(ISSN: 0973-7049(P))

The Bioscan AN INTERNATIONAL QUARTERLY JOURNAL OF LIFE SCIENCES 21(3): S.I (3),1660-1678, 2026 www.thebioscan.com

AI-Enabled Personalized Medicine: Integrating Genomics, Clinical Decision Support & Precision Therapeutics

Muneendra Madam*[1], Hareesh Divadari[2]

[1]ScieGen pharmaceuticals, 89 Arkay Drive, Hauppauge, New York 11788, USA

[2]Department of Pharmaceutical Sciences, Andhra University, Visakhapatnam, Andhra Pradesh 530003, A.P, India

Corresponding Mail: muneendrapharma2015@gmail.com, ORCID: 0009-0002-9547-4761

DOI: https://doi.org/10.63001/tbs.2026.v21.i03.S.I(3).pp1660-1678

KEYWORDS

Artificial intelligence;
Personalized medicine;
Genomics;
Clinical decision support;
Precision therapeutics

Article Info

Received:17.08.2026

Accepted: 04.09.2026

Published: 15.09.2026

Abstract

Personalized medicine aims to provide healthcare based on the biological and clinical characteristics of individual patients. Advancement in genomics has made it possible to identify genetic modifications related to disease risk, drug response, and treatment outcomes, but interpreting large and complex datasets remains challenging. Artificial intelligence (AI) is useful in analyzing genomic, clinical, and treatment-related information and connecting these data with clinical decisions. This review examines the role of AI in personalized medicine, with a focus on genomic analysis, clinical decision support, and precision therapeutics. AI applications in genomic medicine include variant interpretation, disease-risk prediction, pharmacogenomics, and multi-omics analysis. AI-based clinical decision support system can assist in risk assessment, diagnosis, treatment selection, and patient monitoring. In precision therapeutics, AI facilitates support in drug selection, dose optimization, treatment-response prediction, and treatment monitoring. The review also discusses applications in cancer, cardiovascular diseases, diabetes, neurological disorders, and rare diseases. Important challenges include data quality, privacy, algorithmic bias, explainability, clinical validation, cost, and unequal access to advanced technologies. Future progress will depend on reliable data integration, responsible AI development, clinical oversight, and appropriate regulation. The integration of genomics, AI-based decision support, and precision therapeutics could contribute to more personalized, responsive, and patient-centered healthcare.

1. Introduction

Personalized medicine has greatly impacted the healthcare system. It focuses on the characteristics of individual patients. Traditional treatment regimens generally depend on common clinical guidelines and population-level evidence. Personalized medicine has integrated information on genetic variations, clinical history, disease characteristics, lifestyle, and treatment response to support decisions that are more specific to each patient. Genomic medicine has become an important part of this approach because genetic information can help explain differences in disease risk, drug response, and treatment outcomes [1,2]. Precision medicine aims to provide treatment based on each patient's unique biological and clinical features instead of relying on population averages [3].

The growing amount of genomic and clinical data has created a need for better methods to collect, analyze, and interpret complex information. Modern sequencing methods can generate enormous amounts of genetic data, while electronic health records, medical imaging, laboratory investigations, medication histories, and patient-generated data provide additional information about an individual's health. Bringing these diverse sources together can provide a more complete picture of disease and treatment

response. At the same time, the volume and complexity of these datasets can make conventional methods of analysis difficult to apply on their own.

Artificial intelligence (AI) is a promising tool in examining large datasets and identifying patterns that may be difficult to recognize through conventional analysis. Machine learning and deep learning methods are being studied for genomic variant interpretation, disease prediction, patient classification, and treatment response assessment [3]. different areas of healthcare, such as medical imaging, electronic health records, clinical prediction, and drug development are increasingly relying on AI in modern times [5]. These applications have increased interest in using AI to connect biological information with clinical decision-making.

Clinical decision support is an important link between patient data and treatment planning. AI-based systems can help clinicians estimate disease risk, identify relevant clinical findings, compare treatment options, and recognize patients who may need closer monitoring. When genomic information is considered together with clinical findings, these systems may provide a more complete basis for individualized decisions. The usefulness of such systems depends on the quality of the underlying data, proper clinical validation, and clear communication of the results to healthcare professionals [4]. AI should support clinical judgment and patient care, with clinicians remaining responsible for final decisions.

Precision therapeutics takes this process ahead by using patient-specific information to guide treatment selection and dosing. Pharmacogenomics is one important example. Genetic differences can affect drug metabolism, efficacy, and adverse reactions, and pharmacogenomic information can help in guiding the use of selected medicines in clinical practice [2]. Integration of genomic information with clinical and treatment data to improve the selection of therapies and prediction how individual patients may respond, is achieved through AI. This methodology is specifically relevant when numerous biological and clinical factors need to be considered at the same time.

A combination of AI, genomics, clinical decision support, and precision therapeutics has the potential to create a more connected model of patient care. This approach can move from identifying disease risk and interpreting genomic findings to selecting treatment and monitoring the patient's response. It also provides an opportunity to use new clinical information to reassess treatment decisions within a span of time. At the same time, concerns related to data privacy, algorithmic bias, interpretability, clinical validation, and equitable access need careful consideration.

This review discusses the current role of AI in personalized medicine, with particular focus on genomic analysis, clinical decision support, and precision therapeutics. It also examines applications across major disease areas, the challenges that can affect clinical implementation, and future directions for integrating these technologies into patient care. The overall aim is to analyze how AI can help connect patient-specific biological information with clinical knowledge and treatment decisions while maintaining appropriate clinical oversight.

2. Methodology

This narrative review was conducted to examine the current role of artificial intelligence (AI) in personalized medicine, with particular emphasis on genomics, clinical decision support, and precision therapeutics. A comprehensive literature search was performed using

PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar to identify relevant studies published between January 2018 and June 2026. Additional landmark publications and reference lists of selected articles were manually screened to ensure maximum coverage.

Search terms included combinations of artificial intelligence, machine learning, deep learning, personalized medicine, precision medicine, genomics, pharmacogenomics, clinical decision support, precision therapeutics, multi-omics, electronic health records, drug discovery, and treatment response.

Original research articles, systematic reviews, meta-analyses, clinical guidelines, consensus statements, and regulatory reports published in English were considered. Studies focusing on AI applications in genomic analysis, disease-risk prediction, pharmacogenomics, clinical decision support, treatment selection, multi-omics integration, and precision therapeutics were prioritized. Articles with little relevance to personalized medicine or insufficient methodological detail were excluded.

The selected literature was organized into thematic categories including genomic medicine, AI-based clinical decision support, precision therapeutics, disease-specific applications, implementation challenges, and future perspectives. As the studies differed in design, AI methods, clinical outcomes, and reporting standards, the findings were summarized using a qualitative narrative synthesis instead of a quantitative analysis.

3. Overview of Personalized Medicine

Personalized medicine focuses on healthcare decisions based on the individual characteristics of each patient. These may include genetic information, clinical history, disease status, lifestyle, environmental factors, and previous treatment responses. The goal is to provide better care which matches the needs of each patient [1].

3.1 From Conventional Medicine to Personalized Medicine

Conventional medical therapies rely on clinical guidelines developed from large patient populations. These guidelines are important, but patients with the same disease can respond differently to the same treatment. Genetic variation, age, organ function, disease severity, drug metabolism, and lifestyle can affect treatment response [1].

Genomic technologies have expanded the scope of personalized care. Genetic testing assists in identifying variants linked to disease risk and drug response. Pharmacogenomics is an important clinical application because genetic information can help guide the choice or dose of selected medicines [2].

Personalized medicine also uses information beyond genetics. Electronic health records, laboratory results, medical images, wearable devices, and patient-reported data provide additional information about an individual's health [3,4].

3.2 Role of Genomics in Individualized Care

Genomics provides information about biological factors that may influence disease development and treatment response. It has applications in treatment of cancer, inherited disorders, cardiovascular diseases, and other conditions. In cancer care, molecular features can help identify therapeutic targets. In inherited diseases, genomic analysis can support diagnosis, while pharmacogenomic testing can provide information about drug metabolism and response [2].

AI assisted support system is becoming useful for interpreting large genomic datasets. Machine learning methods aid in variant classification, genomic pattern recognition, disease-risk prediction, and analysis of relationships between genetic features and clinical outcomes [3].

3.3 Need for AI in Personalized Medicine

The increasing volume of genomic and clinical data makes analysis more complex. AI can process distinct types of patient information and identify relationships within genomic data, clinical history, laboratory findings, imaging, medications, and treatment outcomes.

AI-based systems can support disease-risk assessment, genomic interpretation, treatment-response prediction, therapeutic selection, and patient monitoring [3,4]. The usefulness of these systems depends on reliable data, proper clinical validation, and careful integration into clinical practice.

The integration of these technologies creates a connected pathway from genomic analysis and clinical decision support to precision treatment and patient monitoring. Fig 1 summarizes this integrated pathway and shows how patient-specific information can move through AI-based analysis toward individualized treatment and continuous monitoring.

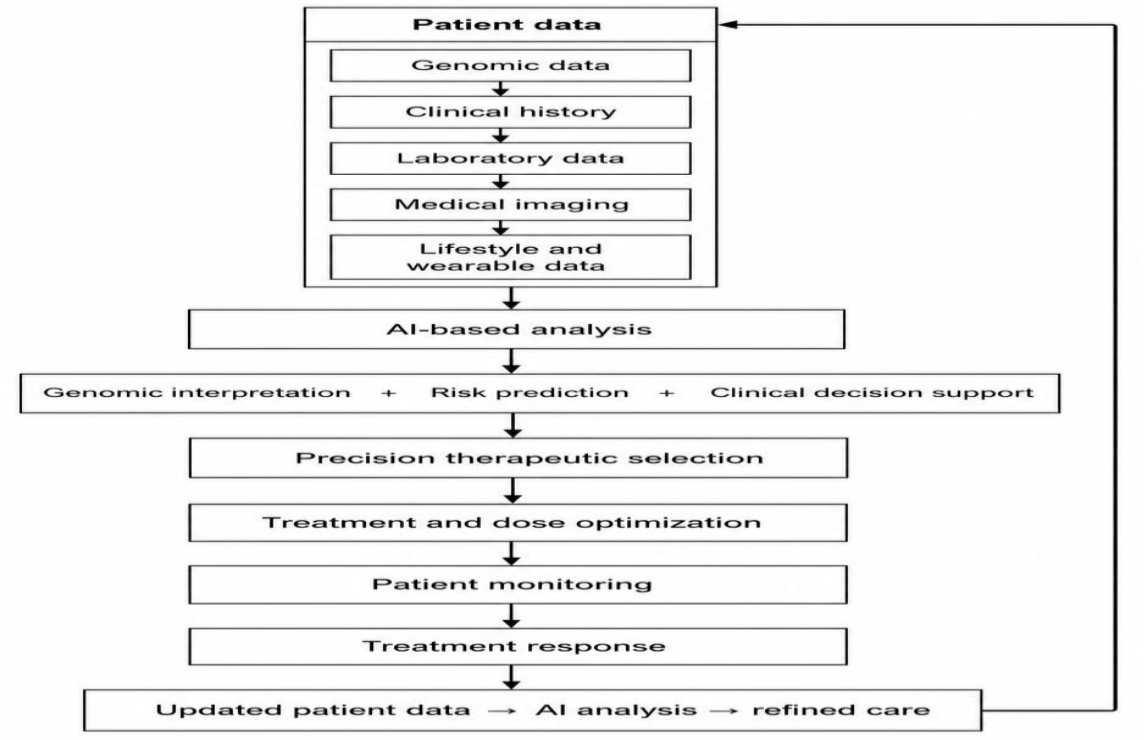

Fig 1. Integrated framework of AI-enabled personalized medicine.

4. AI in Genomic Medicine

Genomic medicine produces detailed information about a patient's genetic makeup, but interpreting this information can be difficult because of the considerable number of genetic variants and their complex relationships with disease. AI can help analyze these data and connect genomic findings with clinical information. This makes AI an important part of the move toward more individualized healthcare [6].

4.1 Genomic Data Analysis

Modern sequencing technologies generate large volumes of genomic data. AI and machine learning can help process these data, identify meaningful genetic patterns, and classify variants according to their possible clinical relevance. These methods can also combine genomic information with clinical records to improve the interpretation of genetic findings [6,7].

Deep learning has gained attention in genomic analysis because it can detect complex patterns within DNA sequences and other biological data. AI-based approaches have been studied for sequence analysis, variant prediction, gene expression analysis, and disease-risk assessment. These applications can reduce the amount of manual analysis required and help researchers to focus on findings with greater clinical importance [7].

4.2 Variant Interpretation and Disease-Risk Prediction

A major challenge in genomic medicine is determining whether a genetic variant has clinical significance. Many variants identified through sequencing do not have a clear relationship with disease. AI models can compare genetic variants with existing genomic databases, functional data, and clinical information to estimate their potential significance [6,8].

AI can also be used to estimate disease risk by combining genetic factors with other patient characteristics. for example, Polygenic risk scores, uses information from multiple genetic variants to estimate an individual's susceptibility to certain diseases. Additionally, Machine learning approaches can combine these genetic scores with clinical and environmental factors to produce more comprehensive risk assessments [8].

4.3 Pharmacogenomics and Drug-Response Prediction

People can respond differently to the same medicine because of genetic differences. Variations in genes involved in drug metabolism, transport, and drug targets can affect treatment response and the risk of adverse reactions. Pharmacogenomics uses this information to support medication selection and dosing [2].

AI can improve pharmacogenomic analysis by combining genetic data with medication history, clinical characteristics, laboratory results, and previous treatment responses. This may help predict which patients are more likely to benefit from a particular drug or experience an adverse reaction. Such approaches are especially relevant in areas such as oncology, where treatment selection can depend on specific molecular characteristics [9].

4.4 AI-Based Multi-Omics Integration

Genomic information represents only one part of a patient's biological profile. Other forms of omics data, such as transcriptomics, proteomics, metabolomics, and epigenomics, provide additional information about disease mechanisms and treatment response. Combining these datasets can provide a broader view of individual disease biology [10].

Integration of multi-omics datasets and identification of relationships that may not be evident when each dataset is studied separately, can be performed accurately by AI. These approaches are being explored for disease classification, biomarker discovery, prognosis, and treatment selection. Multi-omics analysis may therefore provide a stronger biological basis for personalized treatment decisions [10,11].

Overall, AI is helping move genomic medicine from the simple identification of

genetic variants toward deeper interpretation of their clinical meaning. The next step is to connect these genomic findings with patient records and clinical decisions, which forms the basis of AI-based clinical decision support. The major applications of AI in genomic medicine and their roles in personalized care are summarized in Table 1.

Table 1. Major applications of artificial intelligence in genomic medicine

AI Application	Main Data Used	Clinical/Research Use
Variant interpretation	DNA sequencing data	Classification of clinically relevant variants
Disease-risk prediction	Genetic and clinical data	Estimation of disease susceptibility
Pharmacogenomics	Genetic and medication data	Drug selection and dose guidance
Drug-response prediction	Genomic and clinical data	Prediction of treatment response
Multi-omics integration	Genomic, transcriptomic, proteomic and metabolomic data	Disease profiling and biomarker discovery

5. AI-Based Clinical Decision Support

Clinical decision support (CDS) systems help healthcare professionals use patient information when making diagnostic and treatment decisions. Traditional CDS tools mainly depend on predefined rules. AI-based systems can learn from large clinical datasets and recognize patterns across distinct types of patient information. This makes them useful for risk assessment, diagnosis, treatment planning, and patient monitoring [12,13].

5.1 Integration of Patient Data

Electronic health records (EHRs) contain information such as diagnoses, laboratory results, medications, clinical notes, and previous treatment outcomes. AI enables the analysis of these data together and identify patterns that may support individualized care. Natural language processing can also extract useful information from clinical notes and other unstructured records [12].

When genomic data are combined with EHR information, clinicians can obtain a broader picture of a patient's disease and treatment needs. This integration can support more informed decisions and connect genomic findings with real-world clinical information [14].

5.2 Risk Prediction and Early Diagnosis

AI-based prediction models can estimate the risk of disease progression, complications, hospital admission, or other clinical outcomes. These models may use demographic characteristics, laboratory findings, medical history, medications, and genomic information. Early risk identification can help clinicians decide which patients need further assessment or closer monitoring [13,15].

AI has also been studied for disease detection using medical images, pathology data, and clinical records. Combining these findings with patient-specific information may improve diagnostic assessment and support earlier intervention [16].

5.3 Treatment Selection and Clinical Recommendations

AI-based CDS can compare patient characteristics with information from previous patients, clinical studies, and

treatment records. This can help identify treatment options that may be suitable for a particular patient. for example, in oncology, AI systems can combine molecular features with clinical data to support treatment selection [14,16].

These systems should function as decision-support tools. Clinicians need to consider the patient's condition, preferences, available evidence, and clinical context before making the final decision.

5.4 Explainable AI and Clinician Trust

A major concern with AI-based CDS is the difficulty of understanding how some models reach their predictions. Explainable AI methods can provide information about the factors that contribute to a prediction or recommendation. Clear explanations can help clinicians assess whether an AI-generated result is clinically reasonable [17].

Clinical validation is also essential. A model that performs well in one dataset may produce different results when used with patients from another hospital or population. External validation, continuous monitoring, and careful assessment of model performance are therefore important before extensive clinical use [13,18].

AI-based clinical decision support can connect complex patient information with practical clinical decisions. Table 2 summarizes the major applications of AI-based CDS, and the types of patient information used for each application.

Table 2. Major applications of AI-based clinical decision support

Application	Patient Data	Clinical Role
Risk prediction	EHR, laboratory and clinical data	Identify patients at increased risk
Diagnostic support	Clinical records, imaging, pathology	Support disease detection
Treatment selection	Clinical, genomic and treatment data	Compare suitable therapeutic options
Outcome prediction	EHR and time-series health data	Estimate treatment or disease outcomes
Patient monitoring	Clinical and wearable data	Track changes in health status

6. AI in Precision Therapeutics

Precision therapeutics uses patient-specific information to guide drug selection, dosing, and treatment monitoring. Genomic data can provide important clues about drug response, while clinical history, laboratory findings, and previous treatment outcomes add further context. Combining these data sources to support more individualized treatment decisions is facilitated by AI [18,19].

6.1 Drug Selection and Dose Optimization

Patients may respond differently to the same medicine because of genetic variation, age, organ function, disease characteristics, and other factors. AI models are capable of analyzing these variables to estimate treatment response and help identify suitable medicines or doses. Pharmacogenomic information is particularly useful when genetic variants affect drug metabolism or drug targets [18].

6.2 Precision Oncology

Cancer treatment is a major area for AI-supported precision medicine. Tumor

sequencing can identify mutations and molecular features that may guide treatment selection. AI acts as a promising means in analyzing genomic, pathological, imaging, and clinical data to classify tumors, identify potential therapeutic targets, and predict treatment response [19,20].

6.3 AI-Assisted Drug Discovery and Repurposing

AI is also being used earlier in the therapeutic process. Machine learning can analyze molecular structures, biological targets, and drug-related datasets to identify potential drug candidates. These methods can support target identification, prediction of drug properties, and drug repurposing. This approach may help researchers prioritize promising compounds for further laboratory and clinical investigation [18,20].

clinical trial designs are also being supported by AI in helping researchers improve trial planning, identifying suitable participants, and making better use of available clinical data [21].

6.4 Treatment-Response Monitoring

Precision therapeutics does not end when treatment begins. Continuous assessment of treatment response can provide information for adjusting therapy. By reviewing laboratory results, imaging findings, clinical records, and patient-generated data, AI spots shift in a patient's illness and treatment response. [22].

The integration of these applications creates a treatment pathway in which AI assists in drug selection, dose planning, response prediction, and treatment monitoring. The major applications are summarized in Fig 2.

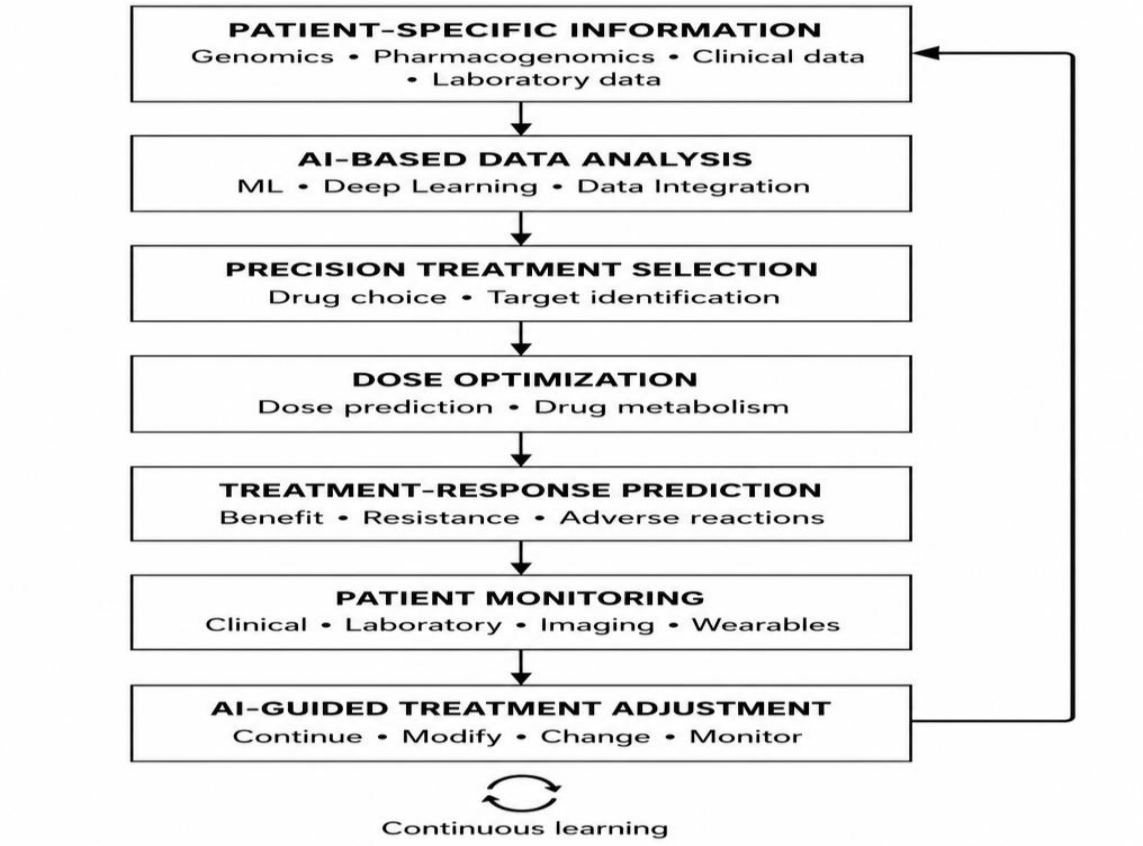

Fig 2. AI applications across the precision therapeutics pathway.

7. Integration of Genomics, Clinical Decision Support and Precision Therapeutics

The real value of AI-enabled personalized medicine comes from connecting genomic information with clinical data and treatment decisions. Genomic testing can identify disease-related variants or factors that may affect drug response. Clinical decision support can then combine these findings with medical history, laboratory results, and disease characteristics to guide treatment planning [23,24].

This integrated approach can create a continuous patient-care pathway. Genomics provides biological information, AI interprets complex data, clinical decision support connects the findings to medical decisions, and precision therapeutics uses them to guide treatment. Patient responses can then be added to the system for further assessment and treatment adjustment.

7.1 From Genomic Data to Clinical Decisions

Genomic findings have limited clinical value when they are considered separately from the patient's overall health status. AI can combine genomic information with clinical records and other patient data to identify patterns that may have direct clinical relevance. This can support disease-risk assessment, diagnosis, treatment selection, and prognosis [23].

7.2 From Clinical Decisions to Individualized Treatment

Clinical decision support provides a practical link between patient information and treatment planning. AI models can assess multiple variables at the same time and provide clinicians with patient-specific predictions or recommendations. In precision therapeutics, these predictions can support drug selection, dose planning, and treatment monitoring [24,25].

7.3 Continuous Treatment Optimization

Personalized medicine should not end with the initial treatment decision. Treatment response can change over time, and new clinical or genomic information may become available. AI can use these updates to reassess the patient's condition and support further treatment adjustments. This creates a cycle of data collection → AI analysis → clinical decision → treatment → response monitoring → updated decision.

This integrated model brings together the major components of personalized medicine and provides a foundation for its use across different disease areas. Fig 3 summarizes how these components interact throughout the patient-care pathway.

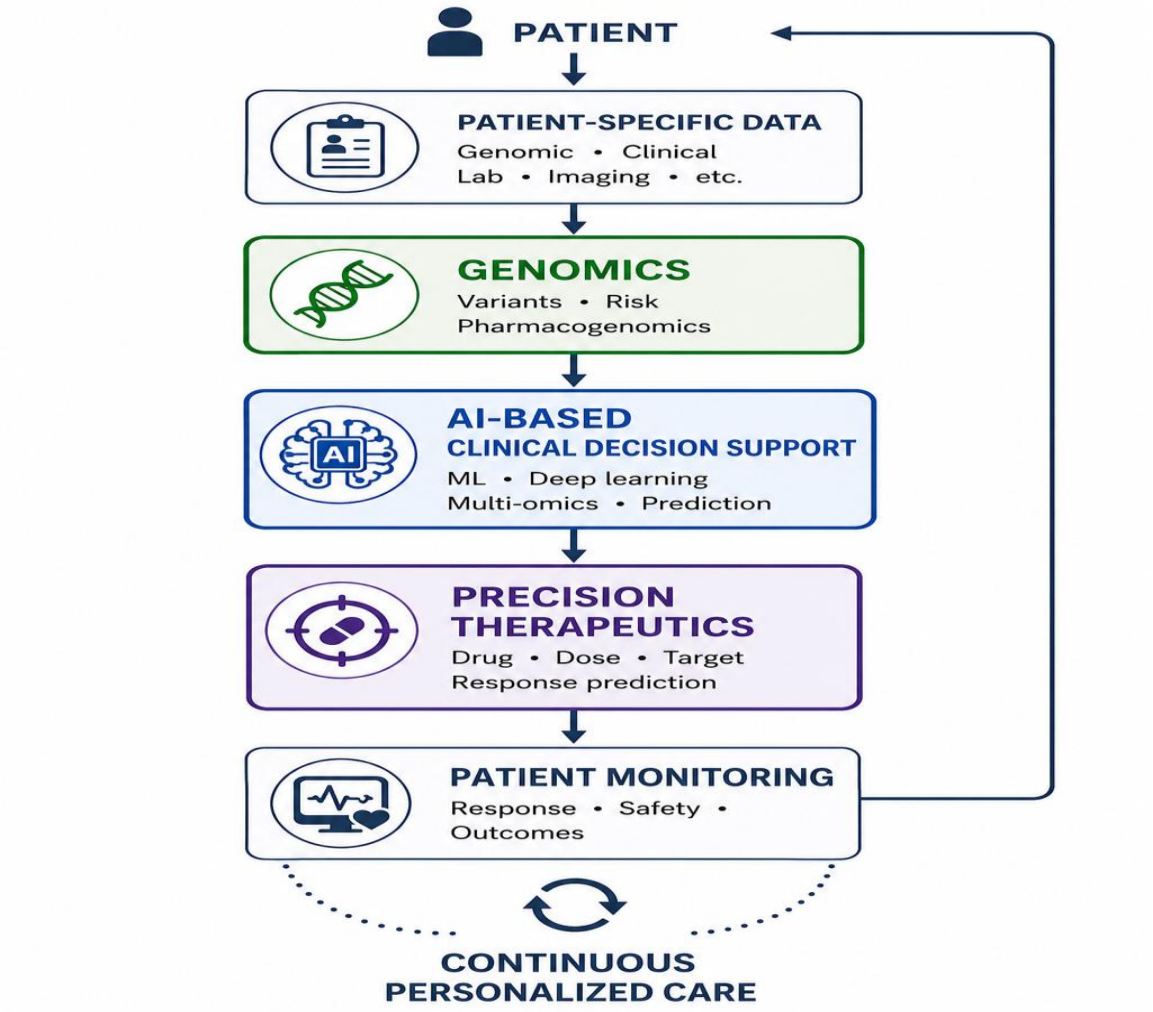

Fig 3. Integration of genomics, AI-based clinical decision support, and precision therapeutics in personalized patient care.

8. Clinical Applications of AI-Enabled Personalized Medicine

AI-enabled personalized medicine is being studied across different disease areas. Its main value comes from combining patient-specific information with clinical and molecular data to support diagnosis, treatment selection, and follow-up. The strongest applications are currently seen in cancer, cardiovascular disease, metabolic disorders, neurological conditions, and rare diseases [26,27].

8.1 Cancer

Cancer is one of the leading areas for precision medicine. Genomic profiling can identify mutations and molecular changes that influence treatment selection. AI enables the analysis of genomic, pathology, imaging, and clinical data to classify tumors, predict treatment response, and identify patients who may benefit from targeted therapies [26,28].

8.2 Cardiovascular Diseases

AI can combine clinical history, laboratory results, imaging, and genetic information to estimate cardiovascular risk and predict disease outcomes. These models may help

identify high-risk patients and support individualized prevention and treatment plans [25].

8.3 Diabetes and Metabolic Disorders

Personalized diabetes care can use information such as glucose patterns, medication history, lifestyle, and patient characteristics. AI models can assist in predicting glucose changes, treatment response, and the risk of complications. Combining this data with genetic information may further improve individual treatment planning [26].

8.4 Neurological Disorders

Neurological diseases often show considerable variation between patients. AI accurately processes the imaging, clinical records, genetic information, and other biological data to support diagnosis, disease progression assessment, and treatment selection. These methods are being explored in conditions such as Alzheimer's disease, Parkinson's disease, and epilepsy [34].

8.5 Rare and Inherited Diseases

Rare diseases can be difficult to diagnose because their clinical features may overlap with other disorders. AI-assisted genomic analysis examines disease-associated variants and connect genetic findings with clinical features. This can shorten the diagnostic process and support more appropriate treatment planning [35].

These applications show how AI can connect genomic and clinical information with disease-specific treatment decisions. Table 3 summarizes the major clinical applications of AI-enabled personalized medicine across different disease areas.

Table 3. Clinical applications of AI-enabled personalized medicine

Disease Area	Main Data Used	AI Application	Potential Clinical Value
Cancer	Genomics, pathology, imaging, clinical data	Tumor classification and treatment-response prediction	Targeted treatment selection
Cardiovascular disease	EHR, imaging, laboratory, and genetic data	Risk prediction and outcome assessment	Individualized prevention and treatment
Diabetes	Glucose, clinical, lifestyle, and medication data	Glucose and treatment-response prediction	Better treatment planning
Neurological disorders	imaging, clinical, and genetic data	Diagnosis and disease progression prediction	Earlier diagnosis and individualized care
Rare diseases	Genomic and clinical data	Variant interpretation and diagnosis	Faster diagnosis and treatment planning

9. Challenges and Limitations

AI-enabled personalized medicine has strong clinical potential, but several barriers must be focused before it can become part of routine care. These challenges involve data quality, privacy, bias, model interpretation, clinical validation, cost, and access [27,28]. Successful implementation will also depend on compliance with evolving regulatory frameworks, including guidance from the FDA, European Medicines Agency (EMA), World Health Organization (WHO), and the European Union Artificial Intelligence Act,

which highlight safety, transparency, and validation of AI-enabled medical technologies.

9.1 Data Quality and Interoperability

AI models depend on accurate and well-organized data. Missing records, inconsistent formats, and differences between healthcare systems can affect model performance. Genomic and clinical datasets also come from dissimilar sources. This makes data integration difficult [27].

9.2 Privacy and Data Security

Genomic and health records contain sensitive patient information. Their use in AI systems raises concerns about privacy, unauthorized access, and data sharing. Strong security measures and responsible data governance are needed to protect patient privacy [29].

9.3 Bias and Health Inequality

AI models can produce less reliable results when training datasets do not represent the populations in which they are later used. Genetic diversity, socioeconomic factors, and differences in access to healthcare can contribute to unequal performance. Varied datasets and regular evaluation across patient groups are important [30].

9.4 Explainability and Clinical Trust

Some AI models provide predictions without making the reasoning easy to understand. Clinicians need sufficient information to judge whether an AI-generated recommendation is appropriate for a particular patient. Explainable AI is essential to improve transparency and support responsible clinical use [15].

9.5 Clinical Validation and Regulation

Superior performance in a research dataset does not guarantee reliable performance in routine clinical practice. AI systems need external validation, prospective evaluation, and continuous monitoring. Regulatory frameworks must also keep pace with rapidly changing AI technologies [16,31].

9.6 Cost and Accessibility

Genomic testing, advanced computing systems, and AI-supported healthcare can be expensive. Differences in infrastructure and technical expertise may reduce access, especially in resource-limited settings. Future implementation should consider affordability and equitable access along with clinical performance. The major challenges associated with AI-enabled personalized medicine and possible strategies for addressing them are summarized in Table 4.

Table 4. Major challenges and possible strategies for implementing AI-enabled personalized medicine.

Challenge	Main concern	Possible strategy
Data quality and interoperability	Missing data, inconsistent formats, poor integration	Standardized data formats and improved data integration
Privacy and data security	Exposure of genomic and clinical information	Strong data protection and responsible data governance
Algorithmic bias	Unequal performance across patient groups	Diverse datasets and regular bias assessment
Explainability	Difficulty understanding AI predictions	Explainable AI and clinician oversight
Clinical validation	Inferior performance outside development settings	External validation and continuous monitoring

Cost and accessibility	Excessive cost and unequal access	Affordable technologies and wider infrastructure

These challenges show that successful personalized medicine requires more than accurate AI models. Fig 4 summarizes the major barriers and possible approaches for responsible implementation of AI-enabled personalized medicine.

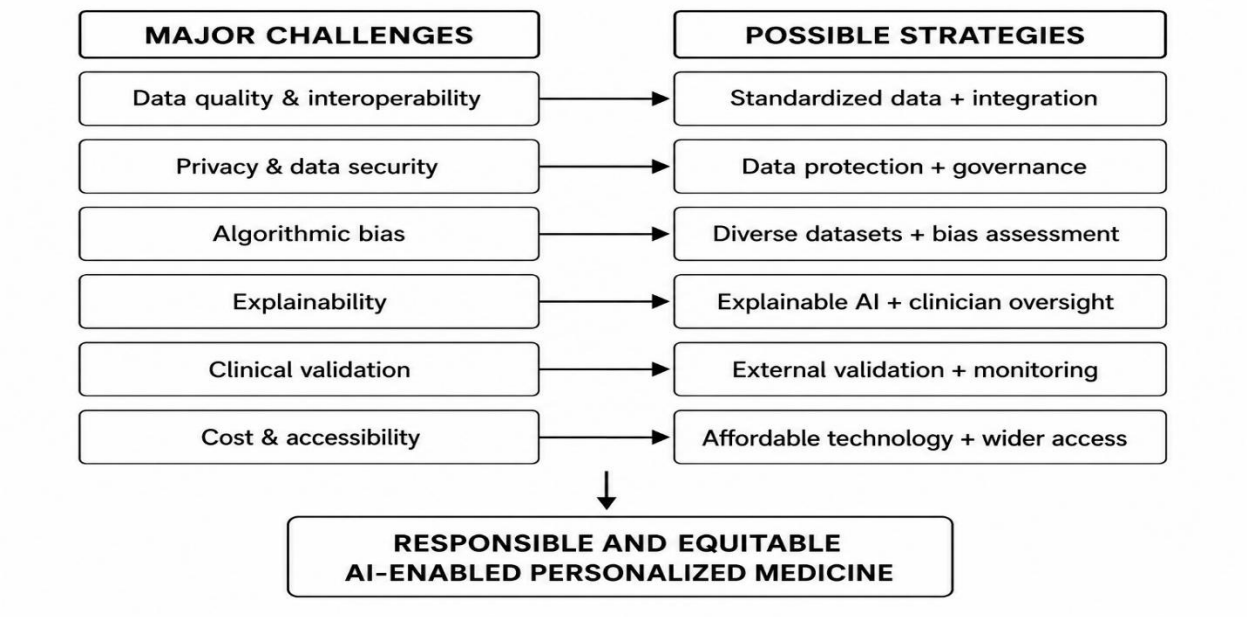

Fig 4. Major challenges and strategies for implementing AI-enabled personalized medicine.

10. Future Perspectives

AI-enabled personalized medicine is expected to become more integrated as genomic, clinical, and treatment data become easier to connect. Future systems may combine these sources to provide more complete patient profiles and support decisions throughout the treatment process [11,15].

10.1 Multimodal AI and Multi-Omics

Future AI systems may unite genomics with transcriptomics, proteomics, metabolomics, imaging, and clinical information. This can provide a broader view of disease biology and help identify biomarkers and treatment options that may not be clear from a single data source [11].

10.2 More Explainable and Reliable AI

Clinical adoption will require AI systems that clinicians can understand and evaluate. Research is moving toward models that provide clear explanations, undergo external validation, and are monitored after implementation. These steps can improve confidence in AI-supported clinical decisions [15].

10.3 Real-World and Continuous Personalized Care

Wearable devices, remote monitoring, and electronic health records can provide continuous information about changes in a patient's health. AI can analyze these data and help update treatment decisions as the patient's condition changes. This could make

personalized medicine more dynamic and responsive [32].

10.4 Wider Access and Responsible Implementation

Future development should focus on making genomic testing and AI-supported care affordable and accessible to diverse populations. Strong data governance, privacy protection, clinical oversight, and appropriate regulation will remain important as these technologies move into routine healthcare [33].

Overall, the future of personalized medicine will depend on how well AI can connect biological information with clinical knowledge and patient needs. The goal should be more accurate, evidence-based, and patient-centered care and clinicians must continue to guide important medical decisions.

11. Limitation

This review has certain limitations. It is a narrative review and therefore does not follow the methodology of a systematic review. multiple databases were searched, but only English-language publications were considered. The rapidly evolving nature of AI means that newly published studies may be available after completion of this review. Several AI applications discussed remain in the developmental or early implementation stage, limiting conclusions related to long-term clinical effectiveness.

12. Discussion

AI-enabled personalized medicine brings together genomic information, clinical records, and treatment-related data to support more individualized care. Genomic information can provide clues about disease risk and drug response, while clinical data provides the patient's current health status, treatment history, laboratory findings, and other factors that influence medical decisions. AI can help analyze these sources together and identify patterns that may be difficult to recognize when each source is considered separately [1,22,36]. The main value of this approach lies in connecting biological information with the actual clinical situation of the patient.

Genomic information alone does not always provide enough information for treatment selection. The meaning of a genetic variant may depend on disease characteristics, age, organ function, current medications, previous treatment response, and other clinical factors. AI-based analysis can help bring these variables together and support the interpretation of complex genomic data [6,7,12]. This is particularly significant when genomic testing produces large datasets that require careful interpretation before findings can be used in clinical care.

Pharmacogenomics provides another important link between genomics and treatment. Genetic differences can affect drug metabolism, therapeutic response, and the risk of adverse reactions. Pharmacogenomic information can therefore contribute to drug selection and dose planning [2,37]. Further value can be added by AI in combining genomic findings with clinical history, laboratory data, medication records, and previous treatment outcomes [18]. This suggests that precision therapeutics should not be viewed as treatment selection based on a single genetic marker. A more useful approach considers several patient-specific factors together.

The clinical applications reviewed in this manuscript also show that AI-enabled personalized medicine differs across disease areas. Cancer remains an important field because molecular profiling already has a role in treatment planning, and AI contributes in analyzing genomic, pathological, imaging, and clinical

information to support treatment decisions [19,26,28]. Cardiovascular disease and diabetes provide opportunities for risk prediction and monitoring through clinical, laboratory, medication, lifestyle, and patient-generated data [25,26]. Rare diseases also benefit from improved genomic diagnosis and interpretation, though the role of AI in these settings still requires further clinical evaluation [35]. These differences show that AI should not be considered a single technology with the same level of clinical readiness across all medical fields.

A key point from the reviewed literature is that technical accuracy alone is not enough to establish clinical value. A model may perform well during development but provide limited benefit when used with patients from another hospital, population, or healthcare system. Differences in data quality, clinical practice, patient characteristics, and healthcare infrastructure can affect performance [16,27]. External validation and prospective evaluation are therefore important before AI systems are used widely. The real measure of success should be whether an AI system improves clinical decisions, patient outcomes, safety, or the efficiency of care.

Clinical workflow is another major factor in successful implementation. AI systems must provide information in a form that healthcare professionals can understand readily and use without adding unnecessary complexity to routine therapy. Poorly integrated systems may increase workload even after having strong technical performance. Clinicians also need clear information about the intended use, limitations, and expected performance of an AI tool. Collaboration between clinicians, researchers, data scientists, healthcare organizations, and regulatory bodies is important for responsible clinical translation [14,16].

Transparency in development and evaluation also has a vital role. TRIPOD+AI provides updated guidance for reporting clinical prediction models based on regression or machine learning methods [40]. The CONSORT-AI and SPIRIT-AI extensions provide guidance for clinical trials involving AI-based interventions [38,39]. These reporting standards can help researchers describe how AI systems were developed, evaluated, and used in clinical settings. Better reporting also makes it easier to compare studies and judge whether reported performance is relevant to real patient care.

Multiple challenges remain before AI-enabled personalized medicine can become part of routine healthcare. Poor-quality or incomplete data can affect model reliability. Privacy concerns are also particularly important when genomic and clinical information are combined [27,29]. Algorithmic bias can also lead to unequal performance across patient groups when training data do not adequately represent the populations in which the system will be used [30]. This is a major concern in personalized medicine because genetic background, disease prevalence, healthcare access, and clinical characteristics can differ between populations. Different datasets and evaluations across relevant patient groups are needed to identify and reduce such problems.

Explainability and clinical judgment remain equally important. Clinicians need enough information to judge whether an AI-generated prediction or recommendation accurately matches the patient's condition [15,17]. Patient preferences, treatment goals, and clinical circumstances should continue to influence medical decisions. AI should therefore be used as a clinical support tool, and healthcare professionals should have responsibility for the final decision.

Another critical issue is the difference between prediction and actual clinical benefit. An AI model may accurately predict disease risk or treatment response without improving patient outcomes when used in practice. Research should move from developing and testing AI models to validating them in different settings, evaluating them in future studies, and measuring their real-world clinical benefits. This is particularly important when AI recommendations affect medication selection, dosing, treatment monitoring, or long-term care.

Cost and access may also determine who benefits from these technologies. Genomic testing, computing infrastructure, skilled personnel, and digital healthcare systems require substantial resources. If these technologies remain concentrated in well-resourced healthcare settings, patients in resource-limited regions may have fewer opportunities to benefit from personalized care. Future implementation should therefore consider affordability, infrastructure, data representation, and access to trained healthcare professionals together with model performance.

Overall, the evidence supports a gradual move toward a more connected model of personalized care. Genomics can provide information about biological variation, AI has the ability to interpret complex datasets, clinical decision support can connect these findings with medical decisions, and precision therapeutics can use this information to guide treatment. The clinical value of this approach will depend on reliable data, appropriate validation, transparent reporting, responsible implementation, and continued clinical oversight [32,33]. The goal should be to use AI where it provides clear clinical value and contributes to safer and more individualized patient care.

13. Conclusion

AI is becoming an important part of personalized medicine by connecting genomic, clinical, and treatment-related information. Genomic analysis can provide information about disease risk and drug response, while AI can integrate these findings with clinical records, laboratory results, imaging, medication history, and treatment outcomes. This approach can support disease-risk assessment, treatment selection, dose planning, treatment-response prediction, and patient monitoring.

The reviewed evidence shows applications across cancer, cardiovascular disease, diabetes, neurological disorders, and rare diseases, but the level of clinical development differs between these areas. Important challenges remain, particularly data quality, privacy, algorithmic bias, explainability, external validation, cost, and equitable access. Technical performance alone cannot establish clinical usefulness. Prospective evaluation and assessment of real-world patient benefits are needed before AI systems become part of routine care [16,27,38-40].

Future progress will be based on better integration of genomic and clinical data, diverse patient populations, secure data governance, appropriate regulation, and stronger clinical evidence. AI should support clinical expertise and patient preferences, with healthcare professionals continuing to guide important medical decisions. When developed, evaluated, and implemented responsibly, the integration of AI, genomics, clinical decision support, and precision therapeutics can contribute to more precise, patient-centered, and responsive healthcare.

Future success will depend not only on technological innovation but also on stringent clinical validation, transparent reporting, regulatory oversight, ethical

governance, and equitable access. AI should complement instead of replacing clinical expertise, permitting healthcare professionals to deliver safer, more effective, and truly personalized patient care.

References

1. Ashley EA. Towards precision medicine. Nat Rev Genet. 2016;17(9):507-522. doi:10.1038/nrg.2016.86.

2. Pirmohamed M. Pharmacogenomics: current status and future perspectives. Nat Rev Genet. 2023;24(6):350-362. doi:10.1038/s41576-022-00572-8.

3. Collins FS, Varmus H. A new initiative on precision medicine. N Engl J Med. 2015;372(9):793-795. doi:10.1056/NEJMp1500523

4. Sutton RT, Pincock D, Baumgart DC, Sadowski DC, Fedorak RN, Kroeker KI. An overview of clinical decision support systems: benefits, risks, and strategies for success. NPJ Digit Med. 2020;3:17. doi:10.1038/s41746-020-0221-y.

5. Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, et al. A guide to deep learning in healthcare. Nat Med. 2019;25(1):24-29. doi:10.1038/s41591-018-0316-z.

6. Zou J, Huss M, Abid A, Mohammadi P, Torkamani A, Telenti A. A primer on deep learning in genomics. Nat Genet. 2019;51(1):12-18. doi:10.1038/s41588-018-0295-5.

7. Eraslan G, Avsec Ž, Gagneur J, Theis FJ. Deep learning: new computational modelling techniques for genomics. Nat Rev Genet. 2019;20(7):389-403. doi:10.1038/s41576-019-0122-6.

8. Libbrecht MW, Noble WS. Machine learning applications in genetics and genomics. Nat Rev Genet. 2015;16(6):321-332. doi:10.1038/nrg3920.

9. Roden DM, McLeod HL, Relling MV, Williams MS, Mensah GA, Peterson JF, et al. Pharmacogenomics. Lancet. 2019;394(10197):521-532. doi:10.1016/S0140-6736(19)31276-0.

10. Subramanian I, Verma S, Kumar S, Jere A, Anamika K. Multi-omics data integration, interpretation, and its application. Bioinform Biol Insights. 2020;14:1177932219899051. doi:10.1177/1177932219899051.

11. Karczewski KJ, Snyder MP. Integrative omics for health and disease. Nat Rev Genet. 2018;19(5):299-310. doi:10.1038/nrg.2018.4.

12. Goldstein BA, Navar AM, Pencina MJ, Ioannidis JP. Opportunities and challenges in developing risk prediction models with electronic health records data: a systematic review. J Am Med Inform Assoc. 2017;24(1):198-208. doi:10.1093/jamia/ocw042.

13. Shickel B, Tighe PJ, Bihorac A, Rashidi P. Deep EHR: a survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. IEEE J Biomed Health Inform. 2018;22(5):1589-1604. doi:10.1109/JBHI.2017.2767063.

14. Sendak MP, D'Arcy J, Kashyap S, Gao M, Nichols M, Corey K, et al. A path for translation of machine learning products into healthcare delivery. EMJ Innov. 2020. doi:10.33590/emjinnov/19-00172.

15. Amann J, Blasimme A, Vayena E, Frey D, Madai VI; Precise4Q Consortium. Explainability for artificial intelligence in healthcare: a multidisciplinary perspective. BMC Med Inform Decis Mak. 2020;20(1):310. doi:10.1186/s12911-020-01332-6.

16. Wiens J, Saria S, Sendak M, Ghassemi M, Liu VX, Doshi-Velez F, et al. Do no harm: a roadmap for responsible machine learning for health care. Nat Med. 2019;25(9):1337-1340. doi:10.1038/s41591-019-0548-6

17. Rajkomar A, Dean J, Kohane I. Machine learning in medicine. N Engl J Med. 2019;380(14):1347-1358. doi:10.1056/NEJMra1814259.

18. Paul D, Sanap G, Shenoy S, Kalyane D, Kalia K, Tekade RK. Artificial intelligence in drug discovery and development. Drug Discov Today. 2021;26(1):80-93. doi:10.1016/j.drudis.2020.10.010.

19. Kourou K, Exarchos TP, Exarchos KP, Karamouzis MV, Fotiadis DI. Machine learning applications in cancer prognosis and prediction. Comput Struct Biotechnol J. 2014;13:8-17. doi:10.1016/j.csbj.2014.11.005**.**

20. Vamathevan J, Clark D, Czodrowski P, Dunham I, Ferran E, Lee G, et al. Applications of machine learning in drug discovery and development. Nat Rev Drug Discov. 2019;18(6):463-477. doi:10.1038/s41573-019-0024-5.

21. Harrer S, Shah P, Antony B, Hu J. Artificial intelligence for clinical trial design. Trends Pharmacol Sci. 2019;40(8):577-591. doi:10.1016/j.tips.2019.05.005.

22. Johnson KB, Wei WQ, Weeraratne D, Frisse ME, Misulis K, Rhee K, et al. Precision medicine, AI, and the future of personalized health care. Clin Transl Sci. 2021;14(1):86-93. doi:10.1111/cts.12884.

23. Meskó B, Görög M. A short guide for medical professionals in the era of artificial intelligence. NPJ Digit Med. 2020;3:126. doi:10.1038/s41746-020-00333-z.

24. Denny JC, Collins FS. Precision medicine in 2030—seven ways to transform healthcare. Cell. 2021;184(6):1415-1419. doi:10.1016/j.cell.2021.01.015.

25. Johnson KW, Torres Soto J, Glicksberg BS, Shameer K, Miotto R, Ali M, et al. Artificial intelligence in cardiology. J Am Coll Cardiol. 2018;71(23):2668-2679. doi:10.1016/j.jacc.2018.03.521.

26. Contreras I, Vehi J. Artificial intelligence for diabetes management and decision support: literature review. J Med Internet Res. 2018;20(5):e10775. doi:10.2196/10775.

27. Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. BMC Med. 2019;17(1):195. doi:10.1186/s12916-019-1426-2.

28. Yu KH, Beam AL, Kohane IS. Artificial intelligence in healthcare. Nat Biomed Eng. 2018;2(10):719-731. doi:10.1038/s41551-018-0305-z.

29. Price WN 2nd, Cohen IG. Privacy in the age of medical big data. Nat Med. 2019;25(1):37-43. doi:10.1038/s41591-018-0272-7.

30. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science. 2019;366(6464):447-453. doi:10.1126/science.aax2342.

31. Muehlematter UJ, Daniore P, Vokinger KN. Approval of artificial intelligence and machine learning-based medical devices in the USA and Europe (2015-20): a comparative analysis. Lancet Digit Health. 2021;3(3):e195-e203. doi:10.1016/S2589-7500(20)30292-2.

32. Coravos A, Khozin S, Mandl KD. Developing and adopting safe and effective digital biomarkers to improve patient

outcomes. NPJ Digit Med. 2019;2(1):14. doi:10.1038/s41746-019-0090-4.

33. World Health Organization. *Ethics and governance of artificial intelligence for health: WHO guidance.* Geneva: World Health Organization; 2021

34. Pellegrini E, Ballerini L, Hernandez MDCV, Chappell FM, González-Castro V, Anblagan D, et al. Machine learning of neuroimaging for assisted diagnosis of cognitive impairment and dementia: a systematic review. Alzheimers Dement (Amst). 2018;10:519-535. doi:10.1016/j.dadm.2018.07.004.

35. Clark MM, Stark Z, Farnaes L, Tan TY, White SM, Dimmock D, et al. Meta-analysis of the diagnostic and clinical utility of genome and exome sequencing and chromosomal microarray in children with suspected genetic diseases. NPJ Genom Med. 2018;3:16. doi:10.1038/s41525-018-0053-8.

36. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44-56. doi:10.1038/s41591-018-0300-7.

37. Relling MV, Evans WE. Pharmacogenomics in the clinic. Nature. 2015;526(7573):343-350. doi:10.1038/nature15817.

38. Liu X, Cruz Rivera S, Moher D, Calvert MJ, Denniston AK; SPIRIT-AI and CONSORT-AI Working Group. Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension. Nat Med. 2020;26(9):1364-1374. doi:10.1038/s41591-020-1034-x.

39. Cruz Rivera S, Liu X, Chan AW, Denniston AK, Calvert MJ; SPIRIT-AI and CONSORT-AI Working Group; SPIRIT-AI and CONSORT-AI Steering Group; SPIRIT-AI and CONSORT-AI Consensus Group. Guidelines for clinical trial protocols for interventions involving artificial intelligence: the SPIRIT-AI extension. Nat Med. 2020;26(9):1351-1363. doi:10.1038/s41591-020-1037-7.

40. Collins GS, Moons KGM, Dhiman P, Riley RD, Beam AL, Van Calster B, et al. TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. BMJ. 2024;385:e078378. doi:10.1136/bmj-2023-078378.