

REVIEW ARTICLE



Applications of Artificial Intelligence and Pharmacogenomics in Cardiovascular and Cancer Treatment

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Abstract: The convergence of Artificial Intelligence (AI) and pharmacogenomics marks a pivotal advancement in precision medicine, particularly in cardiovascular and oncological therapeutics. Modern healthcare has evolved beyond conventional treatment approaches, embracing individualized therapeutic strategies based on genetic profiles, environmental factors, and lifestyle considerations. AI technologies enhance diagnostic precision, accelerate drug development pipelines, and optimize clinical decision-making through complex data interpretation. Pharmacogenomic investigations reveal crucial insights into patient-specific drug responses, enabling the development of genetically tailored therapeutic regimens. The synergy between AI and pharmacogenomics has demonstrated remarkable progress across multiple medical domains. Notable applications include identifying single nucleotide polymorphism markers in metabolic disorders, optimizing antiplatelet therapy in peripheral arterial disease, and predicting chemotherapy resistance patterns. In oncology, machine learning models have revolutionized breast cancer treatment protocols, while deep learning applications combined with neuroimaging data have enhanced the prediction of antidepressant efficacy in psychiatric conditions. Clinical pharmacists serve as essential intermediaries, bridging technological innovations with practical healthcare delivery through genetic interpretation, medication management, and patient education. While this technological integration faces implementation challenges, its potential to transform healthcare delivery remains unprecedented. The successful implementation of these innovations requires expanded accessibility, robust ethical guidelines, and enhanced interdisciplinary collaboration, ultimately leading to more precise, effective, and equitable healthcare delivery.

Keywords: Artificial Intelligence; Pharmacogenomics; Cardiovascular diseases; Oncology; Precision Medicine.

1. Introduction

The paradigm of modern medicine has shifted from a one-size-fits-all approach to individualized therapeutic strategies that account for patients' unique genetic makeup, clinical characteristics, and environmental factors. Precision medicine represents this evolution, where genetic variations play a crucial role in determining patient responses to therapeutic interventions [1]. Pharmacogenomics emerges as a cornerstone in precision medicine by identifying genetic markers that predict drug efficacy and potential adverse reactions. When integrated with AI technologies and extensive clinical databases, pharmacogenomic approaches significantly enhance treatment decisions for complex diseases, including cardiovascular disorders and various malignancies. This integration facilitates a transition from symptom-based treatment to genetically-informed therapeutic decisions [2, 3]. In oncology, genomic profiling directs targeted therapies while AI platforms facilitate complex tumor data interpretation and treatment response prediction [3]. Similarly, cardiovascular medicine has witnessed substantial advancement through AI-driven risk prediction models and genetic risk stratification, supplementing traditional cardiovascular risk assessment methods [4]. The integration of AI capabilities with pharmacogenomic data offers novel opportunities for improving therapeutic strategies and disease management through innovative biomarkers and treatment approaches [5]. Recent technological advancements have enabled rapid genetic sequencing and analysis, generating unprecedented volumes of genomic data. AI algorithms process these extensive datasets, identifying patterns and correlations that might escape human observation. This technological synergy has particular significance in complex disease states where multiple genetic and environmental factors influence treatment outcomes. The clinical implementation of AI-driven pharmacogenomic approaches requires careful consideration of several factors, including data quality, algorithmic validation, and clinical utility. Healthcare providers must take these into consideration while maintaining focus on patient care quality and safety. Pharmacogenomics is an evolution from traditional pharmacogenetics, employing genome-wide analysis to predict drug responses and optimize therapeutic outcomes. This field combines genetic variability as a critical determinant in drug selection and dosing strategies, particularly in targeted therapies. The relationship between genetic variations and drug responses manifests through multiple mechanisms. Single nucleotide polymorphisms (SNPs), copy number variations, and other genetic alterations can

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significantly influence drug metabolism, transport, and target interactions. These genetic differences explain why identical drug regimens may produce varying outcomes in different individuals.

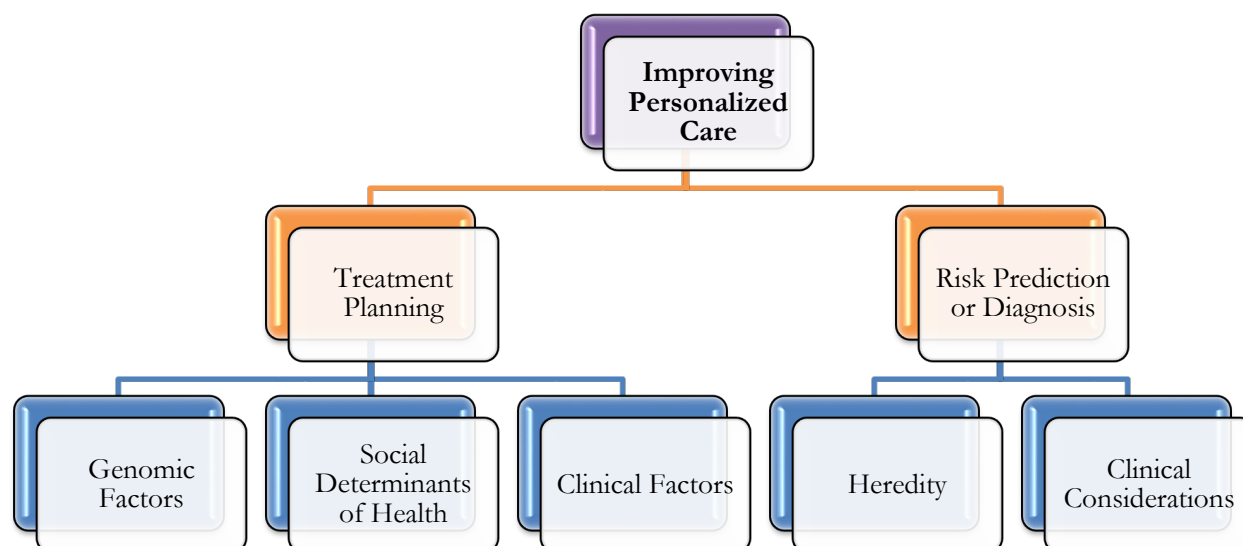


Figure 1. Factors Involved in Improving Personalized Care

In cardiovascular therapeutics, several genetic markers have demonstrated significant clinical relevance. The CYP2C19 gene variants substantially influence clopidogrel metabolism, where poor metabolizers show reduced antiplatelet response and increased risk of adverse cardiovascular events. SLCO1B1 variants affect statin disposition, with certain genotypes predisposing patients to myopathy risk, particularly with high-dose simvastatin therapy. In oncology, pharmacogenomic markers guide treatment selection and dosing strategies. TPMT genetic variations influence thiopurine drug metabolism, where variant carriers require dose adjustments to prevent severe myelosuppression. EGFR mutation status directs the use of tyrosine kinase inhibitors in non-small cell lung cancer, while KRAS mutation analysis guides anti-EGFR therapy decisions in colorectal cancer.

The translation of pharmacogenomic information into clinical practice requires systematic approaches to genetic testing, result interpretation, and clinical decision support. Healthcare providers utilize this information alongside clinical parameters to optimize drug selection and dosing. Modern clinical decision support systems integrate pharmacogenomic data with electronic health records, facilitating evidence-based prescribing decisions. While initial genetic testing costs may seem substantial, pharmacogenomic-guided therapy can prove cost-effective by preventing adverse drug reactions and optimizing treatment selection. This approach reduces trial-and-error prescribing and minimizes the economic burden of drug-related complications.

2. AI in Personalized Medicine

The integration of AI in personalized medicine represents a paradigm shift in healthcare delivery. Modern AI systems employ sophisticated algorithms that encompass various learning approaches. Supervised learning algorithms enable precise disease classification and diagnosis through labeled training data. Unsupervised learning methods excel at discovering hidden patterns in complex medical datasets, while reinforcement learning optimizes treatment strategies through iterative improvement. Natural language processing capabilities allow systems to analyze vast amounts of medical literature, extracting relevant insights for clinical application [2,3].

2.1. Pattern Recognition

2.1.1. Multi-omics Data Integration

AI platforms process multiple layers of complex biological data simultaneously. Genomic analysis includes comprehensive DNA sequencing, gene expression profiling, and genetic variant identification. Proteomic data processing focuses on protein expression patterns and post-translational modifications that influence disease states. Metabolomic analysis examines the complete set of metabolites in biological samples, providing insights into cellular processes and disease mechanisms. Transcriptomic data reveals RNA expression patterns crucial for understanding gene regulation. Epigenomic information, including DNA methylation and histone modifications, adds another layer of biological complexity to the analysis. [4]

2.1.2. Advanced Neural Network Architectures

Modern pattern recognition employs sophisticated neural network architectures. Convolutional Neural Networks analyze medical imaging data with unprecedented accuracy. Recurrent Neural Networks process temporal health data, identifying patterns over time. Transformer models excel at analyzing complex biological sequences and relationships. Graph Neural Networks map and predict molecular interactions within biological systems. [5]

2.1.3. Biomarker Discovery

AI systems demonstrate remarkable capability in biomarker discovery. These platforms identify novel diagnostic markers that indicate disease presence or progression. The systems detect subtle indicators of disease progression that might be missed by conventional analysis. Treatment response markers help predict therapeutic effectiveness, while monitoring systems track ongoing treatment efficacy. [6]

Table 1. AI Applications in Precision Medicine

Application Area	AI Technology	Clinical Use	Advantages
Molecular Profiling	Deep Learning	Tumor mutation analysis	Rapid processing of genomic data
Drug Response	Machine Learning	Treatment outcome prediction	Improved patient stratification
Clinical Decision Support	Neural Networks	Drug selection and dosing	Real-time recommendations
Risk Stratification	Random Forests	Disease progression prediction	Early intervention opportunities
Biomarker Discovery	Clustering Algorithms	Novel target identification	Accelerated drug development

2.2. Clinical Decision Support

2.2.1. Evidence-Based Analytics

Advanced systems synthesize multiple sources of clinical evidence. They incorporate systematic reviews and meta-analyses to provide comprehensive evidence synthesis. Clinical practice guidelines are integrated with real-world evidence to generate practical recommendations. Expert consensus statements inform decision-making, while patient-reported outcomes provide valuable real-world perspectives. [7]

2.2.2. Drug-Related Decision Support

AI platforms provide comprehensive drug-related guidance. These systems analyze potential drug-drug interactions and generate alerts for clinicians. Dose optimization recommendations account for patient-specific factors. Adverse event prediction helps prevent complications, while contraindication warnings ensure patient safety. Alternative therapy suggestions offer clinicians multiple treatment options. [8]

2.2.3. Real-Time Clinical Analysis

Systems perform continuous monitoring of patient status and clinical parameters. Risk stratification occurs dynamically as new data becomes available. Treatment response assessment provides ongoing feedback about therapeutic effectiveness. Emergency intervention alerts help prevent adverse outcomes. Resource allocation optimization ensures efficient healthcare delivery. [9]

2.2.4. Personalized Treatment Planning

AI assists in developing individualized treatment strategies. Treatment protocol selection considers patient-specific factors and preferences. Therapy timing optimization maximizes treatment effectiveness. Drug combination strategies account for complex interactions. Dose modification recommendations adapt to patient responses. Follow-up schedule planning ensures appropriate monitoring. [10]

2.3. Data Processing

2.3.1. Cloud Computing Integration

Modern AI systems utilize advanced cloud computing resources for data processing. Distributed computing enables rapid analysis of complex datasets. Scalable storage solutions accommodate growing data volumes. Real-time data processing ensures timely clinical decision support. Secure data transmission protects sensitive information. Automated backup systems prevent data loss. [11]

2.3.2. Quality Assurance

AI platforms implement comprehensive quality control measures. Data validation ensures accuracy and reliability. Algorithm performance monitoring maintains system effectiveness. Result verification confirms analytical accuracy. Error detection mechanisms identify potential issues. Regular calibration maintains system precision. [12]

2.4. Implementation

2.4.1. Clinical Integration

Successful implementation requires careful attention to operational details. Workflow optimization ensures smooth integration with existing processes. Staff training programs develop necessary skills and competencies. Technical support systems provide ongoing assistance. Performance monitoring tracks system effectiveness. Regular updates maintain system currency. [13]

2.4.2. Security Measures

Systems incorporate robust security protocols to protect sensitive data. Data encryption ensures confidentiality during transmission and storage. Access control mechanisms restrict system use to authorized personnel. Audit trail logging tracks system usage and modifications. Privacy protection measures safeguard patient information. Compliance monitoring ensures adherence to regulatory requirements. [14]

3. Biomarker Discovery and Validation

3.1. Novel Biomarkers

3.1.1. High-Throughput Screening

AI algorithms process vast quantities of genomic and molecular data from multiple experimental platforms. Advanced computational methods analyze next-generation sequencing data, proteomics profiles, and metabolomic signatures simultaneously. These systems integrate data from tissue microarrays, liquid biopsies, and imaging studies to identify novel molecular markers. [15]

Table 2. Pharmacogenomic Markers in Cardiovascular Medicine

Gene	Drug(s)	Clinical Impact
CYP2C19	Clopidogrel	Reduced antiplatelet effect in poor metabolizers
SLCO1B1	Statins	Increased risk of myopathy
VKORC1/CYP2C9	Warfarin	Altered dosing requirements
ADRB1	Beta-blockers	Variable response to treatment
CYP2D6	Metoprolol	Altered drug metabolism

3.1.2. Therapeutic Target Identification

Machine learning approaches examine molecular pathways and cellular networks to identify potential drug targets. The systems analyze protein-protein interactions, signaling cascades, and metabolic networks to understand disease mechanisms. Computational models evaluate target druggability, specificity, and potential off-target effects. [16]

3.1.3. Prognostic Indicators

AI systems identify molecular signatures that predict disease outcomes and progression. These platforms analyze temporal changes in biomarker expression patterns throughout disease progression. Complex algorithms evaluate the relationship between molecular markers and clinical outcomes across different patient subgroups. [17]

3.1.4. Parameter Addition

Advanced analytical systems combine multiple biological parameters to create biomarker profiles. The analysis incorporates genetic variants, gene expression patterns, protein levels, and metabolic markers. These integrated approaches provide more reliable and informative biomarker signatures than single-parameter analyses. [18]

3.2. Validation and Clinical Applications

3.2.1. Clinical Trials

AI platforms evaluate biomarker performance across different clinical trial phases. Systems analyze trial data to assess biomarker consistency and reliability. The validation process examines biomarker behavior in various treatment contexts and patient populations. [19]

3.2.2. Real-World Evidence

Machine learning algorithms analyze real-world data to validate biomarker utility. These assessments examine biomarker performance in diverse clinical settings and patient populations. The analysis considers practical aspects of biomarker implementation in routine clinical care. [20]

3.2.3. Performance

The evaluation of biomarker performance includes multiple statistical measures. Systems assess sensitivity, specificity, positive predictive value, and negative predictive value. Advanced algorithms calculate receiver operating characteristic curves and area under the curve metrics. [21]

Table 3. Outcome Metrics in Precision Medicine

Metric Category	Measurement Parameters	Expected Impact	Success Indicators
Clinical Outcomes	Adverse event rates	30-50% reduction	Documentation of events
	Treatment efficacy	20-40% improvement	Response rates
Economic Impact	Healthcare costs	15-25% savings	Cost analysis
	Resource utilization	20-30% optimization	Utilization metrics
Patient Experience	Treatment satisfaction	>80% positive	Survey results
	Adherence rates	25% improvement	Medication compliance
Quality Metrics	Time to optimal therapy	40% reduction	Treatment initiation data
	Error rates	50% reduction	Safety reports

3.2.4. Clinical Implementation

Validation processes examine practical aspects of biomarker implementation in clinical settings. Studies evaluate sample collection requirements, processing protocols, and storage conditions. Analysis includes cost-effectiveness assessments and implementation feasibility studies. [22]

4. Predictive Analytics in Patient Care

4.1. Risk Stratification

4.1.1. Multivariate Risk Assessment

AI models integrate diverse patient data to create comprehensive risk profiles. The analysis combines demographic information, clinical history, genetic markers, and environmental factors. These systems evaluate complex interactions between different risk factors to generate accurate predictions. [2,3]

4.1.2. Dynamic Risk Monitoring

Predictive systems continuously update risk assessments as new data becomes available. The platforms monitor changes in patient parameters over time to detect emerging risks. Real-time analysis enables early identification of deteriorating clinical conditions. [4]

4.1.3. Population Health Management

Advanced analytics evaluate risk patterns across patient populations. These assessments help identify high-risk subgroups requiring targeted interventions. The analysis supports resource allocation and preventive care planning. [5, 9]

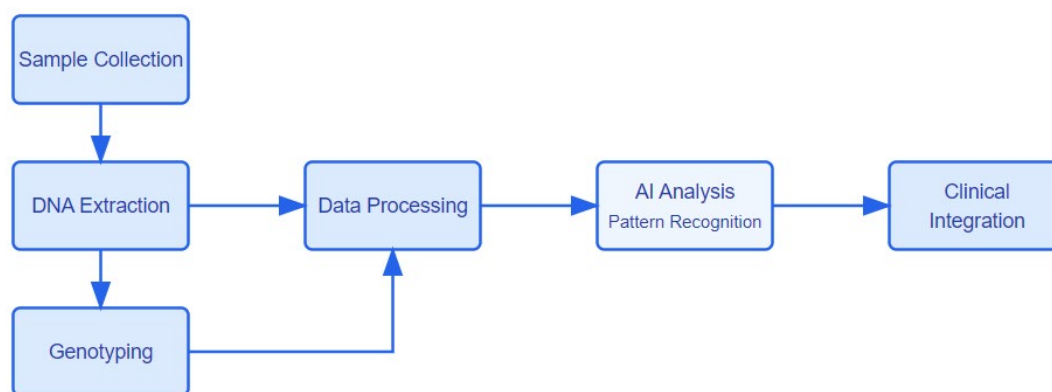


Figure 2. Pharmacogenomic Testing and AI Analysis

4.2. Treatment Response Prediction

4.2.1. Historical Outcome Analysis

Machine learning systems analyze extensive databases of treatment outcomes. The analysis examines responses across different patient subgroups and treatment protocols. These systems identify patterns associated with treatment success or failure. [3]

4.2.2. Patient-Specific Response Modeling

Advanced algorithms create individualized response predictions for specific treatments. These models consider patient characteristics, genetic profiles, and previous treatment responses. The analysis incorporates drug-specific factors and potential interaction effects. [5]

4.2.3. Adverse Event Prediction

Predictive systems evaluate the likelihood of treatment-related complications. The analysis considers patient risk factors, drug properties, and historical adverse event data. These predictions help optimize treatment selection and monitoring. [10]

4.2.4. Treatment Optimization

AI platforms suggest optimal treatment strategies based on predicted responses. The systems evaluate potential treatment combinations and timing options. Advanced algorithms consider cost-effectiveness and quality of life impacts in their recommendations. [11]

4.2.5. Monitoring and Adjustment

Predictive systems continuously evaluate treatment responses and suggest necessary adjustments. The platforms monitor clinical parameters, biomarker levels, and patient-reported outcomes. Real-time analysis enables rapid identification of suboptimal responses and suggests appropriate modifications. [12]

5. AI and Pharmacogenomics in Cardiology

AI applications in cardiology have revolutionized patient care by incorporating genetic information into treatment decisions. These systems process complex cardiovascular data, including genetic profiles, clinical parameters, and imaging results, to optimize therapeutic strategies.

5.1. Antiplatelet Therapy

5.1.1. CYP2C19 Genotype-Guided Therapy

The metabolism of clopidogrel depends significantly on CYP2C19 enzyme activity. AI platforms analyze CYP2C19 genotype data alongside clinical factors to guide antiplatelet therapy selection. Machine learning algorithms integrate genetic information with clinical parameters to predict treatment efficacy and bleeding risks. These systems recommend alternative therapies like prasugrel or ticagrelor for patients with reduced CYP2C19 function [11].

5.2. Real-time Decision Support

Advanced clinical decision support systems provide real-time recommendations by processing genetic test results within electronic health records. These platforms alert healthcare providers to potential drug-gene interactions and suggest appropriate dose modifications or alternative medications.

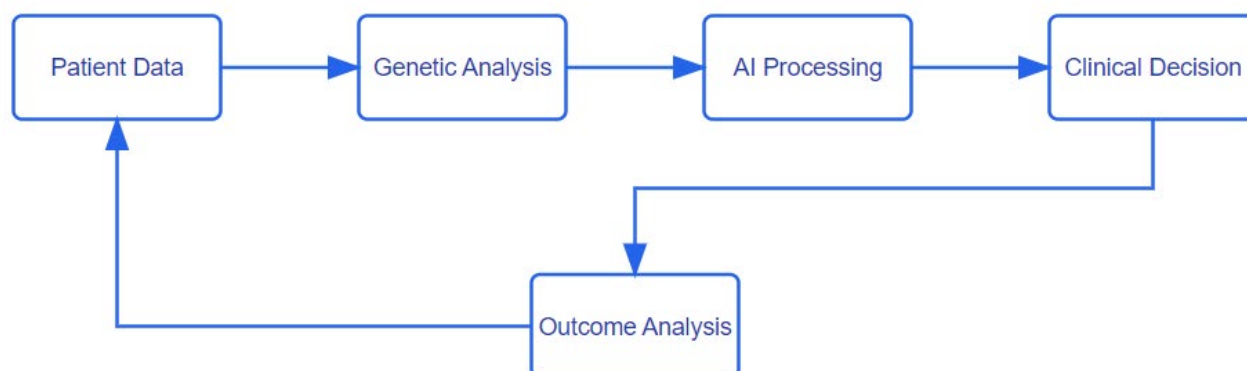


Figure 3. AI-Driven Pharmacogenomic Decision Pipeline

5.3. Anticoagulation

5.3.1. Warfarin Dosing Algorithms

AI models incorporate VKORC1 and CYP2C9 genetic variations with clinical factors to optimize warfarin dosing. These algorithms process multiple variables, including age, body mass index, concurrent medications, and comorbidities, to predict optimal initial dosing strategies. Modern platforms continuously refine dosing recommendations based on INR responses and clinical outcomes [12].

5.3.2. Anticoagulant Selection

Machine learning systems assist in selecting between traditional and novel anticoagulants by analyzing patient-specific genetic and clinical factors. These platforms evaluate bleeding risks, therapeutic efficacy, and cost-effectiveness for individualized treatment decisions.

5.4. Statin Therapy

5.4.1. SLCO1B1 Genetic Variants

AI-driven platforms analyze SLCO1B1 genetic variations to assess statin-induced myopathy risk. These systems integrate genetic data with patient characteristics to recommend appropriate statin selection and dosing strategies. The algorithms consider factors such as drug interactions, comorbidities, and lifestyle factors in generating recommendations [13].

5.4.2. Risk-Benefit Assessment

Advanced algorithms perform comprehensive risk-benefit analyses for statin therapy, considering genetic predispositions to adverse effects alongside cardiovascular risk reduction benefits. These assessments help clinicians make informed decisions about statin intensity and monitoring requirements.

5.5. Beta-Blockers

AI systems analyze CYP2D6 metabolizer status and ADRB1 polymorphisms to guide beta-blocker selection and dosing. These platforms predict drug exposure levels and therapeutic responses, enabling personalized dose adjustments. The integration of genetic data with clinical parameters improves treatment outcomes in heart failure and hypertension management [14].

6. AI and Pharmacogenomics in Oncology

Modern oncology has witnessed rapid advancement through the use of AI and pharmacogenomics. These technologies facilitate rapid analysis of tumor genetics, drug resistance mechanisms, and treatment response patterns, leading to more effective personalized treatment strategies.

6.1. Precision Oncology

6.1.1. Molecular Profiling and Drug Selection

AI algorithms analyze complex molecular profiles of tumors, including genetic mutations, gene expression patterns, and protein modifications. These systems process vast genomic databases to identify actionable mutations and predict optimal drug combinations. Machine learning models evaluate tumor heterogeneity and evolution patterns to anticipate treatment resistance [16].

6.1.2. Drug Resistance Prediction

Advanced AI platforms analyze long non-coding RNAs (lncRNAs) and their influence on drug responses. A comprehensive study incorporating 1,005 cancer cell lines and 265 anticancer agents identified over 27,000 lncRNA-drug predictive relationships. These findings have improved response prediction in various cancers, including ovarian cancer patients receiving tamoxifen and gastric cancer patients treated with 5-FU [17].

6.2. Treatment Optimization

6.2.1. Combination Therapy

AI platforms like CURATE.AI optimize combination therapy dosing strategies. These systems analyze patient responses to determine optimal drug combinations and dosing schedules. For instance, the platform successfully optimized combination therapy with ZEN-3694 and enzalutamide in prostate cancer treatment, improving both efficacy and tolerability [18].

6.2.2. PARP Inhibitor Patient Selection

Deep learning systems have revolutionized patient selection for PARP inhibitor therapy. Advanced algorithms detect homologous recombination deficiency in cancer cells with 74% accuracy, enabling better identification of patients likely to respond to PARP inhibitors. This approach has particular significance in breast cancer treatment, where HR deficiency status guides therapeutic decisions [19].

6.3. Chemotherapy Response Prediction

6.3.1. Preventing Toxicity

Machine learning models predict individual patient tolerance to chemotherapy agents. These systems analyze genetic variations and clinical factors to differentiate patient responses to specific drugs like taxol and gemcitabine. The models help prevent adverse reactions while maintaining treatment efficacy [20].

6.3.2. Immunotherapy Optimization

AI platforms evaluate potential responses to immunotherapy treatments, particularly PD-1 inhibitors in advanced solid tumors. These systems integrate multiple data sources, including imaging biomarkers and genetic profiles, to predict treatment outcomes and guide clinical decision-making [21].

7. Challenges

7.1. Implementation Barriers

The integration of AI and pharmacogenomics in clinical practice faces multiple obstacles. Technical challenges include data standardization, interoperability between different healthcare systems, and the need for robust computational infrastructure. Healthcare providers require specialized training to interpret complex genetic information and AI-generated recommendations effectively.

7.2. Data Privacy

The management of sensitive genetic information and personal health data demands stringent security measures. Healthcare institutions must implement comprehensive data protection protocols while ensuring data accessibility for AI analysis. International regulations and varying privacy laws across jurisdictions create additional compliance challenges.

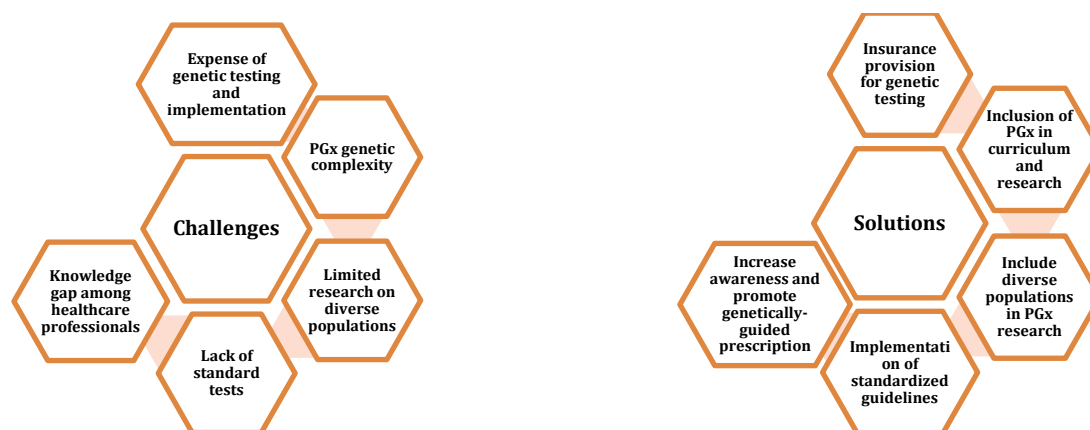


Figure 4. Challenges and Solutions for implementation of Personalized medicine

7.3. Healthcare Disparities

The high cost of genetic testing and advanced AI technologies may limit access to precision medicine approaches. Socioeconomic factors and geographical location influence the availability of these advanced healthcare solutions. These disparities risk creating a two-tiered healthcare system where advanced treatments are available only to select populations.

7.4. Clinical Validation

Validating AI algorithms and pharmacogenomic markers requires extensive clinical trials and real-world evidence. The rapid evolution of AI technology sometimes outpaces traditional validation methods. Establishing the clinical utility and cost-effectiveness of new approaches remains crucial for widespread adoption [22].

Table 4. Implementation Challenges in AI-Driven Pharmacogenomics

Challenge Category	Specific Issues	Potential Solutions	Current Status
Technical	Data standardization	Universal data formats	In development
	Computing infrastructure	Cloud-based solutions	Available
Clinical	Provider training	Educational programs	Ongoing
	Evidence validation	Prospective trials	In progress
Regulatory	Data privacy	Enhanced security protocols	Implemented
	Cross-border compliance	International guidelines	Under review
Economic	Cost barriers	Insurance coverage	Variable
	Resource allocation	Public-private partnerships	Emerging

8. Conclusion

The combination of AI and pharmacogenomics is a significant transformation in modern medicine, particularly in cardiovascular and oncology treatment. This enables precision in drug selection, dosing strategies, and treatment monitoring. AI algorithms process complex genetic and clinical data to generate actionable insights, while pharmacogenomic analysis provides crucial information about individual drug responses. Clinical applications of these approaches have shown significant improvements in patient outcomes across multiple therapeutic areas. In cardiology, genotype-guided therapy selection has enhanced anticoagulation management and antiplatelet therapy. Oncology has benefited from improved patient stratification, more accurate prediction of treatment responses, and optimized combination therapy strategies. Despite current challenges in implementation, data management, and healthcare equity, the potential benefits of these technologies continue to drive innovation and adoption. The role of clinical pharmacists remains crucial in translating technical capabilities into practical patient care.

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