



# Harnessing Artificial Intelligence for the Future of Precision Medicine: Transforming Patient-Centric Care Through Data- Driven Innovation

Heli Patel, Deep Sathwara, Vivekraj Maheshwari, Disha Joshi

<sup>1</sup>*Department of Pharmaceutical Technology, L. J. Institute of Pharmacy, LJ University, Ahmedabad,  
Gujarat-382210.*

**Corresponding author:** Disha Joshi

**Email:** [dishaa2612@gmail.com](mailto:dishaa2612@gmail.com)

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## **Abstract:**

Advancements in artificial intelligence (AI) are steadily reshaping the landscape of modern medicine, particularly in the context of precision healthcare. In 2024, the global AI healthcare market surged to \$ 32.34 billion, with 80 % of hospitals adopting AI to enhance patient care and workflow efficiency. By drawing on complex datasets that range from genomic profiles to real-time health signals, AI is paving the way for more personalized diagnosis, treatment, and prevention strategies. In clinical settings, technologies such as digital twins and federated learning enable safer, privacy-preserving models of care while improving disease outcome predictions and therapy responses. Moreover, the integration of AI with wearable devices and Internet of Things (IoT) platforms supports continuous patient monitoring and early detection of chronic and acute conditions. These innovations facilitate proactive health interventions and empower individuals to take charge of their health beyond clinical environments. AI's influence extends to drug discovery and dosing optimization, making treatment plans more effective and cost-efficient. However, these technological gains are accompanied by pressing ethical and regulatory considerations, ranging from algorithmic bias and data privacy to trust in AI systems and the need for flexible, forward-thinking policies. Addressing these concerns requires robust governance frameworks and collaborative efforts across disciplines. Altogether, AI-driven precision medicine marks a shift from generalized treatment models toward targeted, patient- centered care, with the potential to enhance therapeutic outcomes, reduce healthcare disparities, and contribute meaningfully to global health improvement.

**Keywords:** Artificial Intelligence (AI), Precision Medicine, Digital Twins, Federated Learning, Wearable Technology, Predictive Healthcare

## **Introduction:**

Precision medicine redefines therapy and prevention according to genetic, environmental, and behavioral determinants [1]. Integration of "OMICS" and "EXPOsOMICS" with body wearables makes advanced diagnostics possible and demands increased data infrastructure for the analysis and quantification of wide-range health data [2]. AI including ML, DL, and ANN makes personalized medicine possible through analysis of patterns from structured data and increased prediction precision and effectiveness against disease [1,2]. Automated diagnostic systems merge human experience with the precision of AI through the use of rule-based intelligent systems for assisting clinical decision-making and controlling workflow [3]. AI-driven automation supplants traditional processes, and ANN mimics the brain neuron for enabling efficient therapies, customize therapeutic practices, and improving patient outcomes [4]. AI also facilitates drug discovery, repurposing, and customized dosing via adverse event prediction and optimization of treatment regimens. With more AI

development, its application in medicine will enhance medical precision, rationalize treatments, and optimize overall health outcomes, leading to more preventive and patient- centered care.

*Applications of AI in Healthcare field:*

Technologies driven by AI are set to significantly transform the functioning, optimization, and patient interaction of healthcare systems, while also enhancing care services to improve the overall efficiency of patient outcomes [1].

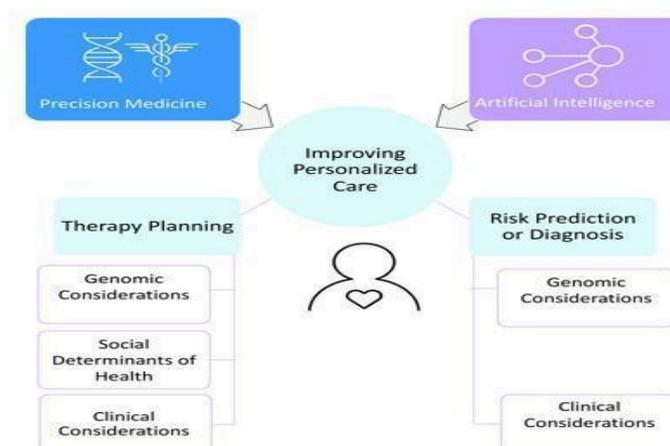
1. Diagnostic Assistance
2. Nursing and Managerial Assistance
3. Risk Prediction and Early Intervention
4. Integration with Human Expertise
5. Clinical Decision Support and Augmented Intelligence

*Challenges Involved with AI Applications:*

Although AI applications provide new opportunities for enhancing day-to-day life, they also create issues that should be resolved carefully. In the healthcare field, thus-created issues can be more in quantity since they have direct impacts on human lives. Some of the issues that should be resolved carefully are elaborated in detail below:

1. Accountability of System Usage
2. Privacy and Security Cybersecurity
3. Loss of Managerial Control
4. Loss of Employment, Vocational Rehabilitation/skill Training Necessary, and Persecution due to Change [2] Example: An emergency department physician seeing a febrile child ought to make a diagnosis of severe illness like meningococcal meningitis to justify immediate therapy and reassure patients with self-limited infection not to risk exposure to inapplicable therapy. Stratified diagnosis is useful to decrease inappropriate testing and treatment of low- risk patients and improve decision-making at the bedside. Research cited with improved results for new diagnosis technology before its use—either through added disease detection, cost reduction, or safety. Innovations need to be ultimately for the betterment of the prognosis of the patients even if supporting evidence often times falls short in quantity [3].

Precision Medicine, AI, and the Future of Personalized Health Care



## 1 Convergence of AI and Precision Medicine:

### 1.1 Omics and AI:

Omics provide an unprecedented overview of any biological system of interest at an exceptional resolution. The combination of high resolution and high-throughput results is referred to as “Omics,” a term widely used to describe the comprehensive analysis of molecular characteristics and the quantification of biological molecules from various areas of molecular biology through the use of high-throughput technology. Numerous “omics” terms have emerged based on the different types of biomolecules present in human cells [4]. Furthermore, AI holds significant potential for integrative multi-omics analysis, thereby propelling the field of systems biology forward.

Types of multi-omics fusion:

Multi-omics integration is the combination of information from two or more omics layers (such as genomics, transcriptomics, proteomics, and metabolomics) to obtain an integrated view of biological systems and disease mechanisms. The major multi-omics integration forms are:

1. Personalized proteomic analysis improves the diagnostic sensitivity to establish the extent of disease in accessible samples of tissue in order to ensure timely medical management for better results [5]. Biomarker surveillance and proteomics enable research using better treatment success and diagnosis for orphan diseases but are technology and cost constrained [6]. In the clinic, they enable diagnosis, biomarker surveillance, and best therapy selection.
2. Metabolomics is studying the metabolome, a biochemical network within liquids, tissues, and cells, and genomics and other omics technologies [13]. Mass spectrometry and nuclear magnetic resonance spectroscopy are tools to unveil complex patterns to allow accurate predictions. Metabolomics is enabled by AI to convert raw data, find biomarkers, and construct predictive models for clinical discovery [14].
3. Genomics allows genome mapping, organization, and function, and pharmacogenomics uses genetic markers to tailor drug and dose [5]. CRISPR-Cas9 is a gene editor that improves species editing boundaries, improving disease modeling and comprehension [6]. The technology allows treatment of chronic illnesses like cancer, leukemia, HIV,  $\beta$ -thalassemia, and sickle cell anemia [7].
4. Transcriptomic resources form a very important part of biomedical science, especially in diagnosis and disease profiling [18]. The RNA-Seq resource allows us to interrogate human health by locating transcription start sites, splicing isoforms, and alternative promoters [19]. It also detects disease-associated SNPs, allele-specific expression, and gene fusions, which are valuable information regarding disease mechanisms [20].

### 1.2 AI in Imaging and Diagnosis:

AI recasts radiologic evaluation, redefining cardiology, genomics, pathology, drug discovery, and healthcare delivery, raising the level of care [5]. Deep learning maximizes MRI, CT, and PET imaging acquisition, speeding the scan without compromising on quality [6]. Panomics unifies genomics, transcriptomics, proteomics, and metabolomics to deliver medicine targeted to an individual [7]. AI pathology revolutionizes microscopic examination of tissue, improving diagnosis and allowing telemedicine through digital pathology [8,9]. Radiomics recasts advanced radiologic data sets, improving medical decision making in the spirit of reproducibility, standardization, and validation challenges [10,11]. AI radiomics makes it possible to predict progression of disease, response to treatment, and survival, revolutionizing oncology [12]. Wearable health sensors provide extended monitoring, allowing early detection of change in health and the impact of targeted interventions [13]. Democratizing digital healthcare, they allow extended monitoring at home and allow derivation of predictors of health events [14]. Clinical biomarkers are measurable markers of disease diagnosis, outcome prediction, and monitoring for response to treatment, allowing deployment of AI to new medicine.

## 2 Smart Drug Discovery and Dose

### 2.1 Drug Discovery and dosing to shorten drug development

The process of development of new drugs is expensive and time-consuming; it can take more than ten years. Target identification, lead compound optimisation, preclinical research, and clinical trials are some of the phases that are involved, and they demand a substantial investment of time and money. The high failure rate suggests that the majority of potential medications fail at an advanced stage, which raises expenses [5].

### 2.2 Generative AI in Lead Compound Design

Lead compound discovery is a vital process in drug design that earlier was conducted traditionally with large amounts synthesis, high-throughput screening, and multiple testing. This is optimized by AI using deep generative models that, independently, create molecules with the best drug-like pharmacokinetic and pharmacodynamic properties [6]. ML- trained software such as variational autoencoders (VAEs), generative adversarial networks (GANs), and reinforcement learning algorithms predict molecular structure and interaction and screen top drug candidates many orders of magnitude quicker than classical ways [7]. These computational codes enable real-time molecular design and lower lab experiments by several orders of magnitude. Furthermore, AI-based virtual screening also enables molecular interaction modeling, prediction of efficacy and toxicity of drugs before they are subjected to preclinical screening. Pre-screening the strongest candidates in advance increases the possibility of identifying potential treatments with lesser wastage of resources [8].

For instance, Jia Xu et al. 2019 explored AI application in de novo drug discovery and demonstrated how DL models predict and optimize lead compounds using molecular interaction simulations model of antimicrobial agents and led to the identification of novel antibiotics by reducing research cycles by quite a significant amount. In line with structure molecular design, AI is applied in drug optimization of features such as bioavailability, toxicity, stability, and drug interaction profiles [9]. By predicting valuable features prior to laboratory confirmation, machine learning models enhance the success of subsequent development. AI-based drug discovery platforms are being used by pharmaceutical companies to increase productivity and reduce expenses. AI is transforming therapeutic development by providing opportunities for low-cost drug manufacturing and speeding up the discovery of lead compounds [10].

Num ber	Drug discovery software based on AI	Auxiliary direction	Advantages	Referen ces
1	DeepDrug	Detecting the genomes of pathogen	Can access very large datasets and quickly identify new compounds	[11]
2	Reinvent	Mainly used for molecular generation	Can conduct AI molecular design	[12]
3	AlphaFold	Predicting the structure of proteins	Help understand the interaction between drugs and targets	[13]
4	SwissADME	Predicting the oral bioavailability of compounds, etc.	Quickly screen potential drug candidates in the early stages of drug development	[14]

5	ADMETSAR	Predicting the toxicity of drug molecules	Plays an important role in drug development and safety evaluation	[15]
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### 2.3 AI Drug Repurposing: Example with COVID-19

Drug repurposing, or the science of finding new uses for already approved drugs, is one area in which AI has transformed pharma development. Since repurposed drugs have an existing safety profile, they bypass much of the frontloading of preclinical and early clinic trials, cutting down approval times by a whopping percentage [16].

By searching for antiviral compounds and deactivating SARS-CoV-2, AI expedited the drug search during COVID-

19. AI selected Remdesivir and Dexamethasone as possible treatments after machine learning programs used biomedical databases to predict effective compounds [17]. Faster patient care is now possible thanks to AI's acceleration of clinical trials and emergency use authorisations for medications. During international health emergencies, AI-screened compounds based on hydroxychloroquine and other molecules to prevent virus replication can be used as live therapeutic solutions. AI has also been applied to the repurposing of drugs for the treatment of cancer, neurodegenerative diseases, metabolic disorders, and orphan diseases. Using patient data, gene biomarkers, and drug-target interactions, machine learning techniques forecast potential therapeutic uses [18].

## 3 Personalized Therapeutics and Treatment Optimization

### 3.1 Dose Optimization Using AI models

Pharmacogenomics, or the union of drug and genetics, is very crucial in the rationalization of medication dosing. ML models predict drug efficacy, absorption, and metabolism as a function of patient-specific genetic variation [1]. Practice today's standard dosing usually depends on population means and thus results in inefficiencies, less-than-optimal effects, or even ADRs in patients with a rare genetic basis. The pharmacokinetics of ML models improves precision dosing with genetic markers, metabolic rate, and drug-drug interaction. AI enhances precision prescribing through drug regimens that are personalized and target maximal effect with minimum harm [3]. A peer-reviewed article on Antibiotics showcased the future potential of AI in suggesting optimal doses for antibiotics and by-products of minimizing resistance and side effects [19]. Pharmacogenomic tools enabled by AI have also been effective at tailoring chemotherapy doses according to a patient's drug clearance rates, with the aim of minimizing side effects without compromising therapeutic effect.

For instance, AI pharmacogenomic applications maximized warfarin dosage in order to prevent excessive bleeding from genetic heterogeneity patients due to drug metabolization. Similarly, personalized medicine approach of oncology provides the desired dose to an individual subtype of cancer and inhibits toxic misuse while guaranteeing optimal efficacy [20].

### 3.2 Real-Time Monitoring with Wearables for Dose Adjustments

Wearable tech is transforming medicine with the potential to monitor biomarkers from patients in real time, which can be interpreted by AI to dynamically control dosing of drugs. Wearables like biosensors, smartwatches, and implantable sensors track vital signs around the clock, allowing medication schedules to react to changes in physiology. AI-empowered wearables track parameters such as blood glucose, blood pressure, heart rate variability, and breathing patterns, allowing AI algorithms to optimize dosing schedules [21].

Trevor T. Duarte et al. 2016 was about the part that is played by AI for real-time tracking of health and how AI-wearables make medication shifting possible in chronic disease. Continuous glucose monitors, for instance, if

coupled with AI, regulate insulin dosing automatically in order to gain maximum control of blood sugar in diabetic patients [22]. AI-based wearables for the disorder Parkinson's disease track severity of tremor and adjust dosing accordingly, achieving maximum symptom control with decreased side effects. Cardiovascular patients also benefit from real-time monitoring, with wearable sensors tracking blood pressure fluctuations that enable AI models to fine-tune antihypertensive therapy most optimally [23].

### 3.3 AI-Based ADR Prediction and Case Study

ADR prediction is essential in trying to maximize drug safety. Pharmacovigilance through the use of AI employs machine learning software to conduct electronic health records, genomic information, patient-reported outcomes, and molecular interaction and identify the risk factors of ADRs [24]. J. Chi *et al.* 2024 discussed how AI minimizes drug errors and ADR predictions are well predicted, hence hospital stays and drug issues are minimized. AI models flag drug interaction patterns so that clinicians can avoid harmful side effects beforehand [25].

#### 3.3.1 Case Study: AI-Based ADR Predictions

AI-based models forecast chemotherapy-induced toxicity on the basis of patient-specific genetic biomarkers and metabolic rates [26]. An example is AI-based screening of cisplatin-induced nephrotoxicity to facilitate dose adjustment without loss of therapeutic effect and prevent kidney damage. AI improves drug safety in neurological disorders by forecasting ADR from antiepileptic drugs. AI systems evaluate genetic variation in drug metabolism to optimize valproate dosing more effectively in an attempt to avoid liver toxicity and neurotoxicity. AI pharmacogenomics has been enhanced to provide a more effective therapy approach for Fabry disease, a deficiency genetic disease of enzyme function [27]. AI models forecast the outcome of one patient's response to enzyme replacement therapy, such as individualized dosing optimization and fewer complications during treatment [28].

## 4 Future Trends and Innovations

### 4.1 Digital Twins In Precision Medicine

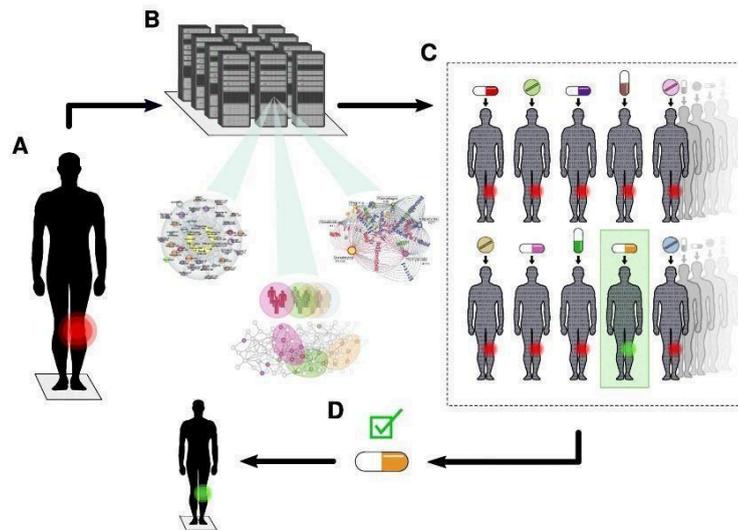
Digital twins (DTs) are virtual models that continuously update real-time data from their physical counterparts, so allowing the simulation, monitoring, and system optimization of many kinds [7]. Their integration of cutting-edge technologies, such AI and ML, has changed them across several sectors, especially in healthcare [9]. DTs, also referred to as Digital Human Twins, or DHTs, are used in silico simulations and customized medicine to create comprehensive digital representations of patients in order to enhance disease prevention, diagnosis, and treatment [10].

Using DTs in healthcare calls for a sophisticated architecture combining multidisciplinary cooperation, cloud computing, ANNs, and vast biological data repositories. DTs are under investigation as the demand for better care increases, since they could enhance patient outcomes and medical diagnostics [17]. Future trends indicate that, despite potential implementation challenges, the ongoing development of DT technology will gradually increase its relevance in personalized medicine and public health, supported by advancements in IoT and data analytics [1].

#### Case Studies Deployment of DHTs in Healthcare:

1. **Personalized Treatment in Oncology:** Individualized cancer treatment depends much on DTs. Björnsson *et al.* conducted a 2020 study showing their capacity to forecast individual treatment responses, enabling oncologists to customize treatments for maximum efficacy. DTs have great potential to improve patient outcomes and lower side effects by simulating different therapy results, so optimizing cancer treatment [3].
2. **Surgical Planning and Optimization:** Particularly in high-risk cardiovascular operations, DTs are absolutely important in surgical planning and optimization. A 2020 Corral-Acero *et al.* study shows that by simulating interventions and foreseeing possible complications by modeling patient hearts with DTs, surgeons can help to lower postoperative complications. This technology underlines its great influence on precision since it improves recovery times and general patient outcomes and helps to create individualized surgical plans [4].

3. **Chronic Disease Management with IoT-Enabled Digital Twins:** By allowing real-time monitoring using IoT technology, DTs significantly help to manage chronic diseases including diabetes. A 2024 report by Katsoulakis et al. claims that these systems constantly monitor important indicators including glucose levels, which enables dynamic changes to therapy plans. Through precision health management, pilot studies have shown that this continuous feedback loop improves glycemic control and lowers hospitalization rates, so stressing the need of DTs in improving patient quality of life [21].
4. **Predicting Outcomes in Cardiovascular Disease:** Predicting outcomes in patients with cardiovascular disease is where DTs are becoming quite important. A 2020 Corral-Acero et al. study revealed their capacity to predict patient reactions to drugs in heart failure cases, so improving outcomes 25% above baseline treatment. By allowing more customized and efficient treatment plans, DTs show their potential to improve precision medicine [22].



The digital twin concept for personalized medicine. a An individual patient has a local sign of disease (red). b A digital twin of this patient is constructed in unlimited copies, based on computational network models of thousands of disease-relevant variables. c Each twin is computationally treated with one or more of the thousands of drugs. This results in digital cure of one patient (green). d The drug that has the best effect on the digital twin is selected for treatment of the patient. (<https://doi.org/10.1186/s13073-019-0701-3>)

#### 4.2 Edge Of Ai and Federated Learning

Because of its ability to avoid privacy issues related to conventional centralized ML approaches, FL is gaining paramount importance in the healthcare industry. FL enables health organizations to take advantage of big-scale ML without revealing raw patient information by enabling distributed model training at the data source—hospitals, mobile devices, and IoT-based medical devices [13]. This strategy is privation compliant with privacies like the Health Insurance Portability and Accountability Act of 1996. (HIPAA) and the General Data Protection Regulation (GDPR), and thus reducing the data exposure risks [15].

In intelligent health systems that leverage IoT sensors, wearables, and electronic health records (EHRs) for real-time monitoring of patients, FL provides high utility [43]. As these systems generate huge amounts of precious data, FL ensures security by ensuring updates aggregate without the sharing of confidential information [18]. It relies on such use cases as remote patient monitoring, personalized medicine, clinical decision support, analysis of large medical images, and patient risk prediction. In total, FL not only safeguards personal data in hospital IoT networks but also renders providers and patients of AI systems trustful [19].

Application	FL Improvement over Centralized Models	Critical Limitations/Effectiveness/Impa	Evaluation of	Reference
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Disease Prediction	FL ensures privacy and reduces the risk of data breaches by offering secure, decentralized training on patient data across hospitals.	Models can be biased by limited cross-institutional cooperation and data heterogeneity; hence, real-world validation is essential to guarantee their efficacy.	[29]
Remote Monitoring	FL analyzes wearable device	The variations in device data quality	[30]

	data to facilitate cross-device continuous learning without revealing personal health information.	and irregular availability seriously compromise model accuracy and training.	
Medical Image Diagnosis	By using a variety of dispersed medical image datasets without centralizing storage, FL improves model performance.	Data imbalance and communication overhead impede generalizing and real-time use of FL.	[31]
Personalized Treatment Plans	More accurate and individualized treatments are made possible by FL, which protects patient data while facilitating the exchange of knowledge from various patient populations.	Variations in local datasets complicate the integration of treatment strategies; high computational costs could thus impede their scalability.	[32]
Clinical Trial Recruitment	FL improves recruitment tactics, protects sensitive data, and helps identify trial candidates across institutions.	The recruitment accuracy may be reduced due to inconsistent inclusion/exclusion criteria and lack of central oversight.	[33]
Chronic Disease Management	By gathering information from long-term patients, FL improves prediction models for the course and treatment of diseases.	Lack of data from underrepresented groups might skew forecasts, compromising accuracy and fairness.	[34]

Predictive Health Analytics	While protecting patient privacy, FL enables predictive models to learn from a variety of data sources, including wearables and medical records.	Limited data can result in erroneous forecasts; consistency in data will help FL models to struggle with rare diseases.	[35]
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#### 4.3 AI, Wearables, and IoT in Precision Medicine

Healthcare's blending of wearables, artificial intelligence, and Internet of Things (IoT) is transforming the management of diseases and monitoring of patients. Wearable health tracking devices such as fitness bands, smartwatches, smart rings, Biofeedback wearables, smart patches and sensing devices [27]. Continual, noninvasive estimation of physiological and biochemical parameters in real-time via sophisticated sensors. [28]. Advances in technology have made devices more sensitive, affordable, and with the feature of continuous flow of data[29].

Through ML algorithms, wearables are transforming healthcare by enabling remote monitoring of health signals during daily activities, so enabling early detection of diseases, including type 2 diabetes, atrial fibrillation, and cardiovascular diseases, with great accuracy [36], [37], [38], [39]. Wearable continuous glucose monitoring also offers insights into individual glucose dynamics, guiding personal nutrition [40]. New studies show that wearables can also identify psychological states, which opens the path for exact mental health treatments [41].

All things considered, the synergy of IoT, wearables, and AI is generating opportunities for customized health management, so shifting care outside of clinical environments and allowing focused interventions depending on ongoing data monitoring [42]. Wearables are becoming crucial instruments for tracking health changes and enhancing healthcare outcomes as consumers adopt them with increasing rates [42].

#### 4.4 Precision Prevention with AI

AI is transforming the treatment of cancer by enabling precision medicine for the patient. Regenerative AI is interpreting the mammograms for early and precise diagnosis and customized therapies in the treatment of breast cancer [47]. AI radiomics improves lung cancer diagnosis by modeling tumor behavior and treatment response, enabling patients to be identified to targeted therapy, supporting clinical decision-making [48].

### 5 Ethical and Regulatory Challenges in AI-Driven Precision Medicine

Algorithmic bias, data privacy, trust in AI judgments, regulatory obstacles, and interdisciplinary cooperation are some of the ethical and legal issues that arise when AI is integrated into precision medicine.

#### 5.1 Algorithmic Bias

AI models educated on non-representative datasets can aggravate already existing health inequalities; thus, careful dataset curation and algorithmic transparency are necessary to address biases [43].

#### 5.2 Data Privacy and Governance

Strong data governance frameworks must be put in place because the use of AI in healthcare raises privacy and data governance issues. Some of the main issues are algorithmic bias, informed consent, accountability, and the effect of AI on patient-provider dynamics [44].

#### 5.3 Trust in AI Decisions

Enhancing the explainability of AI decision-making processes in medicine is essential for establishing and preserving patient and clinician trust. These ethical concerns include transparency, privacy, bias, and moral responsibility [45].

#### 5.4 Regulatory Barriers

Often surpassing current regulatory systems, the fast development of AI technologies calls for the creation of flexible regulations to guarantee the safe and efficient application of AI in personalised medicine, including the FDA and different stakeholders [46].

### 5.5 Need for Multidisciplinary Collaboration

The development and implementation of reliable AI tools in healthcare require international agreement and interdisciplinary collaboration, according to the FUTURE-AI initiative, which guarantees thorough comprehension of ethical, clinical, and technical factors [47]

## 6 Conclusion

AI is revolutionizing medicine by enhancing disease diagnosis, treatment, and prevention through precision medicine. By analyzing complex biological data, AI enables personalized medical care, early disease detection, risk prediction, and tailored therapies. Deep learning improves diagnostic accuracy and treatment personalization in numerous domains. AI accelerates drug discovery, repurposing, and personalized dosing, reducing costs while predicting adverse effects. Combining AI with wearables allows real-time tracking of patients, preventive measures, and adjustments to treatment. Cutting-edge technologies like digital twins and federated learning are transforming healthcare, though challenges in overcoming data bias, regulatory ambiguity, and cybersecurity must be addressed. AI must be deployed with good governance, testing, and coordination to enable fair, safe, and accessible care. By combining clinical, molecular, and real-world evidence, AI removes healthcare from generalized, reactive care to a predictive, preventive, and patient-centered one. In the process, it aims to improve treatment outcomes, quality of life, and global health by using more effective and targeted medicine solutions.

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