Journal of Artificial Intelligence for Medical Sciences
Vol 6 (1–4), 2025, pp. 27–41
Journal home: https://www.nexus-press.com/journal/JAIMS
DOI: https://doi.org/10.55578/joaims.250908.001; eISSN: 2666-1470

REVIEW ARTICLE

AI-Driven Healthcare: Advancing Precision Medicine and Strengthening Antibiotic Resistance Surveillance

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ARTICLE DATA

Article History

Received 16 February 2025
Revised 06 August 2025
Accepted 07 September 2025

Keywords
Artificial intelligence
Machine learning
Healthcare
Predictive analytics
Precision medicine
Medical imaging
Drug discovery
Antibiotic resistance
Healthcare administration
Ethical challenges

ABSTRACT

Background: Artificial Intelligence (AI) is revolutionizing the healthcare industry by providing advanced tools for diagnosis, treatment, and patient management with increased accuracy and efficiency. This narrative review delves into the evolving role of AI technologies, specifically machine learning (ML) and deep learning (DL), in improving various aspects of clinical care, decision-making, and operational efficiency.
Approach: This article presents a descriptive and interpretive synthesis of current literature on the use of AI in healthcare. By examining key publications from 2000 to 2024, the review highlights trends and insights from peer-reviewed sources discussing AI's integration in areas such as predictive analytics, personalized medicine, medical imaging, and antibiotic resistance surveillance.
Key Insights: Artificial intelligence (AI) has shown significant potential in driving innovation in healthcare, particularly in disease prediction, diagnostic accuracy, and drug discovery. Its role in addressing antibiotic resistance is particularly noteworthy, with applications in real-time surveillance and adaptive treatment planning. However, there are still challenges that need to be addressed, such as data privacy, model bias, and interpretability, in order to ensure fair and reliable integration of AI.
Conclusion: While AI has the potential to revolutionize healthcare systems, its successful implementation relies on addressing ethical, technical, and regulatory obstacles. This review highlights the importance of ongoing interdisciplinary research to guide the responsible use of AI in clinical practice.

1. INTRODUCTION

Artificial Intelligence (AI) is reshaping healthcare through enhanced diagnosis, optimized treatment, and improved patient management. Advancements in machine learning (ML), data mining (DM), and deep learning (DL) accelerate drug development, streamline clinical processes, and elevate patient care. AI-driven tools enable healthcare providers to predict outcomes, personalize treatments, and improve clinical decision-making, fostering a more proactive and precise approach to healthcare (Figure 1).

ML is significantly affecting predictive analytics by analyzing large datasets, including patient demographics and genetic data. Using ML algorithms, disease progression can be forecasted, risk factors can be identified, and early interventions can be enabled, ultimately leading to improved patient outcomes [1–3]. Precision medicine, a data-driven approach, involves stratifying patient populations based on genetic, molecular, phenotypic, or clinical characteristics in order to guide more effective and targeted medical interventions [4,5]. While the term "personalized medicine" is often used interchangeably with precision medicine, it encompasses a broader scope, taking into account not only biological variation but also patient preferences, environmental exposures, and lifestyle factors. Additionally, AI has the potential to enhance medical imaging, improving early disease detection, particularly in the field of cancer diagnosis [6,7].

In healthcare administration, AI plays a crucial role in improving operational efficiency through DM. By identifying patterns, AI can enhance population health management, resource allocation, and fraud detection [8,9]. Additionally, AI has the potential to accelerate drug discovery by analyzing complex data and identifying new candidates, ultimately reducing the time and cost of bringing drugs to market [10,11]. However, the integration of AI into healthcare also presents challenges, particularly in regards to data privacy and security concerns. It is essential to protect sensitive patient data, and regulations such as HIPAA in the U.S. and GDPR in Europe

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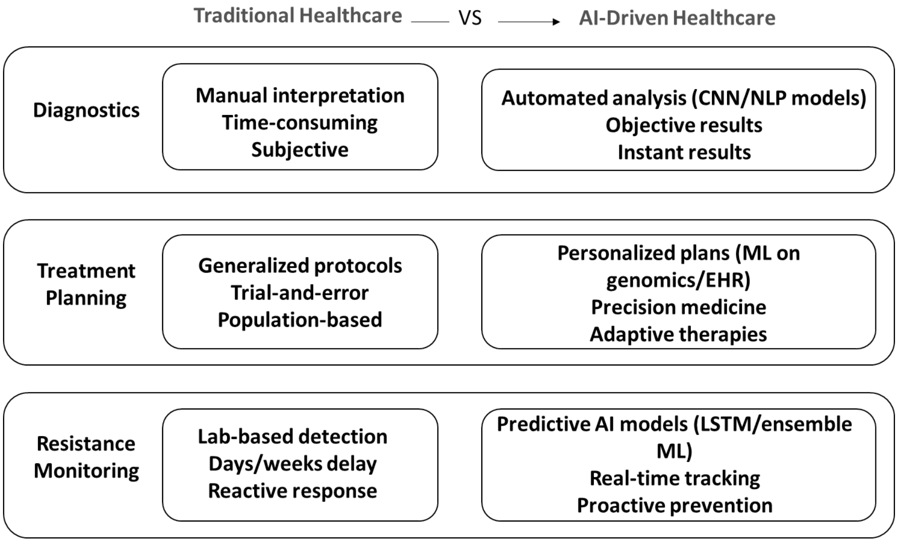

Figure 1 | Comparison between traditional and AI-driven healthcare.

are crucial in maintaining trust and data integrity [12,13]. Furthermore, it is important to acknowledge that AI models may reflect biases, potentially leading to unequal outcomes for marginalized groups. This highlights the need for fairness in AI solutions [14,15]. The "black box" nature of DL models further complicates transparency, making it difficult for healthcare providers to understand and trust AI recommendations [16,17].

Despite the challenges it presents, AI plays a vital role in monitoring antibiotic resistance. By tracking the spread of resistant bacteria, it allows public health officials to address new threats more effectively [18,19]. AI-based diagnostic tools can also detect resistant strains, enabling timely adjustments to treatment plans [20,21]. Additionally, AI has the ability to predict bacterial resistance mechanisms, providing valuable information for public health strategies and antibiotic stewardship [22,23]. In conclusion, AI has the potential to transform healthcare by improving patient care, streamlining operations, and reducing costs. However, in order to fully maximize its potential, healthcare organizations must address ethical, regulatory, and technical challenges. By using AI technologies responsibly and equitably, we can create a more efficient, effective, and patient-centered healthcare system [24,25].

This review aims to provide a comprehensive analysis of the significant impact of AI on the healthcare industry, with a focus on the transformative effects of AI technologies, specifically ML and DL, on patient care, diagnostics, treatment, and healthcare management. It explores the various applications of AI in areas such as predictive analytics, precision medicine, medical imaging, and drug discovery, which have the potential to improve patient outcomes and streamline operational efficiency. The review also addresses key challenges, including data privacy, security, bias, and the need for transparency in AI systems. Additionally, it highlights the role of AI in addressing antibiotic resistance and its potential to monitor and adjust treatment strategies. Ultimately, the review highlights the potential of AI to revolutionize healthcare while also addressing ethical and technical concerns for its responsible implementation.

2. AI IN HEALTHCARE

AI is revolutionizing the healthcare industry by enhancing the precision of diagnoses, treatments, and patient management (Table 1). Using ML, DM, and DL, AI offers incredible potential to improve patient care, increase healthcare efficiency, and expedite drug discovery efforts [24,25].

2.1. ML in Healthcare

ML, a branch of artificial intelligence, is focused on creating algorithms that can use past data to make decisions or predictions without human programming. In the healthcare industry, ML has become a crucial tool for enhancing various aspects of patient care (Figure 2). Despite its potential, the practical implementation of ML remains challenging and can differ greatly depending on the specific application.

2.1.1. Predictive Analytics

ML algorithms such as Random Forests, Support Vector Machines, and ensemble methods like XGBoost have shown notable performance in forecasting disease progression, hospital readmissions, and treatment outcomes [26,27]. Comparative studies have consistently demonstrated that ensemble models outperform traditional regression models, particularly in capturing nonlinear relationships and interactions among clinical variables [28]. However, these benefits come at a cost. Many models are trained on retrospective datasets with limited population diversity, reducing their generalizability across ethnic and socioeconomic groups [14,15]. Furthermore, despite high accuracy metrics in controlled studies, these models often struggle when applied in real-world clinical settings due to missing data, model drift, and poor interoperability with existing health IT systems.

2.1.2. Personalized Medicine

ML enables personalized medicine by analyzing large, heterogeneous datasets to identify genetic and clinical patterns associated with treatment response. A notable case involves the use of Random Forest classifiers trained on The Cancer Genome Atlas (TCGA) data to predict EGFR mutations in lung adenocarcinoma, using gene expression profiles and clinical metadata. These models output mutation probability scores and have demonstrated robust predictive capacity, achieving an AUC of 0.802

Table 1 | **Summary of AI techniques and their healthcare applications**

AI technique	Healthcare application	Description	Key algorithms/tools	Examples/References
Machine Learning (ML)	**Predictive analytics**	Analyzes patient data (EHRs, genomics) to forecast disease progression, readmissions, or complications.	Random Forests, XGBoost, Logistic Regression	Risk stratification for chronic diseases [1–3,25]
Deep Learning (DL)	**Medical imaging**	Detects anomalies in X-rays, MRIs, or CT scans with high accuracy.	CNNs (U-Net, ResNet), GANs	Tumor detection in radiology [6,7,54,55]
Data Mining	**Drug discovery**	Identifies patterns in molecular datasets to accelerate drug candidate screening.	Association rule mining, clustering	Virtual screening for antibiotics [10,11,89]
ML + DL	**Personalized medicine**	Tailors therapies based on genetic profiles, lifestyle, and medical history.	Bayesian networks, reinforcement learning	Oncology treatment optimization [30–32]
DL + NLP	**Clinical decision support**	Analyzes clinical notes and literature to suggest evidence-based treatments.	Transformer models (BERT), RNNs	IBM Watson for Oncology [36–38]
ML + Data Mining	**Antibiotic resistance**	Tracks resistance trends using genomic/EHR data and predicts outbreaks.	LSTMs, association mining	ResFinder, CARD [75–77]
DL (CNNs)	**Rapid diagnostics**	Accelerates detection of antibiotic-resistant pathogens from lab cultures.	Image analysis pipelines	AI-guided microscopy [20,21,93,94]
ML (Ensemble)	**Fraud detection**	Identifies billing fraud or resource misuse in healthcare systems.	Decision trees, anomaly detection	Insurance claim analysis [40,41]

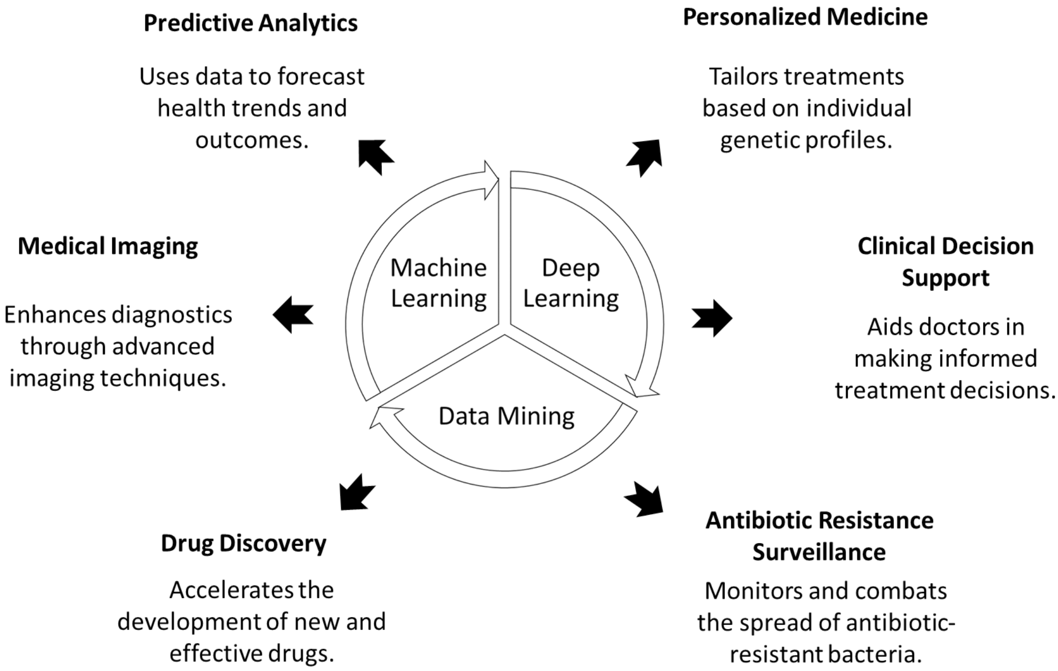

Figure 2 | AI applications across healthcare domains.

and was further improved to 0.828 by adding sex and smoking history [29]. Such approaches allow for pre-selection of patients who may benefit from tyrosine kinase inhibitors. However, despite their promise, these models face challenges in generalizability, particularly when trained on datasets with limited ethnic or geographic diversity [16].

ML algorithms enhance personalized medicine by tailoring treatments to an individual's genetic profile, medical history, and other relevant factors. In fields such as oncology and chronic disease management, ML facilitates this customization by synthesizing genetic, clinical, and lifestyle information. Techniques like Bayesian networks and reinforcement learning have been employed to suggest targeted therapies based on tumor mutation profiles [30–32]. However, several challenges hinder these approaches. They rely on extensive, well-organized datasets that are often unevenly available worldwide. Additionally, many personalized medicine tools lack transparency, which can undermine clinician confidence and impede regulatory approval. Furthermore, only a limited number of ML-driven personalization tools have advanced beyond pilot studies into standard clinical practice. While ML holds significant potential for optimizing treatment strategies, its implementation is limited by data availability, validation challenges, and the necessity for interpretability from a clinician's perspective. For these models to be truly effective in clinical settings, they must also account for patient preferences and long-term outcomes.

2.1.3. Medical Imaging

ML demonstrates significant proficiency in the evaluation of medical imaging, including modalities such as MRI, CT scans, and X-rays. DL-powered ML systems, especially Convolutional Neural Networks (CNNs), are redefining diagnostic imaging. Tools like U-Net and ResNet have demonstrated high sensitivity in detecting pathologies such as tumors, fractures, and diabetic retinopathy [33–35]. In several cases, AI models have matched or exceeded human radiologists in accuracy. Nonetheless, studies often use curated image datasets under ideal conditions, failing to account for artifacts, low-resolution inputs, or atypical cases that are common in clinical practice. Moreover, the "black box" nature of CNNs complicates regulatory approval and clinician adoption, especially when errors occur without explainable justification. While CNNs show exceptional performance in image classification, issues of data bias, generalization, and explainability limit their clinical reliability. Future research should focus on interpretable DL architectures and robust performance under real-world imaging variability.

2.1.4. Clinical Decision Support Systems (CDSS)

ML-based CDSS platforms, such as IBM Watson Health, integrate structured and unstructured data to recommend evidence-based treatment options [36–38]. While promising, these systems are not without challenges. Evaluations of Watson have shown mixed concordance with human experts, and some implementations have faced criticism for relying on outdated or overly narrow datasets. Furthermore, the legal and ethical implications of AI-driven decisions, especially when they conflict with physician judgment, remain unresolved. CDSS tools hold potential for enhancing clinical decisions but must be rigorously validated and updated regularly. Co-development with clinicians, transparent recommendation logic, and clear accountability frameworks are essential for safe adoption.

2.2. DM in Healthcare

DM is the process of uncovering patterns and deriving significant insights from extensive datasets. In the healthcare sector, this practice is crucial for recognizing trends that can enhance patient outcomes and optimize operational efficiency (Figure 2). However, their effectiveness is often contingent on the quality and consistency of the data being mined, and their outputs are limited by the statistical assumptions underlying the models.

2.2.1. Pattern Discovery in Disease Outbreaks and Treatment Effectiveness

Frequent pattern mining, clustering, and association rule learning have been used to track disease outbreaks and evaluate treatment protocols [39]. For instance, during the COVID-19 pandemic, real-time mining of hospital records enabled the identification of regional infection surges and treatment response trends. However, DM is often reactive rather than predictive. Its utility is limited when data is sparse, noisy, or delayed, and it lacks the adaptability of ML systems to dynamically update models as new data is received. DM is effective for retrospective pattern discovery, but its reactive nature and reliance on clean, structured datasets limit its usefulness for real-time interventions. Combining DM with ML may improve prediction and scalability.

2.2.2. Fraud Detection

Healthcare fraud detection has benefited from anomaly detection techniques applied to claims and billing data [40,41]. These methods successfully identify outlier patterns in insurance claims, such as unusually high billing frequencies. However, overreliance on static rule-based systems can lead to false positives, overwhelming reviewers and reducing trust in AI-based alerts. Moreover, many fraud detection algorithms lack adaptability to evolving fraud strategies. Regular algorithm retraining and feedback loops from human reviewers are necessary for system improvement.

2.2.3. Population Health Management

DM of extensive health records enables the identification of risk factors and prevalent health trends within large populations, thereby assisting hospitals and public health organizations in the more effective management of chronic conditions like diabetes and hypertension.

Mining electronic health records (EHRs) enables population-level risk stratification and chronic disease management [42,43]. However, privacy regulations often restrict access to comprehensive datasets, and heterogeneity in data formats across institutions complicates integration. In addition, DM often overlooks social determinants of health, which are crucial in understanding population risk profiles. DM supports macro-level planning in healthcare, but integration with ML and social data is needed to address equity and precision. Standardizing EHR formats could enhance cross-institutional mining efforts.

2.2.4. Drug Discovery

In the field of pharmaceutical research, DM and DL techniques play a crucial role in identifying novel therapeutic candidates, especially against emerging and resistant pathogens. These tools analyze complex biological, chemical, and genomic datasets to discover hidden patterns and optimize early-stage drug screening.

Advanced platforms such as DeepChem, DeepPurpose, and MT-DTI utilize DL models, including graph neural networks (GNNs), CNNs, and attention-based transformers, to predict drug–target interactions (DTIs), bioactivity scores, and binding affinities directly from molecular representations like SMILES strings or 3D conformers [44]. For instance, MT-DTI successfully predicted potential inhibitors for *Mycobacterium tuberculosis* enzymes by learning chemical-protein interaction patterns from large bioassay datasets [45].

In the context of antibacterial drug development, AlphaFold, a deep neural network developed by DeepMind, has revolutionized the field by predicting the 3D structures of bacterial proteins with atomic-level accuracy [46]. This structural insight is instrumental in identifying essential bacterial targets for new antibiotic scaffolds. Recent studies used AlphaFold-generated structures to virtually screen molecules against resistance-associated proteins such as β-lactamases and efflux pump regulators in multidrug-resistant Gram-negative bacteria [47].

Furthermore, predictive AI models, such as those used in epidemic disease modeling, demonstrate promising potential in identifying high-risk pathogens and guiding antibacterial target prioritization and drug repurposing strategies [48].

Additionally, tools like DeepARG and CARD not only support resistance gene detection but also guide compound selection by flagging targets with known resistance mechanisms. This integration of resistome analysis with predictive pharmacology facilitates informed drug design decisions, improving the likelihood of developing effective antibiotics [49].

AI is demonstrably transforming drug discovery across multiple stages, significantly accelerating timelines and improving efficiency. Generative AI platforms like Insilico Medicine's Pharma.AI/Chemistry42 have designed novel drug candidates, such as the idiopathic pulmonary fibrosis drug INS018_055, progressing to Phase II trials in under 18 months, a fraction of traditional timelines [50]. Exscientia's Centaur Chemist platform optimized leads like DSP-1181 (for OCD) and EXS21546 (for immuno-oncology) for potency and safety, rapidly advancing them into clinical trials [51]. BenevolentAI's knowledge graph identified the rheumatoid arthritis drug baricitinib for repurposing against COVID-19, leading to emergency authorization [52]. Recursion Pharmaceuticals uses AI-driven image analysis (Recursion OS) to predict toxicity early from cellular phenotypes, while CytoReason's models assist partners like Pfizer in clinical trial design and patient stratification [53]. These examples highlight AI's tangible impact in generating novel therapeutics, validating targets, optimizing candidates, repurposing drugs, de-risking development, and enabling precision medicine.

2.3. DL in Healthcare

DL an advanced branch of ML, employs multi-layered neural networks to capture intricate patterns within data. It has achieved significant success, especially in handling unstructured data types, including images, text, and genomic sequences (Figure 2). DL through neural network architectures like CNNs, RNNs, and transformers, is driving advances in unstructured data analysis. However, DL's power often comes with high computational demands, limited transparency, and challenges in clinical validation.

2.3.1. Medical Image Analysis

CNN-based DL models achieve state-of-the-art performance in radiology and pathology image classification [54,55]. These advanced models excel in the analysis of medical images, facilitating the early identification of conditions such as cancer, diabetic retinopathy, and Alzheimer's disease. These models, such as U-Net and ResNet, detect fine-grained features undetectable to the human eye. However, a major limitation is that most models are trained on well-annotated, high-quality datasets, conditions that rarely reflect real-world diversity. Additionally, adversarial examples (subtle image changes that mislead models) highlight the fragility of even high-performing networks.

While CNNs remain widely used in medical image analysis, recent work has demonstrated the effectiveness of Vision Transformers (ViTs), which apply self-attention mechanisms to learn long-range spatial dependencies. In contrast to CNNs that focus on local patterns, ViTs enable a global context-aware representation of images, improving performance in tasks such as tumor segmentation, skin lesion classification, and multi-organ diagnosis [56,57].

For example, in a multi-institutional study applying ViTs to histopathology images, ViTs outperformed ResNet-based models with F1-scores exceeding 0.93, while also offering better explainability via attention maps. Additionally, hybrid architectures that combine CNN feature extraction with transformer-based encoders have shown superior performance in noisy or heterogeneous imaging datasets. These developments suggest that ViTs are a promising architecture for future AI tools in radiology and digital pathology, particularly where image variability and spatial resolution are critical.

DL has revolutionized medical imaging, but its dependency on pristine data and its vulnerability to adversarial inputs challenge its reliability. Future systems should incorporate uncertainty quantification and robustness testing to ensure clinical safety.

2.3.2. Natural Language Processing (NLP)

DL-enabled NLP tools process clinical notes, radiology reports, and scientific literature to extract insights from unstructured text [58]. Transformer-based models (e.g., BERT) outperform traditional rule-based NLP, especially in understanding medical terminology and context. Yet, these models often require fine-tuning on domain-specific corpora, and their outputs can be difficult to validate or interpret, especially in ambiguous clinical contexts. DL-based NLP models excel in parsing complex clinical text, but require large, domain-specific datasets for optimal performance. Incorporating clinician feedback during development can enhance contextual relevance and model explainability.

Recent advances in large language models (LLMs) have significantly expanded the capabilities of medical NLP. Tools such as Med-PaLM, BioGPT, and GatorTron have demonstrated impressive performance in clinical question answering, summarization of EHRs, and evidence-based decision support [59,60]. For instance, Med-PaLM 2, trained on a combination of biomedical and general domain data, achieved over 85% accuracy on USMLE-style questions, rivaling medical professionals in diagnostic reasoning. These models use transformer architectures with billions of parameters, enabling contextual understanding of medical language far beyond rule-based or earlier ML-based systems.

Despite their power, LLMs pose new challenges in clinical settings. Concerns include hallucination of incorrect information, lack of transparency in reasoning, and difficulty validating model outputs against clinical standards. Ethical frameworks and regulatory pathways for LLMs in healthcare are still in development, requiring further work to ensure safe deployment.

2.3.3. Virtual Health Assistants and Chatbots

DL-powered virtual assistants, using NLP and reinforcement learning, are increasingly employed in chronic disease management and patient support [61]. While they improve patient engagement and reduce routine clinical burden, their capabilities remain basic in decision-making. Moreover, safety concerns arise from unverified recommendations in sensitive scenarios like symptom triage. Virtual health assistants are useful adjuncts for education and monitoring but should not replace clinician judgment. Standardizing regulatory evaluation and adding escalation protocols will enhance their safe integration into care pathways.

2.3.4. Genomics and Drug Discovery

DL models such as DeepVariant and AlphaFold have transformed genomics and protein structure prediction [62–64]. These tools can identify genetic variants with clinical significance and simulate protein folding with remarkable accuracy. However, interpretability remains minimal, and clinical translation is slow due to the complexity of downstream validation. DL's impact on genomics is profound, yet its real-world integration requires collaboration between bioinformaticians and clinicians. Interpretability frameworks and regulatory pathways must evolve in parallel to facilitate translational progress.

3. CHALLENGES IN AI HEALTHCARE INTEGRATION

Despite the rapid advancements in AI for healthcare and biomedical research, its implementation remains constrained by a multitude of interconnected challenges. These limitations extend beyond technical performance to include ethical, regulatory, infrastructural, and sociocultural barriers (Table 2).

3.1. Data Availability and Quality

High-quality, representative data is the foundation for effective AI models. However, most available clinical datasets are fragmented, inconsistent, or biased toward high-income settings. Missing values, poorly structured formats, and limited longitudinal follow-up reduce the utility of these datasets for robust model training and validation [65,66].

Furthermore, rare disease datasets or those from underrepresented populations are often insufficient in size, limiting the generalizability of AI systems. Transfer learning and data augmentation techniques can partially compensate for this limitation, but these approaches may also introduce synthetic biases or fail in context-specific applications. Improving AI reliability requires standardization of health data, increased data sharing (especially across low- and middle-income countries), and incentivized contributions to open datasets. Ethical frameworks must evolve alongside technical innovations to ensure equity in dataset curation.

3.2. Bias, Fairness and Equity

Bias in AI systems represents a critical barrier to the equitable implementation of AI in healthcare. These models frequently inherit biases embedded in their training data, which may be unrepresentative of the broader population or reflect existing structural inequalities [14]. As a result, AI-driven outcomes can disproportionately disadvantage marginalized groups [15]. The most common types of bias include sampling bias, which occurs when datasets lack adequate representation of minority populations; labeling bias, often stemming from subjective or inconsistent clinical annotations; and algorithmic bias, which emerges when model training prioritizes performance for majority groups over others [67]. These issues can lead to misdiagnosis, unequal treatment decisions, and the amplification of existing health disparities. For instance, diagnostic tools trained predominantly on lighter-skinned individuals exhibit reduced accuracy for patients with darker skin tones, perpetuating inequities in dermatology and radiology [65,68].

Mitigating biases in AI necessitates a comprehensive strategy that encompasses various elements [14]. Key approaches include gathering diverse and representative datasets to combat sampling bias, creating fairness-aware algorithms to prevent discriminatory outcomes [67], and employing interpretable AI models for auditing and correcting labeling errors [15]. Despite their importance, these strategies are frequently applied inconsistently, leading to challenging trade-offs between fairness, model efficacy, and usability in clinical settings [68]. To effectively tackle these issues, ongoing collaboration among data scientists, healthcare practitioners, and ethicists is essential, supported by transparent evaluation methods and inclusive design principles [65]. Only through such collective efforts, can AI technologies be responsibly developed and implemented to promote equitable healthcare outcomes. Furthermore, ethical AI demands not just fairness in algorithms but also structural changes in data governance and collection, making equity-focused audits and demographic performance assessments essential components of clinical AI development.

3.3. Interpretability and Trust

Many advanced AI models, especially DL architectures, function as "black boxes," producing results without providing clear insights into their decision-making processes [66–69]. This opacity can undermine trust among clinicians, complicate regulatory approvals, and affect patient acceptance, particularly when AI suggestions conflict with medical professionals' assessments. To tackle these issues, explainable AI (XAI) techniques such as SHAP and LIME have been developed [70]. However, these methods often offer merely post hoc explanations rather than genuine interpretability, which can lead to confusion rather than clarity. For AI to be deemed trustworthy in healthcare, it is essential to emphasize transparency throughout the entire lifecycle of the model, from its initial design to its implementation. While interpretable models may sacrifice some degree of accuracy, they are more likely to gain acceptance from regulators and clinicians, particularly in critical decision-making scenarios.

3.4. Integration into Clinical Workflow

AI tools are often created without consideration for real-world clinical workflows, leading to challenges in their adoption despite validation. This disconnect results in issues such as poor compatibility with EHRs systems, an increased burden of documentation, and disruptions to established clinical routines [71,72]. Additionally, the fast-paced nature of healthcare limits clinicians' ability to effectively interpret and act on AI-generated

Table 2 | **Key challenges in AI healthcare integration: limitations, examples, and future directions**

Challenge	Description	Example/Impact	Future directions
Data quality & availability	Fragmented, biased, or incomplete datasets limit model training, generalizability, and performance	Poor performance of ML models trained on high-income country datasets when applied to LMIC patient populations	Promote standardized data collection, incentivize global data sharing, and expand inclusion of underrepresented groups
Interpretability & trust	Black-box models (e.g., deep learning) lack transparency, reducing clinician trust and regulatory acceptability	Resistance to AI diagnostic outputs in radiology due to unclear decision rationale	Develop explainable AI (XAI) frameworks (e.g., SHAP, LIME); prioritize inherently interpretable models for clinical use
Clinical workflow integration	AI tools often disrupt existing workflows, lack EHR interoperability, and increase clinician burden	CDSS tools abandoned due to alert fatigue or requiring manual data entry	Co-design AI systems with clinicians; ensure seamless EHR integration and real-time, low-burden interfaces
Bias & equity	AI models may reinforce existing healthcare disparities if trained on biased or non-representative data	Dermatology models misclassifying skin lesions on darker skin tones	Require demographic auditing of model outputs; develop equity-by-design frameworks
Regulatory & legal uncertainty	Lack of clear standards for approval, monitoring, and accountability of adaptive AI systems	Few DL-based diagnostic tools receive FDA or EMA clearance	Establish adaptive regulatory frameworks, real-world performance monitoring, and shared responsibility models
Privacy & data security	AI development demands large, sensitive datasets, raising concerns over consent, data misuse, and cybersecurity	Breach of genomic data repositories; secondary data use without patient awareness	Adopt federated learning, differential privacy, and transparent governance protocols
Model generalizability & validation	AI models trained in specific environments often fail to perform in new clinical settings or populations	Drop in predictive accuracy of sepsis models when deployed across hospitals	Mandate external and prospective validation; include uncertainty quantification
Human-AI collaboration	Lack of defined roles and collaboration mechanisms between AI tools and human decision-makers	Clinician override of accurate AI suggestions; over-reliance on flawed AI outputs	Build "clinician-in-the-loop" systems with shared control and continuous feedback integration

recommendations. Systems that introduce extra alerts or necessitate manual data entry typically encounter resistance from users. To achieve effective AI integration, it is essential to involve healthcare providers in the design process, ensure interoperability with current health IT systems, and create user interfaces that facilitate real-time decision-making without adding to clinicians' workloads. Focusing on designs that keep clinicians engaged can significantly improve usability and foster trust in these technologies.

3.5. Regulatory and Legal Barriers

AI systems encounter significant regulatory challenges, particularly concerning accountability for errors in diagnosis or treatment. The absence of standardized evaluation frameworks complicates the approval process across different jurisdictions [73,74]. Furthermore, many current medical device regulations are ill-suited for adaptive or continuously learning systems, creating a conflict between fostering innovation and ensuring compliance. Key issues for regulatory authorities include real-world validation, ongoing monitoring, and appropriate risk categorization. To address these challenges, a global effort toward regulatory harmonization is essential for the consistent evaluation of AI-driven medical tools. Implementing regulatory sandboxes and adaptive approval pathways could facilitate safe innovation while upholding accountability.

3.6. Data Privacy and Security

The integration of artificial intelligence in healthcare presents significant challenges related to data privacy, algorithmic bias, and legal accountability, all of which must be carefully navigated to ensure a secure and equitable implementation. In the United States, the Health Insurance Portability and Accountability Act (HIPAA) establishes stringent regulations on the collection, storage, and utilization of patient health information, emphasizing the importance of privacy and data sharing limitations [75]. Meanwhile, the European Union's General Data Protection Regulation (GDPR) enhances these protections by requiring explicit consent, data minimization, and a "right to explanation" for automated decisions [76]. These legal frameworks create substantial design hurdles for AI developers, particularly when it comes to utilizing cross-institutional datasets. To address these issues, privacy-preserving ML methods, such as federated learning and differential privacy, are being employed to facilitate collaborative model development without direct access to sensitive patient data. Additionally, ethical concerns surrounding algorithmic bias have emerged, exemplified by a dermatology

AI system that failed to accurately diagnose skin conditions in individuals with darker skin tones due to insufficient representation in its training data, leading to a higher incidence of false negatives [77]. Similarly, an algorithm for healthcare resource allocation was found to systematically underestimate the health needs of Black patients, stemming from biased training data [78]. To combat these disparities, current strategies focus on utilizing diverse demographic datasets, implementing fairness evaluation metrics like demographic parity and equal opportunity, and conducting bias audits throughout the model development process.

The legal and regulatory framework surrounding accountability for clinical harm caused by AI systems remains ambiguous. When an AI-assisted decision leads to a misdiagnosis, it is unclear whether liability lies with the software developer, the healthcare provider, or the institution itself. Regulatory agencies are beginning to tackle these issues, as evidenced by the FDA's proposed guidelines for AI/ML-based Software as a Medical Device, which highlight the importance of monitoring real-world performance [79]. Similarly, the European AI Act aims to establish transparency and risk-based classification for AI applications in healthcare. To ensure safety and maintain clinician trust, many healthcare organizations are implementing a clinician-in-the-loop model, where AI acts as a supportive tool while final decisions are made by humans [80]. Ultimately, the effective and responsible integration of AI in healthcare necessitates a comprehensive approach that includes privacy safeguards, bias reduction, regulatory adherence, and ethical collaboration between humans and AI.

Table 2 outlines key barriers to successful AI integration in clinical and research settings, including data limitations, model interpretability, workflow disruption, and regulatory uncertainty. Each challenge is contextualized with practical examples and potential mitigation strategies to guide future development and adoption.

4. AI IN ANTIBIOTIC RESISTANCE SURVEILLANCE

Antimicrobial resistance (AMR) is an increasingly significant threat to global health, complicating infection treatment and leading to higher mortality rates, which necessitates the development of innovative surveillance and prediction systems. Advanced AI technologies, particularly in ML and NLP, present promising opportunities for improving the detection, prediction, and monitoring of AMR (Figure 1). These AI-driven systems can analyze large datasets to uncover patterns and provide timely alerts, thereby enhancing clinical practices and informing public health strategies (Figure 3, Table 3). However, the effectiveness of these technologies can vary widely depending on the platform, context, and type of data utilized.

4.1. Monitoring Resistance

AI systems have the capability to track the dissemination of antibiotic resistance by examining information from multiple sources, including EHRs, laboratory findings, and genomic data in real-time.

4.1.1. EHR Analysis

AI algorithms have the capability to analyze EHRs to monitor antibiotic usage, patient outcomes, trends in resistance in real-time and data-driven interventions.

For instance, deep learning models applied to EHRs, such as GNNs, predict pathogen resistance (e.g., in urinary tract infections) before lab results return, improving antibiotic selection accuracy and reducing treatment delays [81]. Real-time EHR surveillance systems, like RatchetEHR demonstrates superior predictive performance compared to other methods, including RNN, LSTM, and XGBoost, on bloodstream infection (BSI) prediction [82].

Population-level mapping of EHR data, exemplified by NYC Macroscope, identifies community prevalence of chronic conditions, such as obesity, diabetes and hypertension, as well as smoking rates and flu vaccine uptake [83]. Additionally, causal inference tools (e.g., Ehrapy) analyze pediatric pneumonia treatments in EHRs to optimize antibiotic regimens based on resistance risks and clinical outcomes, while simultaneously detecting and correcting surveillance biases, such as under-testing in elderly populations, to ensure data representativeness [84]. Furthermore, a retrospective study in the United States demonstrated that integrating patient contact networks with machine learning models substantially improved the accuracy of predicting MRSA risk

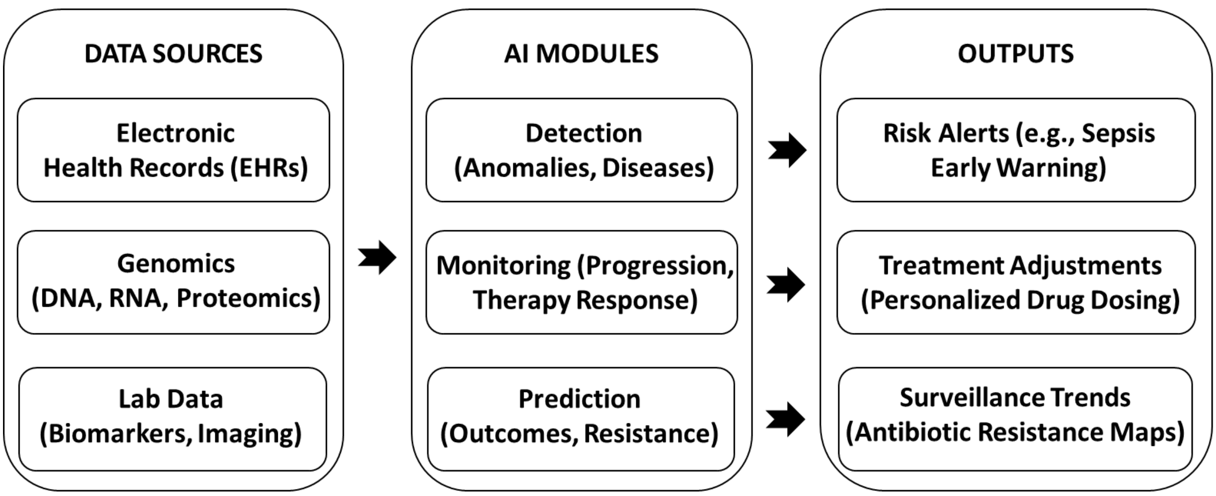

Figure 3 | Conceptual workflow showing how AI systems integrate clinical, genomic, and surveillance data to support real-time AMR detection, trend monitoring, and treatment guidance.

Table 3 | Tools and platforms used in AI-based antibiotic resistance surveillance

Tool/Platform	Purpose	Data type	Key features	References
ResFinder	Resistance gene identification	Genomic data	ML-based detection of resistance genes; integrates with bacterial genomes	[86]
CARD (Comprehensive Antibiotic Resistance Database)	Resistance gene annotation	Microbial genomics	Curated database + ML-driven prediction of resistance mechanisms	[85]
WHO GLASS	Global resistance surveillance	Epidemiological data	AI-enhanced trend analysis for global AMR monitoring	[88,89]
AREScloud	Real-time resistance tracking	EHRs, lab reports	ML models for outbreak prediction and resistance pattern detection	[72]
DeepARG	Metagenomic resistance detection	Metagenomic sequencing data	DL models (CNNs) to predict antibiotic resistance genes in complex microbiomes	[118]
AMR++	Genomic resistance analysis	Sequencing data	Pipeline combining ML and rule-based algorithms for resistance prediction	[85]
BacWGSTdb	Bacterial genome surveillance	Pathogen genomes	ML-powered clustering and resistance gene tracking across strains	[86]
ARIMA Models	Temporal resistance trend forecasting	Historical resistance data	Time-series ML models to predict future resistance rates	[84]
Meta-MARC	Resistome analysis in microbiomes	Metagenomic data	DL-driven identification of resistance genes in environmental/human samples	[84]
IBM Watson Health	Clinical decision support for AMR	EHRs, clinical notes	NLP + ML to analyze patient records and recommend antibiotic therapies	[55,57]
AlphaFold	Resistance mechanism prediction	Protein structures	DL models predicting protein structures linked to antibiotic resistance	[62,63]
ARGs-OAP	Antibiotic resistance gene detection	Environmental metagenomes	AI-driven pipeline for resistome profiling in diverse ecosystems	[118]

among hospitalized patients. The inclusion of network-based features, such as shared room exposure and transfer patterns, enhanced the detection of high-risk individuals compared to conventional clinical models [85].

These applications demonstrate EHRs' critical role in advancing proactive, precision-driven AMR containment.

4.1.2. Genomic Data Integration

AI models are capable of analyzing bacterial genomic data to identify mutations that lead to resistance against particular antibiotics. For instance, AI can correlate bacterial genomes with established resistance genes, thereby enhancing the monitoring of resistance trends.

For example, ResFinder has been applied in clinical microbiology settings to identify acquired resistance genes in *Klebsiella pneumoniae* and *Escherichia coli* isolates, enabling precise genomic-based resistance profiling and faster therapeutic decision-making [86]. Also, the Comprehensive Antibiotic Resistance Database (CARD) has been widely used to annotate resistance determinants, including efflux pumps, β-lactamases, and target alteration mechanisms, enabling detailed resistome profiling across clinical and environmental isolates [87].

4.1.3. Global Surveillance

AI improves the surveillance networks for global antibiotic resistance, such as the WHO's GLASS (Global Antimicrobial Resistance Surveillance System), by consolidating data from various countries and healthcare systems. These networks monitor resistance trends across local, national, and international scales, providing a comprehensive view of AMR patterns and guiding policy-making efforts [88,89]. While surveillance systems highlight where resistance is spreading, detecting specific resistant pathogens is critical for targeted interventions.

For instance, GLASS data formed the essential evidence base for the landmark 2022 Lancet study quantifying the global burden of AMR, revealing millions of deaths linked to resistance and highlighting regional priorities [90]. At the national level, data from Tanzania revealed critically high penicillin resistance in pneumonia-causing bacteria, prompting a vital revision of pediatric treatment protocols [91]. Furthermore, GLASS harmonized standards allow regional networks like Europe's EARS-Net to benchmark data and coordinate responses [92]. Ultimately, GLASS transforms surveillance into tangible interventions, policy changes, and a coordinated global defense against antimicrobial resistance.

4.2. Resistance Detection

AI systems provide swift diagnostic tools for identifying antibiotic resistance, thereby assisting in the reduction of the transmission of resistant infections:

4.2.1. Rapid Diagnostics

AI-driven technologies expedite the identification of resistant bacteria by analyzing laboratory tests and microbial cultures more efficiently than conventional techniques. For example, the integration of time-lapse microscopy with AI algorithms enables the rapid differentiation between antibiotic-susceptible and resistant bacterial strains, significantly reducing the time required for analysis [20,21,93,94].

AI-driven technologies are revolutionizing rapid AMR diagnostics by enabling real-time, high-accuracy detection across diverse clinical contexts. For instance, deep learning systems like COMPOSER analyze EHRs to predict sepsis-causing resistant pathogens 4–6 hours faster than traditional methods, reducing mortality by 17% in hospital settings [95]. Image-based AI tools, such as CNNs applied to Raman spectroscopy, identify *E. coli* within 15 minutes with 95% accuracy and the lowest accuracy was for *P. aeruginosa* (81%), bypassing time-consuming cultures settings [95]. Point-of-care innovations integrate different types of biosensors with AI to flag rapid and sensitive detection of carbapenem resistance genes, offering advantages in terms of speed, sensitivity, and portability, showcasing their potential in clinical diagnostics [96]. These technologies collectively transform resistance detection from reactive to proactive, accelerating life-saving interventions and precision therapy.

4.2.2. Metagenomics and Resistome Detection

DL models are capable of examining metagenomic data to uncover the resistome, which encompasses all resistance genes found within a microbial community.

For example, targeted capture platforms like ResCap enhance sensitivity 300-fold in clinical and environmental samples, uncovering rare resistance variants (e.g., tigecycline-resistant TetX genes in infant gut microbiomes) that evade conventional diagnostics [97]. Analysis of antibiotic-naïve infants' fecal samples revealed novel ARGs (e.g., *TetX1*/*TetX2*), which confer resistance to tigecycline, a last-resort antibiotic. This highlights the gut microbiome as an early ARG reservoir, influenced by maternal transmission [98].

In One Health surveillance, shotgun metagenomics of human, animal, and environmental samples in Kathmandu, Nepal, revealed high-risk transmission pathways such as *Stx-2* phages carrying resistance genes in river sediments receiving hospital waste and identified poultry farming as a hotspot for ARG diversity linked to antibiotic overuse [99]. Metagenomics of pristine soils (tundra, prairie, Amazon) revealed 242 ARG subtypes, with 55 background ARGs present universally. Conversion of Amazon rainforest to pasture increased ARG diversity by 18%, enriching clinically relevant genes (e.g., ermB) [100]. Longitudinal monitoring of wastewater treatment plants further tracks plasmid-mediated spread of priority resistance genes [101], while soil metagenomics quantifies anthropogenic impacts, showing manure-amended prairies harbor 100-fold higher *tetM*/*sul1* levels identical to livestock pathogens [100]. However, metagenomics identified phage genomes in hospital sewage carried ARG, revealing a route for HGT to human gut bacteria [102].

These methodologies are especially beneficial for analyzing environmental and human microbiome samples, facilitating the early identification of resistance trends prior to their proliferation.

4.2.3. NLP

NLP techniques allow AI systems to analyze clinical notes and laboratory reports for indications of antibiotic resistance that might not be captured in structured data fields. This approach facilitates a more thorough comprehension of resistance patterns. Building upon these detection tools, AI can also forecast how resistance will evolve and spread.

For example, transformer-based models like BioBERT have been fine-tuned to extract resistance-related genes and mechanisms from PubMed abstracts, facilitating large-scale mining of resistance data [103]. In clinical settings, NLP tools such as MetaMap and cTAKES have been employed to analyze EHRs and identify resistant infections, even accounting for contextual cues such as negations [104]. Moreover, NLP enhances automated AMR surveillance systems by extracting resistance profiles and organism names from microbiology reports in real time [105]. These techniques also support the development of AMR knowledge graphs, integrating literature and genomic data to uncover resistance networks [106], and assist in the automated curation of resistance databases such as CARD by prioritizing relevant content from emerging publications [107]. Collectively, these applications demonstrate the potential of NLP to streamline resistance detection and strengthen global AMR monitoring efforts.

4.3. Predicting Resistance

AI models have the capability to forecast the development and dissemination of antibiotic resistance, assisting healthcare professionals in choosing suitable treatments and strategizing public health initiatives:

4.3.1. Predictive Modeling for Resistance Emergence

AI algorithms evaluate genetic information, patterns of antibiotic use, and environmental influences to forecast the evolution of bacterial populations and their development of resistance. This capability enables healthcare professionals to select antibiotics that reduce the likelihood of resistance within specific populations [22,23].

ML algorithms, such as random forests and support vector machines, have been trained on bacterial whole-genome sequences and antibiotic susceptibility data to accurately predict resistance phenotypes, as shown in *Salmonella* [108]. DL approaches, including convolutional and recurrent neural networks, have been applied to forecast resistance evolution in pathogens like *Mycobacterium tuberculosis*, identifying future mutations that confer drug resistance [109]. Additionally, AI models have been used to integrate environmental, genomic, and clinical data to predict AMR emergence hotspots, demonstrating the role of environmental factors such as antibiotic pollution and temperature in resistance development [110]. AI-driven surveillance systems have also been developed to analyze national AMR datasets, enabling early warnings of emerging resistance patterns [111]. Furthermore, evolutionary modeling with AI has helped simulate resistance development under selective antibiotic pressure, providing insight into how resistance may evolve against novel treatments [112]. These applications highlight the transformative potential of AI in anticipating and managing the spread of antimicrobial resistance.

4.3.2. Geospatial and Temporal Predictions

AI can simulate the geographic and temporal distribution of antibiotic-resistant bacteria by factoring in patient mobility, healthcare resources, and patterns of antibiotic use. Such models assist public health authorities in forecasting potential hotspots for resistance, thereby facilitating targeted interventions in areas deemed high-risk.

Spatial ML approaches, such as random forests and gradient boosting, have been applied to environmental and geographic data, like land use, temperature, and wastewater contamination, to identify AMR hotspots in regions such as European water systems [113]. Temporally, models like Long Short-Term Memory (LSTM) networks have been used to forecast resistance trends in pathogens based on longitudinal hospital data [114]. Spatiotemporal models have further allowed researchers to simulate the spread of resistance across rural and urban zones, incorporating data from farms, hospitals, and water sources [115]. Additionally, AI integrated with Geographic Information Systems (GIS) has been used to visualize AMR risk zones using global datasets, such as those from WHO GLASS, particularly in low- and middle-income countries [116]. Some models have even projected resistance patterns under future climate scenarios, revealing how environmental changes may shift the global AMR landscape [117]. These applications demonstrate the capacity of AI to support surveillance, risk mapping, and strategic interventions against AMR.

4.4. AI Tools in AMR Surveillance: Opportunities and Constraints

Numerous AI-driven tools and platforms have emerged to tackle the escalating global issue of AMR, as detailed in Table 3. These tools differ significantly in their data sources, technological frameworks, and surveillance capabilities, presenting both opportunities and challenges for practical application. For instance, platforms like Res-Finder [86], CARD [85], and Deep-ARG [118] employ ML and DL techniques to identify AMR genes within microbial genomes or metagenomic datasets. Their effectiveness is particularly notable in detecting known resistance mechanisms, boasting high sensitivity and specificity. However, their performance is contingent upon the quality of reference databases, which can hinder their ability to identify novel or less common resistance genes [85]. Additionally, the reliance on whole-genome sequencing data limits their applicability in resource-constrained environments where such infrastructure is unavailable [86]. For example, Res-Finder has been utilized in a hospital microbiology lab to analyze *Klebsiella pneumoniae* isolates from bloodstream infections, successfully identifying specific resistance genes with over 95% specificity [75]. Nonetheless, it is restricted to known antibiotic resistance genes and cannot detect new or significantly divergent variants. Conversely, DeepARG, which leverages DL to uncover hidden sequence patterns, demonstrates enhanced sensitivity in complex metagenomic samples but tends to generate more false positives, especially in non-clinical datasets [43]. These instances highlight the inherent trade-offs between accuracy, sensitivity, and interpretability in AMR surveillance tools [41].

Recent advancements in tools like Meta-MARC and AlphaFold demonstrate the integration of AI into resistome analysis and protein structure prediction. However, it is important to note that these applications are still in the early stages of translation into practical use [84].

Platforms like ARES-cloud [72] and IBM Watson Health [55,57] advantage artificial intelligence to analyze clinical and laboratory data, facilitating real-time risk assessment and treatment enhancement. However, the success of these tools is contingent upon the availability of standardized and interoperable EHRs systems, which often vary significantly across different healthcare institutions and countries [12,13]. Additionally, the complexity of AI-generated predictions poses challenges in clinical settings, where the need for transparency and explain ability is crucial for gaining provider trust and ensuring widespread adoption [66,68].

Global initiatives such as WHO GLASS [88,89] strive to standardize AMR surveillance data internationally and utilize AI for trend analysis and predictive modeling. Despite its promise for comprehensive global monitoring, GLASS encounters practical obstacles, including incomplete data reporting, variability in data quality, and limited capabilities for real-time analysis [88]. These challenges impede timely interventions against emerging resistance threats, particularly in resource-limited or underserved regions [89].

Finally, tools like AlphaFold [62,63], although not specific to AMR, demonstrate the potential of AI to predict structural and functional properties of resistance proteins, offering future applications in drug design and resistance mechanism elucidation. However, the translation of such predictive insights into clinical or epidemiological action remains a developing area [62].

In summary, while AI tools for AMR surveillance offer substantial opportunities for improving detection, prediction, and intervention, their current deployment is constrained by issues related to data quality [85], infrastructure disparities [86], model interpretability [66,68], and integration into public health systems [88,89]. Addressing these limitations will be critical for maximizing their impact on global AMR mitigation strategies.

5. CONCLUSION

AI is significantly advancing the healthcare landscape by improving diagnostic precision, therapeutic decision-making, and the overall coordination of patient care. ML plays a central role in predictive analytics, personalized medicine, imaging, and clinical decision support, enabling more tailored and efficient care. DM helps uncover patterns for fraud detection, population health monitoring, and drug discovery, while DL enhances the analysis of complex data such as medical images and genomic information.

Despite its promise, AI integration faces challenges related to data privacy, bias, and interpretability. Notably, AI's application in tracking antibiotic resistance demonstrates its value in addressing global health threats. Overall, AI continues to reshape healthcare by advancing precision treatment and strengthening public health responses.

Looking ahead, future research should prioritize enhancing the interpretability of AI models, particularly DL systems, to foster clinical trust and adoption. Efforts are also needed to reduce algorithmic bias and improve data diversity to ensure equitable healthcare outcomes. In the context of AMR, further development of real-time AI surveillance systems and integration with genomic data could significantly improve early detection and intervention strategies. Cross-disciplinary collaboration and regulatory frameworks will be essential to guide the responsible and effective implementation of AI in healthcare.

DECLARATIONS

Ethical Statement

As this work was a literature review, no human or animal subjects were directly involved in this review.

Conflict of Interest

The author declares no conflicts of interest.

Author Contribution

Bilel Hassen collected and interpreted data, and wrote the manuscript.

Funding

The author declares no funding for this project.

Data Availability Statement

The data that support the findings of this study area available from the author upon reasonable request.

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