Precision Medicine and Opportunities with Artificial Intelligence

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ABSTRACT

Precision medicine offers tailored treatment solutions based on genetic and pharmacogenomic data, lifestyle, and medical history, departing from the conventional 'one-size-fits-all' approach. Beyond genetics, precision medicine encompasses medical imaging and wearable technology. Nonetheless, issues such as the need for regulatory frameworks, privacy concerns, cost-effectiveness, and data standards need to be resolved. Artificial intelligence (AI) in precision medicine presents promising avenues for improvement, including individualized treatment regimens using high-throughput data for predictive and diagnostic analyses. Precision medicine has made great strides, but it still confronts obstacles that call for a diversified strategy, including legislative alignment, technology innovation, provider education, and AI is poised to help in this mission for current and future endeavors.

Keywords: Precision medicine, Artificial intelligence, Genomics, Medical imaging, Data privacy, Electronic medical records, AI models

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Precision Medicine—Medicine 2.0

Modern medicine has undergone transformative leaps over the last decade, striving to address persistent gaps with its 'one-size-fits-all' approach to provide the 'best care' that all clinicians hope for their patients. A key enabler in this pursuit has been technological advances delivering precision medicine, designed to provide therapeutic solutions for patients based on multi-omics data (genetic, metabolic, pharmacogenomics), medical history, and environmental/lifestyle factors.[1] Since the Human Genome Project and the 100,000 Genomes Project were brought to fruition,[2,3] in 2015, the precision medicine initiative was rolled out in the United States.

Currently running under the moniker of the All of Us program,[4] this project integrates genetic (whole-genome sequencing, WGS) and medical data (electronic health records, EHRs) with the intent to support disease prevention and treatment. Concurrently, several other initiatives worldwide, namely the UK Biobank,[5] Biobank Japan,[6] FinnGen,[7] Australian Genomics Health Alliance,[8] and Singapore National Precision Medicine Initiative[9] were launched with similar objectives. Precision medicine built upon genomic data has slowly been finding its place in routine medical practice through genetic testing for treatment stratification or predicting disease susceptibility in rare, inherited, cardiovascular, or neurodegenerative diseases, cancer, and psychiatric disorders through public–private ventures. However, the flurry of direct-to-customer genetic testing has spurred the regulatory framework to place guardrails on testing guidelines.[10–12] Precision medicine has also brought into its realm the fields of proteomics,[13] pharmacogenomics (drug dosing based on a patient's genetic make-up),[14] and wearable devices.[15]

Technologies Enabling Precision Medicine

A cornerstone of precision medicine is the technological platforms enabling unprecedented volume and insights in combined data. This section will highlight the existing and upcoming platforms with recent notable examples of clinical application, while a comprehensive overview has been described elsewhere.[16] Next-generation sequencing (NGS) allows massive parallel sequencing of short DNA sequences in a 'high-throughput' format and then assembling information.[17] Over the past decade, NGS has accelerated academic discoveries and is now translating to the clinic as an actionable tool for patient care. WGS has aided the discovery of disease-causative or -associated gene variants in rare diseases, somatic variant calling in cancer, and predicting polygenic risk scores for genome-wide association studies (GWAS) that have spurred direct-to-customer genetic testing platforms.[18] A comprehensively equivalent data-enriched platform and economic alternative is whole-exome sequencing (WES), which involves targeted sequencing of only the coding regions of the genome. This has led to the FDA approval of two test panels currently available for diagnosing and supporting treatment regimens by matching cancer patients (solid tumors) to clinical trials.[19,20] To overcome limitations of WGS/WES that do not address the impact of aberrant gene expression and alternative gene splicing and to complement/improve the accuracy of diagnosis through genomic approaches, RNA (coding, non-coding, regulatory) sequencing or transcriptomics was developed.[21] Clinical use of RNA sequencing has improved the diagnosis of Mendelian diseases[22] and hematological malignancies.[23] NGS has supported treatment/care management decisions or predicting cardiovascular, neurogenetic, and neurological disease susceptibility.[24–26] Infectious disease surveillance and management has benefited from NGS and RNA-Seq platforms,[27,28] which use the long read or deep-sequencing approach to facilitate host–pathogen genetic distinction.[29]

NGS provides a wealth of data, albeit 'bulky,' which underappreciates the complexity of disease states and their heterogeneity, something paradoxical to precision medicine. Analytical platforms at the single-cell and single-nucleus levels have been developed over the past decade to bridge this knowledge gap. These interrogate the genome (single-cell genome sequencing),[30] the transcriptome (single-cell RNA sequencing)[31–33], and the proteome (single-cell proteome sequencing),[34,35] and in a truly multi-modal methodology is integrating spatial information in tissues to understand the complexity of cellular organization that can

provide insights into disease states.[36,37] The miniaturization and high throughput of single-cell technologies were enabled by microfluidics, a technique using parallel microchambers on specially fabricated material also known as 'lab-on-a-chip.'[38] Whole-genome application using droplet-based microfluidics platforms allows the identification of single nucleotide variants at the single-cell level. Similarly, droplet-based massively parallel RNA sequencing methodologies have resulted in cost-effectiveness and high throughput using the 10X Genomics Chromium and Drop-Seq platforms.[39–43] These are integrated to understand the epigenome (e.g., methylation) using single-cell bisulfite sequencing, chromatin assembly (transposase-accessible chromatic sequencing, ATAC-seq), and single-cell protein repertoire investigations using mass spectrometry methods such as matrix-assisted laser desorption/ionization to provide a holistic picture of the individual cellular organization.[44]

Although many of these have yet to be translated into the clinical setting, notable use cases are in the field of oncology due to the inherent complexity of cancer. Liquid biopsy (using blood samples) has gained traction for the detection of circulating tumor cells, cell-free RNA, circulating tumor DNA, and protein biomarkers for detecting minimal residual disease using WGS/WES in cancer patients.[45,46] Single-cell RNA sequencing is now used for patient stratification for drug response and biomarker discovery and aiding in drug discovery in oncology.[47] Precision medicine has enabled the approval of 11 gene therapies between the US FDA and the European Medical Association.[48] Gene editing tools such as CRISPR/Cas9 (clustered regularly interspaced palindromic repeats) have contributed to precision medicine in the clinic with the most recent FDA approval of a therapy for sickle cell disease.[49] Viral or non-viral gene delivery methods enabling the approval of chimeric antigen receptor T cell therapies, Tisagenlecleucel and axicabtagene ciloleucel,[50,51] and the next generation of these platforms are progressively moving to the clinic.[52]

Genomic medicine has been used to limit the 'one-size-fits-all approach' by considering that knowledge of gene–drug interactions can better tailor and predict a patient's chances of managing their treatment regimen and curtail any potential adverse events resulting from combination therapeutic regimens.[53,54] For instance, advances in pharmacogenomics have enabled the understanding of the COVID-19 disease spectrum for susceptibility and response to existing drugs.[55] Another key area where precision medicine is impacting patient care is the field of 'radiomics.' Traditionally, 'radiomics' is defined as "the high-throughput mining of quantitative image features from standard-of-care medical imaging that enables data to be extracted and applied within clinical decision support systems to improve diagnostic, prognostic, and predictive accuracy".[56] Using high-quality imaging techniques and integrating patient disease information to develop statistical modeling, 'radiomics' aims to develop a biomarker-guided approach for precision disease prognosis/diagnosis.[57]

Particularly, in oncology, supplementing genomic and molecular information from tumor heterogeneity with imaging phenotypes has enabled patient stratification for better disease management. Finally, clinical studies are being redesigned with an underpinning of using disease biology and potential biomarkers across therapeutic indications to improve real-time clinical decisions to maximize benefit for the patients.[58]

Barriers and Resolutions to the Implementation of Precision Medicine: The Case for AI

Precision medicine implementation presents several problems that call for an all-encompassing strategy that includes regulatory changes, technological developments, collaboration, and educational programs. Integrating various data sources used in precision medicine requires standardizing data formats and enhancing interoperability across various healthcare systems. The absence of established data formats and interoperable systems makes it difficult to integrate different types of data (such as genetic, clinical, and environmental). Data fragmentation can be avoided by taking steps like creating common data models and following global standards like HL7 FHIR (Fast Healthcare Interoperability Resources).[59]

Many strategies, including differential privacy, blockchain for safe data sharing, and sophisticated encryption mechanisms, have been developed to protect genomic data. While allowing its use in research and individualized care, these strategies seek to safeguard sensitive data.[60] Significant financial obstacles are created by the high expenses of genome sequencing, data processing, and customized treatments, especially in environments with limited resources. Reducing costs can be achieved by implementing sequencing technologies that are cost-effective, encouraging value-based care models, and cultivating public–private collaborations. Enhancing access can also be achieved by increasing insurance coverage for customized treatments and genomic testing.[61]

The regulatory environment around precision medicine is complicated, with different requirements and policies governing the acceptance of customized treatments and diagnostics. It is essential to create precise regulatory frameworks and rules that handle the difficulties presented by precision medicine. To develop standards that are both rigorous and adaptable, regulatory authorities must collaborate extensively with researchers and industry stakeholders. Healthcare professionals, many of whom lack training in genomics or tailored care, must undergo substantial education in addition to considerable modifications in clinical workflows to successfully incorporate precision medicine into clinical practice. It is crucial to provide focused educational initiatives and ongoing professional development programs for healthcare providers.[62]

Several ethical and social concerns are brought up by precision medicine, such as those related to equity,

access to care, genetic prejudice, and the possibility of making health inequities worse. It is crucial to create moral guidelines and regulations that handle these issues. Initiatives for public participation and education can contribute to the development of trust and guarantee that the advantages of precision medicine are shared fairly.

To involve patients in precision medicine, it is necessary for them to comprehend intricate genetic data and the consequences of customized treatment alternatives. Insufficient health literacy may impede patients' involvement. Patient participation can be improved by streamlining communication, educating patients with digital technologies, and developing materials that clearly and concisely outline the advantages and disadvantages of precision medicine.

Precision medicine generates enormous amounts of data, including multi-omic and genomic data, which are difficult to interpret without specialized knowledge and advanced tools. Clinicians can better understand data and make well-informed treatment decisions by utilizing AI and machine learning (ML) in sophisticated clinical decision support systems.

Significant obstacles are presented by worries about the security and privacy of genomic data, including the possibility of re-identification and unlawful access. Particularly in low-resource areas, access may be restricted by the high costs of genome sequencing, data analysis, and individualized medicines. The approval of tailored medicines and diagnostics is subject to varied requirements within the complicated regulatory environment of precision medicine. Changes in clinical processes and healthcare personnel's education are necessary to incorporate precision medicine into clinical practice, as many of them lack genomics training. Artificial intelligence (AI) can greatly aid in overcoming the obstacles that precision medicine now faces in all of this.

Artificial Intelligence

AI is the discipline of research in computer science that creates 'intelligent' machines with augmented capabilities to perform tasks equivalent to those dispensed by human intelligence, mostly without human intervention. This ability of 'supercomputers' relies on their capacity to learn, deduce, interpret, and provide resolution when prompted on specific tasks based on learned material. This section will capture some of AI's chief components and its scope in precision medicine. A plethora of exceptional research articles and opinion reviews exist in this field, some of which are cited here, and the curious reader is encouraged to explore beyond.[63-66] ML and deep learning are two sub-disciplines of AI. The concepts are based on 'neural networks' imitating the neuronal system in humans and replicating how humans learn, memorize, and reason to predict outcomes in a given circumstance.

Machine Learning

Neural networks having an input layer, one or more 'hidden' layers, and an output layer are used in traditional ML techniques. These algorithms are typically limited to supervised learning, which means that for the algorithm to find characteristics in the data, human specialists must arrange or annotate the data. Three steps are involved in the ML process: decision-making, error evaluation, and model optimization. Based on the input data, the algorithm generates predictions, assesses its accuracy, and iteratively modifies weights to increase accuracy. ML models include the following:

- **Supervised learning:** The algorithm compares its performance to the labels supplied to determine how accurate it is. The dataset used in this sort of learning has been labeled and classified by users.
- **Unsupervised learning:** This method involves using an unlabeled raw dataset, and the algorithm finds patterns and relationships in the data without the need for explicit user supervision.
- **Semi-supervised learning:** A dataset including both structured and unstructured data is used in this kind of learning. The algorithm learns to categorize the unstructured data and draws inferences on its own with the help of the structured data.
- **Reinforcement learning (RL):** Using a system of incentives and penalties, this learning technique gives the algorithm feedback as it makes mistakes and learns from them.

Deep Learning

Multiple layers of nodes (neurons) are used in deep learning to bridge the network's inputs and outputs. From the unprocessed input, these layers can gradually extract higher-level information. In image processing, for example, lower layers might detect lines, while higher layers might detect more complicated ideas like faces, letters, or numbers.[67–69] Multiple layers of interconnected nodes make up deep neural networks, and each layer builds on the one before it to improve and optimize the classifications or predictions. We refer to this series of calculations throughout the network as forward propagation.

In a different procedure known as backpropagation, prediction errors are computed using techniques such as gradient descent. The function's weights and biases are then modified by going back through the layers to train the model. A neural network can make predictions and fix mistakes when it uses both forward propagation and backpropagation together. A large amount of processing power is needed for deep learning. The best graphics processing units are those with high performance, as they have many cores and enough memory to execute heavy computations. Dispersed cloud computing could be beneficial as well. Deep learning requires this kind of processing power in order to train deep algorithms.

The algorithm gets increasingly more precise over time. Convolutional neural networks (CNNs) and recurrent relational networks (RNNs) are two examples of deep learning models that are now applicable in the medical industry. Applications related to computer vision and image categorization are the primary uses

for CNNs. They can carry out tasks like object identification, image recognition, pattern recognition, and face recognition because they can identify characteristics and patterns in pictures and videos. Conversely, recurrent neural networks, or RNNs, are typically employed in speech and natural language recognition applications. Their feedback loops set them apart and are intended for use with sequential or time-series data. When working with time-series data to anticipate future outcomes, these learning techniques are frequently used.

Natural Language Processing

Combining rule-based modeling of human language with statistical modeling, ML, and deep learning, natural language processing (NLP) allows computers and digital devices to detect, comprehend, and produce text and speech. NLP is a combination of deep learning, ML, and computational linguistics. A subfield of linguistics called computational linguistics analyzes speech and language using data science. Semantic analysis and syntactic analysis are the two primary forms of analysis involved. Syntactic analysis uses preprogrammed grammar rules to parse word syntax and determine meaning for words, phrases, and sentences. Semantic analysis interprets the meaning of the words inside the sentence structure by using the syntactic analysis output to extract meaning from the words.

Opportunities and Challenges with Implementing AI in Precision Medicine

Given that the possibilities for enhancing medicine with AI in its earliest version have increased exponentially over the past decade, several notable use cases exist.[70]

Genomic Medicine

Based on genetic data, ML algorithms are being used to forecast an individual's risk of contracting diseases like diabetes, cancer, and cardiovascular disorders. ML algorithms are able to identify genetic markers linked to illness risk by examining large-scale genomic datasets. Polygenic risk scores, which evaluate the likelihood of acquiring specific diseases based on many genetic variants, have been developed through the use of ML algorithms. In a study by Torkamani et al., advances in pathogenicity prediction are demonstrated by the use of ML models to understand the clinical relevance of genetic variations.[71] GWAS and other omics data are being combined using advanced ML techniques to find genetic correlations with complicated disorders.[72] In managing diabetes, obesity, cancer, cardiovascular diseases, and neurological diseases, doctors are using ML models for disease risk prediction based on genetic and clinical data increasingly.[73,74] ML models are being used in pharmacogenomics to predict drug responses for patients with certain genetic profiles while simultaneously addressing data and model interpretability issues.[75]

Medical Imaging

Medical imaging has undergone a radical transformation thanks to the use of deep learning. This has made it possible to analyze medical images more precisely, effectively, and automatically. It can be used to improve healthcare procedures, help detect diseases, and improve picture quality and segmentation. CNNs are extensively used in deep learning for the classification of medical pictures and the detection of anomalies. CNNs, for instance, have been used to identify lung nodules in CT scans and to categorize mammograms as benign or malignant. Particularly in fields like lung nodule recognition and breast cancer diagnosis, these algorithms have shown remarkable accuracy, frequently matching or even exceeding human specialists.[76]

CNNs have been used to assess mammograms and forecast the likelihood of breast cancer, increasing the precision of early diagnosis and facilitating more individualized screening procedures. As an illustration of the potential of AI in tailored diagnoses, a deep learning model that outperforms radiologists in breast cancer screening was created.[77] Important clinical data from EHRs, such as patient histories, diagnoses, treatments, and outcomes, are frequently extracted using NLP. In order to identify individuals for clinical trials and to create individualized treatment strategies, this data is essential. To identify patients who are more likely to experience medication-related difficulties, a study has created an NLP pipeline to extract data on adverse drug events from clinical notes in EHRs. By examining unstructured text in medical records, such as symptoms, lifestyle factors, and genetic data, NLP algorithms are used to identify patient phenotypes.

By extracting and evaluating the eligibility requirements from trial descriptions and comparing them with patient data from EHRs, NLP is also used to match people to clinical trials. This procedure aids in quickly locating qualified trial candidates. By evaluating trial eligibility requirements and patient information, an NLP system was created to automate the process of matching cancer patients to clinical trials, leading to quicker and more precise trial enrollment.[78] In the United States alone, several clinical studies across disciplines have been completed (Table 1).

Furthermore, therapeutic procedures are optimized through the application of RL, especially in dynamic contexts like intensive care units or in the management of chronic illnesses. By identifying the most effective tactics based on patient reactions, it helps to customize treatment regimens. By continually learning from patient data and recommending individualized therapy adjustments, RL models have been utilized to optimize insulin dose in diabetes management.[79]

Challenges

Precision medicine's use of AI has the potential to transform healthcare by providing individualized treatment plans, but it also comes with several difficulties.

1. Data accessibility and quality:
For AI models to function well, large-scale, high-quality datasets are necessary. However, inadequate,

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Table 1 | Selected oncology clinical trials involving the use of artificial intelligence in the United States

NCT Number	Study Title	Study URL	Conditions	Interventions	Sponsor	Collaborators	Study Type
NCT04441775	Artificial Intelligence for Prostate Cancer Treatment Planning	https://clinicaltrials.gov/study/NCT04441775	Prostate Cancer|Artificial Intelligence|Radiotherapy	OTHER: AI-assisted RT modelling	Dartmouth-Hitchcock Medical Center	Oregon Health and Science University|University of Massachusetts, Worcester|National Cancer Institute (NCI)|NRG Oncology|Nicolalde R&D	OBSERVATIONAL
NCT05147389	Artificial Intelligence for Digital Cholangioscopy Neoplasia Diagnosis	https://clinicaltrials.gov/study/NCT05147389	Common Bile Duct Neoplasms|Non-Neoplastic Bile Duct Disorder	DIAGNOSTIC_TEST: AI model classification|DIAGNOSTIC_TEST: DSOC endoscopist experts' classification	Instituto Ecuatoriano de Enfermedades Digestivas	The Methodist Hospital Research Institute|University of Sao Paulo|Vrije Universiteit Brussel|Advanced Endoscopy Research, Robert Wood Johnson Medical School Rutgers University|Baylor St. Luke's Medical Center|Universitair Ziekenhuis Brussel	OBSERVATIONAL
NCT04655924	Artificial Intelligence in Depression - Medication Enhancement	https://clinicaltrials.gov/study/NCT04655924	Depression	DEVICE: Clinical Decision Support System	Aifred Health	McGill University	INTERVENTIONAL
NCT05339750	Allergy Skin Patch Artificial Intelligence (AI)	https://clinicaltrials.gov/study/NCT05339750	Allergic Contact Dermatitis	DEVICE: AI-based smartphone application|DIAGNOSTIC_TEST: Allergen patch	Mayo Clinic		INTERVENTIONAL
NCT04223934	Tailored Drug Titration Using Artificial Intelligence	https://clinicaltrials.gov/study/NCT04223934	Hypertension	OTHER: optima4BP	Optima Integrated Health	University of California, San Francisco	INTERVENTIONAL
NCT05594394	Improving Charge Nurse Conflict Resolution Communication Using Artificial Intelligence	https://clinicaltrials.gov/study/NCT05594394	Conflict Resolution	BEHAVIORAL: Orai: Master Public Speaking	Methodist Health System		OBSERVATIONAL
NCT05335889	Wearable Sensors and Artificial Intelligence for Carbohydrate Counting	https://clinicaltrials.gov/study/NCT05335889	Type 2 Diabetes	DEVICE: eButton|DEVICE: Continuous Glucose Monitoring (CGM)	NYU Langone Health		OBSERVATIONAL
NCT04933890	Detection of Heart Conditions Using Artificial Intelligence	https://clinicaltrials.gov/study/NCT04933890	Left Ventricular Dysfunction|Heart Failure	DEVICE: Use of Eko DUO electronic stethoscope	Eko Devices, Inc.		OBSERVATIONAL
NCT04891705	Point of Care Ultrasound Lung Artificial Intelligence (AI) Validation Data Collection Study	https://clinicaltrials.gov/study/NCT04891705	Pleural Effusion|Lung Consolidation	DEVICE: Lung Ultrasound Scan	Philips Clinical & Medical Affairs Global		OBSERVATIONAL
NCT02801877	IntelliCare Study: Artificial Intelligence in a Mobile (AIM) Intervention for Depression	https://clinicaltrials.gov/study/NCT02801877	Depression|Anxiety	BEHAVIORAL: IntelliCare|BEHAVIORAL: Hub App with the Recommender System|BEHAVIORAL: Coaching	Northwestern University		INTERVENTIONAL
NCT02454660	Improving Adherence and Outcomes by Artificial Intelligence- Adapted Text Messages	https://clinicaltrials.gov/study/NCT02454660	Medication Non-adherence	BEHAVIORAL: SMS (Text messages)	University of Michigan	Agency for Healthcare Research and Quality (AHRQ)	INTERVENTIONAL

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Table 1 | (Continued)

NCT Number	Study Title	Study URL	Conditions	Interventions	Sponsor	Collaborators	Study Type
NCT05275556	Gastroenterology Artificial INtelligence System for Detecting Colorectal Polyps (The GAIN Study)	https://clinicaltrials.gov/study/NCT05275556	Colon Adenoma|Colon Polyp|Colon Lesion	DEVICE: Computer-Assisted Detection (CADe) Device	Verily Life Sciences LLC		INTERVENTIONAL
NCT02464449	Patient-Centered Pain Care Using Artificial Intelligence and Mobile Health Tools	https://clinicaltrials.gov/study/NCT02464449	Back Pain	BEHAVIORAL: Behavioral: AI-CBT|BEHAVIORAL: Behavioral: Standard Telephone CBT	VA Office of Research and Development		INTERVENTIONAL
NCT05167058	Electrocardiographic Diagnostic Performance of the Apple Watch Augmented With an Artificial Intelligence Algorithm	https://clinicaltrials.gov/study/NCT05167058	Atrial Fibrillation|Tachycardia|Bradycardia|Premature Supraventricular Beat|Premature Ventricular Contraction	DEVICE: Cardiologs Platform	Cardiologs Technologies		OBSERVATIONAL
NCT05235646	Infiltration of Gadolinium Injection in Brain MR Scans Using Artificial Intelligence	https://clinicaltrials.gov/study/NCT05235646	Magnetic Resonance Imaging		Mayo Clinic		OBSERVATIONAL
NCT03530098	Validation of an Artificial Intelligence-based Algorithm for Skeletal Age Assessment	https://clinicaltrials.gov/study/NCT03530098	Bone Age	DEVICE: BoneAgeModel	Stanford University		INTERVENTIONAL
NCT02176226	IntelliCare: Artificial Intelligence in a Mobile Intervention for Depression and Anxiety (AIM)	https://clinicaltrials.gov/study/NCT02176226	Major Depressive Disorder|Anxiety Disorders	BEHAVIORAL: IntelliCare	Northwestern University		INTERVENTIONAL
NCT02243670	Using Artificial Intelligence To Monitor Medication Adherence in Opioid Replacement Therapy	https://clinicaltrials.gov/study/NCT02243670	Opiate Addiction|Medication Non-adherence| Addiction|Opioid Dependence	DEVICE: AiCure monitoring and intervention	AiCure	Orexo AB|Montefiore Medical Center	INTERVENTIONAL
NCT06337734	An Artificial Intelligence-Assisted Digital Health Lifestyle Intervention for Adults With Hypertension	https://clinicaltrials.gov/study/NCT06337734	Hypertension	BEHAVIORAL: AI-Driven Lifestyle Coaching Program	University of California, San Diego		INTERVENTIONAL
NCT04400435	Detection of Heart Conditions With Single Lead ECG Using Artificial Intelligence	https://clinicaltrials.gov/study/NCT04400435	Left Ventricular Dysfunction	DEVICE: Use of Eko DUO electronic stethoscope	Eko Devices, Inc.		OBSERVATIONAL
NCT02599259	Using Artificial Intelligence to Measure and Optimize Adherence in Patients on Anticoagulation Therapy	https://clinicaltrials.gov/study/NCT02599259	Stroke	DEVICE: Monitored (M+)	AiCure	Montefiore Medical Center	INTERVENTIONAL
NCT04122326	Monitoring and Evaluation of Posture in Office Workstations With Artificial Intelligence	https://clinicaltrials.gov/study/NCT04122326	Musculoskeletal Pain|Musculoskeletal Injury|Musculoskeletal Strain	BEHAVIORAL: Workstation Modification	University of Southern California	U.S. National Science Foundation	INTERVENTIONAL

(Continued)

Table 1 | (Continued)

NCT Number	Study Title	Study URL	Conditions	Interventions	Sponsor	Collaborators	Study Type
NCT04524104	Study of a PST-Trained Voice-Enabled Artificial Intelligence Counselor (SPEAC) for Adults With Emotional Distress (Phase 1)	https://clinicaltrials.gov/study/NCT04524104	Depression|Anxiety	BEHAVIORAL: Lumen Treatment	University of Illinois at Chicago	Penn State University|Washington University School of Medicine|Stanford University|National Institute of Mental Health (NIMH)	INTERVENTIONAL
NCT03976297	Artificial Intelligence/ Machine Learning Modeling on Time to Palliative Care Review in an Inpatient Hospital Population	https://clinicaltrials.gov/study/NCT03976297	Palliative Care	OTHER: Control Tower	Mayo Clinic		INTERVENTIONAL
NCT06561217	Assessing the Performance of Artificial Intelligence (AI)- Augmented Electronic Health Record (EHR) Data Abstraction for Clinical Trial Patient Screening	https://clinicaltrials.gov/study/NCT06561217	Cancer		University of Pennsylvania	Mendel AI	OBSERVATIONAL
NCT03868813	An Artificial Intelligence-Assisted Telehealth Intervention to Promote Self-Management in Patients With Type 2 Diabetes Mellitus (Qualitative Interview)	https://clinicaltrials.gov/study/NCT03868813	Diabetes Mellitus	BEHAVIORAL: Semi-structured Interview	University of Alabama at Birmingham		OBSERVATIONAL
NCT05077722	Monitoring of Sleep and Behavior of Children 3-7 Years Old Receiving Parent-Child Interaction Therapy With the Help of Artificial Intelligence	https://clinicaltrials.gov/study/NCT05077722	Disruptive Behavior|Attention-deficit Hyperactivity|Oppositional Defiant Disorder	DEVICE: Garmin	Mayo Clinic		INTERVENTIONAL
NCT05161065	Comparison of QT Interval Readings Between Smartwatch Combined With Cardiologs Artificial Intelligence and 12-lead ECG	https://clinicaltrials.gov/study/NCT05161065	Atrial Fibrillation	DEVICE: Cardiologs	Cardiologs Technologies		OBSERVATIONAL
NCT05343585	Validity of an AI-based Program to Identify Foods and Estimate Food Portion Size	https://clinicaltrials.gov/study/NCT05343585	Nutrition Assessment	DEVICE: PortionSize AI	Pennington Biomedical Research Center	National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK)	INTERVENTIONAL
NCT04400513	Development of an Algorithm to Differentiate Heart Murmurs Using Electronic Stethoscopes	https://clinicaltrials.gov/study/NCT04400513	Murmur, Heart|Aortic Valve Stenosis|Tricuspid Regurgitation|Mitral Regurgitation|Innocent Murmurs|Heart Murmurs	DEVICE: Use of Eko CORE and Eko DUO electronic stethoscopes	Eko Devices, Inc.		OBSERVATIONAL
NCT01696162	Conventional Home Exercise Programs Versus Electronic Home Exercise Versus Artificial Intelligence 'Virtual Therapy' for Anterior Knee Pain	https://clinicaltrials.gov/study/NCT01696162	Patellofemoral Pain Syndrome	OTHER: Algorithm-based Exercise Videos|OTHER: PDF Exercise Sheets|OTHER: Limited Exercise Videos	Simpletherapy		INTERVENTIONAL

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Table 1 | (Continued)

NCT Number	Study Title	Study URL	Conditions	Interventions	Sponsor	Collaborators	Study Type
NCT05175690	Evaluation of the AudibleHealth Dx AI/ ML-Based Dx SaMD Using FCV-SDS in the Diagnosis of COVID-19 Illness	https://clinicaltrials.gov/study/NCT05175690	COVID19	DIAGNOSTIC_TEST: Diagnostic Software as Medical Device	AudibleHealth AI, Inc.	University of South Florida|R. P. Chiacchierini Consulting, LLC|Analytical Solutions Group, Inc.|Renaissance Worldwide Solutions, LLC|Medical & Regulatory Affairs Specialists, LLC	OBSERVATIONAL
NCT05126173	DERM US and EU Validation Study	https://clinicaltrials.gov/study/NCT05126173	Malignant Skin Melanoma T0|Basal Cell Carcinoma|Squamous Cell Carcinoma	DEVICE: Deep Ensemble for the Recognition of Malignancy (DERM)	Skin Analytics Limited		OBSERVATIONAL
NCT04918693	A Study to Evaluate the Performance and Potential Benefits of an Assistive Artificial Intelligence Device ScanNav Anatomy Peripheral Nerve Block - US V1.0 for Ultrasound-guided Regional Anesthesia	https://clinicaltrials.gov/study/NCT04918693	Ultrasound Imaging of Anatomical Structures	DEVICE: Ultrasound scanning	IntelligentUltrasound Limited		OBSERVATIONAL
NCT03662802	Development of a Novel Convolution Neural Network for Arrhythmia Classification	https://clinicaltrials.gov/study/NCT03662802	Arrhythmias, Cardiac|Cardiac Arrest|Cardiac Arrythmias	OTHER: Neural Network Classifier	Scripps Clinic		OBSERVATIONAL
NCT05455281	A Study to Evaluate the Performance of CHLOE Algorithm on the Prediction of Blastocyst Formation in Women Undergoing IVF [Cultivating Human Life Through Optimal Embryos]	https://clinicaltrials.gov/study/NCT05455281	Fertility Disorders	DEVICE: CHLOE	Fairtility		OBSERVATIONAL
NCT05838456	Deep Learning Enabled Endovascular Stroke Therapy Screening in Community Hospitals	https://clinicaltrials.gov/study/NCT05838456	Acute Ischemic Stroke (AIS)	DEVICE: Viz.AI software	The University of Texas Health Science Center, Houston	National Center for Advancing Translational Sciences (NCATS)	INTERVENTIONAL
NCT06098950	Human Algorithm Interactions for Acute Respiratory Failure Diagnosis	https://clinicaltrials.gov/study/NCT06098950	Acute Respiratory Failure	OTHER: Artificial Intelligence model predictions without explanation|OTHER: Artificial intelligence model predictions with explanation|OTHER: AI model biased against heart failure|OTHER: AI model biased against pneumonia|OTHER: AI model biased against COPD	University of Michigan	National Heart, Lung, and Blood Institute (NHLBI)	INTERVENTIONAL
NCT06017089	The Pediatric Artificial Pancreas Automated Initialization Trial	https://clinicaltrials.gov/study/NCT06017089	Type 1 Diabetes	DEVICE: AI-based Advisor system	Marc Breton	National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK)|Jaeb Center for Health Research|University of Colorado, Denver| Stanford University	INTERVENTIONAL

(Continued)

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Table 1 | (Continued)

NCT Number	Study Title	Study URL	Conditions	Interventions	Sponsor	Collaborators	Study Type
NCT05745480	Natural Language Processing for Screening Opioid Misuse	https://clinicaltrials.gov/study/NCT05745480	Opioid Use Disorder|Opioid Misuse	OTHER: Opioid Misuse Screening with an Addiction Consult Service	University of Wisconsin, Madison		OBSERVATIONAL/
NCT05455905	Voice Biomarkers Predictive of Depression and Anxiety	https://clinicaltrials.gov/study/NCT05455905	Depression, Anxiety|Healthy|Mental Health Wellness 1	DIAGNOSTIC_TEST: Patient Health Questionnaire-9|DIAGNOSTIC_TEST: Generalized Anxiety Disorder- 7|DIAGNOSTIC_TEST: Hamilton Depression Rating Scale|DIAGNOSTIC_TEST: Hamilton Anxiety Rating Scale	Kintsugi Mindful Wellness, Inc.		OBSERVATIONAL
NCT05600101	Development and Piloting an Avatar-based Intervention to Support Patients Undergoing Stem Cell Transplantation	https://clinicaltrials.gov/study/NCT05600101	Hematopoietic Cell Transplantation	BEHAVIORAL: Care.Coach	Dana-Farber Cancer Institute	National Cancer Institute (NCI)	INTERVENTIONAL
NCT03688906	AI-EMERGE: Development and Validation of a Multi-analyte, Blood-based Colorectal Cancer Screening Test	https://clinicaltrials.gov/study/NCT03688906	Colorectal Cancer|Cancer Colon|Cancer, Rectum|Neoplasms,Colorectal|Polyps|Polyp of Colon|Adenoma|Adenoma Colon		Freenome Holdings Inc.		OBSERVATIONAL
NCT05364268	Evaluation of the AudibleHealth Dx AI/ML-Based Dx SaMD Using FCV-SDS in the Diagnosis of COVID-19 Illness: Clinical Validation	https://clinicaltrials.gov/study/NCT05364268	2019 Novel Coronavirus Disease|2019 Novel Coronavirus Infection|2019-nCoV Disease|COVID-19 Pandemic|COVID-19 Virus Disease|COVID-19 Virus Infection|Coronavirus Disease 2019|Coronavirus Disease-19|SARS-CoV-2 Infection	DEVICE: Diagnostic Test: Diagnostic Software as Medical Device	AudibleHealth AI, Inc.	Sunrise Research Institute|Analytical Solutions Group, Inc.|Kelley Medical Consultants LLC|R. P. Chiacchierini Consulting, LLC	OBSERVATIONAL
NCT05081011	Managing Insulin With a Voice AI	https://clinicaltrials.gov/study/NCT05081011	Medication Adherence	DEVICE: Voice Assistant Device|DEVICE: Voice Assistant Device	Stanford University		INTERVENTIONAL
NCT05009251	Using Explainable AI Risk Predictions to Nudge Influenza Vaccine Uptake	https://clinicaltrials.gov/study/NCT05009251	Influenza|Vaccination|Health Promotion|Health Behavior|Risk Reduction	BEHAVIORAL: Reminder|BEHAVIORAL: Risk reduction|BEHAVIORAL: Medical records-based recommendation|BEHAVIORAL: Algorithm-based recommendation	National Bureau of Economic Research, Inc.	Geisinger Clinic|Massachusetts Institute of Technology|National Institute on Aging (NIA)	INTERVENTIONAL
NCT04323137	Encouraging Flu Vaccination Among High-Risk Patients Identified by ML	https://clinicaltrials.gov/study/NCT04323137	Influenza|Vaccination|Health Promotion|Health Behavior|Risk Reduction	BEHAVIORAL: Risk reduction|BEHAVIORAL: Medical records-based recommendation|BEHAVIORAL: Algorithm-based recommendation	Geisinger Clinic	National Institute on Aging (NIA)	INTERVENTIONAL
NCT00564122	The Accuracy of an Artificially-intelligent Stethoscope	https://clinicaltrials.gov/study/NCT00564122	Heart Murmurs|Congenital Heart Disease|Structural Heart Disease	DEVICE: Artificially-Intelligent Stethoscope|OTHER: Physical Examination	Akron Children's Hospital	Thomas C. Dispenza, M.D.|John R. Bockoven, M.D. M.B.A.	OBSERVATIONAL

(Continued)

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Fig 1 | The impact of artificial intelligence (AI) in precision medicine, influencing drug discovery, predictive analytics for treatment options, and translating into clinical data decisions

inconsistent, or fragmented medical data might lead to biased or erroneous AI models.[80]

2. Transparency and interpretability:
Many AI models, particularly deep learning models, operate as 'black boxes,' making it challenging for medical professionals to understand the reasoning behind judgments. The use of AI in therapeutic contexts, where knowing the reasoning behind choices is essential, may be hampered by this lack of interpretability.[81]

3. Bias and fairness:
AI models may carry biases from the training data, which could result in outcomes that are unjust or unequal in treatment. Biased models have the potential to disproportionately affect vulnerable populations, which is particularly problematic in precision medicine.[82]

4. Ethical and regulatory concerns:
Significant ethical and regulatory issues, such as patient privacy, permission, and the possibility of AI making clinical choices on its own, are raised by the use of AI in healthcare. The use of AI technology in precision medicine may be hindered by the lack of explicit regulatory requirements.[83]

5. The ability of AI models to generalize:
AI models that are trained on data from certain populations or surroundings might not adapt effectively to different contexts. This can be problematic in precision medicine, since suggestions for treatments must work for a variety of patient populations.[84]

Initiatives to Overcome Challenges in the Implementation of AI in Precision Medicine

High-quality, varied, and well-integrated datasets are necessary for AI models; however, inconsistent, fragmented, and incomplete medical data are frequently encountered. Strong data cleaning and preprocessing approaches are necessary to ensure that the data supplied into AI models is reliable and correct. Federated learning techniques preserve privacy and increase data diversity by enabling AI models to learn from distributed data that is dispersed across multiple sites without the need for data centralization. Standardized EHRs and data sharing initiatives like the NIH's All of Us Research Program may enhance data integration and quality.

Due to AI models' propensity to reinforce biases included in training data, different population groups may be treated differently. A key component of bias mitigation is making sure that training datasets are representative of different demographic groups and are varied. Clinicians' acceptance and trust of AI models can be increased by the development of explainable AI techniques that provide insights into the models' decision-making process.[85]

The creation of ethics committees to examine AI applications in the healthcare industry can be a useful

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way to resolve ethical challenges related to equity, consent, and data ownership. The General Data Protection Regulation of the European Union and the AI Act offer frameworks that may direct the moral and legal application of AI in precision medicine.

Collaborative efforts between public health agencies and private enterprises hold the potential to alleviate the financial burden on healthcare providers. Initiatives like the Global Health Initiative are dedicated to rendering AI-driven precision medicine accessible to under-resourced regions.[86] AI has promising potential for improving the outreach and impact of precision medicine in the future (Figure 1).

Conclusions

Precision medicine, using AI to create highly personalized treatment plans based on each patient's unique genetic profile, lifestyle, and environmental conditions, has the potential to revolutionize healthcare. Genomes, medical imaging, and patient records are just a few examples of the massive amounts of data that AI will make easier to analyze. Because AI can speed up the development of new medications and predict treatment responses, it holds great potential for enhancing patient outcomes, reducing healthcare costs, and democratizing access to state-of-the-art medical care. Better treatment strategies, early illness detection, and more accurate diagnoses can be the product of AI. As AI technologies develop and become more integrated with clinical practice, precision medicine will become more precise, efficient, and widely accessible.

References

1 Denny JC, Collins FS. Precision medicine in 2030-seven ways to transform healthcare. Cell. 2021;184(6):1415–19.
2 National Human Genome Research Institute. The Human Genome Project. Available from: https://www.genome.gov/human-genome-project.
3 NHS. 100,000 Genomes Project. Available from: https://www.england.nhs.uk/genomics/genomic-research/100000-genomes-project.
4 National Institute of Health. All of Us. Available from: https://allofus.nih.gov.
5 UK biobank. Available from: https://www.ukbiobank.ac.uk.
6 Biobank Japan. Available from: https://www.ukbiobank.ac.uk.
7 University of Helsinki. FinnGen. Available from: https://www.finngen.fi/en/access_results.
8 Australian Genomics. Available from: https://www.australiangenomics.org.au.
9 Singapore National Precision Medicine. Available from: https://www.npm.sg.
10 Hershberger RE, Givertz MM, Ho CY, Judge DP, Kantor PF, McBride KL, et al. Genetic evaluation of cardiomyopathy-a heart failure society of America Practice Guideline. J Card Fail. 2018;24(5):281–302.
11 Krey I, Platzer K, Esterhuizen A, Berkovic SF, Helbig I, Hildebrand MS, et al. Current practice in diagnostic genetic testing of the epilepsies. Epileptic Disord. 2022;24(5):765–86.
12 Hampel H, Bennett RL, Buchanan A, Pearlman R, Wiesner GL, Guideline Development Group ACoMG, et al. A practice guideline from the American College of Medical Genetics and Genomics and the National Society of Genetic Counselors: referral indications for cancer predisposition assessment. Genet Med. 2015;17(1):70–87.
13 Duarte TT, Spencer CT. Personalized proteomics: the future of precision medicine. Proteomes. 2016;4(4).
14 Hockings JK, Pasternak AL, Erwin AL, Mason NT, Eng C, Hicks JK. Pharmacogenomics: an evolving clinical tool for precision medicine. Cleve Clin J Med. 2020;87(2):91–9.
15 Babu M, Lautman Z, Lin X, Sobota MHB, Snyder MP. Wearable devices: implications for precision medicine and the future of Health Care Annu Rev Med. 2024;75:401–15.
16 Ho D, Quake SR, McCabe ERB, Chng WJ, Chow EK, Ding X, et al. Enabling technologies for personalized and precision medicine. Trends Biotechnol. 2020;38(5):497–518.
17 Satam H, Joshi K, Mangrolia U, Waghoo S, Zaidi G, Rawool S, et al. Next-generation sequencing technology: current trends and advancements. Biology (Basel). 2023;12(7).
18 Bagger FO, Borgwardt L, Jespersen AS, Hansen AR, Bertelsen B, Kodama M, et al. Whole genome sequencing in clinical practice. BMC Med Genomics. 2024;17(1):39.
19 Thermo Fisher Scientific. Oncomine. Available from: https://www.oncomine.com/.
20 MSKCC. MSKImpact. Available from: https://www.mskcc.org/msk-impact.
21 Peymani F, Farzeen A, Prokisch H. RNA sequencing role and application in clinical diagnostic. Pediatr Investig. 2022;6(1):29–35.
22 Cummings BB, Marshall JL, Tukiainen T, Lek M, Donkervoort S, Foley AR, et al. Improving genetic diagnosis in Mendelian disease with transcriptome sequencing. Sci Transl Med. 2017;9(386).
23 Cho YU. The role of next-generation sequencing in hematologic malignancies. Blood Res. 2024;59(1):11.
24 Papadopoulou E, Bouzarelou D, Tsaousis G, Papathanasiou A, Vogiatzi G, Vlachopoulos C, et al. Application of next generation sequencing in cardiology: current and future precision medicine implications. Front Cardiovasc Med. 2023;10:1202381.
25 Rexach J, Lee H, Martinez-Agosto JA, Nemeth AH, Fogel BL. Clinical application of next-generation sequencing to the practice of neurology. Lancet Neurol. 2019;18(5):492–503.
26 Sun H, Shen XR, Fang ZB, Jiang ZZ, Wei XJ, Wang ZY, et al. Next-generation sequencing technologies and neurogenetic diseases. Life (Basel). 2021;11(4).
27 Gwinn M, MacCannell D, Armstrong GL. Next-generation sequencing of infectious pathogens. JAMA. 2019;321(9):893–4.
28 Chiu CY, Miller SA. Clinical metagenomics. Nat Rev Genet. 2019;20(6):341–55.
29 Wang Y, Zhao Y, Bollas A, Wang Y, Au KF. Nanopore sequencing technology, bioinformatics and applications. Nat Biotechnol. 2021;39(11):1348–65.
30 Wang Y, Navin NE. Advances and applications of single-cell sequencing technologies. Mol Cell. 2015;58(4):598–609.
31 Wang S, Sun ST, Zhang XY, Ding HR, Yuan Y, He JJ, et al. The evolution of single-Cell RNA sequencing technology and application: progress and perspectives. Int J Mol Sci. 2023;24(3):2943.
32 Van de Sande B, Lee JS, Mutasa-Gottgens E, Naughton B, Bacon W, Manning J, et al. Applications of single-cell RNA sequencing in drug discovery and development. Nat Rev Drug Discov. 2023;22(6):496–520.
33 Baysoy A, Bai Z, Satija R, Fan R. The technological landscape and applications of single-cell multi-omics. Nat Rev Mol Cell Biol. 2023;24(10):695–713.
34 Mansouri S, Pessoni AM, Marroquin-Rivera A, Parise EM, Tamminga CA, Turecki G, et al. Transcriptional dissection of symptomatic profiles across the brain of men and women with depression. Nat Commun. 2023;14(1):6835.
35 Alfaro JA, Bohlander P, Dai M, Filius M, Howard CJ, van Kooten XF, et al. The emerging landscape of single-molecule protein sequencing technologies. Nat Methods. 2021;18(6):604–17.
36 Bressan D, Battistoni G, Hannon GJ. The dawn of spatial omics. Science. 2023;381(6657):eabq4964.
37 Vandereyken K, Sifrim A, Thienpont B, Voet T. Methods and applications for single-cell and spatial multi-omics. Nat Rev Genet. 2023;24(8):494–515.
38 Yin H, Marshall D. Microfluidics for single cell analysis. Curr Opin Biotechnol. 2012;23(1):110–9.
39 Macosko EZ, Basu A, Satija R, Nemesh J, Shekhar K, Goldman M, et al. Highly parallel genome-wide expression profiling of individual cells using nanoliter droplets. Cell. 2015;161(5):1202–14.
40 Habib N, Avraham-Davidi I, Basu A, Burks T, Shekhar K, Hofree M, et al. Massively parallel single-nucleus RNA-seq with DroNc-seq. Nat Methods. 2017;14(10):955–8.
41 Zhang X, Li T, Liu F, Chen Y, Yao J, Li Z, et al. Comparative analysis of droplet-based ultra-high-throughput single-cell RNA-seq systems. Mol Cell. 2019;73(1):130–42 e5.

42 Datlinger P, Rendeiro AF, Boenke T, Senekowitsch M, Krausgruber T, Barreca D, et al. Ultra-high-throughput single-cell RNA sequencing and perturbation screening with combinatorial fluidic indexing. Nat Methods. 2021;18(6):635–42.
43 Chen L, Fan R, Tang F. Advanced single-cell omics technologies and informatics tools for genomics, proteomics, and bioinformatics analysis. Genomic Proteomic Bioinform. 2021;19(3):343–5.
44 Ctortecka C, Clark NM, Boyle BW, Seth A, Mani DR, Udeshi ND, et al. Automated single-cell proteomics providing sufficient proteome depth to study complex biology beyond cell type classifications. Nat Commun. 2024;15(1):5707.
45 Nikanjam M, Kato S, Kurzrock R. Liquid biopsy: current technology and clinical applications. J Hematol Oncol. 2022;15(1):131.
46 Alix-Panabieres C, Marchetti D, Lang JE. Liquid biopsy: from concept to clinical application. Sci Rep. 2023;13(1):21685.
47 Sultana A, Alam MS, Liu X, Sharma R, Singla RK, Gundamaraju R, et al. Single-cell RNA-seq analysis to identify potential biomarkers for diagnosis, and prognosis of non- small cell lung cancer by using comprehensive bioinformatics approaches. Transl Oncol. 2023;27:101571.
48 Schambach A, Buchholz CJ, Torres-Ruiz R, Cichutek K, Morgan M, Trapani I, et al. A new age of precision gene therapy. Lancet. 2024;403(10426):568–82.
49 Food and Drug Administration. FDA. Available from: https://www.fda.gov/news- events/press-announcements/fda-approves-first-gene-therapies-treat-patients-sickle- cell-disease.
50 Food and Drug Administration. FDA. Available from: https://www.fda.gov/news- events/press-announcements/fda-approves-car-t-cell-therapy-treat-adults-certain-types- large-b-cell-lymphoma.
51 Leukemia and Lymphoma Society. Available from: https://www.lls.org/news/fdas- recent-approval-2-car-t-cell-therapies-big-step-toward-long-term-control-myeloma-more.
52 Healey N. Next-generation CRISPR-based gene-editing therapies tested in clinical trials. Nat Med. 2024.
53 Cecchin E, Stocco G. Pharmacogenomics and personalized medicine. Genes (Basel). 2020;11(6).
54 Sadee W, Wang D, Hartmann K, Toland AE. Pharmacogenomics: driving personalized medicine. Pharmacol Rev. 2023;75(4):789–814.
55 Biswas M, Sawajan N, Rungrotmongkol T, Sanachai K, Ershadian M, Sukasem C. Pharmacogenetics and precision medicine approaches for the improvement of COVID-19 therapies. Front Pharmacol. 2022;13:835136.
56 Lambin P, Leijenaar RTH, Deist TM, Peerlings J, de Jong EEC, van Timmeren J, et al. Radiomics: the bridge between medical imaging and personalized medicine. Nat Rev Clin Oncol. 2017;14(12):749–62.
57 Monti S. Precision medicine in radiomics and radiogenomics. J Pers Med. 2022;12(11):1806.
58 Duan XP, Qin BD, Jiao XD, Liu K, Wang Z, Zang YS. New clinical trial design in precision medicine: discovery, development and direction. Signal Transduct Target Ther. 2024;9(1):57.
59 van Panhuis WG, Paul P, Emerson C, Grefenstette J, Wilder R, Herbst AJ, et al. A systematic review of barriers to data sharing in public health. BMC Public Health. 2014;14:1144.
60 Shabani M. The Data Governance Act and the EU's move towards facilitating data sharing. Mol Syst Biol. 2021;17(3):e10229.
61 Trosman JR, Weldon CB, Slavotinek A, Norton ME, Douglas MP, Phillips KA. Perspectives of US private payers on insurance coverage for pediatric and prenatal exome sequencing: results of a study from the Program in Prenatal and Pediatric Genomic Sequencing (P3EGS). Genet Med. 2020;22(2):283–91.
62 Haga SB, Mills R, Moaddeb J, Liu Y, Voora D. Independent community pharmacists' experience in offering pharmacogenetic testing. Pharmgenomics Pers Med. 2021;14:877–86.
63 Russell SJ, Norvig P. Artificial Intelligence: A Modern Approach (4th ed.). Pearson; 2021.
64 Poole DL, Mackworth AK. Artificial Intelligence: Foundations of Computational Agents, 3rd edition: Cambridge University Press; 2023.
65 Luger GaS, W. Artificial Intelligence: Structures and Strategies for Complex Problem Solving. 5th Edition: The Benjamin/Cummings Publishing Company, Inc.; 2004.
66 Crevier D. The Tumultuous History of the Search for Artificial Intelligence: Basic Books, New York, NY; 1993.
67 Goodfellow IaB, Y and Courville, A. Deep Learning: MIT Press; 2016.
68 Deng LY, D. Deep Learning: Methods and Applications: Now Foundations and Trends; 2014.
69 Bajwa J, Munir U, Nori A, Williams B. Artificial intelligence in healthcare: transforming the practice of medicine. Future Healthc J. 2021;8(2):e188–e94.
70 Biocomputing 2023 Proceedings of the Pacific Symposium. Russ B Altman (Stanford University U, Lawrence Hunter (University of Colorado Health Sciences Center, USA), Marylyn D Ritchie (University of Pennsylvania, USA), Tiffany Murray (Stanford University, USA), and Teri E Klein (Stanford University, USA), editor2023.
71 Torkamani A, Wineinger NE, Topol EJ. The personal and clinical utility of polygenic risk scores. Nat Rev Genet. 2018;19(9):581–90.
72 Nguyen L, Van Hoeck A, Cuppen E. Machine learning-based tissue of origin classification for cancer of unknown primary diagnostics using genome-wide mutation features. Nat Commun. 2022;13(1):4013.
73 Wang C, Li Y, Tsuboshita Y, Sakurai T, Goto T, Yamaguchi H, et al. A high-generalizability machine learning framework for predicting the progression of Alzheimer's disease using limited data. NPJ Digit Med. 2022;5(1):43.
74 Gao Y, Cui Y. Optimizing clinico-genomic disease prediction across ancestries: a machine learning strategy with Pareto improvement. Genome Med. 2024;16(1):76.
75 Quazi S. Artificial intelligence and machine learning in precision and genomic medicine. Med Oncol. 2022;39(8):120.
76 Liu X, Faes L, Kale AU, Wagner SK, Fu DJ, Bruynseels A, et al. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. Lancet Digit Health. 2019;1(6):e271–e97.
77 McKinney SM, Sieniek M, Godbole V, Godwin J, Antropova N, Ashrafian H, et al. International evaluation of an AI system for breast cancer screening. Nature. 2020;577(7788):89–94.
78 Jin Q, Wang Z, Floudas CS, Chen F, Gong C, Bracken-Clarke D, et al. Matching patients to clinical trials with large language models. ArXiv. 2024.
79 Liu Y, Liu S, Wang Y, Lombardi F, Han J. A survey of stochastic computing neural networks for machine learning applications. IEEE Trans Neural Netw Learn Syst. 2021;32(7):2809–24.
80 Zhang J, Zhang Z, Zhang H, Ma Z, Ye Q, He P, et al. From electronic health records to terminology base: a novel knowledge base enrichment approach. J Biomed Inform. 2021;113:103628.
81 Markus AF, Kors JA, Rijnbeek PR. The role of explainability in creating trustworthy artificial intelligence for health care: a comprehensive survey of the terminology, design choices, and evaluation strategies. J Biomed Inform. 2021;113:103655.
82 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):447–53.
83 Gerke S, Babic B, Evgeniou T, Cohen IG. The need for a system view to regulate artificial intelligence/machine learning-based software as medical device. NPJ Digit Med. 2020;3:53.
84 Yang Y, Zhang H, Gichoya JW, Katabi D, Ghassemi M. The limits of fair medical imaging AI in real-world generalization. Nat Med. 2024.
85 Chen IY, Pierson E, Rose S, Joshi S, Ferryman K, Ghassemi M. Ethical machine learning in healthcare. Annu Rev Biomed Data Sci. 2021;4:123–44.
86 World Health Organization. Global Initiative on AI for Health. Available from: https://www.who.int/initiatives/global-initiative-on-ai-for-health.