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Artificial Intelligence and the Silent Pandemic of Antimicrobial Resistance: A Comprehensive Exploration

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Abstract

The rise of antimicrobial resistance (AMR) in the 21st century has made it a worldwide disaster. Due to the fast spread of AMR illnesses and the lack of novel antimicrobials, the silent pandemic is well known. This issue requires a fast and meaningful response, not just speculation. To address this dilemma, deep learning (DL) and machine learning (ML) have become essential in many sectors. As a cornerstone of modern research, machine learning helps handle the many aspects of AMR. AI helps researchers construct clinical decision-support systems by collecting clinical data. These methods enable antimicrobial resistance monitoring and wise use. Additionally, AI applications help research new drugs. AI also excels at synergistic medicine combinations, providing new treatment methods. This paper summarizes our extensive study of AI and the silent epidemic of antibiotic resistance. Through deep learning and machine learning applications across multiple dimensions, we hope to contribute to the proactive management of AMR, moving away from its presentation as a future problem to present-day solutions.

Introduction

Treatment and prevention of bacterial infections are done with antibiotics. They've treated bacterial infections and reduced mortality for decades (Ahmad et al., 2021; Turel et al., 2021). Animal husbandry uses antibiotics, which may harm human health. Products like antimicrobial trousers and athletic shoes, as well as healthcare and animal husbandry, employ antibiotics (Al Marjani et al., 2023; Hayali et al., 2022; Araruna et al., 2012). In order to tackle antibiotic-resistant microorganisms, chemical modification of antibiotics is being studied [6, 7, 8]. Changing bacterial cell membrane permeability to increase antibiotic potency (Liew et al., 2023) and developing new peptidomimetics that interfere with important bacterial processes like cell wall synthesis, integrity membrane, protein synthesis, nucleic acid synthesis, and metabolism to fight multidrug-resistant bacteria. Research continues to discover novel medications to address antimicrobial resistance (Shusterman et al., 2021; Boolchandani et al., 2019). The use of machine learning in AMR varies. The sequence-based AI application in (Macesic et al., 2017; Khaledi et al., 2016) studies antibiotic resistance. Artificial intelligence has been used to create novel antibiotics and medication synergies (Davies & Davies, 2010).

The problem statement of the paper is that rising infection rates and a lack of new drugs make the silent pandemic of antimicrobial resistance a major worry. Current crisis response attempts

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are failing, requiring a paradigm shift and modern technology. There is a need for a comprehensive, technology-driven response to antimicrobial resistance, which is silent but looming. Traditional techniques are failing. Artificial intelligence is being studied to be used in this research to fight antibiotic resistance worldwide.

Related Work

This section reviews AMR and its effectliterature. Davies & Davies (2010) the worldwide health crisis of antimicrobial resistance (AMR) affects public health, healthcare, and the economy. AMR affects humans, animals, agriculture, and the environment. The AMR literature and its effects are reviewed in this section. Over the past 50 years, microbial exploitation of resistance genes and horizontal gene transfer have increased antibiotic resistance. Restoration of antibiotic efficacy and environmental microbiomes' role in resistance are stressed. Drugs are needed to cure infections and facilitate surgery, but improper use has caused resistance, burdening global healthcare systems. Healthcare infection control and antibiotic use should be tightened to prevent patient resistance. They use microbial diversity and unexplored therapeutic targets to justify researching novel antimicrobial drugs despite pharmaceutical corporation objections. Structures and systems biology are needed to comprehend inhibitor-target-resistance relationships and discover novel metabolic interactions, according to the review. We recommend identifying and limiting antibiotic use to encourage "niche" antibiotic development. Resistance prevention prioritizes environmental reservoir-based early warning systems. The authors conclude that antibiotic resistance requires strong limitations, careful use, continued research, and proactive measures (Division, 2014). The WHO report on antimicrobial resistance (AMR) by authors, member states, and partners explains its global breadth. They underline concerning levels of resistance to common germs, monitoring gaps, and treatment ineffectiveness. The study emphasizes coordinated worldwide monitoring to develop tactics, monitor initiatives, and guide future action plans (Laxminarayan et al., 2016).

The authors highlight recent life expectancy and antibiotic access gains in low-income nations. Rising pathogen resistance might undo progress, they worry. Resistant organisms threaten serious infection, survival, and treatment interventions. Innovative healthcare funding and delivery are needed to improve antimicrobial availability while reducing inappropriate usage, especially of expensive newer alternatives. The essay emphasizes the need for effective antimicrobials, estimates the illness burden from resistance, and examines vaccines' potential to reduce antibiotic use. Antimicrobial resistance prevention should include "one-health" techniques (O'Neill, 2016). The writers explore AMR and the UK Prime Minister's efforts to tackle it. Jim O'Neill, an economist, conducts the independent Review on Antimicrobial Resistance with worldwide stakeholders. The study summarizes the review's final recommendations, stressing public awareness, sanitation improvement, worldwide surveillance, and new funding approaches to reduce wasteful antimicrobial usage. As UK Commercial Secretary to Her Majesty's Treasury, who coined the phrase BRICs, chairs the review (Tang et al., 2023).

Antimicrobial Resistance (AMR)

Definition and Context

Due to improper antibiotic usage, microbes develop antibiotic resistance, making antimicrobials ineffective in treating illnesses. World-wide, antimicrobial resistance (AMR) threatens public health and healthcare systems. Inappropriate use of antimicrobials, especially antibiotics, leads to AMR, which increases mortality, medical expenses, and antimicrobial efficacy (Gudata & Begna, 2018; Capozzi et al., 2019). Complex factors affecting AMR include alternative survival routes, microorganism genetic resistance determinants, and infection prevention and control (Amann et al., 2019). It happens when bacteria, viruses,

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fungi, and protozoa develop antibiotic resistance mechanisms, rendering them useless. The word "superbug" refers to multidrug-resistant (MDR) microbes. Although AMR is natural, incorrect medicine usage and infection control often worsen it, threatening global health. AMR requires greater dosages of antimicrobials, more expensive medicines, or more toxic alternatives to treat infections. Coordination and worldwide action are needed to combat AMR (Pricop, 2022).

To combat antimicrobial resistance (AMR), antimicrobial stewardship, universal infection prevention and control, and greater research and surveillance are essential (Graduta & Begna, 2018). Antibiotic usage and limitation decisions by healthcare professionals are crucial to AMR management. Consider biofilm resistance, acquired resistance, intrinsic resistance, mutation, and antibiotic inactivation (Prasad et al., 2022). Self-medication, genetic and phenotypic variation, changes in membrane permeability, modifications to antibiotic targets, and gene transfer resistance are additional causes of antibiotic-resistant bacteria (Ozma et al., 2023). In order to fight antibiotic resistance, scientists are looking into phages, quorum-sensing inhibitors, immunotherapeutics, predatory bacteria, antimicrobial adjuvants, hemofiltration, nanoantibiotics, microbiota transplantation, plant-derived antimicrobials, RNA therapy, vaccine development, and probiotics (Zeden & C, 2023). Nanomedicines and molecular methods, such as RNA-mediated gene silencing or biosynthetic gene cluster controls, are being studied to fight antibiotic resistance (Naveed et al., 2020).

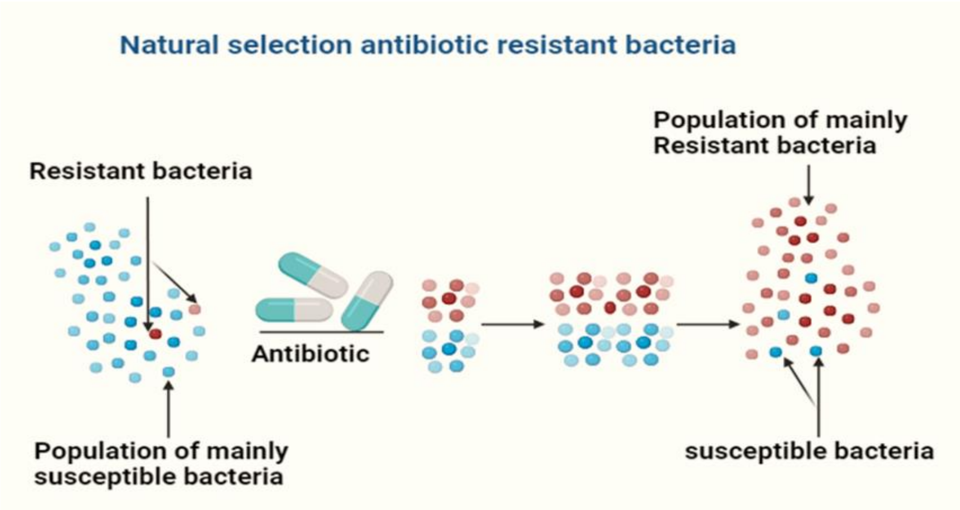

Figure 1. The natural selection of antibiotic-resistant bacteria

Acoustic biosensors with active layers that are immobilized and liquid drugs that can sense them help find out how sensitive and resistant bacteria are so that they can be quickly treated and studied (Guliy et al., 2023). Bacterial mutations can cause antibiotic resistance, as seen in Figure 1. By selectively killing sensitive bacteria, the antibiotic may allow resistant ones to live and flourish in a mixed population. Novel genetic data can also be transferred to bacteria to develop antibiotic-inactivating enzymes. Changes in epigenetics and defense strategies, such as antibiotics, enzymes that break them down, permeability, efflux, and target site mutation, change bacterial genes and make antibiotics harder to target or easier to leave the cell. Antibiotic resistance also depends on biofilm development (Wang et al., 2023; Harris et al., 2023). ESBLs and other plasmid-mediated resistance help disseminate drug-resistant genes among bacteria quickly (Zakaria et al., 2023). Differentiating drug attachment sites, making cell walls more permeable, shutting off antibiotics, and generating efflux pumps can make bacteria resistant (Flemming et al., 2016). In addition, stress situations like antibiotic treatment can trigger controlled adaptive responses in bacteria, causing susceptibility and resistance. Developing new medicines and antibiotic resistance methods requires understanding these pathways.

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The Bacterial Defense System

Biofilms Bacteria can develop antibiotic resistance through the formation of biofilms, bacterial colonies surrounded by a protective matrix. Biofilms make bacteria more resistant to antibiotics, disinfectants, and the immune system (Sharma et al., 2023). Resistance mechanisms include limited antibiotic penetration into biofilms, a decreased growth rate, and the expression of resistance genes (Shree et al., 2023). Furthermore, genetic, physical, and physiological changes in biofilms contribute to their resistance to antimicrobials (Sharma et al., 2023). Biofilms also facilitate the transfer of antibiotic resistance genes between bacterial species, resulting in the spread of resistance [34]. Public health is threatened by the biofilm bacteria's antibiotic resistance. Overall, biofilms help propagate antibiotic resistance among bacteria (Multani & Singh, 2022).

Membrane, cell wall Antibiotic-resistant bacteria can develop in several ways. Adjust their outer membrane's porins or nanopores to allow hydrophilic substances like antibiotics (Trubenová et al., 2022). Inadvertent DNA alterations help bacteria survive (Rajkumar & Mohiddin, 2022). Staphylococcus aureus' cell wall peptidoglycan, teichoic acids, and membrane lipids cause antibiotic resistance (Ahmad et al., 2022). Through cell surface-to-volume ratio adjustments, bacteria can diminish intracellular antibiotic concentrations (Ghai, 2023). Plant phytochemicals that target membrane proteins, efflux pumps, biofilms, and communication prevent multidrug-resistant bacteria. Learning about resistance mechanisms and cell membrane targeting is crucial.

Intracellular Change Bacteria develop antibiotic resistance by changing target locations, transferring resistant genes, and modifying drug structure (Nikolic & Mudgil, 2023). These systems allow bacteria to survive and proliferate under demanding conditions, resulting in multidrug-resistant bacteria. In addition to resistance, bacteria employ tolerance and persistence. Persistence lets certain sensitive bacteria rest and escape antibiotic stress (Ojkic et al., 2022). Understanding bacteria's stress response to antibiotics is essential for producing effective and efficient medicines. Due to antibiotic overuse and misuse, antibiotic resistance is a serious public health concern. Experimental therapeutics include phage therapy (Suganya et al., 2022).

Antibiotic Resistance Transmission Mechanisms

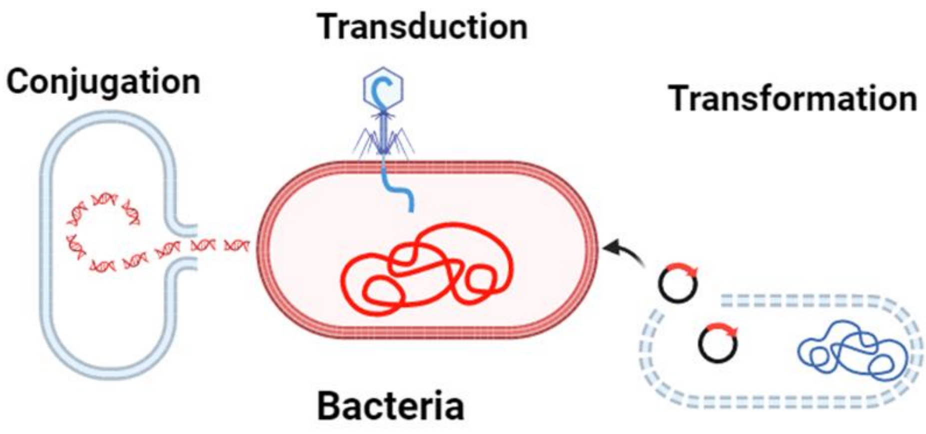

Figure 2. Drivers of antibiotic resistance transmission

Various factors influence the spread of antibiotic resistance (Figure 2). Antimicrobial use in agriculture, veterinary, and medical sectors contributes to the spread of antimicrobial-resistant genes (ARGs) through the environment (Laxminarayan et al., 2016). The indiscriminate use of antimicrobials in humans, animal husbandry, agriculture, fisheries, and the environment accelerates antimicrobial resistance (Kim et al., 2023). Inadequate public health

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infrastructure, a lack of appropriate diagnostic assistance, and inadequate infection control methods all contribute to the spread of antibiotic resistance (Sagar et al., 2019). Potential routes for the spread of resistant bacteria and ARGs include hospital effluent, agricultural waste, and wastewater treatment facilities in soil and surrounding ecosystems (Puvača et al., 2022). Furthermore, non-antibiotic pharmaceuticals, including commonly used drugs, can contribute to the spread of antibiotic resistance via the uptake of exogenous ARGs (Reghukumar,2023).

Artificial Intelligence (AI) in Medicine and biology

AI refers to the use of computers and technology to mimic human intelligence and critical thinking. Computer and AI pioneer Alan Turing (1950). The "turing test" was predicated on the idea that intelligent computers do cognition-related activities like humans. Iskandar et al. (2020) AI interest grew in the 1980s and 1990s. Fuzzy expert systems, Bayesian networks, artificial neural networks, and hybrid intelligent systems were applied in healthcare contexts. Healthcare applications received the most AI research funding in 2016. Irfan et al. (2020) Medical AI might be virtual or tangible. Wang et al. (2020) Virtual applications include electronic health record systems and neural network-based therapy recommendations. The physical portion includes surgery robots, intelligent prosthetics for disabled people, and geriatric care. From the symbolic method, where complicated rules are programmed in computer language, biological AI now allows robots to conduct coordinated sequences of activities. Chess is a symbolic AI game with basic rules but many possibilities if one piece is moved. In this example, the rules are specified, and a computer may be trained to examine all the options before making the next step and selecting the best one. The 1997 Deep Blue computer defeating Garry Kasparov is a famous symbolic AI case. Computing speeds were too slow for a well-trained human brain before Deep Blue. Smart phones currently have computing speeds equivalent to Deep Blue (Mintz & Brodie, 2019).

AI has been utilized in medicine and biology to diagnose patients, design drugs, improve physician-patient communication, transcribe medical papers, and remotely treat patients [53]. Fuzzy expert systems, Bayesian networks, artificial neural networks, and hybrid intelligent systems are applied in clinical contexts (McLachlan et al., 2020). Virtual and physical AI exist in medicine. Virtual applications include electronic health record systems and neural network-based therapeutic advice. The physical portion includes surgery robots, intelligent prosthetics for the disabled, and geriatric care (McLachlan et al., 2020). AI has been used to recognize the 3D shape of biological molecules like proteins, a crucial scientific research issue. AI promotes innovation in labs and throughout a drug's lifespan (Hamet & Tremblay, 2017). AI has digested data in new ways to discover phage infections and bacterial resistance genes (Matinfar & Golpayani, 2022). Artificial intelligence in biology has evolved from the symbolic method, where complicated rules are programmed in computer language to enable coordinated actions. IBM's Deep Blue computer defeated Garry Kasparov in 1997 (Hamet & Tremblay, 2017 & Tremblay, 2017; Greenfield, 209). AI has been used to match patient symptoms to relevant physicians, provide assistance in diagnosis and prognosis, develop medication, and assist clinicians in delivering a better and more customized patient experience. AI has accelerated medication development, personalized therapy, and gene editing.

Artificial intelligence has been used in biology to understand complex data linkages and acquire insights. Assessing complex yet significant medical imaging and pharmaceutical responses requires fast algorithmic techniques. (Hamet & Tremblay, 2017; Bhardwaj et al., 2022). In conclusion, AI has greatly affected medicine and biology, from detecting illnesses, medication discovery, and development to predicting protein structures and drug discovery. As AI technology matures, these areas will use it more, creating more inventive and efficient

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solutions (Hamet & Tremblay, 2017; Hassoun et al., 2021). We offer some examples as illustrations, arranged in approximate order of increasing difficulty of implementation.

Example 1: Behavioral ecology

Suppose we aim to understand the relationship between individual fitness and the environment, including social aspects in a bird species. This involves utilizing data from various biological and spatial scales (e.g., vocalizations, social networks, genetics) and sources (e.g., images, tracking tags). Current analysis is limited, often using a few data modalities with small sample sizes (e.g., RFID tags for movements). We hypothesize that advancements in AI and automated data collection will enable a holistic approach, surpassing current capabilities. This could address complex biological questions, such as the impact of genetics on social behaviors influencing collective actions like migration. Another example involves integrating AI into decision-making models for large herbivores' foraging behavior (Sikchi et al., 2013).

Table 1. The Main Specifications Of The Example1

Aspect	Details
Research Focus	Relationship between individual fitness and environment, including social environment in a bird species.
Data Modalities	Multiple biological and spatial scales, including vocalizations, communication, social networks, movement, morphometric, parasite loads, genetics, biomarkers, etc.
Data Sources	Images, videos, audio recordings, tracking tags, DNA sequencers, etc.
Current Practices	Analysis conducted using one or a few data modalities (e.g., RFID tags for movements, social network analysis for social behaviors) with relatively small sample sizes.
Hypothesized Advances	Simultaneous progress in AI and automated data collection to enable a holistic approach, surpassing current capabilities.
Expected Capabilities	Holistic analysis covering diverse data modalities, larger sample sizes, and a comprehensive understanding of complex biological questions.
Example Questions	How does genetics influence social behaviors affecting collective behaviors like migration? - Integration of AI in hierarchical decision-making models for large herbivore foraging.

Example 2: Genes to phenotypes

Predicting an organism's phenotype is exceptionally challenging due to the need for integration across various biological scales, from molecules to the environment (Malik et al., 2019). We can't fully understand how phenotypes emerge with the AI technologies we have now, but in the future, advances in machine reasoning, learning, and causal inference, along with the constant growth of data, collection methods, and computing power, will allow us to do so. These technologies will enable the utilization of diverse data (e.g., DNA sequences, phylogenetic information, and environmental data) and knowledge (e.g., gene function, results of prior experiments) to explore and validate hypotheses about factors influencing phenotypes. For instance, we can investigate how data from different fields (e.g., imaging, genomics, epigenomics, proteomics, metabolomics, and metagenomics in soils) can predict cellular decision-making or phenotypic changes affecting crop productivity, such as corn (Malik et al., 2019).

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Table 2. The Main Specifications Of The Example2

Aspect	Details
Problem	Predicting an organism's phenotype, integrating information across biological scales.
Challenges	Beyond current AI capabilities, requires advancements in reasoning, learning, and data.
Data Types	Heterogeneous data sources, including DNA sequences, phylogenetic info, and environmental data.
Knowledge Integration	Utilizing gene function, prior experiment results, and diverse data across labs and fields.
Application	Investigating effects on crop productivity (e.g., corn) through diverse data collection (imaging, genomics, etc.).

Example 3: Prediction, evolution, and control of infectious diseases

The transmission of pathogenic microorganism-caused infectious illnesses is direct (human-to-human) or indirect (environment-to-human and vector-to-human). These dangerous, infectious infections can incubate for days or weeks without symptoms. The COVID-19 pandemic illustrates the difficulty of detecting and treating new illnesses. Traditional mathematical and statistical models give restricted forecasts; therefore, establishing successful disease management measures may require more developed methods for informed judgments. Recent works have examined COVID-19 using AI and ML.

For instance, COVID-19 has caused extraordinary instances and fatalities, demonstrating classical modeling unpredictability. Traditional epidemic models based on early COVID-19 data sometimes mispredict pandemic development by an order of magnitude (Basu et al., 2020). Traditional methods struggle to handle varied data and unforeseen scenarios. In contrast, AI might help machines adapt to changing pandemic data (Hawkins & DuRant, 2020 & Sukarman et al., 2016). AI for infectious illnesses, especially COVID-19, is becoming more popular and necessary due to the rapid growth of computer capacity and the abundance of demographic, epidemiological, and human movement data.

Table 3. The Main Specifications Of The Example3

Aspect	Description
Key Challenge	Traditional models inadequately address the unpredictability and heterogeneity of infectious diseases, exemplified by COVID-19.
AI/ML Integration	AI and ML methods are applied to diverse data sources, enhancing adaptability, real-time parameter inference, and accurate forecasting.
Pandemic Focus	The example emphasizes the relevance of AI, particularly in the context of the COVID-19 pandemic.
Potential Impact	AI's integration with existing models holds the potential for breakthroughs in epidemiology, aiding disease control and prevention.
Technological Advances	State-of-the-art supercomputing models demonstrate the capabilities AI brings to forecasting, tracking, diagnosis, and treatment.
Data Utilization	AI leverages diverse data, including demographic, epidemic, and human mobility data, to improve understanding and management.
Methodological Challenges	Some applications of AI to COVID-19 are critiqued for methodological flaws and bias issues, highlighting the need for robust methodologies.
Future Prospects	AI is deemed indispensable for future pandemic prevention and intervention, driving advancements in infectious disease research.

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AI and ML may be used with mechanistic models to quickly and reliably determine illness parameters from case data. This improves policymaking by improving pandemic forecasts. Recent AI applications to COVID-19 have methodological flaws or bias issues (Saarenmaa et al., 1988), but leveraging AI in the digital age is essential to better understand infectious diseases, improve disease outbreak control and management, and promote public health. For pandemic prevention and response, this is essential. AI in epidemiology investigations may be explored using cutting-edge supercomputing models. Recent technological advances in data collection, analysis, and storage allow AI to forecast disease outbreaks and help implement tracking, diagnosis, and treatment methods, which could control and end a pandemic.

Modern AI-augmented biology will create tools, methodologies, and knowledge for bioengineering, biophysics, biochemistry, and medicine. Artificial intelligence-based medication discovery will revolutionize illness prevention and therapy (Abd-Alrazaq et al., 2020; Kuhl, 2020). New AI techniques and accessible data will democratize biology, allowing researchers from low-resource universities to engage in cutting-edge research.

The Current Landscape of AI in Biology: Opportunities and Challenges

The integration of AI in biology has become increasingly relevant. The availability of sensors, Internet of Things (IoT) devices, and environmental monitors in the modern era allows for the unprecedented collection of data. Enormous and diverse datasets, combining information from various streams, are expanding rapidly. These datasets encompass multivariate information across time, space, and biological scales, necessitating integrated analysis to unveil system-wide, multiscale phenomena. Such exploration aims to reveal fundamental life principles applicable to diverse systems.

Table 4. Outline The Objectives And Corresponding Steps For Implementing AI Strategies In Addressing Antimicrobial Resistance.

Objectives	Action Items
Enhance Surveillance and Monitoring:	Develop AI tools for systematic clinical data collection and analysis related to antimicrobial resistance.
	Implement machine learning algorithms for real-time monitoring and prediction.
	Provide timely insights to healthcare professionals.
Clinical Decision Support Systems:	Design and implement AI-powered clinical decision support systems.
	Aid informed decisions on antimicrobial applications.
	Integrate real-time data analytics for evidence-based practices and judicious antimicrobial use.
Accelerate Drug Discovery:	Leverage AI, especially deep learning, to expedite novel antibiotic discovery.
	Explore synergistic medication combinations using machine learning for enhanced therapeutic efficacy.
Public Awareness and Education:	Utilize AI applications to develop educational tools raising awareness about antimicrobial resistance.
	Promote responsible antibiotic use through AI-powered campaigns and informational resources.

The emergence of AI infrastructure is supporting these endeavors. The growing availability of AI software tools complements unprecedented computational capabilities, including storage, CPU/GPU computing, and large-scale distributed computing. This synergy allows for the swift exploration and development of innovative techniques and applications. These

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resources are continuously expanding, paving the way for the next generation of AI solutions to tackle the most complex problems in biology.

However, this promising landscape is not without its challenges. Issues such as still-limited computational input and output capability (Agrebi & Larbi, 2020; Wiemken & Kelley, 2020) and critical ethical concerns (Roberts et al., 2020; Al-Garadi et al., 2016) underscore the need for thoughtful consideration and responsible implementation of AI in biological research. Table 4 lists antimicrobial resistance AI strategy goals and actions (Fleming, 2018 & Smith et al., 2018).

Conclusion

In the battle against antibiotic resistance, the development of new antibiotics effective against multi-resistant bacteria is imperative. Equally crucial is the need to prevent antibiotic overuse and enhance awareness regarding the adverse impacts of resistance. A comprehensive, multidisciplinary, and intersectoral approach is essential to controlling antibiotic consumption across medical and veterinary domains. Moreover, artificial intelligence has already made strides in improving the identification and characterization of infectious diseases, with significant implications for public health. For example, genomic regions that have been found to be predictive for certain classes of antimicrobial resistance (AMR) can be used to quickly identify and classify them using in silico pipelines and wet lab methods like polymerase chain reaction. Looking ahead, the near future holds exciting prospects, including the use of machine learning to identify bacteriophages capable of lysing specific groups of pathogenic bacteria. This advancement opens doors for innovative approaches like phage therapy, potentially replacing traditional antimicrobials. The integration of artificial intelligence into these areas promises transformative developments, marking a positive trajectory in our fight against antibiotic resistance.

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