RESEARCH PAPER

Artificial Intelligence Applications in Antimicrobial Resistance Surveillance and Pharmacy Practice: A Bibliometric Review

Mohd Abdullah Al Mamun[1*], Md. Tahsin Saleh Nirob[2], Nabila Kabir[3], Md. Ahashan Habib[4], Mir Mohammad Azad[5], Md. Masuqul Haque[6], Swagato Dutta[7], Arnob Biswas[8]

[1*]MBA in Information Technology Management, Westcliff University
Email: mamun.westcliffuniversity.usa@gmail.com
ORCID Number: 0009-0008-0954-1651
[2]Department of Pharmaceutical Technology, Faculty of Pharmacy, University of Dhaka
Email: tahsinnirob53@gmail.com
[3]Oncology, Chittagong Medical College
Email: nabilakabir1993@gmail.com
[4]Medical Officer, Directorate General of Health Services, Mohalhali, Dhaka-1212
Email: ahashanhabib128@gmail.com
[5]Department of Computer Science and Engineering, World University of Bangladesh
Email: azadrayhan@gmail.com
[6]Department of Chemistry, University of Rajshahi
Email: masuqul2003@ru.ac.bd
[7]Department of Microbiology, Noakhali Science and Technology University, Noakhali-3814, Bangladesh
Email: duttaankonmbg@gmail.com
[8]Department of Microbiology, Noakhali Science and Technology University, Noakhali-3814, Bangladesh
Email: arnobjhalok@gmail.com

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Abstract

Antimicrobial Resistance (AMR) is a significant worldwide health problem and artificial intelligence (AI) is increasingly being applied to analyze large clinical, microbiological, genomic, prescribing and surveillance data. This bibliometric review traces the development of AI applications in AMR surveillance and medicine in the fields of infectious diseases, microbiology, digital health, medical informatics, clinical pharmacy and antimicrobial stewardship in high-quality journals. The five clusters of interest identified were resistance prediction, genetic and phenotypic surveillance, antibiotic decision support, clinical applications in the pharmacy and ethical considerations in the health system through the use of AI. The results indicate that the role of the pharmacist in surveillance and prescribing review, dose optimization, medication safety and stewardship is becoming more prominent. However, data quality, external validation, bias, interoperability, privacy and limited pharmacist participation remain challenges. AI should be used in conjunction with, and not as a substitute for, professional judgment. In future, it is important to focus on explainable, validated, pharmacist-integrated systems for safer and workflow-ready implementation.

Keywords: Artificial intelligence, antimicrobial resistance, antimicrobial stewardship, pharmacy practice, bibliometric review, surveillance.

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1. Introduction

Antimicrobial resistance is no longer a distant scientific concern but a direct threat to modern healthcare. Resistant bacteria make it harder to treat easily treatable infections which can lead to longer stays in hospitals. It can put extra strain on healthcare services and can make it more difficult to use antibiotics. Global burden of studies, on one hand, have demonstrated the link between the emergence of bacterial antimicrobial resistance and millions of deaths every year which is a major concern in the field of public health, infectious disease management and medicine safety (Murray et al., 2022). More recent projections have additionally indicated that the incidence of antimicrobial resistance (AMR) could have a significant increase in the future unless there is improved surveillance, prevention, stewardship, diagnostic and effective treatment (Naghavi et al., 2024).

Completeness of antimicrobial resistance monitoring is related to complexity of the problem. Resistance can not only come from one source. Antibiotic use in the hospital, in the community, in agriculture and the prevention of infections, as well as international travel and the evolution of bacteria and inequitable access to diagnostics and effective medicines shape it. Surveillance is not just about reporting in the laboratory. It involves the synergic use of microbiology data, consumption of antimicrobials, electronic health records, prescribing patterns, genetic sequencing, local antibiograms and public health reporting systems. The world health organization (WHO) has stressed the need for surveillance as an integral part of the international response to antimicrobial resistance, given the need for evidence for policy, stewardship, infection prevention and clinical decisions (World Health Organization 2015, 2025).

In this context, AI is becoming more pertinent as the vast and intricate nature of AMR surveillance data. AI and advanced analytics, such as machine learning, deep learning, natural language processing and predictive analytics, can discover patterns that might not be evident in the data based on just traditional statistical monitoring. AI has been utilized in antimicrobial resistance research for predicting antimicrobial resistance phenotypes based on genomic information, assisting in antibiotic selection, identifying high-risk patients, detecting outbreak and identifying antimicrobial resistance, analyzing electronic health records and supporting antimicrobial stewardship programs (Kim et al., 2022; Lv et al., 2021; Sakagianni et al., 2023). In doing so, a new field of research has emerged at the interface of the fields of microbiology, clinical medicine, pharmacy, public health and computer science.

Pharmacy practice is significant, particularly in this field of research. Pharmacists play a key role in antimicrobial stewardship, medication review, dose optimization, checking for medication interactions, counselling, decisions for switching from intravenous to oral administration, therapeutic drug monitoring and education for healthcare professionals. They have a more important role than just dispensing medicines, they must ensure the appropriate, safe, effective and locally appropriate use of antimicrobials. AI could complement this function, as algorithms could help interpret complex patient and microbiology data faster. However, AI could also be a source of problems if the algorithmic recommendations are not well validated or fail to connect with the clinical workflow (Ranchon et al., 2023).

The aim of this bibliometric review is to describe the intellectual and thematic evolution of research on the use of artificial intelligence in the surveillance of antimicrobial resistance and in the pharmacy practice. The paper is based on three main questions for research:

1. What are the major research areas connecting artificial intelligence, antimicrobial resistance surveillance, and pharmacy practice?
2. Which themes dominate the literature in terms of keyword focus, application domains, and bibliometric patterns?
3. What research gaps and implementation challenges must be addressed before artificial intelligence can be used responsibly in pharmacy-led antimicrobial stewardship and surveillance practice?

2. Background and Conceptual Context

Antimicrobial resistance surveillance refers to the organized collection, analysis, interpretation, and sharing of information about resistant organisms, antimicrobial use, and related clinical outcomes. Traditional surveillance systems have depended heavily on laboratory-confirmed susceptibility testing and periodic reporting of resistance rates. This remains essential, but it is no longer sufficient on its own. Modern surveillance increasingly requires links between laboratory results, patient-level clinical data, antimicrobial prescribing data, infection prevention records, and population-level epidemiological trends. A surveillance system that only reports resistance after infections have already spread is reactive. A stronger system should support earlier detection, risk prediction, and timely intervention.

The Global Antimicrobial Resistance and use of surveillance system provides an important international framework for standardized data collection and reporting. Its development reflects a shift from isolated laboratory surveillance toward more integrated systems that include antimicrobial consumption, clinical context, and national reporting capacity (World Health Organization, 2025). This wider surveillance logic is directly relevant to artificial intelligence because AI models depend on large, structured, and meaningful datasets. If surveillance data are incomplete, delayed, biased, or poorly standardized, artificial intelligence models may reproduce those weaknesses rather than solve them.

Artificial intelligence is an umbrella term covering computational systems that can perform tasks normally associated with human intelligence, including learning from data, recognizing patterns, classifying cases, predicting outcomes, and supporting decisions. In antimicrobial resistance research, supervised machine learning is commonly used to predict resistant or susceptible phenotypes from genomic, microbiological or clinical variables. Deep learning can process complex molecular or sequence data. Natural language processing can extract information from clinical notes, discharge summaries, pharmacy interventions, and antimicrobial review documentation. Predictive analytics can estimate patient-level risk of resistant infection or forecast institutional resistance trends (Kim et al., 2022; Lv et al., 2021).

The value of artificial intelligence in antimicrobial resistance is not limited to prediction. AI can also support antimicrobial stewardship. Stewardship aims to improve antimicrobial use by ensuring the right drug, dose, route, and duration for the right patient. This requires a balance between effective infection treatment and resistance prevention. Clinical decision support systems can help identify inappropriate prescribing, suggest de-escalation, recommend intravenous-to-oral conversion, flag duplicate antimicrobial therapy, and align treatment with local guidelines. Such systems may be rule-based, machine learning-based, or hybrid. However, their success depends on usability, trust, local adaptation, and professional oversight (Barlam et al., 2016; Bolton et al., 2025).

Pharmacy practice provides a professional setting where artificial intelligence can be translated into practical antimicrobial decisions. Pharmacists often review antimicrobial therapy after prescriptions are made, identify opportunities for optimization, and communicate with prescribers. In hospitals, antimicrobial stewardship pharmacists may work with infectious disease physicians, microbiologists, infection prevention teams, and nurses. In community settings, pharmacists can influence antibiotic use through patient education, referral decisions, adherence support, and resistance awareness. AI can support these activities by prioritizing high-risk prescriptions, identifying patients likely to benefit from pharmacist intervention, and detecting patterns in prescribing data (American Society of Health-System Pharmacists, 2010; Ranchon et al., 2023).

Despite this promise, AI adoption in pharmacy and antimicrobial resistance surveillance must be approached carefully. A model that performs well in one hospital may fail in another because resistance patterns, prescribing behavior, laboratory methods, patient populations, and data systems differ. Many models are developed retrospectively and are not tested in real clinical environments. This creates a gap between model performance and implementation value. For pharmacy practice, this gap is crucial because pharmacists need tools that fit real workflows, support professional judgment, and improve patient outcomes rather than simply producing technical predictions.

3. Methodology

3.1 Study Design

In this paper, the design of the research is bibliometric review, with thematic synthesis. A bibliometric review analyzes the structure, evolution and focus of a research field by analyzing the publication patterns, source areas, the trends in keyword usage, the relationships between publications and the thematic clusters. Since the field includes three areas of artificial intelligence, antimicrobial resistance, surveillance and pharmacy practice, the bibliometric approach is appropriate to determine the contribution of each of these areas. Thematic analysis is also used in the review as the topic will be understood in the context of the application domains, challenges faced in implementation and relevance to professionals.

The review followed the PRISMA 2020 guidelines to ensure transparent and systematic identification, screening, eligibility assessment, and inclusion of relevant studies (Page et al., 2021). However, the aim of the paper is not to do a clinical effectiveness meta-analysis. Instead, it is to outline the knowledge structure and to determine key themes of research in a multi-disciplinary field.

3.2 Journal and Source Selection

Peer-reviewed articles from leading international microbiology, infectious diseases, antimicrobial resistance, biomedical informatics, public health, clinical pharmacy, digital health, artificial intelligence and pharmacy practice journals were used for the review. Studies that appeared in international journals like The Lancet, The Lancet Infectious Diseases, The Lancet Microbe, Journal of Antimicrobial Chemotherapy, Antimicrobial Agents and Chemotherapy, Clinical Microbiology Reviews, Clinical Microbiology and Infection, Nature Medicine, Nature Microbiology, Cell, npj Digital Medicine, The Lancet Digital Health, Artificial Intelligence in Medicine, International Journal of Medical Informatics, Research in Social and Administrative Pharmacy, International Journal of Clinical Pharmacy, American Journal of Health-System Pharmacy, and Journal of the American Pharmacists Association were preferred. The method papers written on bibliometrics were chosen from a well-known and respected science communication journal, particularly science mapping, citation analysis and keyword co-occurrence analysis.

3.3 Search Strategy

Four concept groups artificial intelligence, antimicrobial resistance, surveillance and pharmacy practice were used to search for the terms. The main search term was derived to be:

Table 1. Search Concepts Used for Literature Identification

Concept group	Search terms
Artificial intelligence	“artificial intelligence,” “machine learning,” “deep learning,” “natural language processing,” “predictive analytics,” “clinical decision support”

Antimicrobial resistance	“antimicrobial resistance,” “antibiotic resistance,” “drug resistance,” “resistant bacteria,” “AMR”
Surveillance	“surveillance,” “genomic surveillance,” “antimicrobial consumption,” “early warning,” “outbreak prediction,” “resistance prediction”
Pharmacy practice	“pharmacy practice,” “clinical pharmacy,” “pharmacist,” “antimicrobial stewardship,” “medication review,” “prescribing support”

The logical search criteria combined were artificial intelligence-related terms, antimicrobial resistance-related terms and surveillance or pharmacy-related terms. Manual backward and forward reference checking was performed to identify important background studies and high impact studies, particularly in the field of antimicrobial stewardship, bibliometric methodology and antimicrobial resistance prediction using AI.

3.4 Inclusion and Exclusion Criteria

Studies were eligible for inclusion if they studied antimicrobial resistance, antibiotic prescribing, antimicrobial stewardship, surveillance, genomic resistance prediction, or pharmacy practice and the use of artificial intelligence, machine learning, deep learning, natural language processing, predictive analytics or clinical decision support. The review articles, original research articles, methodological papers and major global surveillance reports were considered relevant. English-language publications were given priority as the paper was to be used within an English academic task.

Studies that were only on general computer science and did not have an explicit connection with antimicrobial resistance, the use of antibiotics, pharmacy practice or surveillance were not included. Only papers that were clearly relevant to knowledge development about antimicrobial resistance and were pure drug discovery papers were included. Articles that were not scholarly or commercial blogs, editorials with no analysis, and studies with no bibliographic information were excluded.

3.5 Bibliometric and Thematic Analysis

The bibliometric analysis was performed on the areas of sources, research themes, groups of keywords and the intellectual structure. VOSviewer and bibliometrix are used for bibliometric mapping and offer all main features of bibliometric mapping, such as co-authorship analysis, citation analysis, co-citation networks, bibliographic coupling, and keyword co-occurrence mapping, (Aria & Cuccurullo, 2017; van Eck & Waltman, 2010). The bibliometric discussion is included here as a structured evidence map: it is not intended to be a data set exported from Scopus or Web of Science, but to help in the professional review paper.

The literature was grouped thematically into five research clusters: prediction of antimicrobial resistance using AI, genomic and phenotypic surveillance, AI assistance to antimicrobial stewardship, applications of AI in the pharmacy practice, and ethical implementation challenges. These clusters highlight the common phrases and uses of the keywords throughout the top-quality publications.

4. Bibliometric Mapping and Results

4.1 Growth of the Research Field

In recent years, the research on the use of artificial intelligence and antimicrobial resistance (AMR) has increased significantly. Previous research was primarily devoted to the rule-based interpretation, the statistical prediction and clinical decision support. More current studies have adopted increasingly a machine learning, deep learning, whole genome sequencing, electronic health records and large surveillance datasets. This is part of a broader transformation in health care data science, in which clinical and microbiological data are viewed as assets to be used for prediction, surveillance and decision-making.

The trend of the publication series also indicates that the work in the model development phase is being replaced by research that is more geared toward implementation. Initial studies on AI-AMR involved tests to determine if algorithms could predict resistant phenotypes utilizing genomic or laboratory information. Subsequent research started to question if these can be used to guide antibiotic prescribing, antimicrobial stewardship, outbreak detection, and clinical workflow. This change is significant since a model does not necessarily have to be clinically useful because of its performance on a retrospective data set. It facilitates timely decision-making, minimizes inappropriate use of antimicrobials, improves patient safety and is in line with professional practice.

4.2 Leading Source Areas

There are a number of disciplines in which the literature is spread. Research is published in infectious disease and microbiology journals relating to resistance prediction, susceptibility testing, pathogen genomics and surveillance. Articles on clinical decision support, implementation issues and integration with EHRs are published in digital health and medical informatics journals. Research articles on AI and clinical pharmacy services, medication review, pharmacy workflow, and stewardship roles are published in the pharmacy journals. Bibliometric methodology journals offer the instruments which help to chart the field.

Table 2. **Major Source Areas in the Reviewed Literature**

Source area	Main contribution to the topic
Infectious diseases	Antimicrobial stewardship, prescribing guidelines, resistant infection management
Microbiology	Phenotypic resistance testing, genomic prediction, pathogen surveillance
Digital health	AI decision support, electronic health records, implementation science
Pharmacy practice	Medication review, stewardship interventions, pharmacist-led optimization
Public health	National surveillance, antimicrobial consumption, One Health monitoring
Bibliometrics	Science mapping, keyword networks, citation and co-citation analysis

It spans multiple disciplines and is not limited to a single profession. It is a joint effort between pharmacists, physicians, microbiologists, epidemiologists, data scientists and health system leaders.

4.3 Keyword and Thematic Clusters

The literature can be clustered into 5 most salient points, as determined by the keywords. The first cluster focuses on the machine learning, prediction, resistance genes and susceptibility testing. This cluster is composed of studies that involve genomic/phenotypic data to predict antimicrobial resistance. The second cluster is on surveillance and outbreak detection, antimicrobial use and public health monitoring. The third cluster is about antimicrobial stewardship, antibiotic prescribing, clinical decision support and treatment optimization. The fourth cluster includes links to the practice of pharmacy, medication review, pharmacist intervention and medication safety. The 5th cluster focusses on explainability, bias, privacy, validation, implementation.

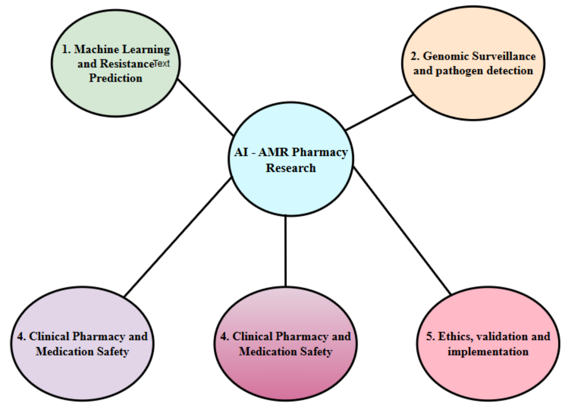

Figure 1: **Proposed keyword co-occurrence map for AI-AMR-pharmacy research**

The highest level of association seems to be between resistance prediction and surveillance, both of which rely on good microbiology, genomic and clinical data. The link between the practice of Pharmacy and surveillance is developing but is not as mature. This is one important gap as much of the decisions related to antimicrobial use are discussed and optimized in the pharmacy.

4.4 Influential Themes and Studies

The field has a number of seminal studies that provide a foundation for the field. Recently whole genome sequencing data has been used to predict antimicrobial resistance by machine learning, with the potential to speed up the interpretation of bacterial resistance profile (Kim et al., 2022; Pesesky et al., 2016). In addition, patient-level clinical history has been employed to predict antibiotic resistance in UTIs, indicating that antibiotic resistance prediction is a microbiological and a clinical, prescribing-history problem (Yelin et al., 2019). While the core of pharmacy surveillance practice is not just the discovery of new drugs, deep learning has been used in the discovery of new antibiotics, and AI can contribute to the general antimicrobial pipeline (Stokes et al., 2020).

AI utilization in the field of AMR prediction, rational antibiotic use, AMR related antimicrobial peptides and antimicrobial stewardship support has been reviewed (Lv et al., 2021; Sakagianni et al., 2023). Clinical pharmacy focused reviews indicated the development of AI tools for medication order review, medication support, therapeutic education, and other services provided by a clinical pharmacist. However, many of these were still in early stages and needed to be better evaluated in the real world (Ranchon et al., 2023). Taken together these studies demonstrate a shift from proof-of-concept models to applied health-system decision support in the field.

5. Thematic Discussion

5.1 Artificial Intelligence for AMR Prediction

The literature is one of the most developed areas concerning antimicrobial resistance prediction. Using machine learning models, genomic, phenotypic, laboratory and clinical data can be used to classify isolates as resistant or susceptible to a particular antibiotic. The introduction of whole genome sequencing has opened up new opportunities as bacterial genomes have resistance genes, mutations, plasmids etc. which are now correlated with the phenotypic resistance. Machine learning can be used to interpret the complex patterns more flexibly than can simple rule-based systems (Kim et al., 2022).

The usefulness of prediction models is that phenotypic susceptibility testing sometimes takes time. Lack of resistance information can result in broad-spectrum prescribing that can increase selection pressure and help develop antimicrobial resistance. Clinicians and pharmacists could make more-precise and timely treatment decisions if AI models can give earlier probability estimates of resistance. These models, however, require careful interpretation as the degree of accuracy with which the model predicts the outcome depends on the type of pathogen, the class of antimicrobial drugs, local resistance prevalence, quality of samples and similarity in training and target populations.

Clinical data may also be used to enhance prediction of resistance. History of antibiotic use, past culture and sensitivity reports, co-existent illness, contact with health-care providers, age and travel history are factors that may affect the risk of resistant infection. The use of prediction at the level of the patient is particularly important in the context of pharmacy practice as pharmacists usually assess antimicrobial therapy and consider previous antimicrobial usage during a patient's medication history. AI models based on the combination of microbiology and medication history might then be a better tool than pathogen genomics (Yelin et al., 2019).

5.2 AI for Surveillance and Early Warning

AI-driven surveillance can shift the focus on antimicrobial resistance monitoring from reactive to proactive by enabling more early detection and risk forecasting. Laboratory susceptibility data, hospital admission data, antibiotic use data, infection control data, environmental monitoring data and genomic sequencing data are examples of surveillance data. AI will be able to recognize any unusual resistance patterns, group resistant infections, predict the likelihood of an outbreak and help allocate resources.

At the level of public health, AI can help monitor national and regional populations in a quicker timeframe than manual methods, analyzing a larger amount of data. It is important to know this since resistance patterns can be different among geographical areas, health care facilities, pathogens and antibiotic categories. AI surveillance is still as powerful as the data infrastructure it's built on though. Comprehensive AI tools might not have the same impact in countries or hospitals with limited laboratory capacity or digital health infrastructure or a lack of well-coordinated reporting systems. The risk is that this could exacerbate surveillance inequity if there is no capacity building as part of implementation plans.

Pharmacy surveillance data should be thought of as being an important component of surveillance. Records of antibiotic use, dose, duration, route, indication, behaviours of prescribers and intervention by pharmacists may provide valuable insights into the use of antibiotics. If combined with resistance data, information from pharmacies can be used to identify if alterations in prescribing are associated with alterations in resistance pressure. This suggests that the gap between the information on surveillance and behaviour of antimicrobial use is filled by the Pharmacy Practice.

5.3 AI in Antimicrobial Stewardship

AI has a significant role to play in antimicrobial stewardship as stewardship decisions are based on data and must be made in a timely manner. AI-powered stewardship can be used to identify patients who are being unnecessarily broadly treated, being over-treated with antibiotics, having duplicate antibiotic cover, incorrect dosages, or opportunities for antibiotic de-escalation. It can also be used to aid surgical to oral switch decisions particularly when the patient is clinically stable and oral therapy is appropriate. The functions overlap with the responsibilities of routine work of antimicrobial stewardship pharmacists.

Clinical decision support systems are either rule based or AI based, or hybrid. Rule-based systems are easier to explain as they work based on the set rules, while they may not be as flexible in case of patients with high complexity. Large sets of data can be used to train machine learning systems, although they might be more difficult to interpret. A combination of both evidence-based rules and prediction of the patient's individual situation may be the most realistic, as stewardship decisions often involve both of these. For instance, a system can incorporate guideline rules for reducing therapy, and machine learning algorithms to assess the risk of resistant infection.

AI should not be presented as replacing antimicrobial stewardship teams. Uncertainty is inherent with antibiotic prescribing, patient preferences, local guidelines, clinical severity, microbiology interpretation, allergies, renal function and the risk for drug interactions. Professional judgment must be used with these factors. However, AI can work in tandem with stewardship by prioritizing cases and summarizing evidence, and emphasizing risk, while ultimately decisions are still human rights decisions made by trained healthcare professionals.

5.4 AI Applications in Pharmacy Practice

Clinical pharmacy is another of the most promising avenues for the use of AI due to its interdisciplinary nature, and because pharmacists already have a role to play in the intersection of medicines, patient information, safety, and clinical decision-making. AI can support medication order review, drug interaction and dose adjustment, renal dosing, therapeutic drug monitoring, adverse drug event prediction, adherence support and workflow prioritization. In antibiotic practice these roles are even more significant since antibiotics are time sensitive and resistance sensitive.

AI can assist with prioritizing the antimicrobial reviews for pharmacists. In many hospitals, the pharmacists are not able to scrutinize each prescription in detail. A risk-scoring model might apply to those with MDR organisms, renal impairment, sepsis, extended antibiotic courses, or exposure to broad-spectrum antibiotics, or those with prior infections with MDR organisms. This may help to optimize the efficiency of pharmacy services and their clinical direction. But a prioritization tool needs to be carefully validated. Otherwise, the false reassurance might result in high risk patients being overlooked.

Another area that is being developed is that of community pharmacy. Community pharmacists can help build awareness of the importance of antibiotics, adherence, symptom triage, promoting vaccination, and referral when antibiotics are not indicated. The use of AI chatbots or decision tools could help to standardize counselling but they should not be used to encourage unsupervised use of antibiotics. In areas where antibiotics are available on demand, AI tools in the pharmacy should be used to improve the learning and information of using antibiotics and not promote commercial overuse.

Pharmacists' role as professionals should be at the heart of AI design. Pharmacists are familiar with drug systems, the prescribing behavior, medication safety and patient communication. AI tools that are not developed with the input from pharmacists may not meet the needs of actual practice. This makes the role of the pharmacist crucial in the design, validation, integration of the workflow, training, governance and post-implementation monitoring of the model.

5.5 Integration of Surveillance and Pharmacy Practice

The best direction for the future is integrating antimicrobial resistance surveillance into the practice of Pharmacy. One common way that surveillance data are used is in reports, dashboards or institutional antibiograms. Those data are translated to a patient-level by the pharmacy practice. AI can bridge these layers through the conversion of the trends in surveillance to prescriptive recommendations, stewardship alerts and medication review priorities.

In this instance, the hospital AI system could integrate the local resistance data, patient history, lab test results, and information regarding the patient's pharmacy history to calculate the likelihood of resistance before the results of the final culture are known. This information could then be reviewed by a pharmacist and would be available for them to narrow or escalate empirical therapy, suggest dose changes and to keep it in their stewardship notes. This integration may minimize unindicated broad-spectrum usage, and keep patients safe.

This integration includes learning health systems as well. The model can be used to feed back with interventions in the pharmacy and patient outcomes, which can further enhance recommendations. However, this calls for good governance. You need to check for bias, drift and unintended consequences on AI systems, and ensure that they are accurate. The resistance patterns will evolve over time and models based on historical data might not be as accurate. Therefore, ongoing monitoring is required.

6. Challenges, Limitations and Ethical Issues

The first problem is the quality of the data. Accurate, representative and standardized data is the need of an AI model. A major challenge with antimicrobial resistance datasets is the fact that susceptibility testing of all infections is seldom carried out, particularly in low-resource countries. The outputs from models may be biased due to missing data, inconsistent laboratory standards and selective testing. Models trained on skewed data sets may not be accurate for minority groups.

The second challenge is the validation from outside. A lot of AI models are created and evaluated in a single institute or data set. Internal performance is not a guarantee for performance in another hospital, a different country or patient group. A model that works in a given health system may not work in another, due to different pathogens, different lab workflows, and/or different prescribing practices.

Explainability is the third challenge. Pharmacists and clinicians are less likely to be convinced by recommendations that will not be explained. Explainability goes beyond being a technical concern; it is a patient safety concern when making decisions about antimicrobials. The pharmacist needs to be aware of the rationale for escalation, de-escalation and/or continuation of treatment as advocated by the system. The use of black-box recommendations could be challenging to document clinically and to claim professionally.

The 4th challenge is implementation. The use of AI tools can be complicated when they are not integrated into current workflows of pharmacy and prescribing. Alert Fatigue is an important problem. Too many alerts that are low value can mean that the clinician ignores them. Adoption may be lacking if the tool needs to be duplicated with data entry or multiple logins are necessary. Usability testing, training, leadership support along with the incorporation with EHRs are essential for successful implementation.

Ethical issues are also of importance. If the data on which AI systems are trained are unequal, so will be the systems' outputs. Combining genomic, clinical, pharmacy and prescribing data adds to the risks for privacy. Governance structures should establish responsibility for recommendations and identify ways to track errors as well as data security for patients. AI tools for antimicrobial resistance should thus be designed as a trustworthy, controllable and professional assistance and not as a replacement for human agency.

7. Future Research Directions

The need for future studies involves prioritizing antimicrobial stewardship AI models focusing on the pharmacist rather than physicians. While there are various existing models that primarily concentrate on technical forecasting, fewer research is available that examine the practical application of AI outputs by pharmacists in genuine clinical choices. The effect of AI facilitated pharmacy interventions on inappropriate use of antimicrobials, time to optimal therapy, adverse drug events and outcomes should be studied.

There is a need for more research to be done into the Explainable AI as well. A rational thought process is essential in pharmacy practice, particularly with recommendations for antibiotic escalation, de-escalation, renal dosing and/or treatment duration. Explainable models can be used to facilitate communication of recommendations from the pharmacist to the prescriber and patient.

The integration of genomic, clinical, laboratory, pharmacy and public health data should be incorporated into future studies. There is no single source to predict antimicrobial resistance. Combined datasets may assist to monitor more accurately and also to more practical decision making. This, however, necessitates good interoperability, data governance and data standards.

There is a need for strengthening of research in low and middle-income countries. These settings are usually heavily affected by antimicrobial. AI tools need to be created for the real-world resource limitations and not just for digitally advanced hospitals. Finally, bibliometric studies in the future should be based on exported datasets from the Scopus, Web of Science or PubMed databases to generate exact publication counts, publication networks, maps of country collaboration and keyword co-occurrence diagrams.

8. Conclusion

AI for antimicrobial resistance surveillance and in the field of pharmacy practice is an emerging multi-disciplinary research area. Bibliometric mapping indicates that the literature is evolving on the theme of resistance prediction, genomic surveillance, antimicrobial stewardship, making decisions in the pharmacy, and implementation ethics. From the general enthusiasm for AI in the field, it is now time to ask more practical questions regarding the validation, integration, explainability, and professional accountability of AI.

The review emphasizes that AI plays a pivotal role in tackling AR with the pharmacy practice clearly identified as a key element in its practical application. Between surveillance data and antimicrobial level decisions at the patient level, pharmacists are standing. AI can assist pharmacists in recognizing high-risk scenarios, play a role in stewardship review, aid in optimizing dosing, and understanding complex resistance information. AI, however, should not take the place of pharmacists' judgment. It should be used as a decision support tool to enhance humans' knowledge and expertise.

To ensure the future of antimicrobial resistance in AI, the data quality, external validation, explainability, equity and responsible implementation will be critical. There needs to be good cooperation among pharmacists, clinicians, microbiologists, public health expertise and data scientists. In a nutshell, AI can enhance antimicrobial resistance surveillance and facilitate more responsible, safer, precise and sustainable use of antimicrobials when used responsibly.

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10. Conflict of Interest Statement

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stewardship, and the responsible use of artificial intelligence in healthcare.

12. Data Availability Statement

No new primary data were generated for this study. The review was based on publicly available scholarly articles, global health reports, and bibliometric methodology papers cited in the reference list. Any extracted bibliographic information used for thematic organization and analysis can be made available upon reasonable request.

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