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Practical Recommendations for Artificial Intelligence and Machine Learning in Antimicrobial Stewardship for Africa

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ABSTRACT

The challenge of antimicrobial resistance (AMR) represents one of the most pressing global health crises, particularly, in resource-constrained settings like Africa. In this paper, we explore artificial intelligence (AI) and machine learning (ML) potential in transforming the potential for antimicrobial stewardship (AMS) to improve precision, efficiency, and effectiveness of antibiotic use. The deployment of AI-driven solutions presents unprecedented opportunities for optimizing treatment regimens, predicting resistance patterns, and improving clinical workflows. However, successfully integrating these technologies into Africa's health systems faces considerable obstacles, including limited human capacity and expertise, widespread public distrust, insufficient funding, inadequate infrastructure, fragmented data sources, and weak regulatory and policy enforcement. To harness the full potential of AI and ML in AMS, there is a need to first address these foundational barriers. Capacity-building initiatives are essential to equip healthcare professionals with the skills needed to leverage AI technologies effectively. Public trust must be cultivated through community engagement and transparent communication about the benefits and limitations of AI. Furthermore, technological solutions should be tailored to the unique constraints of resource-limited settings, with a focus on developing low-computational, explainable models that can operate with minimal infrastructure. Financial investment is critical to scaling successful pilot projects and integrating them into national health systems. Effective policy development is equally essential to establishing regulatory frameworks that ensure data security, algorithmic fairness, and ethical AI use. This comprehensive approach will not only improve the deployment of AI systems but also address the underlying issues that exacerbate AMR, such as unauthorized antibiotic sales and inadequate enforcement of guidelines. To effectively and sustainably combat AMR, a concerted effort involving governments, health organizations, communities, and technology developers is essential. Through collaborations and sharing a common goal, we can build resilient and effective AMS programs in Africa.

1 | Introduction

AMR has been identified by the World Health Organization (WHO) as one of the Top 10 global health threats [1]. AMR is a phenomenon that occurs when microorganisms develop the ability to resist the drugs designed to kill them. AMR threatens to render the cornerstone of modern medicine ineffective against infections, which consequently lead to prolonged illnesses, increased healthcare costs, and even mortality [2]. Africa stands particularly vulnerable in the face of AMR due to limited healthcare resources and the high burden of infectious diseases, coupled with poor or inadequate diagnostic capacity.

In 2015, the World Health Assembly adopted a global action plan (GAP) on AMR, which outlines five objectives: improve awareness and understanding of AMR through effective communication, education, and training; strengthen the knowledge and evidence base through surveillance and research; reduce the incidence of infection through effective sanitation, hygiene, and infection prevention measures; optimize the use of antimicrobial medicines in human and animal health; and develop the economic case for sustainable investment that takes account of the needs of all countries and to increase investment in new medicines, diagnostic tools, vaccines, and other interventions [3]. Following the 2015 declaration, several countries adopted the GAP on AMR and developed their National Action Plans (NAPs) in line with the five GAP objectives. Although African countries have made strides in establishing antimicrobial stewardship (AMS) programs, the effective implementation of activities varies from country to country, with different challenges, ranging from limited resources and inadequate local funding, poor infrastructure, lack of trained personnel, and poor surveillance systems with limited electronic health records (EHRs). This results in inconsistent data collection practices and creates a data gap, thereby hindering African countries from making informed decisions and establishing comprehensive AMS programs [4–6]. Most of the activities included in the NAPs focus their efforts on raising awareness among healthcare workers, strengthening surveillance of antibiotic resistance patterns, and promoting the development of local clinical prescribing guidelines [5].

AMS falls under the fourth objective, which is to optimize the use of antimicrobial medicines. It has been identified as one of the key strategies to combat AMR. AMS refers to the multifaceted approach (including policies, guidelines, surveillance, prevalence reports, education, and audit of practice) that healthcare organizations have adopted to optimize prescribing [7, 8]. These coordinated interventions are designed to improve and measure the appropriate use of antimicrobial agents by promoting the selection of the optimal antimicrobial drug regimen, including dosing, duration of therapy, and route of administration. This helps to preserve the efficacy of existing antibiotics and optimize clinical outcomes while minimizing unintended consequences of antimicrobial use, such as toxicity and the selection and emergence of resistant pathogenic organisms [9]. The WHO has developed regional policy guidelines to support countries in implementing comprehensive and integrated AMS activities. These guidelines provide a set of evidence-based recommendations aimed at optimizing antibiotic use and reducing AMR [10, 11]. They align with the broader Global Action Plan on Antimicrobial Resistance and complement the WHO's practical toolkit for AMS programs in healthcare facilities.

Notably, Africa has made strides in establishing AMS programs. These concerted efforts often focus on raising awareness among healthcare workers, strengthening surveillance of antibiotic resistance patterns, and promoting the development of local clinical prescribing guidelines [5]. However, implementing effective AMS programs in Africa can be challenging due to several factors. Limited resources such as inadequate funding, infrastructure, and personnel hinder African countries from establishing comprehensive AMS programs [6]. Additionally, inconsistent data collection practices and limited EHRs create a data gap that hinders informed decision-making [12] and restricts the reach and effectiveness of existing programs [13]. Advanced technologies, including artificial intelligence (AI), have been developed to enhance AMS programs.

AI refers to the ability of machines to mimic human cognitive functions such as learning and problem-solving [14]. Machine learning (ML) is a subfield of AI focusing on algorithms that can learn from data without being explicitly programmed [1, 2, 15, 16]. Throughout this article, both AI and ML will be discussed. While ML is a subset of AI, this distinction will be highlighted to emphasize the specific role and potential of ML in AMS.

AI and ML offer a multitude of possibilities for optimizing antibiotic use in Africa. Such powerful emerging computational technologies can transform African healthcare systems and potentially overcome existing challenges while making significant improvements in AMS [17–21]. Furthermore, the advent of large language models (LLMs) that use advanced neural networks to read, interpret, and manipulate data and generate human-like responses with probabilistic modeling has further brought transformative shifts in health systems. For instance, chatbots developed through LLMs have been widely used in diagnosis, pre-consultation, assistance, answering medical queries [22], text analysis [23], management, education, and training [24]. With all these capabilities, AI concepts such as ML, deep learning, and large language models can tremendously transform AMS programs in Africa. For instance, AI-based algorithms have been utilized to develop non-knowledge-based and knowledge-based clinical decision support systems (CDSS). Nonknowledge-based CDSS uses genetic algorithms, ML, and multi-dimensional statistical pattern recognition techniques to generate recommendations by simply learning from clinical data of the past performance of specific tasks [25, 26]. In contrast, knowledge-based CDSS relies on clearly defined rules embedded in the knowledge base [27], with the inference engine generating recommendations to the end user through the communication interface based on these rules [26]. These CDSSs tremendously assist clinicians and other healthcare professionals in optimizing antibiotic prescribing, analyzing patient medical data, predicting antibiotic resistance [28], and recommending the most effective antibiotic based on established guidelines and local resistance patterns [28]. Additionally, they can improve prescribing practices [29] and support remote training or clinical support lines using chatbots. ML algorithms, in particular, can analyze vast datasets to predict patients at high risk of developing AMR [30], enabling earlier intervention and more targeted treatment approaches. Furthermore, AI-powered CDSS can support monitoring antibiotic prescriptions, dosage, and distribution patterns across healthcare facilities [31], thereby facilitating real-time identification of potential misuse and informing policy decisions to enhance AMS efforts [32]. However, translating this potential into reality requires careful consideration of several key factors for successful implementation in the African context.

2 | The Potential Benefits of AI and ML for AMS in Africa

Implementing AMS can be challenging and a daunting task, particularly in resource-constrained settings such as rural and marginalized communities in Africa. The difficulties arise from limited resources such as the shortage of infectious disease and antimicrobial experts, inadequate infrastructure, and difficulties in tracking data across various electronic health systems and pharmacies [31].

Despite these challenges, AI and ML offer significant potential to enhance AMS in Africa. AI-based decision support systems assist physicians and clinicians by reducing antibiotic misuse and diagnosis errors. In resource-constrained settings, CDSS helps reduce challenges associated with staff shortages such as lack of awareness and community engagement. AI algorithms and models consider different predictors when analyzing patient data including prior antimicrobial use, culture and susceptibility data. This helps clinicians to determine the likelihood of an infection with a resistant strain and choose the best empiric and targeted regimens, optimize dose and reduce resistance. Such capability enhances the clinical treatment of infections [33]. Non-knowledge-based CDSS, which employ ML and genetic algorithms, can assess real-time patient and microbiological data to recommend optimal treatments based on clinical history and local resistance patterns. These algorithms can be continuously updated with new data to refine their recommendations and enhance treatment outcomes [32, 34].

Moreover, integrating standard operating procedures, analytic tools, data types, and quality control into a laboratory data warehouse accessed by large language models could improve clinical microbiology laboratory workflow [33]. When LLMs are used to access and interpret integrated data, they can streamline laboratory processes and improve efficiency. AI applications extend beyond traditional methods; for example, predicting AMR patterns from mass spectra profiles offers an alternative to conventional laboratory-based susceptibility testing [35]. Additionally, whole genome sequencing of bacterial isolates, combined with EHR mining and ML, can retrospectively identify previously unreported hospital epidemics. This capability enhances infection prevention and control planning. Evidence-based studies indicate that AI-based systems can also identify regions with high rates of antibiotic misuse. This detection enables targeted treatments and helps secure funding for stewardship programs [33, 34].

3 | Challenges to Implementation of AI and ML in AMS in Africa

Evidence-based studies on the significance of AI, ML, and deep learning in improving African health systems have been conducted and shown promising results. However, the integration of AI-based systems into health systems is still moving at a slow pace because of several impediments. Inadequate resources [36] and technological infrastructure [37] coupled with limited access to reliable Internet connectivity and high-processing computers, hinder the deployment of AI systems in many African countries' health systems [38]. There is also a lack of readily available quality data for training, testing, and validating AI and ML algorithms and models. The effectiveness and efficiency of CDSS developed using deep learning, ML, and other AI-based computational techniques rely on the vast amount of quality data. Noisy, incomplete, inconsistent, and biased data affect the performance of AI algorithms and models [39]. These challenges are exacerbated by limited healthcare infrastructure, existing healthcare inequalities, inconsistent data collection procedures, limited EHRs, and security and privacy concerns in Africa [7]. Such impediments hinder the development and deployment of robust AI-based intelligent technologies for accurate detection and prediction of AMR. In addition, the development and integration of AI with healthcare information systems for detecting and predicting AMR requires huge financial investment, which might not always be available in many African health systems. Many healthcare systems in Africa are commonly funded through donors, health insurance schemes, out-of-pocket payments, and non-profit organizations [40].

Developing AI systems for AMR requires highly skilled experts in ML, deep learning, AI, physicians, clinicians, and other disciplines in medical informatics. Such professionals are inadequate in Africa due to green pastures, which consequently lead to high staff shortages in health systems and ultimately hinder the adoption of AI systems for detecting and predicting AMR [7]. In addition, there is also a lack of health policies and frameworks that support the integration of AI systems at national, provincial, regional, and district levels, with the national health information systems [41]. Once such policies are made available, issues around AI algorithm bias, security and privacy concerns, and ethical use of AI in health systems can be partially addressed through national health policies, frameworks, and guidelines. In this context, addressing the misuse of antibiotics and weak regulatory frameworks, which are critical factors in the rise of AMR, becomes relevant [42]. Weak regulatory frameworks and ineffective policy implementation contribute to the over-the-counter sale of antibiotics without prescriptions. Such practices exacerbate AMR. These issues, coupled with limited access to healthcare and socio-economic factors, further hinder effective AMR management. Therefore, the successful implementation of AI for AMS in Africa must also tackle these broader challenges to fully realize its potential.

4 | Practical Recommendations and a Way Forward

Despite the challenges faced in implementing AI and ML for AMS in Africa, several practical recommendations can guide the successful development, deployment, and integration of these technologies.

4.1 | Capacity Building

Developing capacity-building in AI programs such as ML and deep learning becomes imperative. It is essential to engage healthcare professionals, key health system actors, and policymakers in comprehensive training initiatives [36]. Such programs will enhance their understanding of AI's role in combating AMR and how to integrate these technologies into their daily workflows. A phased approach can be adopted, starting with piloting AI projects for detecting and predicting AMR in well-resourced healthcare facilities. These initial efforts should be gradually expanded based on lessons learned and successes achieved, allowing for iterative improvements and broader implementation.

4.2 | Building Trust Among Key Stakeholders

Gaining the trust of key stakeholders, including the public, healthcare providers, and policymakers, is essential for the successful adoption and implementation of AI systems for AMS. Engaging these groups throughout the development and deployment process can significantly enhance trust and acceptance and potentially increase the adoption and utilization of AI technology. This can be achieved through open communication, educational initiatives, and demonstrating the ethical and beneficial applications of AI in healthcare.

4.3 | Technology and Infrastructure

Given the limited resources and technological infrastructure in many African settings, it is essential to develop AI algorithms and models that are robust yet optimized for low computational power and minimal Internet connectivity. These solutions should be designed to work efficiently on portable digital devices, making them accessible in resource-limited environments. AI systems must be developed, trained, tested, and validated using relevant local datasets, which include data on prevalent pathogens, resistance patterns, and antibiotic availability. Furthermore, addressing algorithmic bias is critical. AI systems should be trained on diverse and representative local datasets to ensure fairness and accuracy in predictions and recommendations.

4.4 | Financing

Conducting well-designed pilot projects to demonstrate the feasibility and effectiveness of AI solutions in real-world settings, while also conducting rigorous cost-effectiveness research studies to quantify the benefits of AI interventions will inform resource allocation decisions. Moreover, mobilizing significant financial investment is necessary to support the scaling and integration of successful AI projects. Funding should be directed towards scaling pilots based on empirical evidence and integrating these systems with existing national health information systems. This integration will strengthen electronic medical record systems and standardize data collection practices to ensure high-quality data for AI applications.

TABLE 1 | Glossary of abbreviations.

Abbreviation	Definition
Antimicrobial resistance (AMR)	The ability of microorganisms to resist the drugs designed to kill them.
Antimicrobial stewardship (AMS)	Coordinated interventions aimed at optimizing antimicrobial use.
Artificial intelligence (AI)	The simulation of human intelligence processes by machines.
Machine learning (ML)	A subset of AI that focuses on algorithms learning from data.
Large language models (LLM)	Advanced neural networks used for interpreting and generating human-like text.
Antimicrobial resistance (AMR)	The ability of microorganisms to resist the drugs designed to kill them.
Clinical decision support systems (CDSS)	Computer-based systems that assist clinicians in decision-making.
World Health Organization (WHO)	A specialized agency of the United Nations focused on public health.
Global action plan (GAP)	Refers to the WHO's plan on antimicrobial resistance.
National action plan (NAP)	A country's strategic plan to address antimicrobial resistance.
Electronic health record (EHR)	Digital version of a patient's paper record.

4.5 | Policy

Educational workshops for policy advocacy could be an important starting point. This could involve organizing workshops for policymakers, healthcare professionals, and experts to demystify AI and ML concepts and showcase real-world applications. This has the potential to contribute to the development of local regulatory policies and frameworks that are crucial for the effective integration of AI into AMS programs. These policies should address standards, interoperability, interpretability, trustworthiness, and explainability of AI algorithms. Ensuring that AI systems adhere to ethical guidelines and data privacy standards

TABLE 2 | Potential benefits and challenges of AI and ML in AMS.

Aspect	Potential benefits	Challenges
Clinical decision-making	Enhanced precision in antibiotic prescribing; real-time analysis of patient data to predict resistance patterns.	Lack of quality, comprehensive data; difficulty in model training due to incomplete or noisy datasets.
Efficiency and workflow	Optimizes clinical workflows; streamlines laboratory processes and supports remote decision-making through chatbots and automated systems.	Limited technological infrastructure; inadequate human expertise in AI and ML applications in resource-poor settings.
Surveillance and monitoring	Improves surveillance of antibiotic usage and resistance patterns; enables early detection of misuse and emerging resistance trends.	Fragmented data sources; inconsistent data collection practices; challenges in integrating multiple systems.
Capacity building	Supports training initiatives and enhances clinical support; builds capacity by providing decision support in resource-constrained environments.	Requires substantial financial investment; staff shortages and the need for ongoing professional training.
Policy and standardization	Informs policy decisions with data-driven insights; helps standardize clinical guidelines and prescribing practices.	Weak regulatory frameworks; ethical and privacy concerns; potential algorithm bias impacting fairness.

TABLE 3 | Examples of evidence-based CDSS interventions and their impact on AMS.

CDSS intervention type	Approach	Impact on AMS
Non-knowledge-based CDSS	Uses machine learning, genetic algorithms, and statistical pattern recognition to learn from historical clinical data.	Provides personalized, data-driven treatment recommendations; reduces antibiotic misuse and supports early intervention.
Knowledge-based CDSS	Relies on predefined rules and clinical guidelines embedded in a knowledge base to generate recommendations.	Standardizes prescribing practices; improves adherence to evidence-based guidelines and reduces inappropriate antibiotic use.
LLM-powered chatbots	Utilizes large language models to offer remote clinical support, preconsultation advice, and training via conversational interfaces.	Enhances clinician training, supports remote decision-making, and increases patient engagement through accessible guidance.

is essential for their successful deployment. Specifically, these control measures should mitigate the limitations of AI systems, such as the "black box" problem, where decision-making processes are not transparent. Regulations should focus on enhancing data security, privacy, and algorithmic fairness to support the ethical use of AI in health systems [34].

5 | Conclusion

The integration of AI and ML into AMS programs in Africa holds transformative potential for enhancing healthcare outcomes and combating AMR. AI-driven decision support systems can optimize antibiotic use, predict resistance patterns, and streamline clinical processes. However, successful implementation requires addressing critical barriers, including capacity building, technological infrastructure, and policy development. With targeted investments and collaborative efforts, AI and ML can revolutionize AMS in Africa, leading to more effective management of infections and preservation of antimicrobial efficacy (Tables 1–3).

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

References

1. M. Friedrich, "WHO'S Top Health Threats for 2019," *Journal of the American Medical Association* 321, no. 11 (2019): 1041.

2. N. Gahamanyi, T. Umuhoza, S. I. Saeed, L. N. Mayigane, and J. N. Hakizimana, "A Review of the Important Weapons Against Antimicrobial Resistance in Sub-Saharan Africa," *Applied Biosciences* 2, no. 2 (2023): 136–156.

3. WHO, "Global Action Plan on Antimicrobial Resistance," January 1, 2016, https://www.who.int/publications/i/item/9789241509763.

4. W. L. Fuller, O. T. Hamzat, A. O. Aboderin, et al., "National Action Plan on Antimicrobial Resistance: An Evaluation of Implementation in the World Health Organization Africa Region," *Journal of Public Health in Africa* 13, no. 2 (2022): 2000, https://doi.org/10.4081/jphia.2022.2000.

5. M. R. Akpan, N. U. Isemin, A. E. Udoh, and D. Ashiru-Oredope, "Implementation of Antimicrobial Stewardship Programmes in African Countries: A Systematic Literature Review," *Journal of Global Antimicrobial Resistance* 22 (2020): 317–324.

6. G. J. Porter, S. Owens, and M. Breckons, "A Systematic Review of Qualitative Literature on Antimicrobial Stewardship in Sub-Saharan Africa," *Global Health Research and Policy* 6 (2021): 1–11.

7. B. H. Gulumbe, U. A. Haruna, J. Almazan, I. H. Ibrahim, A. A. Faggo, and A. Y. Bazata, "Combating the Menace of Antimicrobial Resistance in Africa: A Review on Stewardship, Surveillance and Diagnostic Strategies," *Biological Procedures Online* 24, no. 1 (2022): 19.

8. E. Charani, J. Cooke, and A. Holmes, "Antibiotic Stewardship Programmes—What's Missing?," *Journal of Antimicrobial Chemotherapy* 65, no. 11 (2010): 2275–2277.

9. T. H. Dellit, R. C. Owens, J. E. McGowan, et al., "Infectious Diseases Society of America and the Society for Healthcare Epidemiology of America Guidelines for Developing an Institutional Program to Enhance Antimicrobial Stewardship," *Clinical Infectious Diseases* 44, no. 2 (2007): 159–177, https://doi.org/10.1086/510393.

10. WHO, "Antimicrobial Stewardship Programmes in Health-Care Facilities in Low-And Middle-Income Countries: A WHO Practical Toolkit," 2019, accessed August 12, 2024, https://www.who.int/publications/i/item/9789241515481.

11. WHO, "World Health Organization Policy Guidance on Integrated Antimicrobial Stewardship Activities," 2021, accessed July 9, 2024, https://www.who.int/publications/i/item/9789240025530.

12. Z. Saleem, B. Godman, A. Cook, et al., "Ongoing Efforts to Improve Antimicrobial Utilization in Hospitals Among African Countries and Implications for the Future," *Antibiotics* 11, no. 12 (2022): 1824.

13. L. Siachalinga, W. Mufwambi, and I.-H. Lee, "Impact of Antimicrobial Stewardship Interventions to Improve Antibiotic Prescribing for Hospital Inpatients in Africa: A Systematic Review and Meta-Analysis," *Journal of Hospital Infection* 129 (2022): 124–143.

14. WHO, "Ethics and Governance of Artificial Intelligence for Health: Guidance on Large Multi-Modal Models," 2024, accessed July 9, 2024, https://iris.who.int/bitstream/handle/10665/375579/9789240084759-eng.pdf?sequence=1.

15. O. Mugurungi, E. Mbunge, R. Birri-Makota, et al., "Predicting Sexually Transmitted Infections Among Men Who Have Sex With Men in Zimbabwe Using Deep Learning and Ensemble Machine Learning Models," *PLOS Digital Health* 3, no. 7 (2024): e0000541.

16. E. Mbunge, S. G. Fashoto, B. A. Akinnuwesi, et al., "Machine Learning Approaches for Predicting Individual's Financial Inclusion Status With Imbalanced Dataset," in *Computer Science On-Line Conference*, eds. R. Silhavy and P. Silhavy (Springer, 2024).

17. R. Pinto-de-Sá, B. Sousa-Pinto, and S. Costa-de-Oliveira, "Brave New World of Artificial Intelligence: Its Use in Antimicrobial Stewardship—A Systematic Review," *Antibiotics* 13, no. 4 (2024): 307.

18. T. Cai, U. Anceschi, F. Prata, et al., "Artificial Intelligence Can Guide Antibiotic Choice in Recurrent UTIs and Become an Important Aid to Improve Antimicrobial Stewardship," *Antibiotics* 12, no. 2 (2023): 375.

19. D. R. Giacobbe, C. Marelli, S. Guastavino, et al., "Explainable and Interpretable Machine Learning for Antimicrobial Stewardship: Opportunities and Challenges," *Clinical Therapeutics* 46 (2024): 474–480.

20. M. Cavallaro, E. Moran, B. Collyer, N. D. McCarthy, C. Green, and M. J. Keeling, "Informing Antimicrobial Stewardship With Explainable AI," *PLOS Digital Health* 2, no. 1 (2023): e0000162, https://doi.org/10.1371/journal.pdig.0000162.

21. A. Sakagianni, C. Koufopoulou, G. Feretzakis, D. Kalles, V. S. Verykios, and P. Myrianthefs, "Using Machine Learning to Predict Antimicrobial Resistance—A Literature Review," *Antibiotics* 12, no. 3 (2023): 452.

22. K. Nassiri and M. A. Akhloufi, "Recent Advances in Large Language Models for Healthcare," *BioMedInformatics* 4, no. 2 (2024): 1097–1143.

23. R. Yang, T. F. Tan, W. Lu, A. J. Thirunavukarasu, D. S. W. Ting, and N. Liu, "Large Language Models in Health Care: Development, Applications, and Challenges," *Health Care Science* 2, no. 4 (2023): 255–263.

24. M. Karabacak and K. Margetis, "Embracing Large Language Models for Medical Applications: Opportunities and Challenges," *Cureus* 15, no. 5 (2023): e39305, https://doi.org/10.7759/cureus.39305.

25. K. Chung, R. Boutaba, and S. Hariri, "Knowledge Based Decision Support System," *Information Technology and Management* 17, no. 1 (2016): 1–3.

26. K.-F. Ho, P.-H. Chou, J. C.-J. Chao, C.-Y. Hsu, and M.-H. Chung, "Design and Evaluation of a Knowledge-Based Clinical Decision Support System for the Psychiatric Nursing Process," *Computer Methods and Programs in Biomedicine* 207 (2021): 106128.

27. M. Gholamzadeh, H. Abtahi, and R. Safdari, "The Application of Knowledge-Based Clinical Decision Support Systems to Enhance Adherence to Evidence-Based Medicine in Chronic Disease," *Journal of Healthcare Engineering* 2023, no. 1 (2023): 8550905.

28. U. Fanelli, M. Pappalardo, V. Chinè, et al., "Role of Artificial Intelligence in Fighting Antimicrobial Resistance in Pediatrics," *Antibiotics* 9, no. 11 (2020): 767.

29. A. Harry, "Revolutionizing Healthcare: The Role of Artificial Intelligence in Antibiotic Stewardship and Resistance Management," *International Journal of Multidisciplinary Sciences and Arts* 3, no. 1 (2024): 325–332.

30. S. B. Sridhar, M. S. Karattuthodi, and S. A. Parakkal, "Role of Artificial Intelligence in Clinical and Hospital Pharmacy," in *Application of Artificial Intelligence in Neurological Disorders*, vol. 229, eds. M. Bhupathyraaj, K. R. Vijayarani, M. Dhanasekaran, and M. M. Essa (Springer, 2024).

31. A. A. Rabaan, S. Alhumaid, A. A. Mutair, et al., "Application of Artificial Intelligence in Combating High Antimicrobial Resistance Rates," *Antibiotics* 11, no. 6 (2022): 784.

32. F. Branda and F. Scarpa, "Implications of Artificial Intelligence in Addressing Antimicrobial Resistance: Innovations, Global Challenges, and Healthcare's Future," *Antibiotics* 13, no. 6 (2024): 502.

33. A. R. Marra, B. J. Langford, P. Nori, and G. Bearman, "Revolutionizing Antimicrobial Stewardship, Infection Prevention, and Public Health With Artificial Intelligence: The Middle Path," *Antimicrobial Stewardship and Healthcare Epidemiology* 3, no. 1 (2023): e219.

34. A. A. Theodosiou and R. C. Read, "Artificial Intelligence, Machine Learning and Deep Learning: Potential Resources for the Infection Clinician," *Journal of Infection* 87 (2023): 287–294.

35. M. N. Anahtar, J. H. Yang, and S. Kanjilal, "Applications of Machine Learning to the Problem of Antimicrobial Resistance: An Emerging Model for Translational Research," *Journal of Clinical Microbiology* 59, no. 7 (2021): e0126020, https://doi.org/10.1128/jcm.01260–20.

36. E. Mbunge and J. Batani, "Application of Deep Learning and Machine Learning Models to Improve Healthcare in Sub-Saharan Africa: Emerging Opportunities, Trends and Implications," *Telematics and Informatics Reports* 11 (2023): 100097.

37. R. A. Ibrahim, A. M. Teshal, S. F. Dinku, et al., "Antimicrobial Resistance Surveillance in Ethiopia: Implementation Experiences and Lessons Learned," *African Journal of Laboratory Medicine* 7, no. 2 (2018): 1–4, https://doi.org/10.4102/ajlm.v7i2.770.

38. A. Andigema, N. N. T. Cyrielle, N. D. Laetitia, and E. Ekwelle, "Transforming Healthcare in Africa: The Role of Artificial Intelligence in Combatting Infectious Diseases, Neglected Tropical Diseases, and Antimicrobial Resistance." 2024.

39. T. Ali, S. Ahmed, and M. Aslam, "Artificial Intelligence for Antimicrobial Resistance Prediction: Challenges and Opportunities Towards Practical Implementation," *Antibiotics* 12, no. 3 (2023): 523.

40. C. Cashin and J.-P. Dossou, "Can National Health Insurance Pave the Way to Universal Health Coverage in Sub-Saharan Africa?," *Health Systems & Reform* 7, no. 1 (2021): e2006122.

41. D. Chaplain, B. B. Asutaku, M. Mona, D. Bulafu, and D. Aruhomukama, "The Need to Improve Antimicrobial Susceptibility Testing Capacity in Ugandan Health Facilities: Insights From a Surveillance Primer," *Antimicrobial Resistance & Infection Control* 11, no. 1 (2022): 23.

42. E. Rukambile, V. Sintchenko, G. Muscatello, et al., "Campylobacter and Salmonella in Scavenging Indigenous Chickens in Rural Central Tanzania: Prevalence, Antimicrobial Resistance, and Genomic Features," *Microbiology Research* 12, no. 2 (2021): 440–454.