bias, the lack of transparency often seen in deep neural networks, and the significant infrastructure gaps that exist between high‑income countries and low‑ and middle‑income regions that limit the wider adoption of these technologies.

KEYWORDS: Artificial intelligence (AI); Antimicrobial drugs; Microbial Drug Resistance; Antimicrobial Stewardship; Machine Learning; Diagnosis, Microbiological / methods; Clinical Decision Support Systems; Pharmacokinetics; Health Care Disparities.

INTRODUCTION

The global rise in antimicrobial resistance (AMR) is recognized as one of the most pressing and challenging public health problems of the current century. If these current trends are ignored, epidemiological projections indicate a catastrophic outcome. By the year 2050, AMR is forecasted to cause up to ten million deaths annually, challenging the efficacy of standard medical interventions, surgical prophylaxis, and chemotherapeutic protocols.[1] In-depth retrospective analyses of healthcare-associated infections (HAI) have also quantified this burden. In 2017 alone, invasive infections caused by multidrug-resistant organisms resulted in an estimated 11,852 deaths, 448,224 excess inpatient days, and HAI-rate-attributable healthcare costs of $1.9 billion within the United States. The financial costs of treatment failure vary by pathogen, with costs ranging from $22,293 for methicillin-resistant Staphylococcus aureus (MRSA) to $57,390 for highly resistant Gram-negative pathogens like carbapenem-resistant Acinetobacter. Furthermore, attributable mortality estimates for these hospital-acquired infections range from 14.2% to 24.1%, underscoring the lethal consequences of empirical therapy failure.[2]

To lessen this biological and economic crisis, the World Health Organization (WHO) and major infectious disease societies have made the widespread use of Antimicrobial Stewardship (AMS) programs a top priority. Inherent diagnostic latency affects traditional AMS practices. Conventional, culture-based microbiological diagnostics require 24 to 72 hours of incubation and susceptibility testing to yield definitive phenotypic results. This diagnostic delay forces clinicians into a state of uncertainty, often warranting the administration of empiric, broad-spectrum antimicrobial therapy in the acute phase to prevent patient deterioration and thereby death. The AMS initiatives seek to rationalize prescribing practices, optimize dosing regimens, and mitigate the ecological harm inflicted by broad-spectrum antibiotics on the human microbiome, thereby diminishing the selective pressures that facilitate the emergence of multidrug-resistant organisms (MDROs).[1]

The discovery of novel antimicrobial agents has been at a standstill for the past 15 years, which further compounds this crisis. Scientific hurdles, increased regulatory timelines, and marginal financial returns for pharmaceutical companies constrain the discovery and development of new antibiotics.[1] Therefore, it is essential to preserve the efficacy of the current antimicrobial pipeline through advanced AMS strategies. In this context, the development of artificial intelligence (AI) and machine learning (ML) is a big step forward for analytical proficiency. AI systems can help close the gap in diagnostics by combining electronic health records (EHR), patient demographic data, local patterns of antimicrobial susceptibility, and real-time monitoring of physiological data.[3] These technologies are contributing to a major shift in how infectious diseases are managed, moving the paradigm from reactive, generalizable empirical methods to proactive, data-driven precision medicine.

Machine Learning (ML) in Diagnostic Accuracy and Empirical Therapy Selection

One of the most important applications of ML in AMS is to improve the effectiveness of Clinical Decision Support Systems (CDSS). These systems use predictive models to perform a wide range of complex cognitive tasks that earlier required human expertise. These tasks include optimizing empirical antibiotic selection, accelerating pathogen identification, predicting complex resistance phenotypes, and continuously monitoring patient conditions.[4] Systematic reviews and meta-analyses that evaluated the diagnostic accuracy and predictive efficacy of ML algorithms demonstrated their superiority compared to standard clinical risk stratification scoring systems.[5]

The Area Under the Receiver Operating Characteristic Curve (AUC) is a statistical measure that quantifies the performance of these computational models in distinguishing between susceptibility and resistance to a specific antimicrobial. Comprehensive meta-analyses show that ML algorithms used for AMS tasks have AUC values between 0.64 and 0.992, which means they can reliably predict outcomes in a wide range of patient populations.[6] A more profound analysis of pooled effect sizes provides a deeper understanding of the specific operational characteristics of these computational models in the acute care setting.

Table 1 summarizes pooled estimates of diagnostic accuracy, sensitivity, specificity, Positive Predictive Value (PPV), and Negative Predictive Value (NPV). Machine learning models exhibited strong overall performance and a high NPV that supports the exclusion of resistant phenotypes and assists clinicians in early de-escalation of antimicrobial therapy.[6]

Table 1: Diagnostic performance of machine learning tools for predicting antimicrobial susceptibility.[6]

Performance Metric	Pooled Effect Size (95% CI)	Clinical Implication for Antimicrobial Stewardship
Accuracy	74.97 (73.35–76.58)	Reliable overall classification of appropriate versus inappropriate empiric therapy.
Sensitivity	76.89 (71.90–81.89)	Effective identification of complex patients requiring specific, targeted antimicrobial interventions.
Specificity	73.77 (67.87–79.67)	Avoidance of unnecessary broad-spectrum usage in clinically low-risk patient populations.
Negative Predictive Value	79.92 (76.54–83.31)	High confidence in ruling out the need for aggressive, broad-spectrum empiric coverage.
Positive Predictive Value	69.41 (60.19–78.63)	Moderate reliability when the model indicates that severe resistance is present.

Various algorithmic methodologies for AMR applications, each addressing conflicting demands of computational efficiency and interpretability, are available. Naive Bayes classifiers and decision trees are often used because they are simple to interpret for medical professionals to adhere to the algorithm's logical reasoning. Complex architectures, such as Support Vector Machines (SVMs), Random Forests, and

Artificial Neural Networks (ANNs), are employed to capture deeply hidden nonlinear relationships in large datasets.[6] Gradient-boosting machines and logistic regression models have shown remarkable effectiveness in analyzing complex, irregular temporal data, as evidenced by their ability to predict the rapid onset of multidrug resistance in highly vulnerable Intensive Care Unit (ICU) populations.[5] These algorithms help medical professionals choose the most effective empiric therapy by finding subtle physiological alterations and historical patterns, and this process influences the way in which patients receive treatment.[6]

Despite excellent statistical metrics, the real-world performance of an AI-CDSS depends on complete epidemiological, diverse, and structured training data. Clinical data on antimicrobial prescribing practices often exhibit inconsistencies and missing variables due to diverse practices in the institutions. Failure to address genetic, environmental, and patient-specific factors directly leads to ineffective and inappropriate treatment recommendations, which can paradoxically worsen the AMR problem.[6] Consequently, utilizing validated instruments, such as the Revised Tool for the Quality Assessment of Diagnostic Accuracy Studies Using AI (QUADAS-AI), a systematic evaluation of methodological quality, is considered important to ascertain the reliability and generalizability of these diagnostic interventions before widespread clinical deployment.[5]

Natural Language Processing (NLP), Large Language Models (LLM), and Retrieval-Augmented Generation (RAG) Architectures

Predictive machine learning models operate on highly structured data, such as vital signs, laboratory values, and medication codes. However, substantial clinical information is present in unstructured text, including physician progress notes, pathology reports, radiology interpretations, and consultative narratives. Computers can understand, combine, and extract useful clinical information from unstructured human language through Natural Language Processing (NLP).[7]

In the past five years, NLP has undergone a technological evolution due to the development of transformer-based architectures. Models such as Bidirectional Encoder Representations from Transformers (BERT), T5, LLaMA-2, and Generative Pre-trained Transformer 4 (GPT-4) employ advanced mechanisms to understand the contextual significance of different words in large-scale clinical datasets, achieving a high level of comprehension.[7] In the operational framework of AMS, NLP algorithms can systematically analyze Electronic Health Records (EHRs) to automate the evaluation of adherence to guidelines, extract microbiological data from complex bioassays, and summarize detailed medical histories into concise, actionable summaries for physicians on routine rounds.[8] This automation drastically reduces the burden on infectious disease specialists, allowing time for complex diagnostic reasoning and direct patient care.[9]

Another interesting use of NLP in healthcare administration is the ambient listening technology. Major healthcare networks like Kaiser Permanente employ these systems, which use AI to automatically transcribe and summarize patient-physician encounters in real time. This new solution generates structured clinical notes from natural conversation, reducing the time physicians spend on tedious documentation and improving workflow efficiency, allowing prescribers to focus entirely on comprehensive clinical assessments.[10]

However, one cannot ignore the significant risks associated with using generative large language models (LLMs) for direct clinical decision-making and therapeutic recommendations. LLMs are excellent at generating language and identifying patterns, but they lack an understanding of physiological processes or clinical reasoning. Medical knowledge is growing at an alarming rate, increasing by twofold every 73 days, making LLMs a useful tool for synthesis. However, systematic evaluations of LLMs used to guide antimicrobial therapy have identified significant limitations.[9] Research shows that LLMs often give answers that lead to more mistakes in prescribing and pose serious risks to patient safety, unlike specialized ML predictive models.[11]

A highly dangerous phenomenon about generative models is "hallucination" or "confabulation," which is when the algorithm generates medically incorrect data, fake citations, or very inappropriate dosing recommendations in response to a prompt. Additionally, LLMs operate by synthesizing probabilities from their training datasets, which frequently consist of extensive, unfiltered sections of the internet (such as public forums like Reddit and Wikipedia), making them inherently unable to assess the scientific accuracy or underlying bias of their primary source data.[9]

To mitigate these serious risks in clinical settings, several renowned institutions are transitioning beyond purely generative models and adopting Retrieval-Augmented Generation (RAG) architectures. RAG refuses to allow the LLM to use its enormous, general pre-training data. Instead, it ensures that the algorithm uses only a carefully selected, specialized database of validated clinical guidelines, institutional antibiograms, and peer-reviewed literature to generate standardized responses. A well-known example is the use of a RAG-based conversational agent at Brazil's Albert Einstein Hospital. This system transformed traditional antimicrobial guidelines into a dynamic conversational agent that provided frontline physicians with real-time, contextually relevant, and strictly policy-compliant guidance.[8] Even with RAG architectures and Health Insurance Portability and Accountability Act (HIPAA)-compliant platforms like DocsGPT, the majority acknowledge that LLMs are excellent for briefly summarizing and retrieving information. Still, they lack the reliability to function autonomously in complex clinical settings. This finding implies that stringent, continuous human oversight is required.[9]

Pharmacokinetic/Pharmacodynamic (PK/PD) Modeling and AI-Driven Dosage Optimization

Optimizing antimicrobial dosing is a critical and highly complex step in AMS. The primary clinical goal is to sustain drug concentrations consistently above the Minimum Inhibitory Concentration (MIC) for the target pathogen, thereby ensuring optimal bactericidal or bacteriostatic efficacy while preventing systemic accumulations that lead to severe, life-threatening toxicity, including acute kidney injury (nephrotoxicity) or central nervous system impairment (neurotoxicity). This pharmacokinetic and pharmacodynamic (PK/PD) equilibrium is profoundly complicated in specific patient subpopulations, including neonates, the elderly, and, most notably, critically ill patients suffering from sepsis or septic shock. These cohorts exhibit inter- and intra-individual PK variability due to profound physiological alterations, including massive shifts in the volume of distribution caused by capillary leak syndrome, fluctuating renal and hepatic clearance, as well as multi-organ dysfunction syndrome.[12]

Model-Informed Precision Dosing (MIPD) has been the most prevalent approach to optimizing dosing recently. It employs population pharmacokinetic (PopPK) mathematical models and therapeutic drug monitoring (TDM) in a "top-down" approach.[12] TDM is particularly recommended for patients with expected substantial beta-lactam pharmacokinetic variability, individuals receiving continuous renal replacement therapy, and those with central nervous system infections.[13] Alternatively, "bottom-up" Physiologically Based PK (PBPK) modeling creates compartmental models using only intrinsic anatomical and physiological parameters.[12] However, conventional PopPK models often fail to accurately capture the non-linear, highly dynamic physiological changes that occur in real time in critical illness. Recent randomized multicenter trials found that early MIPD guided by standard PopPK in patients with septic shock did not significantly decrease ICU length of stay or improve target attainment compared to conventional empirical dosing regimens.[13]

Artificial intelligence is rapidly changing the field of pharmacology with advanced regression algorithms and nonlinear mapping techniques, such as artificial neural networks (ANNs) and extreme gradient boosting (XGBoost).[6] These AI-driven models lack strict computational compartmental models. Rather, they work with high-dimensional datasets that include detailed patient information, real-time laboratory biomarkers, continuous physiological data, and omics technologies such as transcriptomics, proteomics, and metabolomics to generate highly personalized, dynamic dosing predictions.[13]

Comparative analyses between AI-driven methodologies and traditional PopPK models consistently demonstrate that ML algorithms provide enhanced predictive accuracy for complex, narrow-therapeutic-index antimicrobials. For example, these algorithms were employed widely to optimize vancomycin, a key glycopeptide antibiotic used to treat severe MRSA infections. Research conducted has shown that XGBoost and ML algorithms substantially enhance exposure target attainment rates while simultaneously minimizing the risk of toxicity. Additionally, ML techniques are very accurate and can make complex PK predictions up to 22 times faster than regular PopPK simulations, which can be a major advantage in the time-sensitive ICU environment.[14]

TABLE 2 shows comparisons between ML‑powered pharmacokinetic tools and conventional PopPK models that consistently demonstrate the superior predictive performance of AI‑driven approaches for narrow‑therapeutic‑index antimicrobials.

Table 2: Comparison of machine learning–based pharmacokinetic models and traditional population pharmacokinetic (Pop PK) approaches in optimizing dosing of narrow‑therapeutic‑index antimicrobials.[12,13]

Pharmacokinetic Optimization Methodology	Underlying Scientific Mechanism	Clinical Advantages in Stewardship	Identified Limitations and Challenges
Traditional Population PK (PopPK)	"Top-down" mathematical modeling based on population averages and rigid compartmental kinetics.	Established theoretical foundation; widely validated and utilized in stable patient populations.	Frequently fails to capture extreme, rapid variability in critically ill patients; computationally slower.
Physiologically Based PK (PBPK)	"Bottom-up" mechanistic modeling utilizing known anatomical, physiological, and physicochemical parameters.	High theoretical precision; highly useful in special populations (e.g., pediatrics, extreme obesity).	Requires extensive physiological data, which may be entirely unavailable in acute clinical settings.
Machine Learning Models (e.g., XGBoost, ANN)	Data-driven, non-linear pattern recognition utilizing high-dimensional, real-time patient datasets.	Achieves superior exposure target attainment, manages complex physiological variability, and performs extremely rapid computation (22x faster).	Requires massive, high-quality training data; risks overfitting; models often lack mechanistic explainability.

In addition, critical challenges remain in distinguishing between antimicrobial concentrations at specific infection sites (e.g., tissue penetration) and plasma concentrations. As a result, the current clinical consensus suggests a hybrid, complementary strategy: AI-driven machine learning techniques should be incorporated as advanced overlays to traditional population pharmacokinetic models, combining the remarkable data-driven pattern recognition abilities of AI with the well-established principles of classical pharmacology.[12]

Explainable AI (XAI)

The "black box" phenomenon is a widespread and deeply embedded problem that impedes the use of advanced AI systems in clinical settings. Deep neural networks and ensemble methods are two types of complex machine learning algorithms that use thousands of hidden computational layers to process data in ways that are incomprehensible to humans.[15] Clinicians, who are ultimately responsible for the ethical, moral, and legal outcomes of their patients, are right to be careful about trusting algorithmic suggestions that can't be verified independently. They are concerned about misdiagnosis, algorithmic bias, and potential legal issues related to medical malpractice.[16]

To bridge this major trust gap, Explainable AI (XAI) frameworks have been developed. XAI's goal is to make the internal processes of complex algorithms clear, comprehensive, and logical for human operators.[15] One method utilizes Shapley values, a mathematical concept that assigns a measurable value to the input based on the extent to which the particular feature contributes to the final output. When used with advanced AMR prediction models like Gradient-Boosted Decision Trees (GBDT), this method gives physicians a clear, logical reason for the AI's output. The XAI system also determines predictive risk factors by mapping complicated, nonlinear relationships. For example, in a study published in PLOS Digital Health, researchers demonstrated that the XAI model highlighted advanced age, septicemia, and complex skin infections as the primary physiological drivers predicting resistance to narrow-spectrum drugs. This system also identified that patient variables such as diagnosis of cystic fibrosis, prolonged hospital admission duration, and specific historical drug exposures were the drivers behind its prediction of resistance to broad-spectrum agents.[16]

The XAI technology transitions from being an untrustworthy "black box" to a collaborative clinical tool because the associations identified by the AI align closely with prior physiological knowledge, existing literature, and the expectations of infectious disease specialists. Adding Gini impurity, a confidence metric, to each prediction, this tool can mathematically assess its own diagnostic uncertainty. This property provides medical professionals with an objective, statistical guide to the extent to which they should trust the algorithmic recommendation during the early stage of therapy. This approach speeds up decision-making and reduces medical errors at the same time.[16]

Agentic AI

Artificial intelligence (AI) in healthcare is advancing, moving from simple decision support to the use of advanced "agentic AI" systems.[17] Conventional AI systems have limited functionality. are governed by rules, and are reactive; they await a specific human cue or a distinct data input, perform a predetermined computational function, and produce a single output.[18] Agentic AI, on the other hand, refers to autonomous systems that are proactive and goal-driven and can continuously perceive, reason, plan strategically, and act independently within strict operational limits, which are mindful of established rules and regulations.[17]

An agentic system in an AMS setting employs a continuous four-layer feedback mechanism. The perception layer continuously receives and tracks real-time telemetry from environmental sensors, electronic health record (EHR) updates, vital signs, and laboratory information systems without requiring manual inquiry. The cognition layer analyzes the large volume of data to interpret context and identify clinical anomalies or protocol violations. The planning layer makes plans for corrective actions based on institutional rules, and the action layer executes the planned workflows autonomously.[17]

This model has plenty of clinical applications that may transform standard practices significantly, as shown in Table 3. An AI agent can perform continuous, 100% systemic audits of all inpatient and outpatient antimicrobial therapies, eliminating the need for an infectious disease pharmacist to manually request a system to check a small number of antibiotic prescriptions.[19] These agents can continually monitor for pathogens and drug discrepancies by automatically comparing new microbiological culture results to the patient's current medication record and alerting the attending physician immediately if there are any.[17]

Table 3: Clinical applications of Agentic AI architectures.[19]

Infectious Disease Subdomain	Example Tasks and Workflows Supported by Agentic AI Architectures
Antimicrobial Stewardship	Continuous bug–drug mismatch detection, autonomous identification of intravenous-to-oral (IV→PO) conversion opportunities, proactive de-escalation suggestions, and automated duration tracking with policy-aware alerts.
Infection Prevention and Control (IPC)	Ongoing checks to ensure isolation rules are followed; quick detection of clusters and outbreaks using electronic health records and sensor data; automatically gathered evidence reports; and live updates sent to public health officials.

Outpatient Parenteral Therapy	Continuous laboratory-level monitoring, patient adherence support, automated device complication surveillance, and risk-based escalation to the specialized ID team.
Consultative Care	Pre-round data assembly with source links, dynamic differential diagnosis drafts, and continuous watch for new positive cultures or sudden patient physiological deterioration.

However, assigning clinical responsibilities to autonomous computational agents calls for meticulous oversight and a strict evaluation of clinical risk. The consensus in the literature is that simple, well-defined administrative tasks include auditing for compliance, flagging inappropriate empirical prescriptions, and detecting missing infection control documentation. In highly complex situations, like treatment of uncommon infections in immunocompromised patients, the agentic AI plays a supportive and collaborative role, assembling data and highlighting clinical risks, but still leaving the final decision-making authority completely up to the clinician.[17] Experts in the field say that agentic AI doesn't replace human workers; instead, it makes their jobs easier by automating very difficult tasks. Human oversight, radical algorithmic transparency, and strict organizational governance must remain the absolute, non-negotiable foundations for the integration of agentic systems into patient care.[18]

Human-Organization-Technology (HOT) -Fit Framework

If an AI predictive model fails to perform well in the complicated and highly regulated environment of clinical practice, all this advanced technology is ineffective. Numerous challenges, like organizational, psychological, and structural barriers, make it difficult to move AI models from controlled, academic computing environments to real-world hospital settings. Research shows this implementation dynamic often employs the Human-Organization-Technology (HOT)-fit model to classify the numerous factors influencing successful adoption and long-term sustainability of an AI tool.[20]

A comprehensive Delphi study involving 36 healthcare professionals examined the deployment of AI-driven decision support systems for antibiotic prescriptions, highlighting 34 consensus-driven factors necessary for success. For the AI-CDSS to function effectively, it needs to be fully integrated into the hospital's current EHR infrastructure. Algorithms should be built directly into the physician's regular prescription workflow instead of being placed on separate and difficult-to-use secondary platforms that require separate logins. The study showed that 98.4% of clinical practice experts preferred a user interface that was easy to use and had clear navigation. 87.3% also said that having enough technical support available at all times is a must for adoption. Furthermore, AI developers' use of proprietary interfaces, hidden licenses, and outdated databases is still a major technological barrier to institutional acquisition, with experts strongly endorsing open interoperability standards.[20]

There is consensus at both the organizational and human levels about the key facilitators. The institution's willingness to embrace technological change, the active and visible support of clinical leadership and hospital boards, and the general openness of medical teams to innovative ideas are paramount. On the contrary, deeply rooted seniority-based hierarchical structures and a strict, rigid dependence on historical standards make it very challenging for institutions to accept data-driven evidence. Moreover, an excessive emphasis on the "technical skills" of an algorithm during its development, at the direct cost of usability assessment and clinical workflow mapping, often results in the system being ultimately disregarded by unsatisfied end-users. The Delphi study, interestingly, did not come to a conclusion about whether a clinician's "professional experience" is an asset or a hindrance. The literature suggests that junior clinicians are generally more open to novel care methodologies, while entrenched systems and seniority-based hierarchies may cultivate resistance to AI interventions among seasoned professionals.[20]

To overcome these structural barriers, implementation strategies must require direct user participation from the very initial stages of software design. This will ensure that the development cycle is truly application-oriented. The creation of comprehensive educational workshops, ongoing f training, and the implementation of systematic feedback loops, such as those based on the Consolidated Framework for Implementation Research (CFIR), guarantee the continuous improvement of AI tools. promoting a culture of collaborative socio-technical alignment and sustainable use.[20]

Global Health Equity: AI-Driven Stewardship in Low- and Middle-Income Countries (LMIC)

Most of the research on artificial intelligence in healthcare is about new technologies and investments from high-income countries (HICs). But the real issue with AMR is in low- and middle-income countries (LMICs).[4] In these areas, the burden of infectious disease is extremely high, but healthcare systems are severely hampered by serious structural and economic problems. A comprehensive scoping review of AMS programs in LMICs used data from 182 relevant articles, including 84 studies from 34 different LMICs. India, China, and Pakistan were the most represented countries. The review showed that there were plenty of major obstacles that made it a challenge to execute the initiative, like a lack of trained infectious disease physicians and clinical pharmacists, a lack of governmental funding, and a lack of leadership in institutions.[21]

Even though there are systemic and infrastructural issues, research findings show that prescribers in LMICs possess positive views of stewardship and understand that it is essential for controlling AMR. However, their practical understanding of local resistance patterns and the epidemiological factors contributing to AMR is still inadequate.[21] This critical deficit of knowledge becomes exacerbated by poor laboratory infrastructure and delayed reporting of results, which makes it extremely difficult for microbiology labs and treating teams to communicate with each other. This results in a lot of diagnostic uncertainty and, hence, irrational prescribing of broad-spectrum antimicrobials.[2]

Artificial intelligence possesses a lot of theoretical potential to make up for these problems with infrastructure. AI-driven predictive modeling can help quickly find pathogens and predict resistance without the need for expensive, large-scale lab infrastructure. Even with fragmented data, automated NLP surveillance systems can map regional resistance trends.[22] A scoping review found that 79% of studies showed a significant decrease in overall antibiotic use, 42% showed a reduction in the prevalence of multidrug-resistant strains, and 15 studies showed a major reduction in the costs of hospital procurement and hospitalization.[21]

Table 4 summarizes the primary barriers, facilitators, and clinical and economic impact of AI in LMICs.

Table 4: Barriers, facilitators, clinical, and economic impact of AI in AMS in LMICS.[21]

Domain	Key Findings from LMIC Scoping Reviews
Primary Barriers to AMS	Inadequate human resources, lack of microbiology laboratory support, unreliable institutional antibiograms, absence of national guidelines, minimal funding, and unrestricted over-the-counter access to antimicrobials.
Facilitators for Implementation	Availability of accessible antibiotic guidelines, dedicated multidisciplinary ASP committees, prompt laboratory support, and continuous education regarding resistance profiles.
Clinical and Economic Impacts	79% documented decreased antibiotic consumption; 42% reported decreased MDR strain prevalence; distinct reductions in hospital procurement and overall patient hospitalization costs.

However, shifting advanced AI models from high-income countries (HICs) to low- and middle-income countries (LMICs) is fundamentally incorrect and highly risky. AI models are strictly context-dependent; if machine learning algorithms are trained solely on privileged Western populations, healthcare workflows, and localized pathogens, they will show severe algorithmic bias and high rates of clinical failure when used in areas with very distinct epidemiological profiles and genetic diversity.[3]

A major shift in conventional thinking is required to guarantee that everyone across the world has access to the same resources, as shown by detailed reports from institutions like Imperial College London. Stakeholders should create open-source data infrastructures that actively encourage the standardization of AMR data for LMICs, which is a top priority.[23] Furthermore, technological innovation needs to focus on making AI tools that are lightweight, energy-efficient, and may operate offline. These tools need to work well regardless of resource-compromised settings that suffer from inconsistent internet connectivity and poor computational hardware.[22] The effectiveness of AI in addressing global AMR is dependent not only upon algorithmic sophistication but also on a "responsible by design" methodology that enhances local abilities, standardizes data formats across geographic areas, and actively eliminates the systemic inequalities obstructing access to essential digital healthcare interventions.[3]

Table 5 summarizes AI utilization in real-world case studies.

Table 5: AI in Action: Real‑World Case Studies—Summary Table.

Case Study	Setting/Location	AI System/Approach	Clinical Focus	Key Outcomes
AI Outperforming Human Prescribers[24]	Spain—12 hospitals in the HM system	iAST AI antibiotic-prescribing support	Empiric antibiotic selection for UTIs, bacteremia, and pneumonia	• AI success rate: 91–98% (top 3 choices) • Physician success rate: 84.16% • AI recommended more targeted, appropriate antibiotics
Rapid Resistance Detection[25]	Clinical trial treating Stenotrophomonas maltophilia infections	ML model analyzing mass spectrometry data integrated into EHR	Rapid detection of antimicrobial resistance	• Resistance detection time reduced: 24 hours → minutes • Mortality reduced: 11.5% (AI group) vs 15.1% (control)
KINBIOTICS Project Implementation[26]	Germany – Intensive Care Units	KINBIOTICS AI tool using routine blood tests	Early sepsis prediction and antibiotic selection	• AI accurately predicted sepsis early • Implementation challenges:

				poor digital infrastructure limited adoption
AI Chatbots for Stewardship[27]	Brazil – Albert Einstein Hospital	RAG-based AI chatbot converting static guidelines into dynamic advice	Antimicrobial stewardship and clinical decision support	• Replaced manual guideline lookup with conversational queries • Improved communication and automated monitoring • Faster detection of resistance trends

Ethical, Legal, and Regulatory Dimensions of AI in Prescribing

The advanced computational abilities of artificial intelligence inherently give rise to a range of intricate ethical, legal, and regulatory challenges that undermine the conventional, human-centered principles of medical jurisprudence. The most important among these is the considerably serious issue of legal liability and accountability. The current legal consensus, although still evolving, states that regardless of AI advancement, the physician retains the status of the primary legal representative and bears complete liability for any medical malpractice. This emphasizes the necessity for algorithms to function solely as assistive, not definitive, factors in the clinical workflow.[17]

The implementation of AI requires a constant and mindful balance between the bioethical principles of autonomy and beneficence. Survey data indicate that two-thirds of participating physicians prioritized beneficence, the ethical duty to act in the patient's optimal medical interest.[28] This method, while valid, carries the risk of employing the "expertise paradox" and automation bias of AI to override a patient's fundamental right to informed refusal.

Simultaneously, algorithmic bias poses a serious threat to the ethical principles. Training historical data inherently limits machine learning models due to societal biases, unequal access to care, and the significant underrepresentation of marginalized groups, which leads algorithms to potentially internalize and systematically exacerbate these disparities. To combat these issues, ethical frameworks require the use of highly diverse, globally representative training datasets, along with constant, ongoing algorithmic auditing by independent regulatory bodies to identify and address bias before clinical harm occurs.[15]

Finally, there should be robust data privacy policies and cybersecurity systems as these AI systems get trained on highly confidential patient data. To keep patient information private and mitigate the risk of major data breaches, healthcare must strictly enforce regulatory standards, such as the Health Insurance Portability and Accountability Act (HIPAA).[9] For the successful, long-term integration of AI into healthcare, it requires an adaptable regulatory environment that simultaneously ensures that AI stays connected to the highest ethical standards of medical science.[15]

CONCLUSION

Artificial intelligence (AI) is becoming a powerful tool in the implementation of antimicrobial stewardship (AMS). Current research shows that ML tools and predictive models can outperform traditional methods in diagnosing infections, forecasting resistance, and advising complex antibiotic dosing. New agentic AI systems could make stewardship even easier by automating surveillance, audits, and other routine administrative tasks, reducing the workload for healthcare teams and improving policy compliance. Adoption of these tools comes with structural, ethical, and socio-economic challenges. To build trust and keep human expertise at the center of decision-making, AI algorithms need to be clear and easy to understand. AI systems need to be adaptable, affordable, and designed for the realities of low- and middle-income countries to avoid widening global health inequities. Robust guidance for ethics, data privacy, and bias reduction in AI is critical.

AI will not solve antimicrobial resistance on its own. But if used responsibly with rigorous oversight and a commitment to fairness, it can help protect the effectiveness of antibiotics for generations to come.

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