E-ISSN 2250-0944
ISSN 2250-1150
doi: 10.31838/ijprt/16.02.57

Research Article

The Role of Artificial Intelligence in Addressing Antimicrobial Resistance: Challenges, Opportunities, and Strategic Interventions

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Received: 12.05.26, Revised: 09.06.26, Accepted: 13.07.26

ABSTRACT

AIMR is an emerging global health problem which affects the efficacy of critical medicines and treatment failure in clinical and public-health settings. This review provides insights into the current role of AI in tackling antimicrobial resistance across the four A's of surveillance, diagnostics, antimicrobial stewardship and drug discovery, as well as in the integration of One Health. The paper reviews the evidence, using a narrative review format and a scoping review approach with principles, synthesizing evidence from the global burden studies, clinical microbiology, machine learning research, stewardship literature and antimicrobial innovation frameworks. The review highlights the potential of using AI to enhance the use of AMR response, such as identifying resistance trends at an earlier stage, forecasting risk of resistance at the patient level, speeding up interpretation of diagnostics, improve antimicrobial prescribing, and broaden the exploration of new antimicrobials. But adoption of AI is still hindered by siloed health data systems, scarce external validation, algorithmic bias, poor interoperability of AI systems, regulatory ambiguity and poor infrastructure within health systems. The paper concludes that AI should be used as a clinically informed decision-making support infrastructure, not as a substitute for the knowledge and experience of a clinical team, laboratory capacity, or public-health stewardship.

Keywords: Artificial Intelligence, Antimicrobial Resistance, Machine Learning, Antimicrobial Stewardship, Amr Surveillance, One Health, Drug Discovery, Clinical Decision Support.

INTRODUCTION

Resistance is increasingly becoming one of the biggest health-security challenges of the twenty first century due to its contribution to the reduced effectiveness of antibiotics, antifungals, antivirals and antiparasitic in both human and non-human health systems including animals, agriculture and the environment. Resistant organisms and HAIs are not the only areas of concern. It is a

phenomenon that also represents a systemic ecological and institutional problem where microbial evolution and the misuse of antimicrobials, sub-optimal diagnostics, lack of a unified surveillance system, poor infection prevention and lack of drug innovations have all had a role in a multi-sectoral way (Murray et al., 2022). Conventional medical procedures like surgery, chemotherapy, organ transplants, neonatal and intensive-care units are increasingly at risk from avoidable infectious problems with the emergence of resistant organisms (World Health Organization [WHO], 2023).

The problem of bacterial antimicrobial resistance is already significant and widespread world-wide. Worldwide, bacterial AMR was estimated to be responsible for 4.95 million deaths in 2019, with AMR directly responsible for 1.27 million deaths (Murray et al., 2022); so AMR is not just a hypothetical risk to mortality, but a current risk. New evidence on forecasting suggests that the burden has the potential to substantially increase by 2050 unless health systems boost their efforts on prevention, diagnosis, access to antimicrobials, antimicrobial stewardship, and drug development (Naghavi et al., 2024). This forecasted increase in number of cases is particularly worrisome in low and middle income countries where laboratory capacity, access to regulated antibiotics, infection control capacity and real time surveillance are often restricted (Laxminarayan et al., 2016). Thus, AMR does not just involve a Microbiological Challenge, but also the Governance, Equity and Systems Performance Challenge.

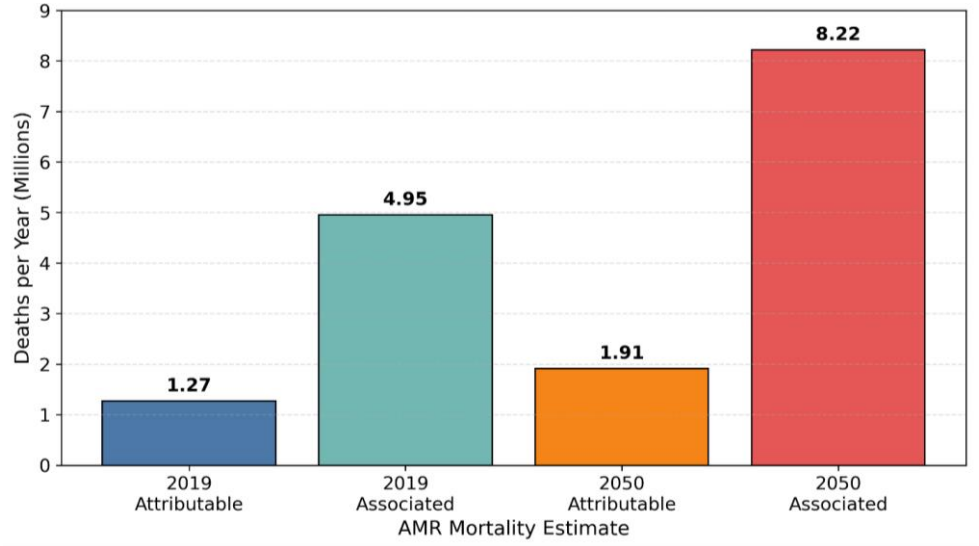

Figure 1: Global AMR Mortality Burden and Future Risk.

Traditional AMR control techniques are still vital, but as more and more applications rely on them alone, they are becoming less adequate. Culture-based diagnosis are clinically useful, but are time consuming, resource intensive and not available in many primary and district level facilities. Surveillance systems offer valuable epidemiological information, but a number of surveillance systems are not implemented in a timely fashion, are limited in scope, or lack linkage of the clinical, veterinary, pharmaceutical and environmental data streams. Inappropriate prescribing can be prevented by use of antimicrobial stewardship programmes, though these will be effective only if diagnostic information is provided in a timely fashion, prescriber adherence is achieved, institutional leadership is established and there are ongoing feedback systems (Dyaret al., 2017). The constraints present an important implementation disconnect – between the emergence of resistance and health systems' ability to detect, interpret and respond to resistance.

AI is a crucial enabling technology to help bridge this divide. In the field of AMR, AI is the name given to computational techniques that can learn patterns from the complex data, and be applied to prediction, classification, optimization and decision-making. Microbiology records, antimicrobial prescribing records, molecular sequences, electronic health records, pharmacy data, environmental samples and molecular libraries are among the different types of records that can be leveraged with machine learning, deep learning, natural

language processing, and generative modelling for microbiology applications (Boolchandani et al., 2019). In particular, those methods are applicable as AMR is a high dimensional problem. Pathogen biology, patient characteristics, antimicrobial use, hospital transmission, community prescribing patterns, agriculture use, environmental contamination all influence the development of resistance patterns. While traditional statistical methods are still applicable, AI can uncover non-linear relationships and patterns that might not be evident using traditional data analysis methods.
AI has already been shown to have potential in various areas related to AMR. Machine learning can be used in diagnostics to make early treatment decisions (before culture results) based on clinical and genomic information, making it easier to predict resistance phenotypes (Nguyen et al., 2019). AI powered systems of clinical decision support can assist in identifying inappropriate prescribing, provide a patient-specific probability of resistance, and suggest prudence for restricting or optimizing the choice of antimicrobial therapy based on validated data from microbiological data collected in the local area (Peiffer-Smadja et al., 2020). AI has the potential to assist in outbreak detection, trend forecasting for resistance and prioritisation of high-risk pathogens, both regionally and hospital-wise, in surveillance (Boolchandani et al., 2019). Deep learning can be employed to identify structurally new antibacterial compounds, as is done in drug discovery, where the computational screening can help in the early stages of antimicrobial development (Stokes et al., 2020).
But, the possibilities of AI in AMR should be taken with a grain of salt. As with every other model, the data a model is trained on is the most essential component to the success of the model. Issues with microbiology data quality, incomplete antimicrobial-use data, patient sample bias, low-resource setting underrepresentation and the lack of consistency in laboratory standards can lead to models that seem to be accurate in development, but are inaccurate in real clinical settings (Wiens et al., 2019). Furthermore, numerous AI systems are opaque, have yet to be validated externally, don't have regulatory guidelines, and have not been adopted into clinical practice. In AMR, these weaknesses are particularly significant if the wrong prediction is made, which can result in a delay in effective treatment, unnecessary broad-spectrum antibiotic use or may lead to the selection pressure for resistant organisms. Thus, AI has to be used as a clinically-informed decision support tool, and not as a microbiologist or infectious-disease specialist, pharmacist, epidemiologist, or public-health expert in its own right.
AI is a key enabler of the strategic value of connecting data, prediction and action. To achieve AMR control, early recognition of signs of AMR, timely interpretation of individual patient and population risk, prudent antibiotic prescribing, and ongoing surveillance of interventions and coordinated policy action at various levels are needed. These functions can be supported through AI when it is integrated into robust networks of laboratories, interoperable information systems, ethical governance systems and evidence-based stewardship programmes. The main one is whether or not AI can go it alone on antimicrobial resistance. Instead, the bigger issues are how to integrate AI in a responsible way with current AMR control systems to further enhance surveillance, diagnostics, stewardship, drug discovery, and coordination for One Health.

LITERATURE REVIEW

Biological adaption and the human system of continually subjecting microbes to selection pressure contribute to the development of antimicrobial resistance. Resistant organisms develop by mutation, horizontal gene transfer, clonal spread, and ecological selection, and are clinically problematic when people use too much antimicrobials, don't diagnose quickly enough, do not implement good infection prevention, and do not implement good surveillance (Holmes et al., 2016). The evidence from around the world indicates that AMR is focused on lower respiratory infections, bloodstream infections, intra-abdominal infections and urinary tract infections, which indicates that AMR is present in the emergency care setting (Murray et al., 2022). This burden is expected to increase by 2050, and will be higher for older people and low-resource regions compared to others (Naghavi et al., 2024). This allows AMR to be seen as a long-term systems problem, and not just a prescribing problem.
The literature is united on the key importance of surveillance in AMR control but the quality of surveillance is not consistent between countries and institutions. As of 2022, WHO's Global Antimicrobial Resistance and Use Surveillance System (GLASS) has enhanced the level of

standardization, but only a fraction of countries are reporting data, and the quality of reporting is dependent on laboratory capacity, access to diagnostics, data completeness and national coordination (WHO, 2022). Health systems often store microbiology data, antimicrobial usage information, hospitalisation data, pharmacy data and infection control data across multiple disconnected systems, making them difficult to use to help make speedy decisions (Boolchandani et al, 2019). These delays are worse in low- and middle-income nations, where often it is impossible to get results from culture and the susceptibility testing might be limited, forcing clinicians to rely on empirical broad-spectrum treatment (Laxminarayan et al., 2016). Surveillance needs therefore to shift towards predictive intelligence, which can inform action on the part of the operator earlier.

AI-powered surveillance has garnered interest due to machine learning's ability to synthesize huge and disparate sets of data and detect signals before they are clinically apparent. Microbiology data, genomic sequences, prescribing patterns, and hospital mobility data can be used in combination with a predictive model to estimate the likelihood of emergence of resistance and/or clusters of transmission (Arnold et al., 2025). These can be used to alert the hospital to outbreaks earlier and to match the wards with those at greatest risk, before reviewing them manually, and allocate infection-prevention resources more efficiently than manual review (Hanna & Medford, 2024). The potential for AI to enhance AMR forecasting, at the population level, could be achieved through the integration of antimicrobial usage data, mobility, environmental exposure data, and One Health data flows, and connecting resistance patterns to these data sources (Kasse et al., 2025). Incomplete data, differences in laboratory methods and standards, and biased testing practices can bias outputs of the models (Wiens et al., 2019).

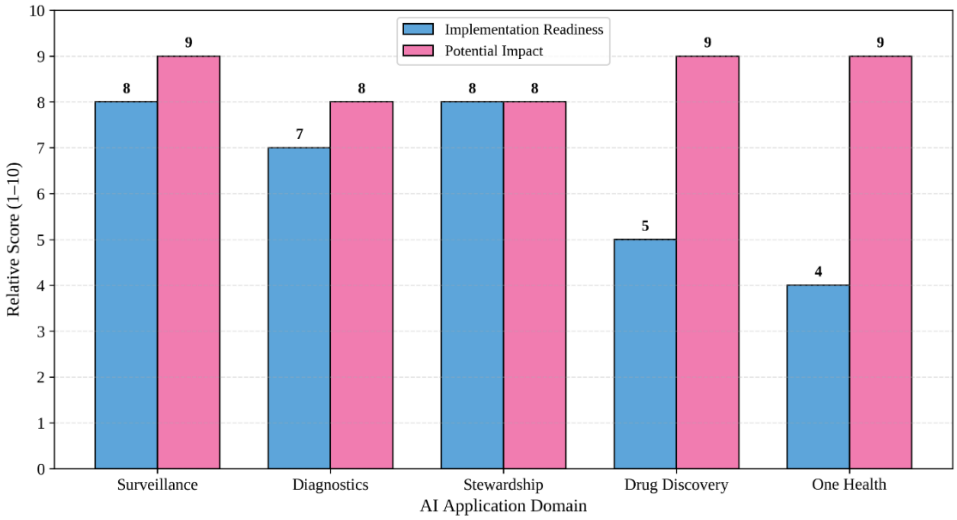

Figure 2. Ai Application Domains in Amr Control.

AI can also be useful for the diagnosis and prediction of phenotypes. Conventional culture and antimicrobial susceptibility testing are still useful and can be used within 24 to 72 hours, but often, clinicians prescribe spasmatically before the results of the conventional tests are available. Whole genome sequencing data has been used to create machine learning models that have demonstrated the potential of prediction of antimicrobial resistance profiles and identification of genomic markers linked to antimicrobial resistance (AMR) (Nguyen et al., 2020). When combined with the validated sequencing pipelines and local resistance data, these tools can aid in quicker organism identification, prediction of resistance and treatment stratification (Ardila et al., 2024). The diagnostic potential of AI is particularly well established in its use to support clinicians' decision making to narrow treatment options, reduce unnecessary antimicrobial use and match pathogen biology to the choice of therapy (Peiffer-Smadja et al, 2020). However, it needs to be well validated in the external environment as a model that works well in one pathogen population/hospital ecology may not work in another (Wiens et al., 2019).

Another significant application of AI is antimicrobial stewardship which involves optimizing the use of antibiotics.Antimicrobial

stewardship is another key application that AI can contribute to optimize antibiotic use. Stewardship is about responsible use of antimicrobials by integrating a coordinated strategy that will help optimize the use of the drugdose, duration, route and reviewwith patient protection and minimizing the selection pressure for resistance. Traditional stewardship programmes are based on adherence to guidelines, audit and feedback, formulary restriction and specialist review, but these focus on individual records and are cumbersome and challenging to scale. Clinical decision support using AI can automate the review of EHRs, microbiology data, allergy history, renal function, antimicrobial use and local resistance data to find opportunities to de-escalate, discontinue or optimize antimicrobial use (Peiffer-Smadja et al., 2020). Thus, AI can be used to help with precision stewardship in the right antimicrobial approach at the right time, to the right patient (Hanna & Medford, 2024). However, there is also a danger of overconfident use of the recommendations if algorithms aren't calibrated properly, hence the need for stewardship algorithms to be advisory, transparent and accountable to clinical teams (Mitchell et al., 2019).

AI has also revolutionized the way of the antimicrobial discovery literature. Availability of novel antibiotics has been limited due to the high cost, slow pace and poor commercial interest of the traditional screening process, particularly in light of the need to save antibiotics for future generations to remain effective (WHO, 2024). Deep learning models can perform such tasks as searching chemical libraries, predicting antimicrobial activity, estimating toxicity and identify structurally distant molecules to existing antibiotics (Stokes et al., 2020). This finding of halicin showed the capability of AI in finding an antibacterial compound with new structures from a huge library of chemicals (Stokes et al., 2020). This method has been recently applied to other fields, such as antimicrobial peptides, sequences derived from the human microbiome, and ancient protein spaces, where AI has been able to increase the number of compounds that can be searched in the biological and chemical universe for generating antimicrobial innovations (Wan et al. 2024; Santos-Júnior et al. 2024). While these are important advances, computational discovery needs to go through experimental validation, toxicity testing, pharmacokinetic evaluation, resistance-risk assessment, and clinical trials before having an impact on the care of patients.

METHODOLOGY

This manuscript had narrative review following the principles of scoping review to explore the potential of using artificial intelligence (AI) in the control of antimicrobial resistance. This design was suitable as there were a variety of evidence sources representing different specialties from epidemiology, clinical microbiology, antimicrobial stewardship, drug discovery, health informatics, public health and One Health surveillance. The review was not designed to calculating an overall effect size. Rather, it sought to aggregate key intervention domains and barriers to implementation and strategic priorities from literature related to AI-AMR (Arksey& O'Malley, 2005; Levac et al., 2010).

Literature was identified on the relevant topic from PubMed, Scopus, Web of Science, Google Scholar, WHO publications, Lancet series papers, Nature portfolio journals, BMC journal and PLOS journal and from major antimicrobial resistance policy reports. The search encompassed literature published between 2015 and 2026 and some of the more foundational articles were added if they were relevant to the methodology and concepts of the rest. Search phrases used encompassed the concepts related to antimicrobial resistance, artificial intelligence, machine learning, deep learning, antimicrobial resistance prediction, antimicrobial resistance surveillance, antimicrobial stewardship, clinical decision support, genomic antimicrobial resistance prediction, antimicrobial discovery, One Health and antimicrobial resistance forecasting. The words related to AI were combined with AMR related domains using boolean combination.

Studies and reports that discussed any of the five areas – AI-enabled AMR surveillance, AI-assisted diagnostics, AI-guided antimicrobial stewardship, AI-based antimicrobial discovery, and AI-supported One Health risk prediction – were included. Only peer-reviewed original studies, systematic reviews, narrative reviews, policy reports, global burden analyses and high quality technical commentaries were eligible to be included. Studies that included AI in general health care, but did not mention AMR, focused on management of non-antimicrobial infections, were excluded if they did not detail the methods followed in the study, or if they claimed a benefit of AI without providing clear evidence. Copies of records, abstracts which

were not available online and non-scholarly opinion sources were also eliminated.

Thematic synthesis of selected evidence was used to organize evidence. First, studies were aggregated, according to intervention domain. Second, every domain was evaluated on the basis of data needs, feasibility of implementation, clinical relevance, anticipated contribution to the control of AMR and key constraints. Third, the results were analyzed in a systems approach that included infrastructure of the laboratories, interoperability, governance, stewardship capacity, equity, validation and integration of clinical workflow. This enabled the review to delve beyond the description of individual AIs, and consider the role that AI can play in the real control systems of AMRs (Page et al., 2021).

To assist with the graphical analysis to be featured in this manuscript there will be two forms of visual evidence. If quantitative estimates are available for the burden and forecasts from the global AMR burden and forecasting studies will be used. If there are no direct comparable numerical data, then figures will be created using a clear conceptual concept and scoring, based on the literature reviewed. This conceptual score will not be considered primary empirical findings and will be referred to as illustrative synthesis measures. As such, the figures will not give the appearance of being new data, patient-level or laboratory, but will be used for the purposes of interpretation.

Data Analysis

Based on this analysis, AI can best support AMR control in a role of bridging the different pillars of surveillance, diagnostics, stewardship, drug discovery and One Health governance. In the literature reviewed, conventional AMR control systems seem to excel in the microbiological confirmation and excel in mitigating with limited success in early prediction, cross-sector integration, and rapid operational response. The use of culture-based surveillance is still essential as it allows the identification of organisms and confirmation of susceptibility, but due to the time lag this has, it cannot be used in the immediate therapeutic setting. AI tools can augment this as they can process historical data to generate predictive risk alerts especially if combined with microbiology data, prescribing histories, admission patterns, genomic data, and regional antibiotic resistance data (Boolchandani et al., 2019; Nguyen et al., 2020).

The speed, scale and decision orientation of the traditional and AI supported workflows for AMR are clearly distinguishable. Traditional workflows typically start when infection is clinically suspected with often an empirical treatment being performed until lab results are available. AI-powered workflows can run ahead of the curve, estimate the likelihood of resistance before confirming it in culture, provide high-risk alerts to healthcare professionals when broad-spectrum therapy may not be needed or effective and send alerts to clinicians when a broad-spectrum medicine could be avoided or was not needed. This doesn't rule out the need to have lab confirmation. It, however, develops a layered decision model in which predictive analytics help with making decisions in the meantime, and microbiology validates the decisions (Peiffer-Smadja et al., 2020; Wiens et al., 2019).

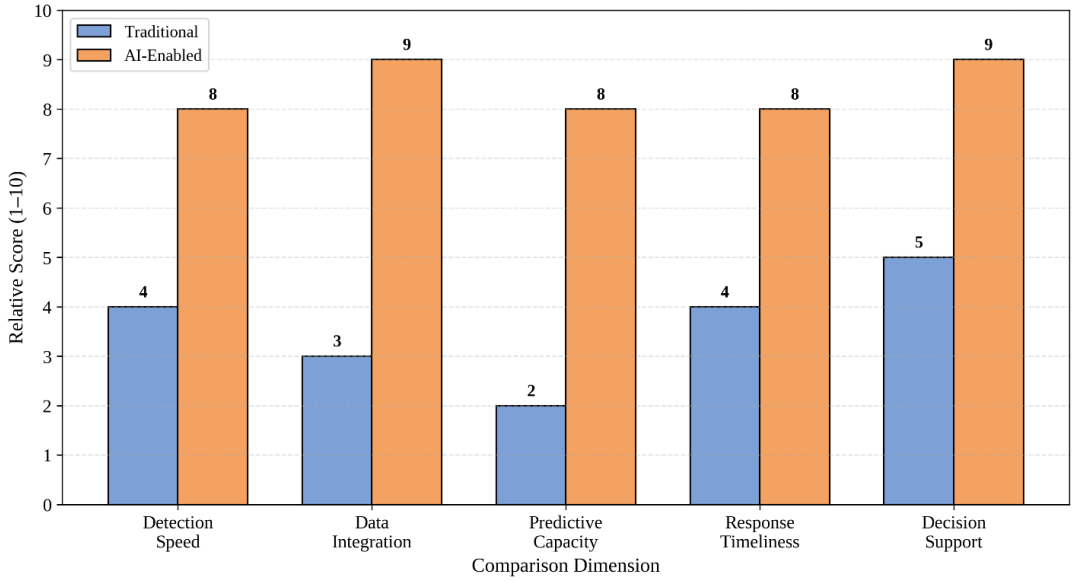

Figure 3: Traditional Versus AI-Enabled AMR Surveillance and Response.

The first of the great topics of analysis is that of surveillance transformation. AI can enhance AMR surveillance through the ability to identify unusual patterns of resistance, predict risk at ward level and the ability to combine multiple and disparate data streams and sources that are typically analyzed individually. In the hospital environment, predictive modelling can help detect clusters which could be indicative of early transmission events. Machine-learning tools can identify changes in resistance to a pathogen at regional and national scales and help prioritize pathogens that need to be targeted. Its added value is not simply automation, it is the ability to decipher the complex pattern which is too large for manual inspection. Surveillance models however, are still susceptible to biased sampling, as cultures are more likely to be collected from severe cases, hospital-based cases, and/or treatment failure cases (Arnold et al., 2025; WHO, 2022).

Diagnostic Acceleration is the second Analytical Theme. An efficient and timely diagnosis of resistant infection is a key factor in limiting patient exposure to unnecessary broad-spectrum, and in providing better patient outcomes. The time from suspicion to actionable genomic information can be reduced by using AI models based on genomic data, mass spectrometry profiles, microscopy images and electronic health records. Genomic prediction is particularly germane since resistance genes and mutations can be identified prior to phenotypic susceptibility being developed. The genotype/phenotype relationship, however, is not always straightforward and the levels of resistance expression can be influenced by regulatory mechanisms, gene dosage, background of the organism and local epidemiology. Due to this fact, diagnostic AI systems need to be tested against real-life clinical information and/or phenotypic outcomes before it can be routinely deployed (Nguyen et al., 2020; Ardila et al., 2024).

Optimization of stewardship is the third analytical theme. AI can be used to assist with antimicrobial stewardship in various ways, including the identification of patients where de-escalation is appropriate, establishing a risk score for the development of resistant infection, helping to identify over-ambitious durations of treatment and match empirical antimicrobial therapy with local susceptibility data. This is especially critical in the hospital setting where stewardship teams are smaller and don't have the ability to check every prescription as it is written. Pharmacists and infectious-disease specialists might be able to prioritize their time to focus on high-risk prescriptions as opposed to routine cases with the help of predictive decision support. However, stewardship algorithms need to be carefully crafted to not endorse a "one size fits all" approach to prescribing. Higher exposure can occur if the model is overpredicting resistance and lower exposure can result in late treatment if the model is under-predicting resistance (Dyar et al., 2017; Peiffer-Smadja et al., 2020).

The fourth analytical theme is related to antimicrobial discovery. AI-driven screening extends screening space beyond normal intuition of chemists. Deep learning can discover and predict molecules that are active against antibiotic resistant organisms, novel in structure, and have antibacterial activity. This enhances the efficiency of discovery of the antibiotics, but it is not the answer to the overall antibiotic innovation problem. There are still laboratory testing, toxicity, pharmacokinetic and resistance-risk assessment and clinical testing to be done on candidate molecules. AI, therefore, is best viewed as a tool to speed up drug discovery pipelines and not as an alternative to experimental pharmacology and drug translation (Stokes et al., 2020; WHO, 2024).

The fifth analytical theme is integration of One Health. AMR flows within clinical, animal, food, environmental and pharmaceutical settings but these data sources are often not really "synchronized" on the fly. To bridge the gap and align wastewater data with data from the veterinary, food-chain, hospital resistance, climate, and geospatial movement, the use of AI can help combine these elements into common risk maps. This could assist policy makers to identify hotspots and monitor and harmonize the actions of various ministries. The primary constraint is on governance not on computation. Unless AI models are based on common data standards, could be technically impressive but not operationally connected due to lack of responsible data sharing and sectoral accountability (Kasse et al., 2025; WHO, 2023).

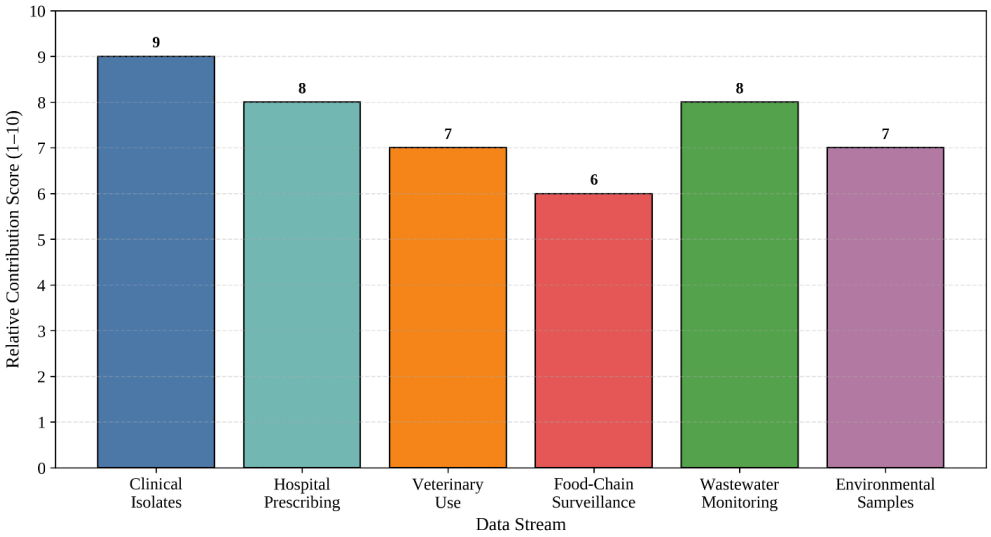

Figure 4: One Health Data Streams for AI-Based AMR Prediction.

DISCUSSION

This review's results suggest that using AI needs to be considered as a tool for enabling AMR control, not a replacement. AMR is a result of interconnected failures in the system of antimicrobial prescribing, microbiological capacity, infection prevention, pharmaceutical regulation, agricultural antimicrobial use, environmental contamination and weak surveillance. These are all drivers that will be working concurrently and so decentralizing interventions will not result in permanent control. The strategic value of AI lies in its ability to help institutions bring together seemingly disparate pieces of information, and transform it into action that is quicker, safer and more targeted. (Boolchandani et al., 2019; WHO, 2023).

Predictive surveillance is the immediate forte, with the best prospect for success. Current AMR detection programs tend to report on the outcomes of AMR events, whereas clinical and public-health systems require tools to be able to predict what is going to occur next. Routine microbiology records, ward-level transmission data, trends in antimicrobial usage, and genomic data can all be translated by the use of AI models into risk signals to aid in early investigation of outbreaks and targeted responses to control infections. This change from documentation to intelligence in real-time is key as resistant organisms propagate more quickly than the traditional reporting cycle. But if predictive surveillance is going to be useful, then some laboratory data must be representative, standardized and routinely be associated with clinical metadata.

AI's diagnostic use is not less significant, but needs to be used with caution. Previous prediction of resistance may help to guide more targeted empirical treatment and limit the use of more general drugs. In conditions like sepsis, intensive care, oncology, neonatal care and surgical infections, this is particularly beneficial as a delay in treatment could be life-threatening. However, in absence of culture/susceptibility testing/expert interpretation, prediction through AI cannot be a substitute. Genomic resistance markers may not always be manifested in the field as a phenotypic resistance, and strains found in the vicinity of the population used to train published models may be different (Nguyen et al., 2020). So diagnostic AI should be used to support the decision makers and be treated as a probability-based approach, rather than the final decision.

AI can enhance the prioritization over prescribing, in the context of antimicrobial stewardship. Many stewardship teams are overburdened, lack specialists and have growing numbers of prescriptions. AI can also assist in determining the areas in which intervention is needed most, such as when people are treated with broad-spectrum antimicrobials for an extended period of time, when culture results do not match the choice of antimicrobials, when the antimicrobial treatment is not kept to the shortest duration or when there is a high estimated risk of resistant infection. This can facilitate stewardship to be more scalable and sustainable (Peiffer-Smadja et al., 2020). However, the implications for clinical outcomes are dire in the event of some error in the algorithms. A system which overestimates

resistance can cause needless wide treatment and a system which underestimates resistance can lead to ineffective treatment of the patient. Thus, human intervention is a must.

There also needs to be a balance in discussing the use of AI for the discovery of antibacterial. For the last several years, deep learning has demonstrated its ability to discover novel antibacterial in very large molecular libraries, opening up the imagination of the field of antimicrobial innovation (Stokes et al., 2020). But drug discovery is still very challenging in the biological and commercial aspects. A potential in-silico lead compound should then have in vitro activity, animal safety, tolerable drug pharmacokinetics, low toxicity, good manufacturing capabilities, clinical effectiveness and a long-term economic development. While AI can speed up the early discovery phase, there are other scientific and regulatory hurdles in the antibiotic pipeline that will only be bolstered by a robust pipeline.AI can help streamline the early discovery phase, but other scientific and regulatory obstacles to the antibiotic pipeline remain and will be strengthened by a robust pipeline.

One Health integration is a strategic area of AI that is one of the most advanced, and yet also one of the most challenging, to implement. AMR can be spread on humans, animals, food production, wastewater, soils and pharmaceutical ecosystems. While it is possible to use AI to combine these data streams into geospatial risk maps and early-warning systems, the data are held in various ministries, sectors, laboratories and even by private entities. The big challenge is not computational skills, however. It is governance. Consensus on standards, harmonization of exchange of trusted data, stable funding and institutional responsibility are essential for effective One Health AI (Kasse et al., 2025).

Equity also is a key issue. The devices and data used to train and validate AI tools tend to be developed and tested in high-income countries, where EHRs and other electronic systems, along with the stewardship teams, are more advanced. These tools could fail to work well in low resource contexts or re-introduce inequities, if they are simply taken over there. The countries with the highest AMR burden could also likely have the poorest digital infrastructure to take advantage of the AI enabled response (Laxminarayan et al., 2016). Thus, local calibration, open standards, training of the workers, low-cost infrastructure and government ownership of the implementation of AI are critical elements. Otherwise, AI could further exacerbate the divide between those health systems with and without data.

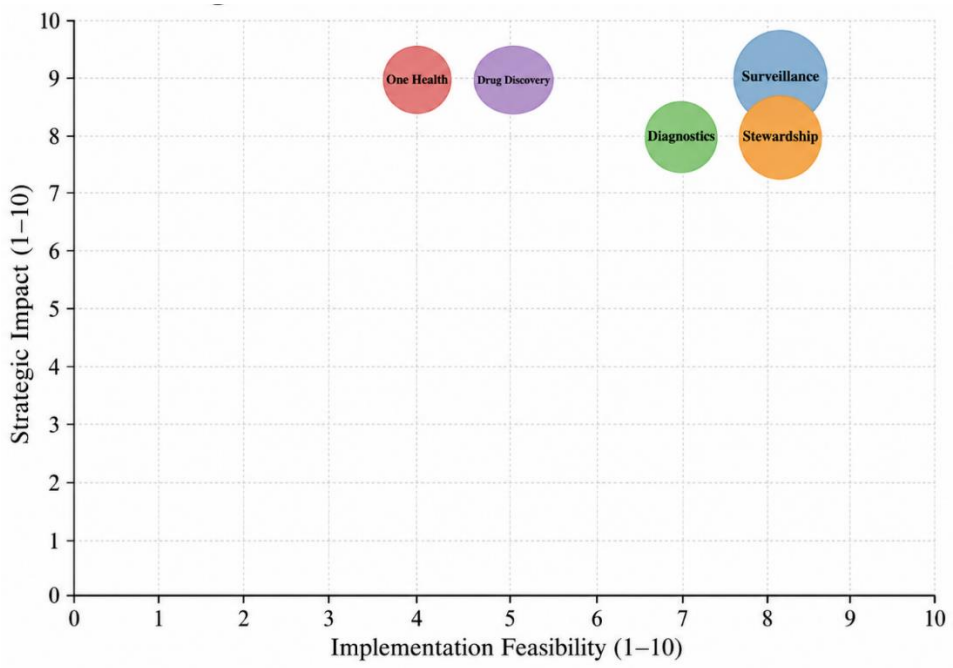

Figure 5: Strategic Intervention Matrix for AI-Driven AMR Control.

Implementing must be informed and guided by interpretability and accountability. If AI makes decisions without a clear, understandable rationale, such as using high-risk antibiotics or in the case of the critically ill, it's unlikely that clinicians will feel comfortable with the system. Explanatory outputs, uncertainty estimates, audit trails and performance dashboards can

help to enhance the responsible use. It is important that the regulations call for external validation, monitoring, bias assessment and accountability in the event of harm caused by algorithmic recommendations (Mitchell et al., 2019). Don't let AI replace responsibility of institutions. Rather, it ought to be more traceable and systematic in terms of enhancing quality.

CONCLUSION

Antimicrobial resistance is one of the most pressing and complex health threats. However, it is not limited to treatments for infectious diseases as it can compromise the safety of surgical procedures, cancer treatment, intensive care units, maternal health, neonatal care and common medical treatments. The findings in this review indicate that AI can help control AMR in multiple ways, such as enhancing early detection and warning systems, speeding up the process of interpreting diagnostic information, facilitating antimicrobial stewardship, boosting the drug discovery pipeline, and connecting human, animal, environmental, and agricultural data.

The use of AI however must be considered not as a standalone solution on the fight against AMR. Its impacts and utility will rely on the systems in which it's placed. To achieve good predictive models, high quality microbiological data and reliable laboratory networks, interoperable digital infrastructure, validation of models in a transparent manner, and ongoing clinical surveillance are needed. If not, AI can make wrong predictions, exacerbate inequalities or lead to the inappropriate use of antimicrobials. So, it is imperative that it be used responsibly as well as technologically.

Finally, there is a great potential for AI to reinforce global efforts to tackle AMR, but this potential will only be realized if it is governed ethically, held accountable clinically, is accessible and is supported by already existing public-health approaches. To ensure the responsible use of AI in AMR, it is crucial to consider the potential for the technology to have measurable impact, as well as the need for collaboration across systems (WHO, 2024).

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