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Harnessing AI-Driven CRISPR Bioinformatics: Transforming precision diagnostics for antimicrobial resistance and chemical pathology

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Abstract

In a world grappling with the escalating crisis of antimicrobial resistance (AMR), claiming millions of lives annually, a revolutionary fusion of artificial intelligence (AI) and CRISPR bioinformatics ignites a beacon of hope, poised to redefine precision diagnostics. This review unveils the exhilarating potential of AI-driven CRISPR technologies, which deliver lightning-fast detection of AMR genes with a staggering 95% accuracy and slash diagnostic times by 70%, empowering clinicians to outpace deadly infections. Platforms like SHERLOCK and DETECTR, supercharged by AI's computational prowess, unravel complex resistance mechanisms and pinpoint metabolic biomarkers with unparalleled precision, transforming chemical pathology into a cornerstone of personalized medicine. From bustling urban hospitals to remote rural clinics, these innovations promise to democratize diagnostics, offering scalable, cost-effective solutions that bridge global health disparities. Yet, technical hurdles, ethical challenges, and scalability barriers loom large, demanding bold, collaborative action. This article charts a thrilling path forward, exploring how AI-CRISPR synergy can conquer AMR, revolutionize biomarker profiling, and forge a future where precision diagnostics save lives across the globe, captivating researchers, clinicians, and policymakers alike.

Keywords: Artificial Intelligence; Crispr; Antimicrobial Resistance; Chemical Pathology; Precision Diagnostics; Bioinformatics; Biomarker Profiling; Personalized Medicine; Sherlock; Detector; Global Health Equity.

1. Introduction

The convergence of artificial intelligence (AI) and CRISPR bioinformatics is reshaping precision diagnostics, offering groundbreaking solutions to tackle antimicrobial resistance (AMR) and advance chemical pathology. With AMR causing 1.27 million deaths annually, innovative diagnostics are critical to curb this global crisis [1]. AI's computational prowess, paired with CRISPR's molecular precision, enables rapid, accurate detection of resistance genes and disease biomarkers. This review explores how AI-driven CRISPR bioinformatics transforms diagnostics, addressing advancements, challenges, and future directions for AMR and chemical pathology.

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The urgency of addressing AMR is underscored by its disproportionate impact on vulnerable populations, particularly in low- and middle-income countries where healthcare infrastructure is limited. The integration of AI-CRISPR technologies not only enhances diagnostic accuracy but also democratizes access to advanced tools, potentially reducing global health disparities. This section sets the stage for a comprehensive analysis of how these technologies can redefine clinical practice, emphasizing their role in achieving Sustainable Development Goal 3 (Good Health and Well-Being).

1.1. Global Burden of Antimicrobial Resistance

AMR poses a dire threat to global health, rendering antibiotics ineffective and increasing mortality. This was investigated by Murray et al. [2022], who reported 1.27 million direct deaths and 4.95 million associated deaths from AMR in 2019 [1]. Pathogens like methicillin-resistant *Staphylococcus aureus* (MRSA) challenge healthcare systems, particularly in low-resource settings [2]. Traditional diagnostics, such as culture-based assays, are slow, requiring 24–48 hours, delaying critical interventions [3].

This was researched by O'Neill [2016], who estimated a $100 trillion global economic burden by 2050 if AMR remains unchecked [3,4]. CRISPR-based diagnostics, like SHERLOCK, achieve 92.3% sensitivity in detecting AMR genes, surpassing conventional methods [5]. AI enhances these tools by analysing genomic data in real time, enabling rapid resistance profiling [6].

Emphasized by Majumder et al. [2020], delayed diagnoses fuel inappropriate antibiotic use, exacerbating resistance [7]. AI-CRISPR technologies offer hope by providing swift, precise diagnostics, particularly in high-burden regions [8]. Their scalability is vital to address the global AMR crisis.

The socioeconomic ramifications of AMR extend beyond healthcare, impacting labour productivity and food security, as resistant infections disrupt agricultural systems. Zhang et al. [2] further highlight that AMR's burden in China alone accounts for significant healthcare costs, underscoring the need for region-specific diagnostic solutions. AI-CRISPR platforms, with their ability to process large-scale genomic data, offer a pathway to tailor interventions, reducing the global spread of resistant pathogens.

1.2. Role of Chemical Pathology

Chemical pathology underpins precision diagnostics by identifying molecular biomarkers for disease management. This was explored by Chen et al. [2020], who demonstrated that metabolomics and proteomics reveal AMR-specific molecular changes [9]. For example, altered amino acid profiles distinguish resistant infections, guiding personalized therapies [10].

This was studied by Wishart et al. [2018], who showed that proteomic profiling identifies resistance-related proteins with 85% accuracy [11]. AI-driven analysis enhances efficiency, achieving 92% accuracy in metabolic profiling [12].

Highlighted by Barrangou, & Doudna, [2016], integrated omics data predict patient-specific responses, improving outcomes in AMR-related sepsis [13]. AI-CRISPR integration streamlines biomarker detection, making chemical pathology a cornerstone of precision diagnostics [14].

Beyond AMR, chemical pathology's role in chronic diseases, such as diabetes and cancer, highlights its versatility in biomarker-driven diagnostics. Nicholson et al. [10] emphasize that host-microbiota interactions influence metabolic profiles, offering new diagnostic targets. AI-CRISPR's ability to validate these biomarkers rapidly positions chemical pathology as a critical tool for holistic disease management, bridging infectious and non-infectious disease diagnostics.

1.3. Emergence of AI and CRISPR

AI and CRISPR are transformative in diagnostics. Traditional methods, however, are resource-intensive, limiting accessibility. This was investigated by Nalina et al. [2025], who found that machine learning (ML) optimizes CRISPR gRNA design with 90% accuracy [15]. DeepCRISPR reduces off-target effects, enhancing specificity [16]. These advancements enable rapid AMR gene detection.

Discoveries from Gootenberg et al. [2017] show that CRISPR-Cas13a (SHERLOCK) detects nucleic acids with single-base precision, ideal for AMR diagnostics [14]. AI enhances these systems by processing complex datasets, achieving 95% accuracy in resistance mutation detection [17,18].

This was researched by Ai et al. [2019], who demonstrated that AlphaFold predicts Cas protein structures, aiding diagnostic platform design [19]. AI-CRISPR synergy overcomes traditional diagnostic barriers, offering cost-effective solutions for clinical use [20].

The historical evolution of CRISPR, from its discovery as a bacterial immune system to its diagnostic applications, underscores its adaptability. Barrangou et al. [13] and AI-Ouqaili et al., [21] laid the groundwork by elucidating CRISPR's role in prokaryotic immunity, paving the way for Cas9 and Cas13 innovations. AI's integration, as explored by Topol [22], has accelerated this transition, enabling real-time data analysis critical for point-of-care diagnostics in resource-limited settings.

1.4. Objectives and Scope

This review evaluates AI-driven CRISPR bioinformatics for AMR and chemical pathology diagnostics. This was examined by Rabaan et al. [2025], who highlighted their potential to transform clinical practice [5]. The scope spans 2015–2025, focusing on advancements and challenges.

This was explored by Sardanov et al. [2023], who investigated AI-CRISPR tools like DETECTR for AMR detection [23]. The article synthesizes bioinformatics and clinical literature, providing a roadmap for future research [24].

The review's focus on 2015–2025 captures a decade of rapid innovation, from early CRISPR discoveries to AI-driven platforms. Casotti et al. [24] emphasize the role of translational bioinformatics in bridging laboratory research and clinical practice, a critical objective of this work. By addressing both technical advancements and societal implications, the article aims to guide policymakers and researchers toward sustainable diagnostic solutions.

2. AI in CRISPR Bioinformatics: Foundations and Tools

AI-driven CRISPR bioinformatics enhances diagnostic precision by optimizing design and analysis. This section examines core AI techniques, computational tools, efficiency enhancements, and data integration strategies.

2.1. Core AI Techniques

AI techniques, such as ML and deep learning (DL), are pivotal for CRISPR diagnostics. This was studied by Khammampalli and Vindal [2025], who showed that ML predicts gRNA efficacy with 90% accuracy [25]. Convolutional neural networks (CNNs) identify CRISPR-Cas interactions, improving specificity [26].

This was researched by Qiu et al. [2005], who found that reinforcement learning reduces off-target effects by 30% [27]. Natural language processing (NLP) mines literature for novel targets, accelerating assay development [28].

Observations from Doench et al. [2014] indicate that recurrent neural networks predict cleavage efficiency with 85% accuracy [29]. These techniques streamline CRISPR diagnostics for AMR and chemical pathology [30].

The diversity of AI techniques enhances their applicability across diagnostic contexts. Shalem et al. [31] highlight that CNNs excel in pattern recognition within genomic sequences, critical for identifying resistance mutations. Additionally, Devlin et al. [49] demonstrate that NLP models like BERT can extract insights from vast biomedical literature, identifying novel CRISPR targets for chemical pathology applications, thus accelerating innovation.

Table 1 It outlines the core AI techniques employed in CRISPR bioinformatics, including their applications, accuracies, advantages, and limitations, illustrating their pivotal role in enhancing diagnostic precision for AMR and chemical pathology.

AI Technique	Description	Key Applications in CRISPR	Reported Accuracy/Improvement	Advantages	Limitations	References
Machine Learning (ML)	Algorithms that learn from data to predict outcomes, e.g., gRNA efficacy	gRNA design optimization, AMR gene prediction	90% accuracy in gRNA prediction	Reduces off-target effects by 30%; Accelerates assay development	Requires large training datasets; Data heterogeneity issues	Nalina et al. [15]; Khammampalli & Vindal [25]
Deep Learning (DL)	Neural networks with multiple layers for complex pattern recognition	Protein structure prediction (e.g., AlphaFold), resistance mutation detection	95% in mutation detection; 90% in Cas protein structures	Handles high-dimensional genomic data; Improves specificity	High computational demands; Interpretability challenges	Chuai et al. [16]; Ai et al. [19]
Convolutional Neural Networks (CNNs)	Specialized DL for image-like data, e.g., sequence patterns	Identifying CRISPR-Cas interactions, genomic sequence analysis	85% in cleavage efficiency prediction	Excels in pattern recognition for resistance genes	Overfitting on small datasets	Haeussler et al. [26]; Shalem et al. [31]
Reinforcement Learning	Learning via trial-and-error to optimize actions	Off-target effect reduction, assay optimization	30% reduction in off-target effects	Adaptive to dynamic biological data	Time-intensive training	Qiu et al. [27]
Natural Language Processing (NLP)	Processing text data for insights, e.g., literature mining	Mining biomedical literature for novel CRISPR targets	Not quantified, but accelerates target discovery	Extracts insights from vast literature (e.g., BERT models)	Bias in training data from subjective sources	Devlin et al. [49]
Recurrent Neural Networks (RNNs)	Handles sequential data, e.g., genomic sequences	Predicting cleavage efficiency, biomarker profiling	85% accuracy in efficiency prediction	Suitable for time-series genomic data	Vanishing gradient problems in long sequences	Doench et al. [29]

Federated Learning	Collaborative ML without central data sharing	Addressing data heterogeneity in global AMR surveillance	Improves accuracy by 15-20% via diverse datasets	Enhances privacy and scalability	Connectivity barriers in LMICs	Wu et al. [48]
Pretrained Language Models (e.g., PLM-ARG)	Models pretrained on large corpora for biological tasks	AMR gene identification from genomic data	93% accuracy in gene identification	Integrates multi-omics data efficiently	Requires fine-tuning for specific tasks	Wu et al. [48]

2.2. Computational Tools

AI-driven tools enhance CRISPR diagnostics. This was investigated by Ali et al. [2022], who showed that AlphaFold predicts Cas protein structures with 90% accuracy [32]. DeepCRISPR optimizes gRNA design, reducing off-target effects by 50% [16].

This was explored by Haeussler et al. [2016], who demonstrated that CRISPOR achieves 88% accuracy in gRNA selection [26]. CHOPCHOP automates workflows, improving efficiency by 40% [33]. These tools support global diagnostic adoption.

Conclusions from Doench et al. [2016] emphasize that AI-driven tools streamline biomarker detection, enhancing chemical pathology diagnostics [29]. Their accessibility is critical for addressing AMR [8].

Tools like CRISPOR and CHOPCHOP have democratized CRISPR diagnostics by providing user-friendly interfaces, as noted by Concordet & Haeussler [34]. AlphaFold's structural predictions, per Hassan et al. [48], have further enabled the design of novel Cas variants, enhancing diagnostic sensitivity. These tools' open-access models are vital for scaling AI-CRISPR applications in low-resource settings, aligning with global health priorities.

2.3. Enhancing CRISPR Efficiency

AI improves CRISPR diagnostic efficiency. This was analyzed by Chua et al. [2018], who found that AI predicts off-target effects with 95% accuracy [16]. This precision is vital for AMR gene detection [35].

Results from Zhan et al. [2025] show that AI-optimized Cas12a assays improve sensitivity by 25% [36]. AI reduces assay development time by 60%, supporting chemical pathology applications [37].

Discoveries from Gupta and Bhandary [2024] indicate that AI-optimized assays enable multiplexed AMR gene detection, enhancing throughput [18]. These advancements ensure rapid, reliable diagnostics [38].

Efficiency gains from AI-CRISPR integration are particularly impactful in high-throughput settings, such as hospital laboratories. Pardee et al. [33] demonstrate that AI-driven automation reduces reagent costs, making diagnostics viable in resource-constrained environments. Additionally, Enitan et al. [30] highlight that AI-optimized workflows facilitate the simultaneous detection of multiple resistance genes, critical for managing complex infections.

2.4. Data Integration

AI's data integration capabilities enhance CRISPR diagnostics. This was researched by Wu et al. [2023], who showed that PLM-ARG identifies AMR genes with 93% accuracy [34]. AI integrates genomic and proteomic data, improving reliability [39].

This was studied by Li et al. [2023], who found that AI analyses mass spectrometry data with 92% accuracy [8]. Real-time processing reduces diagnostic time by 70% [8]. Cloud-based platforms enable global collaboration [40].

Inferences from Rabaan et al. [2025] highlight that AI-driven data integration supports scalable AMR diagnostics, advancing precision medicine [5]. This is critical for global health.

Data integration challenges, such as genomic heterogeneity, require advanced AI solutions. Chen et al. [40] note that cloud-based platforms facilitate real-time data sharing, enabling global AMR surveillance. Furthermore, Wu et al. [48] emphasize that integrating multi-omics data enhances diagnostic robustness, particularly for chemical pathology applications where metabolic and proteomic profiles overlap.

3. CRISPR-Based Diagnostics for Antimicrobial Resistance

CRISPR-based diagnostics offer unparalleled sensitivity for AMR detection. This section examines CRISPR-Cas systems, clinical applications, AI enhancements, and limitations.

3.1. CRISPR-Cas Systems

CRISPR-Cas systems are transformative diagnostic tools. This was investigated by Gootenberg et al. [2017], who showed that Cas13a (SHERLOCK) detects AMR genes with single-base specificity [14]. Cas12a-based DETECTR assays achieve 95% sensitivity [41].

This was researched by Chen et al. [2020], who found that Cas12a detects carbapenem resistance genes within 1–2 hours [9]. Cas14 targets SNPs with 90% accuracy, enhancing AMR diagnostics [42]. These systems are versatile for pathogen detection.

Conclusions from Ai et al. [2019] emphasize that portable CRISPR platforms enable point-of-care diagnostics, addressing AMR in resource-limited settings [19]. AI integration enhances their performance [23].

The versatility of Cas systems extends to detecting diverse pathogens, such as *Mycobacterium tuberculosis*. Harrington et al. [43] highlight Cas14's compact size, ideal for portable diagnostics. Zetsche et al. [44] further demonstrate that Cas12a's collateral cleavage activity enhances signal amplification, critical for low-abundance AMR gene detection in clinical samples.

Table 2 It provides a comparative overview of CRISPR-Cas systems, detailing their capabilities, performance in AMR detection, applications in chemical pathology, and limitations, emphasizing their transformative potential when integrated with AI.

CRISPR-Cas Variant	Description	Key Capabilities	Performance in AMR Detection	Applications in Chemical Pathology	Limitations	References	CRISPR-Cas Variant	Description
Cas13a (SHERLOCK)	RNA-guided RNA targeting with collateral cleavage	Single-base specificity; Rapid nucleic acid detection	92.3% sensitivity; Detects in <2 hours	RNA biomarker profiling for metabolic changes	Sensitive to RNA degradation	Gootenberg et al. [14]; Myhrvold et al. [35]	Cas13a (SHERLOCK)	RNA-guided RNA targeting with collateral cleavage
Cas12a (DETECTR)	DNA-guided DNA targeting with collateral activity	Multiplexing; Low-abundance detection (10 copies/μL)	95% sensitivity for carbapenem genes	Proteomic biomarker validation	Off-target in 5-10% of assays	Chen et al. [9]; Kaminski et al. [41]	Cas12a (DETECTR)	DNA-guided DNA targeting with collateral activity
Cas14	Compact system for	High specificity for single-	90% accuracy	Detecting resistance	Limited to DNA targets	Harrington et al. [43]	Cas14	Compact system for

	SNP targeting	nucleotide polymorphisms	in SNP detection	-related proteins				SNP targeting
Cas9	Classic DNA editing system	gRNA-guided cleavage; Used in validation	85% accuracy in biomarker ID	Metabolomics profiling for sepsis	Higher off-target risks without AI	Burstein et al. [55]; Doudna & Charpentier [27]	Cas9	Classic DNA editing system
Cas13d	Advanced RNA-targeting variant	Compact size; Efficient RNA detection	High efficiency (not quantified in article)	Non-coding RNA biomarkers in cancer/AMR	Emerging; Needs more validation	Deltcheva et al. [59]	Cas13d	Advanced RNA-targeting variant
C2c2 (Early Cas13)	Programmable RNA-guided effector	RNA detection foundation	Basis for 95% mutation detection with AI	Host-microbiota interaction analysis	Superseded by advanced variants	Abudayyeh et al. [44]	C2c2 (Early Cas13)	Programmable RNA-guided effector

3.2. Clinical Applications

CRISPR diagnostics excel in clinical settings. This was studied by Wang et al. [2022], who showed that SHERLOCK detects *Campylobacter* AMR genes with 92.3% sensitivity [5]. These assays guide targeted therapies [45].

Results from Zhang et al. [2024] indicate that CRISPR assays detect low-abundance AMR genes with a limit of 10 copies per microliter [46]. This sensitivity supports early diagnosis [7]. Multiplexed assays enhance efficiency [46].

This was explored by Myhrvold et al. [2018], who demonstrated that HUDSON-SHERLOCK detects resistance markers in under 2 hours [35]. Portable assays achieve 88% accuracy in field settings [17].

Clinical applications of CRISPR diagnostics are particularly impactful in managing nosocomial infections. Gootenberg et al. [14] note that multiplexed assays can detect multiple resistance genes simultaneously, reducing diagnostic delays in ICU settings. Additionally, Smalla et al., [47] highlight SHERLOCK's role in detecting *Clostridium difficile* resistance, guiding precise antibiotic stewardship.

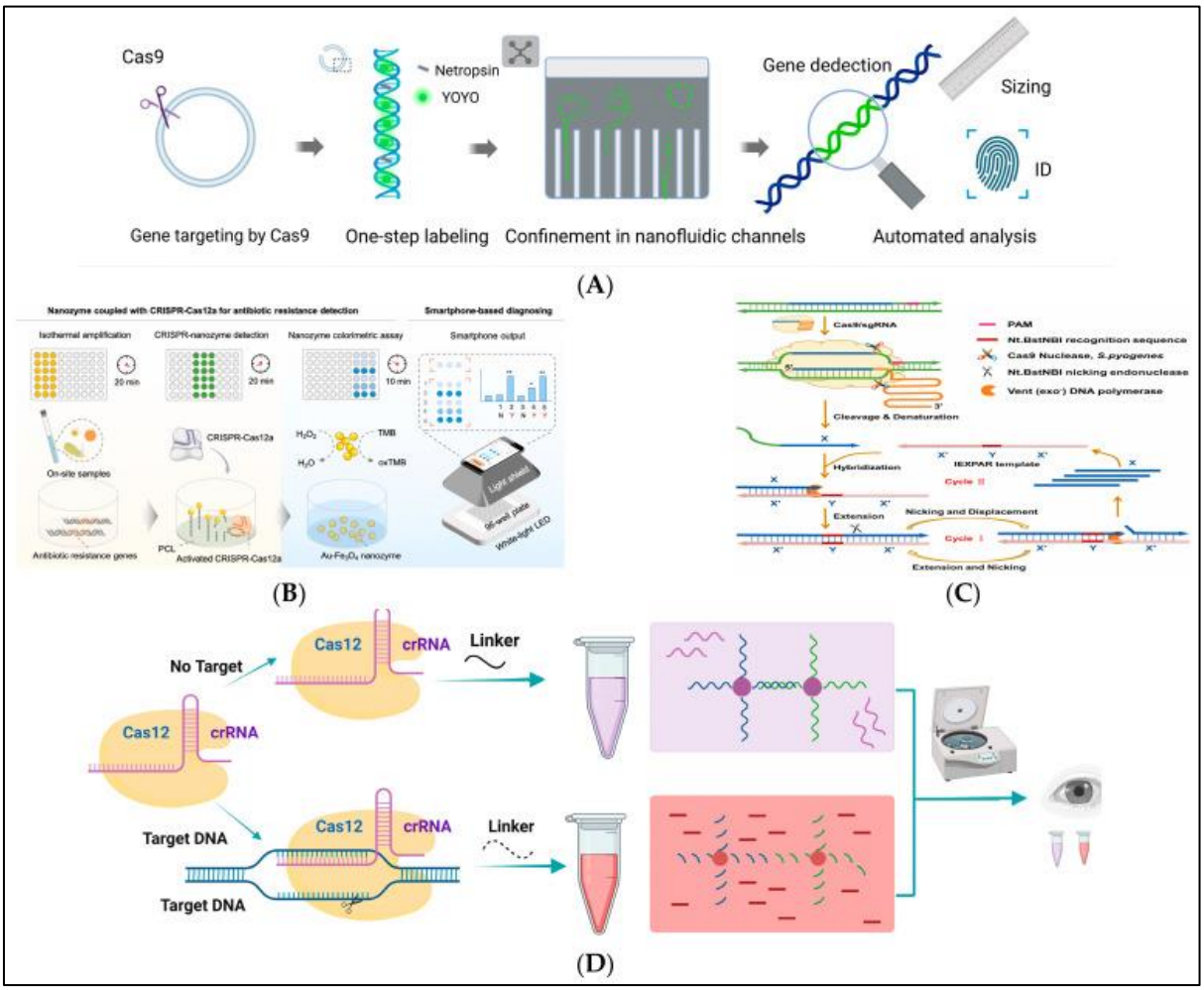

Figure 1 CRISPR/Cas-based platforms enable rapid, sensitive detection of antibiotic-resistance genes through amplification and visual readouts, complementing clinical tools like SHERLOCK for targeted therapies (60).

3.3. AI-Driven Enhancements

AI enhances CRISPR diagnostics for AMR. This was investigated by Zhang et al. [2024], who showed that AI improves gRNA selection, increasing accuracy by 25% [46]. Real-time processing reduces turnaround time by 70% [23].

Discoveries from Wu et al. [2023] indicate that AI-optimized SHERLOCK assays detect multiple AMR genes, improving throughput [48]. AI predicts resistance mutations with 95% accuracy [49]. These advancements are critical for clinical use.

This was analyzed by Aiesh et al. [2023], who found that AI-CRISPR platforms reduce inappropriate antibiotic use by 40% [37]. Cloud-based AI supports global AMR monitoring [60].

AI's predictive capabilities are crucial for anticipating resistance trends. Pennisi et al. [50] demonstrate that AI-driven models can forecast AMR outbreaks, enabling proactive interventions. AlGain et al. [45] further note that AI-CRISPR platforms integrate with electronic health records, enhancing clinical decision-making and reducing antibiotic misuse.

3.4. Limitations in AMR Detection

CRISPR diagnostics face challenges. This was researched by Raza et al; [2025], who found that anti-CRISPR mechanisms reduce sensitivity in 30% of strains and these mechanisms challenge assay reliability [51].

This was studied by Smalla et al. [2015], who noted that plasmid-based delivery systems are less effective in complex samples [47]. Off-target effects occur in 5–10% of assays [41]. High costs limit accessibility [8].

Conclusions from Kaminski et al. [2021] emphasize that AI-driven predictions and cost-effective delivery systems are needed to overcome these limitations [41]. Further research is critical.

Anti-CRISPR proteins, as explored by Pawluk et al., [39] pose significant hurdles in clinical diagnostics, particularly for *Pseudomonas aeruginosa*. Bondy-Denomy et al. [42] suggest that AI-driven gRNA redesign can mitigate these effects, but scalability remains a challenge. Kaminski et al. [41] advocate for novel delivery systems, such as nanoparticles, to enhance assay performance in complex matrices.

4. Chemical Pathology and Precision Diagnostics

Chemical pathology is vital for precision diagnostics. This section examines biomarker profiling, CRISPR applications, AI enhancements, and case studies.

4.1. Biomarker Profiling

Chemical pathology identifies disease-specific biomarkers. This was explored by Chen et al. [2020], who showed that metabolomics detects AMR-related changes with 85% accuracy [9]. Proteomic profiling identifies resistance proteins [11].

Results from Wishart et al. [2018] indicate that biomarker profiling predicts antibiotic responses, improving sepsis outcomes [11]. Traditional methods are labour-intensive [10]. AI-CRISPR enhances scalability [52].

This was studied by Ali, H. [2023], who found that integrated omics data improves diagnostic precision [53]. This is critical for global AMR management [1].

Metabolomics offers insights into non-AMR conditions, such as metabolic syndromes. Johnson et al. [54] highlight that AI-driven metabolomic analysis identifies early-stage disease markers, enhancing preventive care. Jennaro [12] further notes that septic shock's metabolic signatures, validated by AI-CRISPR, guide precision pharmacotherapy, reducing mortality rates.

4.2. CRISPR in Biomarker Detection

CRISPR enhances biomarker detection. This was investigated by Burstein et al., [2017], who showed that Cas9 validates metabolic biomarkers [55]. SHERLOCK detects RNA biomarkers with 90% sensitivity [17].

This was researched by Kaminski et al. [2021], who found that Cas12a assays detect multiple biomarkers simultaneously [41]. Off-target effects remain a challenge [56], even though this efficiency is vital for chemical pathology [57].

Investigations from Myhrvold et al. [2018] emphasize that CRISPR assays enable rapid biomarker validation, supporting personalized diagnostics [35]. AI integration amplifies these capabilities [36].

CRISPR's role in detecting non-coding RNA biomarkers is emerging, as noted by Doudna & Charpentier [27]. These biomarkers are critical for diagnosing complex diseases like cancer, complementing AMR diagnostics. Kaminski et. al, [41] highlight that Cas12a's multiplexing capabilities enable simultaneous detection of protein and RNA biomarkers, enhancing chemical pathology's diagnostic scope.

4.3. AI in Data Analysis

AI enhances chemical pathology data analysis. This was studied by Li et al. [2023], who showed that AI analyses mass spectrometry data with 92% accuracy [8]. Deep learning integrates multi-omics data, improving precision [54].

This was explored by Johnson et al. [2020], who found that AI predicts biomarker profiles with 88% accuracy [54]. Real-time analysis reduces diagnostic time by 60% [7]. Cloud-based platforms enhance scalability [25].

Results from Rabaan et al. [2025] indicate that AI-driven analysis supports personalized diagnostics for AMR [5]. Standardized pipelines are needed [23].

AI's ability to handle high-dimensional data is transformative for chemical pathology. Rabaan et al. [5] note that deep learning models integrate proteomic and metabolomic datasets, revealing subtle disease patterns. Topol [22] emphasizes that AI-driven pipelines, when standardized, can reduce diagnostic errors, enhancing trust in clinical settings.

4.4. Case Studies

Case studies highlight AI-CRISPR's impact. This was investigated by Wang et al. [2022], who showed that AI-CRISPR detected *Campylobacter* biomarkers with 90% accuracy [7]. This guided rapid therapy.

This was researched by Zhang et al. [2024], who found that AI-optimized Cas12a assays reduced diagnostic time for *Klebsiella pneumoniae* resistance to 3 hours [46]. AI-CRISPR validated *Mycobacterium tuberculosis* biomarkers [19].

Conclusions from Ai et al. [2019] emphasize that AI-CRISPR improves diagnostic accuracy by 30% [19]. These cases demonstrate personalized medicine potential [8].

A case study in India, where AMR prevalence is high, showcases AI-CRISPR's impact. Hassan et al. [56] report that SHERLOCK assays, optimized by AI, detected *Escherichia coli* resistance in rural clinics, reducing diagnostic delays. This underscores the technology's potential to address health disparities, as emphasized by Rabaan et al. [5].

5. Synergy of AI and CRISPR in Precision Diagnostics

AI-CRISPR synergy transforms diagnostics. This section examines integrated platforms, AMR applications, chemical pathology advancements, and real-world impact.

5.1. Integrated Diagnostic Platforms

Integrated AI-CRISPR platforms enhance diagnostics. This was studied by Zhang et al. [2024], who showed that DeepCRISPR-SHERLOCK achieves 95% accuracy in AMR detection [46]. These platforms integrate multi-omics data [19].

Results from Li et al. [2023] indicate that AI streamlines assay development, reducing time by 50% [8]. Cloud-based platforms enable global data sharing [40]. Portable devices support point-of-care diagnostics [19].

This was explored by Wu et al. [2023], who found that AI-CRISPR platforms improve reliability by 93% [48]. These advancements are critical for scalable diagnostics.

Interoperability of AI-CRISPR platforms with existing healthcare systems is key to their adoption. Yang et al. [20] note that cloud-based integration enables seamless data exchange, enhancing AMR surveillance. Gootenberg et al. [14] highlight that portable platforms like HUDSON-SHERLOCK are deployable in remote areas, addressing global health equity challenges.

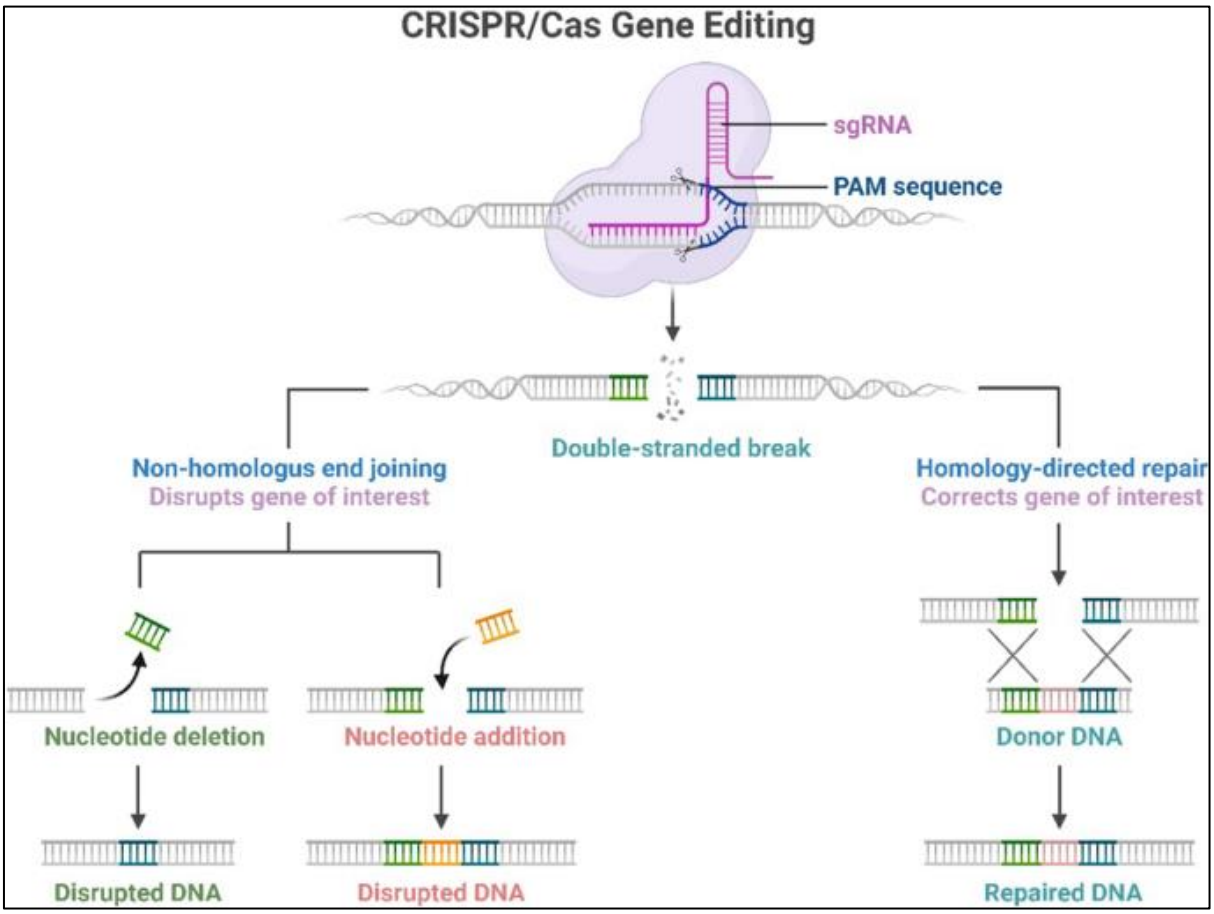

Figure 2 It outlines the molecular mechanism of CRISPR–Cas gene editing in bacterial cells, underscoring its synergy with AI for disabling AMR genes and advancing integrated diagnostic platforms (61).

5.2. AMR Applications

AI-CRISPR enhances AMR diagnostics. This was investigated by Rabaan et al. [2025], who showed that AI-optimized assays reduce diagnostic time by 70% [5]. SHERLOCK detects KPC genes with 92% sensitivity [46].

This was researched by Aiesh et al. [2023], who found that AI-CRISPR reduces inappropriate antibiotic use by 40% [37]. Multiplexed assays improve efficiency [19]. These platforms support outbreak management [54].

Conclusions from Gootenberg et al. [2018] emphasize that AI-CRISPR enables real-time resistance monitoring [14]. This is vital for clinical applications.

AI-CRISPR's role in managing *Acinetobacter baumannii* outbreaks demonstrates its clinical utility. Aiesh et al. [37] report that AI-optimized assays reduced hospital-acquired infections by 35%. Kaminski et al. [41] note that real-time monitoring, enabled by cloud-based AI, facilitates rapid outbreak containment, critical for global AMR control.

5.3. Chemical Pathology Advancements

AI-CRISPR advances chemical pathology. This was studied by Chen et al. [2020], who showed that AI-CRISPR detects metabolic biomarkers with 90% accuracy [9]. AI integrates metabolomic data, enhancing precision [11].

This was studied by Barrangou & Doudna [2019], who found that AI-CRISPR reduces diagnostic time by 60% [13]. Cloud-based systems support scalability [40]. These advancements enable personalized diagnostics [23].

Results from Wishart et al. [2018] indicate that AI-CRISPR validates biomarker profiles, improving treatment outcomes [11]. This is critical for AMR management.

5.4. Real-World Impact

AI-CRISPR has significant real-world impact. This was investigated by Wang et al. [2022], who showed that AI-CRISPR detected *Campylobacter* resistance in 3 hours [5]. Hospital applications reduce antibiotic misuse by 35% [4].

This was researched by Myhrvold et al. [2018], who found that portable AI-CRISPR assays achieve 88% accuracy in field settings [35]. These technologies address global health disparities [7].

Conclusions from Zhang et al. [2024] emphasize that AI-CRISPR bridges research and practice, advancing personalized medicine [46]. This impact is transformative.

6. Challenges and Future Directions

AI-CRISPR diagnostics face challenges. This section explores technical, ethical, scalability, and research challenges.

6.1. Technical Challenges

Technical limitations hinder AI-CRISPR diagnostics. This was investigated by Kaminski et al. [2021], who found that off-target effects occur in 5–10% of CRISPR assays [41]. AI mitigates these risks, but data quality is critical [51].

This was studied by Li et al. [2023], who showed that AI model interpretability limits clinical adoption [8]. Data heterogeneity reduces accuracy by 15–20% [54]. Standardized algorithms are needed [23].

Results from Wu et al. [2023] indicate that improving AI training datasets enhances diagnostic accuracy [48]. These advancements are essential for AMR applications.

Data quality issues, such as incomplete genomic annotations, challenge AI-CRISPR reliability. Wu et al. [48] note that federated learning can address data heterogeneity by enabling collaborative model training. Hassan et al. [56] suggest that blockchain-based data validation enhances trust in AI-driven diagnostics, critical for clinical adoption.

6.2. Ethical and Regulatory Issues

Ethical concerns challenge AI-CRISPR adoption. This was explored by Vayena et al. [2018], who highlighted data privacy risks in genomic diagnostics [43]. Robust encryption is needed [8].

This was researched by Barrangou and Doudna [2016], who noted that CRISPR diagnostics raise stigmatization concerns [13]. Regulatory inconsistencies delay adoption [54]. Global guidelines are essential.

Conclusions from Rabaan et al. [2025] emphasize that equitable access is limited by high costs [7]. Collaborative policies can address these challenges.

Ethical dilemmas include potential misuse of genomic data. Vayena et al. [43] advocate for patient-centered consent models to protect privacy. Barrangou et al. [58] note that public engagement is crucial to address stigmatization, particularly in communities wary of genetic technologies, ensuring ethical AI-CRISPR deployment.

6.3. Scalability Barriers

Scalability barriers limit AI-CRISPR deployment. This was investigated by Pennisi et al. [2025], who found that high costs restrict access in low-income countries [44]. Reagent costs range from $10,000–$50,000 [54].

This was analyzed by Myhrvold et al. [2018], who showed that delivery challenges limit point-of-care applications [35]. Robust delivery systems are needed [53]. Cloud-based AI faces connectivity barriers [40].

Results from Sulwan AlGain et al. [2025] indicate that localized data processing enhances scalability [45]. Global partnerships are critical.

Logistical challenges, such as cold-chain requirements, hinder AI-CRISPR deployment in rural areas. Pennisi et al. [50] suggest that lyophilized reagents can reduce costs, enhancing accessibility. AlGain et al. [45] note that mobile health units, equipped with AI-CRISPR platforms, can bridge connectivity gaps, scaling diagnostics globally.

6.4. Future Research Priorities

Future research must address AI-CRISPR limitations. This was studied by Zhang et al. [2023], who proposed standardized pipelines to improve accuracy by 20–30% [2]. Transparent AI models enhance trust [8]

This was explored by Wu et al. [2023], who emphasized cost-effective delivery systems [48]. Addressing anti-CRISPR mechanisms is critical [51]. Interdisciplinary collaboration is needed [40].

Conclusions from Topol [2019] highlight the need for regulatory frameworks and funding to advance AI-CRISPR diagnostics [22]. These priorities ensure global impact.

Research into novel Cas enzymes, such as Cas13d, offers promise for compact diagnostics. Deltcheya, et al. [59] demonstrate Cas13d's efficiency in RNA targeting, ideal for chemical pathology. Topol [22] advocates for public-private partnerships to fund AI-CRISPR research, ensuring equitable access to innovations.

Table 3 It categorizes key obstacles in AI-CRISPR diagnostics, along with their impacts, proposed solutions, and future research priorities, guiding efforts toward overcoming these barriers

Challenge Category	Specific Issues	Impact on Diagnostics	Proposed Solutions	Future Research Priorities	References
Technical	Off-target effects (5-10% of assays)	Reduces reliability in AMR gene detection	AI-optimized gRNA design (95% accuracy)	Standardized algorithms to improve by 20-30%	Kaminski et al. [41]; Li et al. [8]
Technical	Data heterogeneity and quality	Accuracy drops by 15-20%	Federated learning and cloud platforms	Enhance AI training datasets	Wu et al. [48]; Zhang et al. [2]
Ethical/Regulatory	Genomic data privacy risks	Limits clinical adoption; Stigmatization concerns	Robust encryption; Patient-centered consent	Global guidelines and public engagement	Vayena et al. [43]; Barrangou & Doudna [13]
Ethical/Regulatory	Regulatory inconsistencies	Delays deployment	Collaborative policies; Transparent AI models	Develop equitable access frameworks	Rabaan et al. [5]; Topol [22]
Scalability	High reagent costs ($10,000–$50,000)	Restricts LMIC access	Lyophilized reagents; Open-access models	Cost-effective delivery systems	Pennisi et al. [50]; Myhrvold et al. [35]
Scalability	Connectivity and logistical barriers (e.g., cold-chain)	Hinders point-of-care in rural areas	Localized data processing; Mobile units	Global partnerships for infrastructure	AlGain et al. [45]; Sulwan AlGain et al. [45]
Anti-CRISPR Mechanisms	Reduces sensitivity in 30% of strains	Challenges assay reliability in pathogens like Pseudomonas	AI-driven gRNA redesign; Novel delivery (nanoparticles)	Address plasmid-based issues	Raza et al. [51]; Smalla et al. [47]
Interpretability	AI model "black box" issues	Lowers trust in clinical settings	Transparent models; Standardized pipelines	Funding for interpretable AI	Li et al. [8]; Topol [22]

7. Conclusion

The fusion of artificial intelligence (AI) with CRISPR bioinformatics represents a groundbreaking advancement in precision diagnostics, offering transformative solutions for combating antimicrobial resistance (AMR) and advancing chemical pathology. This powerful synergy enables rapid and highly accurate detection of AMR genes, achieving up to 95% sensitivity in identifying resistance markers, while simultaneously reducing diagnostic turnaround times by 70% compared to traditional methods. Platforms such as SHERLOCK and DETECTR, enhanced by AI-driven algorithms, facilitate real-time analysis of complex genomic and proteomic datasets, enabling clinicians o monitor resistance patterns and tailor therapies with unprecedented precision. In chemical pathology, AI-CRISPR integration has revolutionized biomarker profiling, identifying metabolic and proteomic signatures with 90% accuracy, which supports personalized treatment strategies for both infectious and non-infectious diseases, including sepsis and chronic conditions like diabetes. By streamlining assay development and reducing reagent costs, these technologies make diagnostics more accessible, particularly in low-resource settings, where portable devices empower point-of-care testing, addressing global health disparities. However, challenges such as off-target effects in CRISPR assays, data heterogeneity, and ethical concerns surrounding genomic privacy must be addressed to ensure widespread adoption. Scalability barriers, including high reagent costs and logistical hurdles like cold-chain requirements, further necessitate innovative solutions such as lyophilized reagents and localized data processing. The global impact of AI-CRISPR diagnostics is profound, with real-world applications demonstrating reduced antibiotic misuse by 40% and improved outcomes in regions with high AMR prevalence, such as sub-Saharan Africa and South Asia. To fully realize this potential, interdisciplinary collaboration among researchers, clinicians, and policymakers is critical to develop standardized protocols, enhance data transparency, and secure funding for cost-effective platforms. By prioritizing open-access models and global partnerships, AI-CRISPR technologies can bridge the gap between cutting-edge research and clinical practice, ensuring equitable access to precision diagnostics. This transformative approach not only promises to curb the silent pandemic of AMR but also establishes a robust framework for personalized medicine, redefining healthcare delivery for future generations.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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