

From Silos to Synergy: Artificial Intelligence as an Architect of Interoperable One Health Systems for Antimicrobial Resistance Surveillance

Ally Mwambela^{1,2*}, Said Hassan¹, Yuda Sule³, Joel Makyao⁴, Raywat Deonandan⁵

¹Department of Public Health, St. Francis University College of Health and Allied Sciences, Ifakara, Tanzania

²Department of Public Health, Alma Mater Studiorum University of Bologna, Bologna, Italy

³Department of Antimicrobial Resistance, One Health Society, Dar Es Salaam, Tanzania

⁴Department of Public Health, KCMC University, Moshi, Tanzania

⁵School of Epidemiology and Public Health, University of Ottawa, Ottawa, Canada

Email: *allymwambela2000@gmail.com

How to cite this paper: Mwambela, A., Hassan, S., Sule, Y., Makyao, J. and Deonandan, R. (2026) From Silos to Synergy: Artificial Intelligence as an Architect of Interoperable One Health Systems for Antimicrobial Resistance Surveillance. *Journal of Biosciences and Medicines*, 14, 63-78. <https://doi.org/10.4236/jbm.2026.1410005>

Received: August 30, 2026

Accepted: October 10, 2026

Published: October 13, 2026

Copyright © 2026 by author(s) and Scientific Research Publishing Inc. This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

Antimicrobial resistance (AMR) constitutes one of the most formidable threats to global health security, directly causing approximately 1.27 million deaths annually and contributing to nearly five million more. Despite widespread consensus that the One Health framework offers the most coherent conceptual approach to AMR mitigation, the operational translation of this vision remains critically obstructed by fragmented, non-interoperable information systems that isolate data across human, animal and environmental health domains. This perspective paper advances a novel argument: artificial intelligence's (AI) most consequential contribution to combating AMR resides not in predictive analytics or pharmaceutical discovery alone, but in its capacity to architect interoperability across these entrenched sectoral silos. We critically examine three AI modalities federated learning for privacy-preserving data federation, natural language processing for heterogeneous data harmonization and explainable AI for clinical trust and translational adoption as promising but insufficiently realized pathways to interoperability. We further interrogate persistent structural barriers, including ontological discordance, infrastructural deficits in low- and middle-income countries and regulatory fragmentation that collectively undermine AI's potential. We contend that realizing AI's transformative promise demands deliberate investment in interoperable data architectures, context-sensitive technological solutions and governance frameworks that foreground equity, transparency and sustainability. This perspective concludes by proposing a pragmatic roadmap for opera-

tionalizing AI-enabled One Health surveillance, emphasizing that interoperability must be elevated from a technical afterthought to a foundational design principle in global AMR strategy.

Keywords

Antimicrobial Resistance, One Health, Artificial Intelligence, Interoperability, Surveillance Systems, Global Health Security

1. Introduction

Antimicrobial resistance has been characterized as a “silent pandemic” that fundamentally threatens the viability of modern medicine, undermining the efficacy of antibiotics that have served as the cornerstone of infectious disease management for nearly a century [1]. The World Health Organization estimates that bacterial resistance directly claims approximately 1.27 million lives annually, with an additional 4.95 million deaths associated with resistant infections [2]. Without transformative intervention, AMR could precipitate 10 million annual deaths by 2050, imposing an economic burden exceeding USD 100 trillion a catastrophe that would disproportionately devastate low- and middle-income countries where health systems are least resilient [3].

The One Health framework, which formally recognizes the inextricable linkages between human, animal, plant and environmental health, has been endorsed by the Quadripartite organizations (FAO, UNEP, WHO, WOAH) through the One Health Joint Plan of Action (2022-2026) as the guiding paradigm for coordinated AMR response [4]. This framework implicitly mandates integrated surveillance systems and seamless data sharing across sectors [5]. Yet nearly a decade after the adoption of the WHO Global Action Plan on AMR, a critical implementation gap persists: the information infrastructure required to operationalize One Health surveillance remains deeply fragmented, characterized by sector-specific data silos, incompatible standards and minimal interoperability [6] [7].

The consequences of this fragmentation are profound and multifaceted. Surveillance systems essential for tracking resistance patterns and guiding evidence-based interventions remain underdeveloped in many regions, constrained by inadequate infrastructure, limited laboratory capacity and the absence of standardized reporting protocols [8]. Multisectoral, multidisciplinary AMR research remains exceptional rather than normative and substantial knowledge gaps impede the development of integrated interventions [7]. Divergent analytical methodologies across sectors for instance, culture-based methods versus genomic approaches generate data that resist meaningful integration, partially explaining why One Health solutions have been slow to materialize despite robust conceptual endorsement [7].

This perspective paper advances a distinctive argument: the most pressing challenge confronting AMR mitigation is not a scarcity of data or analytical sophisti-

cation, but rather the fundamental incapacity of existing information systems to share and integrate data meaningfully across human, veterinary and environmental health domains [9] [10]. Artificial intelligence, when strategically oriented toward interoperability, offers a transformative pathway forward. However, realizing this potential demands a conceptual reorientation: we must move beyond AI's celebrated applications in drug discovery and resistance prediction to focus on the foundational, less glamorous work of architecting systems that enable communication across sectoral divides [11] [12].

2. The Interoperability Imperative in One Health AMR Surveillance

Interoperability the capacity of diverse information systems to exchange and utilize data constitutes the sine qua non of effective One Health surveillance [13]. Yet achieving genuine interoperability across human, animal and environmental health sectors presents formidable challenges that are simultaneously technical, organizational and political [14].

At the technical level, data generated across sectors are characterized by profound heterogeneity: human clinical data typically reside in electronic health records structured around diagnostic and treatment codes, veterinary data are often scattered across livestock production systems and companion animal practices and environmental data derive from wastewater surveillance, agricultural runoff monitoring and ecosystem health assessments [15]. These data are collected using disparate instruments, stored in incompatible formats and governed by divergent quality standards [16].

Organizational barriers are equally consequential: health, agriculture and environmental agencies operate under separate mandates, funding streams and accountability structures that disincentivize cross-sectoral collaboration [17]. Professional cultures differ markedly, with human medicine oriented toward individual patient outcomes, veterinary medicine focused on herd health and food safety and environmental science emphasizing ecosystem integrity [18]. These cultural differences manifest in divergent data collection priorities, analytical approaches and communication practices that perpetuate sectoral silos [19].

Political and regulatory barriers compound these challenges. Data governance frameworks addressing ownership, privacy and usage rights are often absent or inconsistent across jurisdictions, creating legal uncertainty that discourages data sharing [20]. In many contexts, data protection regulations that rightfully safeguard patient privacy inadvertently impede the data aggregation necessary for robust surveillance [21].

The imperative for interoperability is not merely technical convenience but epidemiological necessity. AMR does not respect sectoral boundaries; resistant genes and organisms flow seamlessly between humans, animals and environmental reservoirs [22]. Effective surveillance must trace these pathways, identify transmission hotspots and evaluate intervention effectiveness across the entire transmission chain [23]. Without interoperable systems, this comprehensive picture

remains elusive and interventions risk being misdirected or insufficient.

3. AI as an Interoperability Architect: Opportunities and Frontiers

Before turning to specific techniques, it is worth being precise about what “AI as an interoperability architect” means, since the phrase risks overstating what any algorithm can do. Interoperability comprises at least four distinguishable elements: i) data exchange, the technical transport of information between systems; ii) semantic integration, the alignment of meaning across differing vocabularies, ontologies and classification schemes; iii) governance, the political and legal arrangements that determine who may access, share and act on data; and iv) decision support, the translation of integrated data into outputs that clinicians, veterinarians and policymakers can trust and use. AI makes its most direct contribution to ii) and iv)—natural language processing can align heterogeneous vocabularies and explainable AI can render outputs interpretable. Its contribution to i) is more modest, chiefly through architectures such as federated learning that reduce the need to move raw data at all. Governance iii), by contrast, is fundamentally a sociotechnical and institutional prerequisite: no algorithm can substitute for the political agreements, legal frameworks and institutional trust that determine whether data-sharing is permitted in the first place. The sections that follow examine each AI technique against this framework, distinguishing what AI can realistically deliver from what remains contingent on human and institutional decisions.

Artificial intelligence offers a suite of techniques that can systematically address interoperability barriers. However, a critical insight often overlooked in AI-for-AMR discourse is that these techniques are not interchangeable; each addresses a distinct dimension of the interoperability challenge and their strategic combination is essential for comprehensive progress (Figure 1) [24].

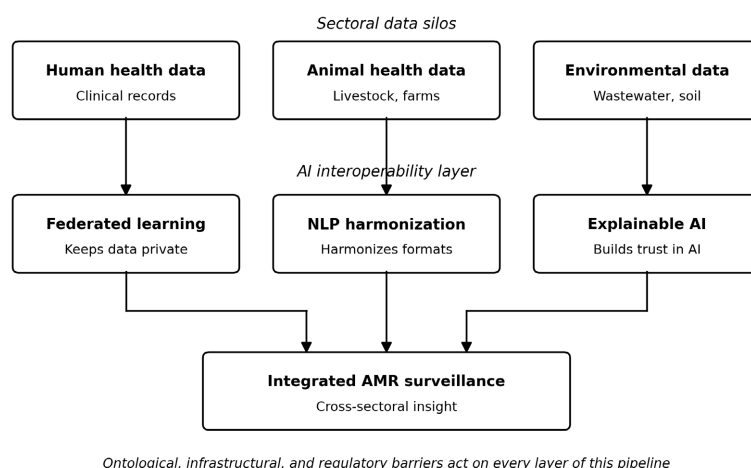


Figure 1. AI as an interoperability architect across One Health sectors. Federated learning, natural language processing and explainable AI each address a distinct interoperability dimension, bridging human, animal and environmental data silos into integrated AMR surveillance.

3.1. Federated Learning: Privacy-Preserving Data Federation

Perhaps the most fundamental obstacle to integrated AMR surveillance is the legal, ethical and competitive constraints that prevent the sharing of sensitive data across institutional and sectoral boundaries [25]. Federated learning directly addresses this challenge by enabling AI model training across distributed datasets without requiring raw data movement, thereby substantially reducing, though not eliminating, as discussed below the privacy burden while enabling collaborative intelligence [26].

A cross-sectoral (human-animal-environmental) federated learning deployment specifically for AMR surveillance has not, to our knowledge, yet been documented in the peer-reviewed literature; readers should treat this as an unrealized but technically feasible opportunity rather than an established practice. Proof-of-concept evidence from clinical federated learning is nonetheless instructive: in a ten-institution consortium training a shared model without any raw patient data leaving participating sites, the resulting model reached 99% of the predictive quality achieved by a fully centralized model trained on pooled data [27]. Translating this architecture to link hospital, veterinary and environmental surveillance nodes for AMR would preserve data sovereignty, accommodate diverse regulatory frameworks and enable cross-sectoral collaboration that centralized data-sharing arrangements currently preclude provided the safeguards discussed below are in place.

This last caveat matters. Federated learning reduces, rather than eliminates, disclosure risk: shared model updates and gradients can still be vulnerable to gradient-inversion or membership-inference attacks capable of partially reconstructing source data [25]. Treating federation alone as a sufficient privacy guarantee would therefore be premature. Realizing its privacy benefits in practice requires complementary safeguards secure aggregation protocols that prevent any single party from inspecting individual updates, formal privacy-risk assessments conducted before deployment and clear institutional accountability for model governance across participating sites [26].

For low- and middle-income countries (LMICs), where data protection infrastructure may be nascent and data governance frameworks often underdeveloped, federated learning offers a technically feasible pathway to participation in global surveillance networks without compromising local data sovereignty [28]. This is particularly significant given that LMICs bear the greatest AMR burden yet often face the most stringent constraints on data sharing [29].

3.2. Natural Language Processing: Harmonizing Heterogeneous Data

The data that could inform AMR surveillance exist in an extraordinary variety of forms: structured laboratory results, free-text clinical narratives, veterinary diagnostic reports, environmental monitoring records, agricultural production data and policy documents [30]. Natural language processing (NLP) offers a powerful

toolkit for extracting structured, machine-readable information from these heterogeneous sources, thereby enabling semantic interoperability the capacity to understand and integrate information across diverse data representations [31].

Recent advances in transformer-based language models have dramatically expanded NLP's capabilities in the biomedical domain [32]. Researchers have successfully employed machine learning frameworks combining transformer architectures and cluster analysis to analyze over 44,000 scientific publications, identifying key AMR research topics, subtopics and detection methods across One Health sectors [33]. More ambitiously, large language models have been developed to assist AMR policy development by synthesizing evidence from national action plans across 146 countries [34]. The AMR-Policy GPT, a large language model with advanced retrieval-augmented generation capabilities, can search and summarize evidence from plans, metadata and technical knowledge, providing traceable references from global document databases [34].

It is important to separate what this evidence actually demonstrates. The topic-clustering application [33] and the policy-synthesis application (AMR-Policy GPT) [34] both show NLP performing well on text corpora scientific literature and policy documents, respectively that are relatively well-structured and written in standardized professional language. Neither constitutes evidence that NLP can reliably extract and harmonize information from the routine, often noisy clinical, veterinary and environmental surveillance records that this paper's interoperability argument actually depends on. Peer-reviewed evaluations of NLP performance specifically on cross-sector routine-record harmonization remain limited; the methodological and ontological groundwork exists [30] [31], but validated performance evidence at the scale needed for operational surveillance is, at present, an evidence gap rather than a demonstrated capability.

The implications of these developments are profound. By converting unstructured text into standardized, machine-readable data, NLP enables the data integration essential for true One Health surveillance. However, critical challenges remain: NLP models must be trained on representative data, evaluated for bias and continuously validated to ensure accuracy across diverse linguistic and cultural contexts [35].

3.3. Explainable AI: Building Trust and Enabling Clinical Translation

Even the most accurate predictive models will fail to influence practice if clinicians, veterinarians and policymakers cannot understand or trust their outputs [36]. The escalating challenge of AMR demands clinician-ready machine learning models that are not merely accurate but interpretable [37]. By treating resistance genes as independent features and augmenting them with curated single-nucleotide polymorphisms and contextual markers, explainable AI approaches deliver scalable, transparent predictions aligned with clinical decision-making needs [38].

Transparency in AI predictions empower evidence-based prescribing decisions,

reduces treatment failure and enables tailored care for patient subgroups at greatest risk of resistance [39]. When models remain interpretable, predictions align with the clinician's mental model of resistance mechanisms, thereby bridging the gap between algorithmic output and clinical action [40]. In the high-stakes environment of AMR management, where treatment decisions have life-or-death consequences, explainable AI is not merely a technical preference but an ethical imperative [41].

Table 1 summarizes these three modalities, the interoperability dimension each addresses and their respective benefits and limitations.

Table 1. Comparison of AI techniques for interoperable One Health AMR surveillance.

AI technique	Interoperability dimension addressed	Core mechanism	Illustrative application	Key benefit	Key limitation
Federated learning	Legal/organizational enables collaboration without moving raw data across institutional or sectoral boundaries	Trains a shared model across distributed datasets held locally at each site	Clinical proof-of-concept: 10-site federated model reached 99% of centralized-model quality; cross-sectoral AMR application not yet demonstrated	Preserves data sovereignty and privacy; well suited to LMIC regulatory environments	Requires reasonably harmonized data structures across sites before training can begin; cross-jurisdictional governance still unresolved
Natural language processing	Semantic converts unstructured, heterogeneous text into standardized, machine-readable data	Extracts structured information from clinical narratives, veterinary reports and policy documents using transformer-based models	AMR-Policy GPT synthesizing evidence from national action plans across 146 countries	Unlocks the large volume of AMR-relevant knowledge trapped in free text	Accuracy depends on representativeness of training data; needs ongoing validation across languages and cultural contexts
Explainable AI (XAI)	Clinical/translational builds the interpretability needed for adoption by end users	Produces transparent, feature-level rationale for predictions (e.g., resistance genes, SNPs) rather than opaque outputs	Interpretable models aligning with clinicians' mental models of resistance mechanisms	Increases clinical trust and uptake; supports evidence-based prescribing	Explainability can trade off against raw predictive performance; still an emerging methodological area

4. Persistent Barriers to AI-Enabled Interoperability

Despite these promising opportunities, several significant challenges threaten to undermine AI's contribution to interoperable One Health systems. These barriers are not merely technical but structural, requiring coordinated action at multiple levels [42].

4.1. Ontological Discordance and Data Standardization

AI models are only as robust as the data on which they are trained [43]. Yet across

human, animal and environmental health sectors, data are collected using disparate methods, definitions and formats that resist harmonization. Divergent analytical methodologies such as culture-based versus genomic approaches generate data that cannot be meaningfully compared, partially explaining why One Health solutions have been slow to materialize [7].

The challenge extends beyond technical data formats to encompass fundamental ontological differences: how different sectors conceptualize and classify resistance, disease and health. For instance, the human health sector typically classifies resistance by clinical significance for patient outcomes, while the veterinary sector emphasizes implications for food production and animal welfare and the environmental sector focuses on ecological persistence and transmission dynamics [44]. These different conceptual frameworks generate data that are not merely stored differently but ask fundamentally different questions [45].

Greater harmonization of research methods, data standards and ontological frameworks across sectors is urgently needed [7]. Effective One Health information systems depend on standardized data protocols, interoperable platforms and strong data sharing networks [46]. Without common standards, ontologies and application programming interfaces, even the most sophisticated AI will struggle to integrate information meaningfully [47].

4.2. Infrastructural Deficits and Capacity Gaps

In LMICs, where the AMR burden is often greatest, limited digital access, funding shortages and lack of technical expertise severely constrain AI implementation [48]. Challenges related to user engagement and incentives, data quality and standardization, infrastructure and connectivity, capacity building and policy alignment are consistently identified as barriers to effective digital One Health surveillance [49]. This unevenness in equipment and technical capacity across countries particularly acute in the low- and middle-income settings where antimicrobial use and resistance are often highest means that any AI-enabled surveillance strategy must be phased and context-appropriate rather than assuming uniform readiness for deployment.

Even in countries with robust infrastructure, incompatible databases, siloed institutions and lack of common standards impede progress [50]. The challenges are compounded by the need for sustained capacity building, reliable electricity and internet connectivity that many regions lack [51]. Investment in capacity development in LMICs must be prioritized, as these are settings where the AMR burden is most acute and the benefits of effective surveillance greatest [49].

4.3. Regulatory and Governance Fragmentation

Data sharing across sectors raises complex questions of ownership, usage rights and privacy [52]. Clear governance frameworks defining these parameters are essential for confident AI deployment, yet such frameworks are often absent or inconsistent across jurisdictions [53]. The Quadripartite organizations have called

for coordinated surveillance systems and launched a Joint Offer for targeted One Health investment, but translating this vision into operational reality requires national-level political commitment and investment that remains uneven [54].

The fragmentation of regulatory frameworks creates particular challenges for federated learning approaches, which operate across institutional and jurisdictional boundaries. Without clear guidance on data ownership, accountability and liability, institutions remain reluctant to participate in cross-sectoral AI initiatives [55].

5. Toward a Roadmap for Operationalizing AI-Enabled One Health Surveillance

The implications of this analysis demand urgent attention from policymakers, researchers and funders [56]. We propose a pragmatic roadmap comprising four interconnected priorities.

5.1. Prioritize Interoperability Infrastructure over Isolated Predictive Tools

Investment in AI for AMR must prioritize foundational interoperability infrastructure over isolated predictive tools [57]. This means dedicating resources to common data standards, shared platforms, governance frameworks and capacity building—not merely algorithmic innovation [58]. When embedded within well-regulated One Health frameworks, AI can strengthen surveillance, improve treatment decisions and support evidence-based interventions [59]. However, this requires deliberate investment in the foundational architectures that enable data to flow across sectors [60].

5.2. Elevate Explainability as a Non-Negotiable Requirement

Explainability must be treated as a non-negotiable requirement for clinical AI deployment [61]. Transparency empowers evidence-based prescribing decisions and reduces treatment failure [38]. AI should be positioned as a decision-support tool that augments, rather than supplants, clinical reasoning [62]. By keeping models interpretable, predictions align with clinical mental models of resistance mechanisms, enabling trust and adoption [40]. This is not merely a technical preference but an ethical and practical imperative for effective AMR management [41].

5.3. Develop Context-Appropriate Solutions

Solutions must be context-appropriate rather than imposing high-resource models on LMIC settings [63]. Offline-capable mobile applications, low-bandwidth platforms and locally relevant training programs may be more suitable than sophisticated cloud-based systems [64]. Co-design with local stakeholders, infrastructure investment, applications integration, cross-sectoral collaboration, continuous training, evidence-based policy support and sustainable funding models are crucial for building effective, inclusive and scalable ICT-driven solutions [65].

5.4. Leverage Current Political Momentum

The current political momentum provides an unprecedented opportunity [66]. The Quadripartite Joint Offer for targeted One Health investment and the inclusion of AMR in the WHO Pandemic Agreement negotiations signal growing political will [67]. However, opportunity alone is insufficient. Realizing AI's potential to combat AMR requires deliberate, coordinated and adequately funded effort to build the interoperable information systems that One Health demands [67].

5.5. Establish an Operational Implementation Sequence

The priorities above remain aspirational unless translated into an actionable sequence. We propose the following operational steps, each a precondition for the next: 1) agree a minimum set of shared data elements that every participating sector commits to reporting in a common format; 2) map these elements onto existing standards and ontologies, resolving the definitional discordance identified in Section 4.1 before any data are pooled or federated; 3) validate data quality at each participating site against agreed thresholds, since AI trained on unvalidated data will simply propagate existing inconsistencies; 4) secure governance and ethics approval covering data ownership, accountability and liability across all participating institutions and jurisdictions; 5) pilot a federated deployment at limited scale, incorporating the privacy safeguards discussed in Section 3.1; and 6) scale deployment only after pilot results are independently evaluated, with continuous monitoring for model drift and equity of access. Sequencing matters: attempting model deployment before data-quality validation and governance approval are in place has been a recurring failure mode in digital One Health initiatives [49] [50].

6. Conclusion

The time for siloed, sector-specific approaches to AMR surveillance has passed. The question is no longer whether AI can help combat AMR, but whether we have the collective will to deploy it in service of the integrated surveillance systems that the crisis demands. Federated learning, natural language processing and explainable AI offer promising pathways to overcome interoperability barriers, but they require intentional investment, context-appropriate implementation and robust governance frameworks. As the global community mobilizes to address AMR through the One Health framework, we must ensure that interoperability is not an afterthought but a foundational principle. AI can help us build bridges between silos, but only if we have the vision and commitment to build them together. We intend this perspective for policymakers and funders as much as for technical audiences, since the barriers described here are institutional and political at least as much as they are algorithmic. This perspective calls for a fundamental reorientation: interoperability must be elevated from a technical afterthought to a central pillar of global AMR strategy, with AI as the enabling architecture that makes integrated One Health surveillance possible.

Acknowledgements

The authors extend sincere gratitude to Professor Raywat Deonandan for invaluable intellectual guidance, scholarly mentorship and critical oversight throughout the development of this perspective paper.

Author Contributions

Ally Mwambela conceived and designed the study and drafted the manuscript. **Said Hassan, Yuda Sule and Joel Makyao** contributed to data acquisition, analysis and interpretation and critically reviewed the manuscript. **Professor Raywat Deonandan** provided critical revisions for important intellectual content and supervision. All authors reviewed and approved the final version and agree to be accountable for all aspects of the work.

Conflicts of Interest

In accordance with ICMJE guidelines, all authors declare no conflicts of interest regarding the publication of this paper.

References

- [1] O'Neill, J. (2016) Tackling Drug-Resistant Infections Globally: Final Report and Recommendations. Review on Antimicrobial Resistance. https://amr-review.org/sites/default/files/160525_Final%20paper_with%20cover.pdf
- [2] Murray, C.J.L., Ikuta, K.S., Sharara, F., Swetschinski, L., Robles Aguilar, G., Gray, A., *et al.* (2022) Global Burden of Bacterial Antimicrobial Resistance in 2019: A Systematic Analysis. *The Lancet*, **399**, 629-655. [https://doi.org/10.1016/s0140-6736\(21\)02724-0](https://doi.org/10.1016/s0140-6736(21)02724-0)
- [3] World Bank Group (2017) Drug-Resistant Infections: A Threat to Our Economic Future. World Bank Publications. <https://doi.org/10.1596/26707>
- [4] FAO, UNEP, WHO and WOAHA (2022) One Health Joint Plan of Action (2022-2026): Working Together for the Health of Humans, Animals, Plants and the Environment. Food and Agriculture Organization of the United Nations. <https://doi.org/10.4060/cc2289en>
- [5] Lerner, H. and Berg, C. (2015) The Concept of Health in One Health and Some Practical Implications for Research and Education: What Is One Health? *Infection Ecology & Epidemiology*, **5**, Article ID: 25300. <https://doi.org/10.3402/iee.v5.25300>
- [6] Dar, O.A., Hasan, R., Schlundt, J., Harbarth, S., Caleo, G., Dar, F.K., *et al.* (2016) Exploring the Evidence Base for National and Regional Policy Interventions to Combat Resistance. *The Lancet*, **387**, 285-295. [https://doi.org/10.1016/s0140-6736\(15\)00520-6](https://doi.org/10.1016/s0140-6736(15)00520-6)
- [7] Chen, C., Li, S., Xu, Y., Liu, J., Graham, D.W. and Zhu, Y. (2024) Characterising Global Antimicrobial Resistance Research Explains Why One Health Solutions Are Slow in Development: An Application of AI-Based Gap Analysis. *Environment International*, **187**, Article ID: 108680. <https://doi.org/10.1016/j.envint.2024.108680>
- [8] Ikuta, K.S., Swetschinski, L.R., Robles Aguilar, G., Sharara, F., Mestrovic, T., Gray, A.P., *et al.* (2022) Global Mortality Associated with 33 Bacterial Pathogens in 2019: A Systematic Analysis for the Global Burden of Disease Study 2019. *The Lancet*, **400**,

- 2221-2248. [https://doi.org/10.1016/s0140-6736\(22\)02185-7](https://doi.org/10.1016/s0140-6736(22)02185-7)
- [9] Salama, R.A., Abdel Kader, R.G. and Wadid, N.A. (2026) Artificial Intelligence in Combating Challenges in Antimicrobial Resistance: A Narrative Review. *Infection Prevention in Practice*, **8**, Article ID: 100522. <https://doi.org/10.1016/j.infpip.2026.100522>
 - [10] Mudenda, S., Chabalenge, B., Daka, V., Mfuno, R.L., Salachi, K.I., Mohamed, S., *et al.* (2023) Global Strategies to Combat Antimicrobial Resistance: A One Health Perspective. *Pharmacology & Pharmacy*, **14**, 271-328. <https://doi.org/10.4236/pp.2023.148020>
 - [11] Otaigbe, I.I. (2023) Achieving Universal Health Coverage in Low- and Middle-Income Countries through Digital Antimicrobial Stewardship. *Frontiers in Digital Health*, **5**, Article 1298861. <https://doi.org/10.3389/fdgh.2023.1298861>
 - [12] Rawson, T.M., Moore, L.S.P., Hernandez, B., Charani, E., Castro-Sanchez, E., Herrero, P., *et al.* (2017) A Systematic Review of Clinical Decision Support Systems for Antimicrobial Management: Are We Failing to Investigate These Interventions Appropriately? *Clinical Microbiology and Infection*, **23**, 524-532. <https://doi.org/10.1016/j.cmi.2017.02.028>
 - [13] World Health Organization (2017) Integrated Surveillance of Antimicrobial Resistance in Foodborne Bacteria: Application of a One Health Approach. World Health Organization. <https://www.who.int/publications/i/item/9789241512411>
 - [14] Auplish, A., Raj, E., Booiyink, Y., de Balogh, K., Peyre, M., Taylor, K., *et al.* (2024) Current Evidence of the Economic Value of One Health Initiatives: A Systematic Literature Review. *One Health*, **18**, 100755. <https://doi.org/10.1016/j.onehlt.2024.100755>
 - [15] Singh, S., Kumar, M., Sarma, D.K., Kumawat, M., Verma, V., Kriti, M., *et al.* (2025) Advancing AMR Surveillance: Confluence of One Health and Big Data Integration. *EcoHealth*, **22**, 403-414. <https://doi.org/10.1007/s10393-025-01724-y>
 - [16] Abramova, A., Berendonk, T.U. and Bengtsson-Palme, J. (2023) A Global Baseline for qPCR-Determined Antimicrobial Resistance Gene Prevalence across Environments. *Environment International*, **178**, Article ID: 108084. <https://doi.org/10.1016/j.envint.2023.108084>
 - [17] Baum, S.E., Machalaba, C., Daszak, P., Salerno, R.H. and Karesh, W.B. (2017) Evaluating One Health: Are We Demonstrating Effectiveness? *One Health*, **3**, 5-10. <https://pubmed.ncbi.nlm.nih.gov/28616496/>
 - [18] Adisasmito, W.B., Almuhaire, S., Behraves, C.B., Bilivogui, P., Bukachi, S.A., Casas, N., *et al.* (2022) One Health: A New Definition for a Sustainable and Healthy Future. *PLOS Pathogens*, **18**, e1010537. <https://doi.org/10.1371/journal.ppat.1010537>
 - [19] Kelly, T.R., Machalaba, C., Karesh, W.B., Crook, P.Z., Gilardi, K., Nziza, J., *et al.* (2020) Implementing One Health Approaches to Confront Emerging and Re-Emerging Zoonotic Disease Threats: Lessons from Predict. *One Health Outlook*, **2**, Article No. 1. <https://doi.org/10.1186/s42522-019-0007-9>
 - [20] Bordier, C., Uea-Anuwong, T., Ratanakorn, P., Luangtongkum, T. and Wilcox, B.A. (2020) Governance of One Health Surveillance Systems for Antimicrobial Resistance and Usage: A Global Landscape Review. *Preventive Veterinary Medicine*, **181**, Article ID: 105064.
 - [21] O'Brien, T.F. and Stelling, J. (2011) Integrated Multilevel Surveillance of the World's Infecting Microbes and Their Resistance to Antimicrobial Agents. *Clinical Microbiology Reviews*, **24**, 281-295. <https://doi.org/10.1128/cmr.00021-10>

- [22] Woolhouse, M.E.J. and Ward, M.J. (2013) Sources of Antimicrobial Resistance. *Science*, **341**, 1460-1461. <https://doi.org/10.1126/science.1243444>
- [23] Collignon, P.J. and McEwen, S.A. (2019) One Health—Its Importance in Helping to Better Control Antimicrobial Resistance. *Tropical Medicine and Infectious Disease*, **4**, Article 22. <https://doi.org/10.3390/tropicalmed4010022>
- [24] Rajpurkar, P., Chen, E., Banerjee, O. and Topol, E.J. (2022) AI in Health and Medicine. *Nature Medicine*, **28**, 31-38. <https://doi.org/10.1038/s41591-021-01614-0>
- [25] Rieke, N., Hancox, J., Li, W., Milletari, F., Roth, H.R., Albarqouni, S., *et al.* (2020) The Future of Digital Health with Federated Learning. *npj Digital Medicine*, **3**, Article No. 119. <https://doi.org/10.1038/s41746-020-00323-1>
- [26] Li, T., Sahu, A.K., Talwalkar, A. and Smith, V. (2020) Federated Learning: Challenges, Methods, and Future Directions. *IEEE Signal Processing Magazine*, **37**, 50-60. <https://doi.org/10.1109/msp.2020.2975749>
- [27] Sheller, M.J., Edwards, B., Reina, G.A., Martin, J., Pati, S., Kotrotsou, A., *et al.* (2020) Federated Learning in Medicine: Facilitating Multi-Institutional Collaborations without Sharing Patient Data. *Scientific Reports*, **10**, Article No. 12598. <https://doi.org/10.1038/s41598-020-69250-1>
- [28] Teo, Z.L., Jin, L., Liu, N., Li, S., Miao, D., Zhang, X., *et al.* (2024) Federated Machine Learning in Healthcare: A Systematic Review on Clinical Applications and Technical Architecture. *Cell Reports Medicine*, **5**, Article ID: 101419. <https://doi.org/10.1016/j.xcrm.2024.101419>
- [29] Tadesse, B.T., Ashley, E.A., Ongarello, S., Havumaki, J., Wijegoonewardena, M., González, I.J., *et al.* (2017) Antimicrobial Resistance in Africa: A Systematic Review. *BMC Infectious Diseases*, **17**, Article No. 616. <https://doi.org/10.1186/s12879-017-2713-1>
- [30] Velasco, E., Agheneza, T., Denecke, K., Kirchner, G. and Eckmanns, T. (2014) Social Media and Internet-Based Data in Global Systems for Public Health Surveillance: A Systematic Review. *The Milbank Quarterly*, **92**, 7-33. <https://doi.org/10.1111/1468-0009.12038>
- [31] Lehne, M., Sass, J., Essenwanger, A., Schepers, J. and Thun, S. (2019) Why Digital Medicine Depends on Interoperability. *npj Digital Medicine*, **2**, Article No. 79. <https://doi.org/10.1038/s41746-019-0158-1>
- [32] Thirunavukarasu, A.J., Ting, D.S.J., Elangovan, K., Gutierrez, L., Tan, T.F. and Ting, D.S.W. (2023) Large Language Models in Medicine. *Nature Medicine*, **29**, 1930-1940. <https://doi.org/10.1038/s41591-023-02448-8>
- [33] Wang, H. (2022) Current and Future Landscape of the Antimicrobial Resistance of Nosocomial Infections in China. *China CDC Weekly*, **4**, 1101-1104. <https://doi.org/10.46234/ccdcw2022.223>
- [34] Chen, C., Li, S., So, A.D., Xu, Y., Guo, Z., Wang, X., *et al.* (2025) Using Large Language Models to Assist Antimicrobial Resistance Policy Development: Integrating the Environment into Health Protection Planning. *Environmental Science & Technology*, **59**, 1243-1252. <https://doi.org/10.1021/acs.est.4c07842>
- [35] Bear Don't Walk, O.J., Reyes Nieva, H., Lee, S.S. and Elhadad, N. (2022) A Scoping Review of Ethics Considerations in Clinical Natural Language Processing. *JAMIA Open*, **5**, ooac039. <https://doi.org/10.1093/jamiaopen/ooac039>
- [36] Cabitza, F., Campagner, A. and Balsano, C. (2020) Bridging the “Last Mile” Gap between AI Implementation and Operation: “Data Awareness” That Matters. *Annals of Translational Medicine*, **8**, Article 501. <https://doi.org/10.21037/atm.2020.03.63>

- [37] Aruhomukama, D. (2025) Balancing Complexity and Clarity—Towards Clinician-Ready Antibiotic Resistance Prediction Models. *Bioinformatics*, **41**, btaf556. <https://doi.org/10.1093/bioinformatics/btaf556>
- [38] Giacobbe, D.R., Marelli, C., Guastavino, S., Mora, S., Rosso, N., Signori, A., *et al.* (2024) Explainable and Interpretable Machine Learning for Antimicrobial Stewardship: Opportunities and Challenges. *Clinical Therapeutics*, **46**, 474-480. <https://doi.org/10.1016/j.clinthera.2024.02.010>
- [39] Lundberg, S.M., Erion, G., Chen, H., DeGrave, A., Prutkin, J.M., Nair, B., *et al.* (2020) From Local Explanations to Global Understanding with Explainable AI for Trees. *Nature Machine Intelligence*, **2**, 56-67. <https://doi.org/10.1038/s42256-019-0138-9>
- [40] Holzinger, A., Langs, G., Denk, H., Zatloukal, K. and Müller, H. (2019) Causability and Explainability of Artificial Intelligence in Medicine. *WIREs Data Mining and Knowledge Discovery*, **9**, e1312. <https://doi.org/10.1002/widm.1312>
- [41] Ursin, F., Lindner, F., Ropinski, T., Salloch, S. and Timmermann, C. (2023) Levels of Explicability for Medical Artificial Intelligence: What Do We Normatively Need and What Can We Technically Reach? *Ethik in der Medizin*, **35**, 173-199. <https://doi.org/10.1007/s00481-023-00761-x>
- [42] Hailu, K.T. and Haddad, R.R. (2025) Structural Barriers and the Future of AI in Global Health: Lessons from Eradicable Diseases. *Cureus*, **17**, e92061. <https://doi.org/10.7759/cureus.92061>
- [43] Futoma, J., Simons, M., Panch, T., Doshi-Velez, F. and Celi, L.A. (2020) The Myth of Generalisability in Clinical Research and Machine Learning in Health Care. *The Lancet Digital Health*, **2**, e489-e492. [https://doi.org/10.1016/s2589-7500\(20\)30186-2](https://doi.org/10.1016/s2589-7500(20)30186-2)
- [44] Lappan, R., Chown, S.L., French, M., Perlaza-Jiménez, L., Macesic, N., Davis, M., *et al.* (2024) Towards Integrated Cross-Sectoral Surveillance of Pathogens and Antimicrobial Resistance: Needs, Approaches, and Considerations for Linking Surveillance to Action. *Environment International*, **192**, Article ID: 109046. <https://doi.org/10.1016/j.envint.2024.109046>
- [45] Oltean, H.N., Lipton, B., Black, A., Snekvik, K., Haman, K., Buswell, M., *et al.* (2025) Developing a One Health Data Integration Framework Focused on Real-Time Pathogen Surveillance and Applied Genomic Epidemiology. *One Health Outlook*, **7**, Article No. 9. <https://doi.org/10.1186/s42522-024-00133-5>
- [46] Food and Agriculture Organization of the United Nations (2025) The Role of Information and Communication Technology in One Health Intelligence. FAO. <https://www.fao.org/one-health/highlights/highlights-detail/the-role-of-information-and-communication-technology-in-one-health-intelligence/en>
- [47] Munk, P., Yang, D., Röder, T., Maier, L., Petersen, T.N., Duarte, A.S.R., *et al.* (2024) The European Livestock Resistome. *mSystems*, **9**, e01328-23. <https://doi.org/10.1128/msystems.01328-23>
- [48] Okeke, I.N., de Kraker, M.E.A., Van Boeckel, T.P., Kumar, C.K., Schmitt, H., Gales, A.C., *et al.* (2024) The Scope of the Antimicrobial Resistance Challenge. *The Lancet*, **403**, 2426-2438. [https://doi.org/10.1016/s0140-6736\(24\)00876-6](https://doi.org/10.1016/s0140-6736(24)00876-6)
- [49] Nguyen-Tien, T., Unger, F., Yano, T., Mutua, F., Cook, E.A.J., Lee, H.S., *et al.* (2025) Challenges and Recommendations for Embracing Digital Tools for One Health Surveillance in LMICs: Viewpoints from a Special Session of 17th ISVEE. *One Health*, **21**, Article ID: 101242. <https://doi.org/10.1016/j.onehlt.2025.101242>
- [50] Masci, F., Gielen, J., Aboye, G.T. and Aerts, J.M. (2025) Navigating the Digital Landscape: Challenges and Advancements in Fostering a One Health Approach through

- Humanity-Centered Design in Mobile Health. *One Health*, **21**, Article ID: 101108. <https://doi.org/10.1016/j.onehlt.2025.101108>
- [51] Hayman, D.T.S., Adisasmito, W.B., Almuhairi, S., Behraves, C.B., Bilivogui, P., Bukachi, S.A., *et al.* (2023) Developing One Health Surveillance Systems. *One Health*, **17**, Article ID: 100617. <https://doi.org/10.1016/j.onehlt.2023.100617>
- [52] Bernier, A., Molnár-Gábor, F. and Knoppers, B.M. (2022) The International Data Governance Landscape. *Journal of Law and the Biosciences*, **9**, lsac005. <https://doi.org/10.1093/jlb/lsac005>
- [53] Tang, D., Xi, X., Li, Y. and Hu, M. (2025) Regulatory Approaches towards AI Medical Devices: A Comparative Study of the United States, the European Union and China. *Health Policy*, **153**, Article ID: 105260. <https://doi.org/10.1016/j.healthpol.2025.105260>
- [54] Food and Agriculture Organization of the United Nations, United Nations Environment Programme, World Health Organization and World Organisation for Animal Health (2023) A Guide to Implementing the One Health Joint Plan of Action at National Level. World Health Organization, 54 p. <https://www.who.int/publications/i/item/9789240082069>
- [55] Price, W.N. and Cohen, I.G. (2019) Privacy in the Age of Medical Big Data. *Nature Medicine*, **25**, 37-43. <https://doi.org/10.1038/s41591-018-0272-7>
- [56] United Nations (2024) Political Declaration of the High-Level Meeting on Antimicrobial Resistance. United Nations General Assembly. <https://digitallibrary.un.org/record/4064023>
- [57] World Health Organization (2026) The World Health Assembly Adopts Updated Global Action Plan on Antimicrobial Resistance (2026-2036). WHO Press. [https://www.who.int/news/item/25-05-2026-the-world-health-assembly-adopts-updated-global-action-plan-on-antimicrobial-resistance-\(2026-2036\)](https://www.who.int/news/item/25-05-2026-the-world-health-assembly-adopts-updated-global-action-plan-on-antimicrobial-resistance-(2026-2036))
- [58] Tacconelli, E., Sifakis, F., Harbarth, S., Schrijver, R., van Mourik, M., Voss, A., *et al.* (2018) Surveillance for Control of Antimicrobial Resistance. *The Lancet Infectious Diseases*, **18**, e99-e106. [https://doi.org/10.1016/s1473-3099\(17\)30485-1](https://doi.org/10.1016/s1473-3099(17)30485-1)
- [59] Laxminarayan, R., Duse, A., Wattal, C., Zaidi, A.K.M., Wertheim, H.F.L., Sumpradit, N., *et al.* (2013) Antibiotic Resistance—The Need for Global Solutions. *The Lancet Infectious Diseases*, **13**, 1057-1098. [https://doi.org/10.1016/s1473-3099\(13\)70318-9](https://doi.org/10.1016/s1473-3099(13)70318-9)
- [60] Delpy, L., Astbury, C.C., Aenishaenslin, C., Ruckert, A., Penney, T.L., Wiktorowicz, M., *et al.* (2024) Integrated Surveillance Systems for Antibiotic Resistance in a One Health Context: A Scoping Review. *BMC Public Health*, **24**, Article No. 1717. <https://doi.org/10.1186/s12889-024-19158-6>
- [61] Amann, J., Blasimme, A., Vayena, E., Frey, D. and Madai, V.I. (2020) Explainability for Artificial Intelligence in Healthcare: A Multidisciplinary Perspective. *BMC Medical Informatics and Decision Making*, **20**, Article No. 310. <https://doi.org/10.1186/s12911-020-01332-6>
- [62] Combi, C. and Pozzi, G. (2019) Clinical Information Systems and Artificial Intelligence: Recent Research Trends. *Yearbook of Medical Informatics*, **28**, 083-094. <https://doi.org/10.1055/s-0039-1677915>
- [63] Chuchu, V.M., Njung'e, J., Muasa, B., Gathira, M., Olela, G., Bubi, K.S., *et al.* (2024) Progress Made in Digitalizing Antimicrobial Resistance Surveillance in a One Health Approach in Kenya. *Frontiers in Public Health*, **12**, Article 1411962. <https://doi.org/10.3389/fpubh.2024.1411962>
- [64] Oberin, M., Badger, S., Faverjon, C., Cameron, A. and Bannister-Tyrrell, M. (2022)

- Electronic Information Systems for One Health Surveillance of Antimicrobial Resistance: A Systematic Scoping Review. *BMJ Global Health*, **7**, e007388.
<https://doi.org/10.1136/bmjgh-2021-007388>
- [65] da Costa, R.C., Serrano, I., Chambel, L. and Oliveira, M. (2024) The Importance of “One Health Approach” to the AMR Study and Surveillance in Angola and Other African Countries. *One Health*, **18**, Article ID: 100691.
<https://doi.org/10.1016/j.onehlt.2024.100691>
- [66] European Commission (2022) EU Global Health Strategy: Better Health for All in a Changing World. European Commission.
[https://ec.europa.eu/transparency/documents-register/detail?ref=COM\(2022\)675&lang=en](https://ec.europa.eu/transparency/documents-register/detail?ref=COM(2022)675&lang=en)
- [67] World Health Organization (2024) WHO Member States Agree Way Forward to Conclude Pandemic Agreement. World Health Organization.
<https://www.who.int/news/item/28-05-2024-who-member-states-agree-way-forward-to-conclude-pandemic-agreement>