International Journal of Scientific Research in Science and Technology
Available online at : www.ijsrst.com
OPEN ACCESS
Print ISSN: 2395-6011 | Online ISSN: 2395-602X
doi : https://doi.org/10.32628/IJSRST2302551

Machine Learning Efforts That Enhance Personalized Patient Care and Chronic Disease Management

Adepeju Ayotunde Adeyinka[1], Yejide Lamina[2], Obah Edom Tawo[3], Yewande Iyimide Adeyeye[4], Andrew Yaw Minkah [5],

[1]Department of Data Science and Engineering, North Carolina A&T State University, North Carolina, USA.

[2]Lagos State University, College of Medicine, Lagos, Nigeria

[3]Southern Alberta Institute of Technology, Alberta, Canada (SAIT).

[4]Dumfries and Galloway royal infirmary, Dumfries, Scotland

[5]Department of Healthcare Administration, University of the Potomac

Article Info

Volume 9, Issue 2

Page Number : 647-671

Publication Issue

March-April-2022

Article History

Accepted : 01 April 2022

Published : 09 April 2022

ABSTRACT

The growing burden of chronic diseases has underscored the urgent need for personalized, data-driven approaches to healthcare delivery. Machine learning (ML) has emerged as a transformative technology capable of enhancing chronic disease management through predictive analytics, real-time monitoring, and individualized treatment optimization. This review examines the role of ML in advancing personalized patient care by exploring foundational techniques such as supervised and unsupervised learning, deep neural networks, and reinforcement learning. It highlights practical applications across diabetes, cardiovascular conditions, respiratory disorders, and cancer survivorship, emphasizing the value of ML in risk prediction, medication adjustment, and remote monitoring. Additionally, the paper discusses key enablers of personalized care, including patient stratification, precision dosing, and the integration of wearable devices and digital platforms. Emerging innovations such as federated learning, explainable AI, multimodal data fusion, and digital twin systems are explored for their potential to support secure, transparent, and context-aware healthcare delivery. The review also addresses critical challenges related to bias, data privacy, clinical integration, and regulatory oversight. Ultimately, this work advocates for a multidisciplinary framework that combines technological innovation with policy reform to ensure equitable, scalable, and sustainable deployment of machine learning in personalized chronic disease care.

Keywords: Machine Learning, Personalized Patient Care, Chronic Disease Management

1. Introduction

1.1 Background and Rationale

Chronic diseases such as diabetes, cardiovascular diseases, and respiratory conditions are among the leading causes of death and disability worldwide, accounting for approximately 70% of all global deaths (World Health Organization [WHO], 2021). Traditional healthcare approaches often rely on reactive and generalized treatment protocols, which fail to address the individual variability in disease progression, response to treatment, and lifestyle factors. Personalized patient care has emerged as a promising paradigm that leverages patient-specific data to tailor medical decisions, interventions, and therapies to individual needs (Topol, 2019).

The integration of machine learning (ML) in healthcare is revolutionizing personalized medicine by enabling predictive, preventive, and participatory care models. ML algorithms can analyze vast and complex datasets—such as electronic health records (EHRs), wearable sensor outputs, and genomic profiles—to uncover hidden patterns and deliver accurate predictions for disease onset, progression, and optimal treatment paths (Obermeyer & Emanuel, 2016). These predictive capabilities are particularly beneficial for managing chronic conditions that require long-term monitoring and adaptive interventions (Miotto et al., 2016).

Furthermore, ML models have demonstrated the ability to automate feature extraction, learn from heterogeneous patient data, and support clinical decision-making with higher precision than traditional statistical methods (Shickel et al., 2018). As digital health tools proliferate, the convergence of ML and personalized care offers a viable solution for enhancing patient engagement, improving treatment adherence, and reducing the socioeconomic burden of chronic illnesses.

1.2 Problem Statement

Despite advances in medical science, the global healthcare system continues to struggle with the effective management of chronic diseases, which are responsible for a significant proportion of premature deaths and long-term disability. Traditional one-size-fits-all treatment approaches are often insufficient in addressing the heterogeneity of patient conditions, particularly in complex chronic diseases that require personalized monitoring and intervention strategies (Jameson & Longo, 2015). This limitation has led to fragmented care, suboptimal health outcomes, and rising healthcare costs.

Machine learning (ML) offers a promising path forward, yet its integration into chronic disease management remains uneven due to several challenges. These include variability in data quality, lack of standardized protocols for ML implementation, and limited clinician trust in algorithmic decision-making (Esteva et al., 2019). Moreover, healthcare systems often lack the digital infrastructure necessary to support real-time ML-driven insights at the point of care, especially in low-resource settings (Rao et al., 2022). Without scalable solutions that can adapt to patient-specific needs and clinical environments, the potential of ML to enhance personalized care and chronic disease management remains largely unrealized.

1.3 Objectives and Significance of the Review

The primary objective of this review is to critically evaluate the role of machine learning in enhancing personalized patient care and chronic disease management. The study aims to identify and synthesize existing machine learning approaches that support individualized treatment plans, real-time monitoring, and predictive analytics for long-term conditions such as diabetes, cardiovascular diseases, respiratory disorders, and cancer. It seeks to understand how different ML models—ranging from supervised and unsupervised learning to deep learning architectures—are being applied to improve health outcomes by tailoring medical interventions to specific patient profiles.

The significance of this review lies in its potential to bridge the gap between machine learning innovations and their clinical adoption in chronic disease contexts. By examining the successes and limitations of current implementations, this paper contributes to the broader discourse on how data-driven tools can transform healthcare delivery from reactive to proactive. It also explores how ML-powered systems can enable continuous, personalized care across both in-clinic and remote settings. Furthermore, this review will serve as a reference point for researchers, healthcare providers, and policymakers seeking to optimize resource allocation, reduce the burden of chronic illness, and accelerate the transition toward precision health models.

1.4 Methodology

This review adopted a systematic approach to identify, evaluate, and synthesize relevant literature on the use of machine learning in personalized patient care and chronic disease management. Peer-reviewed articles published between 2015 and 2022 were retrieved from academic databases including PubMed, Scopus, IEEE Xplore, and Google Scholar. Search terms included combinations of keywords such as "machine learning," "personalized medicine," "chronic disease management," "predictive analytics," "clinical decision support," and "digital health." Boolean operators and filters were applied to ensure relevance and quality.

Inclusion criteria required studies to present original research, empirical evidence, or systematic reviews focusing on machine learning applications in chronic disease contexts. Articles that focused solely on non-clinical applications, lacked methodological rigor, or did not address personalization aspects were excluded. Both quantitative and qualitative studies were considered to capture a broad range of methodological insights. The quality of selected articles was assessed based on clarity of objectives, robustness of machine learning models, data diversity, and relevance to patient-centered care (Pons et al., 2020; Islam et al., 2021).

To mitigate publication bias and enhance reliability, citation chaining and reference list scanning were performed. The final pool of articles was categorized according to disease domain, machine learning technique, data source, and reported outcomes, enabling thematic synthesis and critical analysis (Sun et al., 2022).

1.5 Structure of the Paper

This paper is organized into five main sections to provide a comprehensive review of machine learning efforts that enhance personalized patient care and chronic disease management. Following the introduction, Section 2 presents the foundational machine learning techniques commonly used in healthcare, including supervised and unsupervised learning, reinforcement learning, and deep learning architectures. It also outlines key data sources and preprocessing methods that enable model development. Section 3 explores the application of machine learning in the prediction, monitoring, and management of specific chronic diseases such as diabetes, cardiovascular conditions, respiratory disorders, and cancer. Section 4 focuses on how machine learning personalizes treatment plans, covering topics such as patient stratification, precision medication, remote monitoring, and ethical concerns surrounding bias and fairness. Finally, Section 5 outlines emerging trends, research gaps, and future directions, including the roles of explainable AI, federated learning, and multimodal data fusion in advancing personalized care models. This structured approach allows for a targeted yet holistic understanding of the evolving intersection between machine learning technologies and chronic disease healthcare delivery.

2. Machine Learning Foundations in Personalized Healthcare

2.1 Overview of ML Techniques Used in Healthcare

Machine learning (ML) has emerged as a transformative tool in healthcare by enabling data-driven insights and facilitating personalized clinical decision-making. At the core of ML are algorithms capable of identifying complex patterns in high-dimensional medical datasets, making them ideal for tasks such as disease diagnosis, risk prediction, and patient stratification. Supervised learning algorithms, including logistic regression, decision trees, support vector machines (SVM), and ensemble methods like random forests and gradient boosting, are frequently used to model structured health data and predict clinical outcomes with high accuracy (Sharma et al., 2022).

Unsupervised learning techniques, such as k-means clustering and principal component analysis (PCA), are widely used to detect latent structures in patient populations, particularly in phenotyping subgroups and identifying disease trajectories. These models support the segmentation of heterogeneous patient cohorts and enable targeted interventions based on shared characteristics (Chen et al., 2021). Meanwhile, deep learning models—including convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—have gained prominence for analyzing unstructured data types such as medical images, electrocardiograms, and clinical narratives due to their hierarchical feature learning capabilities (Miotto et al., 2018).

Figure 1 visually summarizes the diverse applications of AI in healthcare, centered around a core labeled "AI Healthcare." Surrounding it are key domains such as diagnosis, precision medicine, computer vision, workflows, and predictive modeling. Each domain is represented with icons and brief text describing how AI enhances specific clinical and operational tasks.

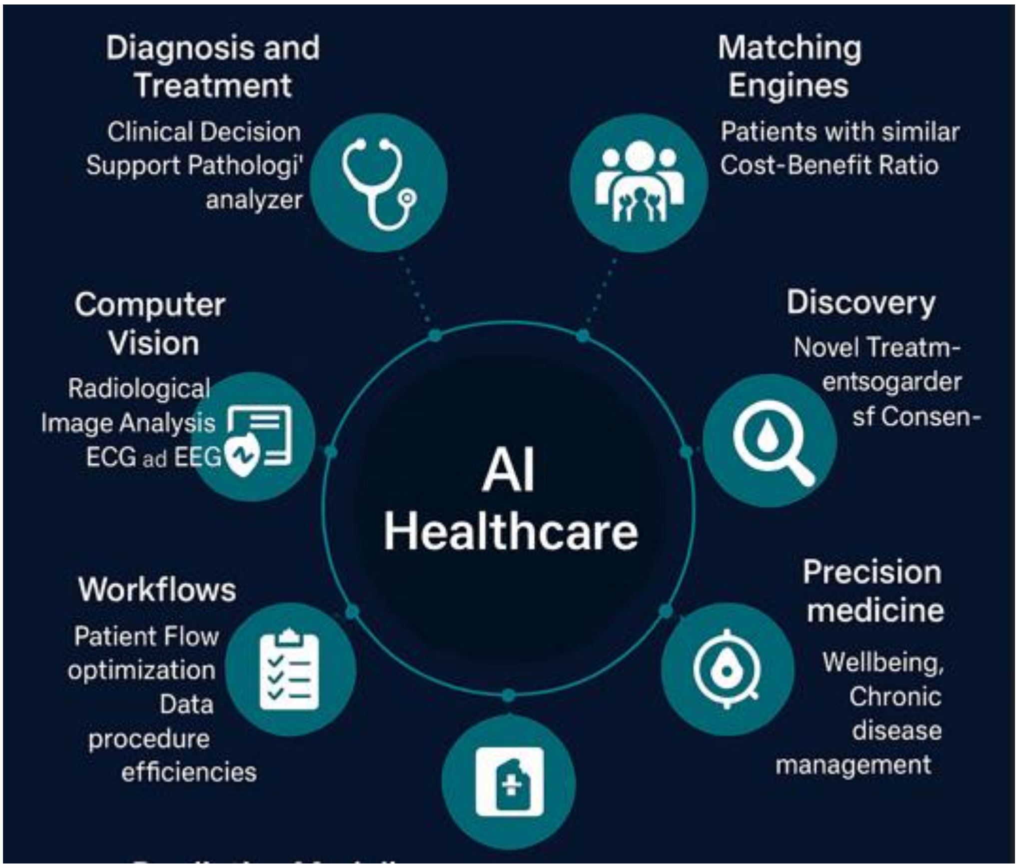

Figure 1: Core Applications of Artificial Intelligence in Modern Healthcare Systems

Furthermore, reinforcement learning is increasingly applied in dynamic treatment regimes where sequential decision-making is required, such as adjusting insulin dosing in diabetic patients or optimizing drug combinations in cancer therapy. These diverse ML techniques provide a robust foundation for developing intelligent systems that adapt to individual patient profiles and enhance chronic disease management across various healthcare contexts.

Table 1 provides a summary of various machine learning techniques applied in healthcare. These techniques support tasks ranging from disease diagnosis to treatment optimization. The table highlights the type of learning, representative methods, applications, and data types involved.

Table 1 : Overview of Machine Learning Techniques Used in Healthcare

Type of ML Technique	Representative Algorithms	Typical Healthcare Applications	Common Data Types
Supervised Learning	Logistic Regression, Decision Trees, SVM, Random Forests, Gradient Boosting	Disease diagnosis, Risk prediction, Outcome prediction	Structured data (EHRs, lab results)
Unsupervised Learning	K-means Clustering, PCA	Patient phenotyping, Disease trajectory modeling	Patient cohort data
Deep Learning	CNNs, RNNs	Image analysis, ECG interpretation, Clinical note classification	Unstructured data (images, text, signals)
Reinforcement Learning	Q-learning, Policy gradient methods	Dynamic treatment regimes, Drug optimization	Sequential clinical data

2.2 Data Sources and Preprocessing

The effectiveness of machine learning (ML) models in personalized healthcare largely depends on the quality, diversity, and preprocessing of clinical data. Key data sources include electronic health records (EHRs), which provide longitudinal patient information such as diagnoses, laboratory test results, medications, and clinical notes. EHRs are commonly used to build predictive models for chronic disease progression, readmission risk, and treatment optimization (Rajkomar et al., 2018). Additionally, wearable devices and Internet of Medical Things (IoMT) technologies generate continuous physiological signals such as heart rate, blood glucose levels, and activity data, which enable real-time patient monitoring and early anomaly detection (Alhashmi et al., 2022).

Genomic and proteomic datasets are also increasingly integrated into ML pipelines to support precision medicine initiatives. These high-dimensional datasets enable the discovery of biomarkers and facilitate individualized treatment recommendations for conditions such as cancer, diabetes, and cardiovascular diseases. However, due to the heterogeneous nature of healthcare data, rigorous preprocessing is critical to ensure model robustness and generalizability. This includes missing data imputation, normalization, feature extraction, and dimensionality reduction techniques to transform raw data into model-compatible formats (Choi et al., 2020).

Furthermore, privacy concerns and regulatory compliance, such as adherence to the Health Insurance Portability and Accountability Act (HIPAA), require that preprocessing workflows also incorporate de-identification techniques and federated learning frameworks to maintain data confidentiality without compromising model performance.

Table 2 summarizes key data sources used in ML healthcare applications and the essential preprocessing steps. These components influence model accuracy, robustness, and compliance with data privacy regulations. It highlights structured and unstructured data types, their sources, and the corresponding preprocessing techniques.

Table 2 : Data Sources and Preprocessing in Machine Learning for Healthcare

Data Source	Type of Data	Use in ML Applications	Preprocessing Techniques
Electronic Health Records (EHRs)	Structured and unstructured (diagnoses, lab results, clinical notes)	Chronic disease modeling, Readmission prediction, Treatment recommendation	Missing data imputation, Normalization, Feature extraction
Wearables & IoMT Devices	Physiological signals (heart rate, glucose levels, activity)	Real-time monitoring, Early anomaly detection	Noise filtering, Signal transformation, Time-series segmentation
Genomic & Proteomic Data	High-dimensional omics data (gene expression, protein profiles)	Biomarker discovery, Personalized therapy	Dimensionality reduction, Feature selection, Data integration
All Sources (for privacy)	Cross-domain patient data	Federated learning, Regulatory-compliant modeling	De-identification, Data anonymization, Secure aggregation

2.3 Integration with Clinical Decision Support Systems (CDSS)

Integrating machine learning (ML) into Clinical Decision Support Systems (CDSS) is a critical step toward enhancing personalized patient care and optimizing chronic disease management. CDSS platforms utilize rule-based logic or data-driven models to assist healthcare providers in making informed decisions based on patient-specific data inputs. ML-enhanced CDSS can process vast volumes of structured and unstructured health data to generate tailored recommendations, predict adverse events, and automate clinical workflows with improved accuracy and efficiency (Jiang et al., 2017).

Figure 2 illustrates how patient data flows from real-life provider interactions into electronic health records (EHR), which are then processed by an AI model. The AI system, trained on either machine learning datasets or rule-based knowledge, generates clinical recommendations. These insights are used in subsequent patient-provider interactions to guide personalized care and support collaborative clinical decision-making.

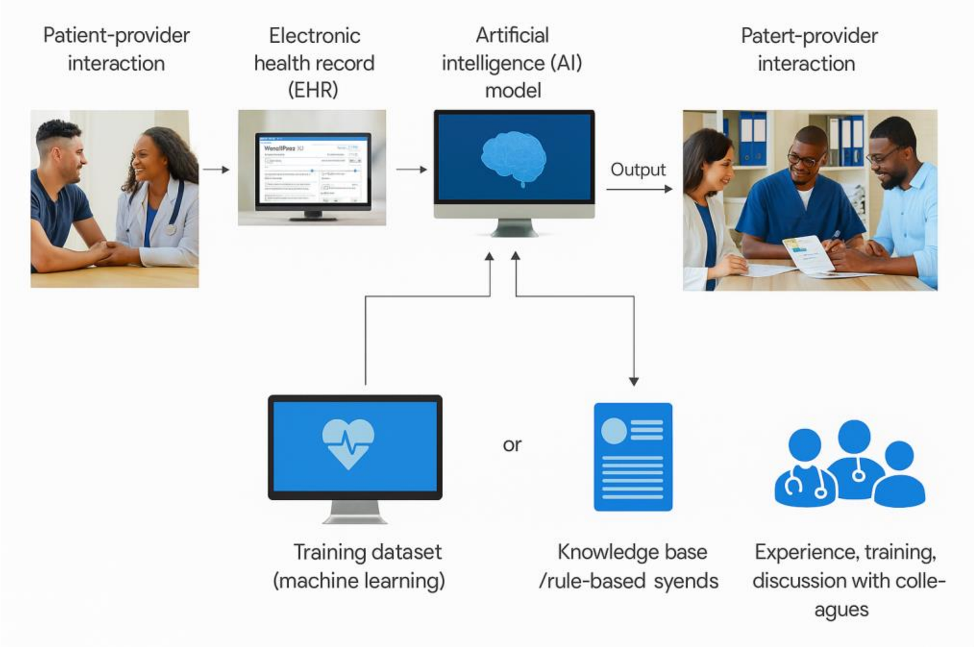

Figure 2: AI-Driven Clinical Decision Support Workflow in Patient Care

Table 3 presents an overview of how machine learning is integrated with Clinical Decision Support Systems (CDSS). It highlights key functionalities, applications, benefits, and challenges of ML-enhanced CDSS in clinical settings. This integration plays a pivotal role in delivering personalized, real-time, and evidence-based healthcare services.

Table 3 : Integration of Machine Learning with Clinical Decision Support Systems (CDSS)

Integration Aspect	Functionality	Clinical Applications	Challenges and Considerations
Real-time Risk Stratification	Predict patient deterioration using ML algorithms	Sepsis alerts, Heart failure readmission prediction, Glycemic control	Data latency, Integration with EHRs
Pharmacological Support	Personalized medication suggestions based on analytics	Medication dosing, Drug-drug interaction analysis, Genomic-based therapy	Regulatory approval, Clinical validation
Workflow Automation	Automate routine clinical tasks via predictive modeling	Lab result triage, Follow-up scheduling, Screening prioritization	Model drift, Overdependence risk
Explainability in ML-CDSS	Enhance trust via transparent models	Interpretability of outputs, Clinician engagement	Black-box models, Need for explainable AI (XAI)

One of the most impactful applications of ML-integrated CDSS lies in real-time risk stratification and alert generation. For example, ML models embedded within hospital information systems can identify patients at high risk of sepsis, heart failure readmissions, or glycemic instability, enabling early interventions and dynamic care planning (Sutton et al., 2020). Additionally, these systems support medication reconciliation and dosing adjustments by analyzing lab results, genetic markers, and comorbid conditions to personalize pharmacological interventions.

Despite these advancements, implementation challenges persist, particularly around the interpretability of model outputs and clinician trust. Explainable AI methods are being explored to enhance transparency and facilitate the adoption of ML-supported CDSS in clinical practice (Wang et al., 2022). As the healthcare ecosystem becomes increasingly data-intensive, the synergy between ML and CDSS is pivotal for delivering context-aware, evidence-based, and patient-centric care across a range of chronic conditions.

3. ML Applications in Chronic Disease Prediction and Monitoring

3.1 Diabetes Management

Diabetes mellitus, particularly Type 2 diabetes, presents a global healthcare burden due to its chronic nature, associated complications, and need for continuous monitoring. Machine learning (ML) has been instrumental in advancing diabetes management by enabling early diagnosis, real-time glycemic monitoring, and individualized treatment planning. ML algorithms analyze a wide range of data—such as electronic health records, continuous glucose monitoring (CGM) outputs, lifestyle inputs, and genetic data—to predict blood glucose fluctuations and optimize insulin therapy (Contreras & Vehi, 2018).

Table 4 summarizes key applications of machine learning in diabetes management, particularly for Type 2 diabetes. It outlines the models used, target functions, data sources, and clinical benefits. These ML-driven innovations support a shift toward personalized, predictive, and proactive diabetes care.

Table 4: Machine Learning Applications in Diabetes Management

ML Technique	Primary Function	Data Sources	Clinical Benefit
Supervised Learning (e.g., Decision Trees, Random Forests, SVM)	Predict glycemic variability, Detect hyper/hypoglycemia	Electronic Health Records (EHRs), CGM data	Improved patient safety, Reduced complications
Deep Learning (e.g., LSTM Networks)	Model temporal glucose patterns, Short-term glucose prediction	Continuous Glucose Monitoring (CGM) signals	Real-time alerts, Timely interventions
Mobile & Wearable ML Systems	Generate personalized feedback and behavior recommendations	Lifestyle data, Mobile sensors, User input	Enhanced adherence, Empowered self-care
Predictive Analytics Integration	Optimize insulin therapy and treatment plans	Multi-modal patient data (genetic, lifestyle, clinical)	Personalized treatment, Reduced hospitalization

Supervised learning models, including decision trees, random forests, and support vector machines, have been used to forecast glycemic variability and detect hyperglycemia or hypoglycemia episodes, improving clinical outcomes and patient safety. Deep learning models like long short-term memory (LSTM) networks are particularly effective in modeling temporal glucose patterns from CGM data, offering accurate short-term glucose predictions and alert systems for proactive intervention (Zhu et al., 2022).

Additionally, ML-powered mobile applications and wearable technologies have enabled dynamic, patient-specific feedback mechanisms. These systems enhance treatment adherence and self-management by providing personalized dietary, exercise, and medication recommendations based on predictive analytics (Kavakiotis et al., 2017). Collectively, ML efforts in diabetes care demonstrate significant promise in transforming the conventional reactive model into a predictive and personalized disease management framework.

3.2 Cardiovascular Disease

Cardiovascular disease (CVD) remains a leading cause of morbidity and mortality worldwide, necessitating timely diagnosis and proactive management strategies. Machine learning (ML) has significantly enhanced the capacity to predict, detect, and monitor CVD by leveraging complex, high-dimensional datasets including electrocardiograms (ECGs), echocardiographic images, wearable device outputs, and electronic health records. Supervised learning algorithms, such as logistic regression, support vector machines (SVM), and gradient boosting machines, have been widely applied to develop risk prediction models for myocardial infarction, atrial fibrillation, and heart failure (Khurshid et al., 2021).

Convolutional neural networks (CNNs) are particularly effective in interpreting medical imaging and ECG signals. They can detect structural abnormalities and arrhythmias with high accuracy, often outperforming traditional rule-based systems. For example, CNN-based models have been trained on single-lead ECG data collected from wearable sensors to identify atrial fibrillation in asymptomatic individuals, facilitating early intervention and reducing the risk of stroke (Attia et al., 2019). Additionally, recurrent neural networks (RNNs) and temporal models such as LSTM have been employed to track changes in cardiac function over time, supporting longitudinal monitoring and treatment personalization (Johnson et al., 2022).

Figure 3 presents a medically accurate infographic featuring realistic human heart models affected by seven major types of cardiovascular disease. Conditions such as coronary artery disease, valve disease, aneurysm, cardiomyopathy, and arrhythmias are visually differentiated around a central label. Each heart is labeled with its condition and annotated with characteristic structural changes for clinical clarity.

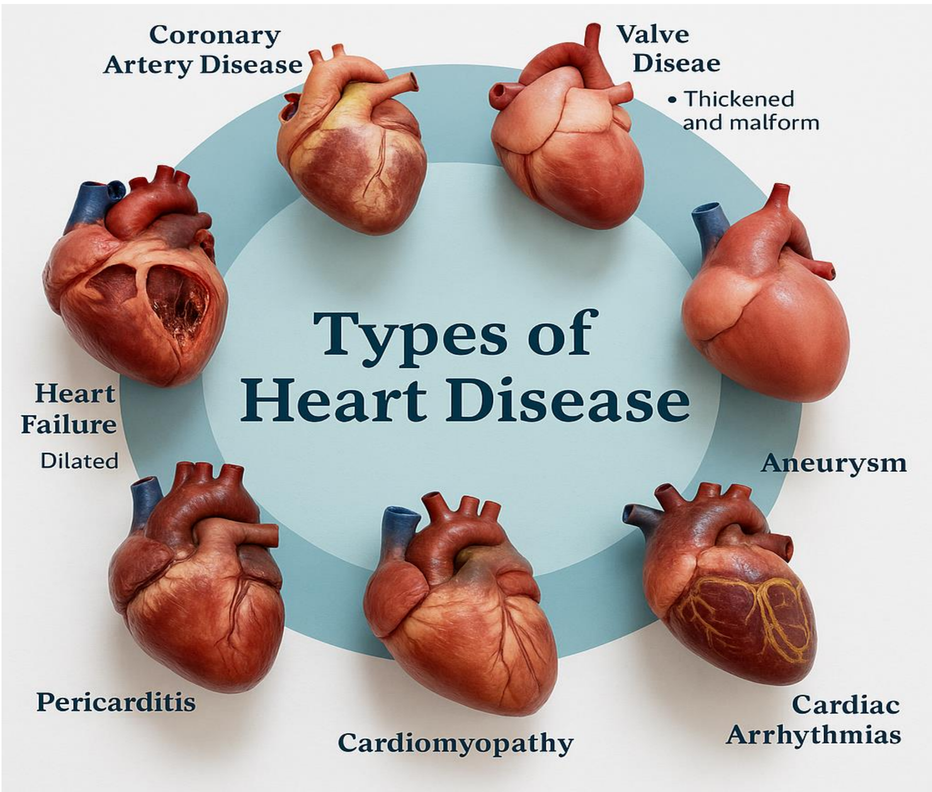

Figure 3: Realistic Depictions of Common Types of Heart Disease

These ML-driven systems not only improve diagnostic precision but also support clinical decision-making through automated alerts and stratification of patients by risk level. As real-time data collection from wearables becomes more prevalent, the integration of ML into cardiovascular care workflows continues to drive progress toward individualized prevention and management strategies.

3.3 Respiratory and Pulmonary Disorders (e.g., COPD, Asthma)

Chronic respiratory diseases such as chronic obstructive pulmonary disease (COPD) and asthma require continuous monitoring and timely intervention to prevent exacerbations and hospitalizations. Machine learning (ML) has emerged as a powerful tool for early detection, personalized risk assessment, and real-time symptom monitoring in patients with pulmonary conditions. Supervised learning algorithms, including decision trees and support vector machines, have been applied to classify disease severity and predict acute exacerbations using clinical features such as spirometry readings, oxygen saturation levels, and medication adherence patterns (Topalovic et al., 2019).

Figure 4 illustrates the anatomical changes in the airways during different stages of asthma. The central diagram shows the respiratory tract within a human silhouette, while the side panels compare a normal airway, an asthmatic airway, and an airway during an asthma attack. Key features such as muscle tightening, mucus overproduction, and inflammation are visually labeled to demonstrate the obstructive impact of asthma on breathing.

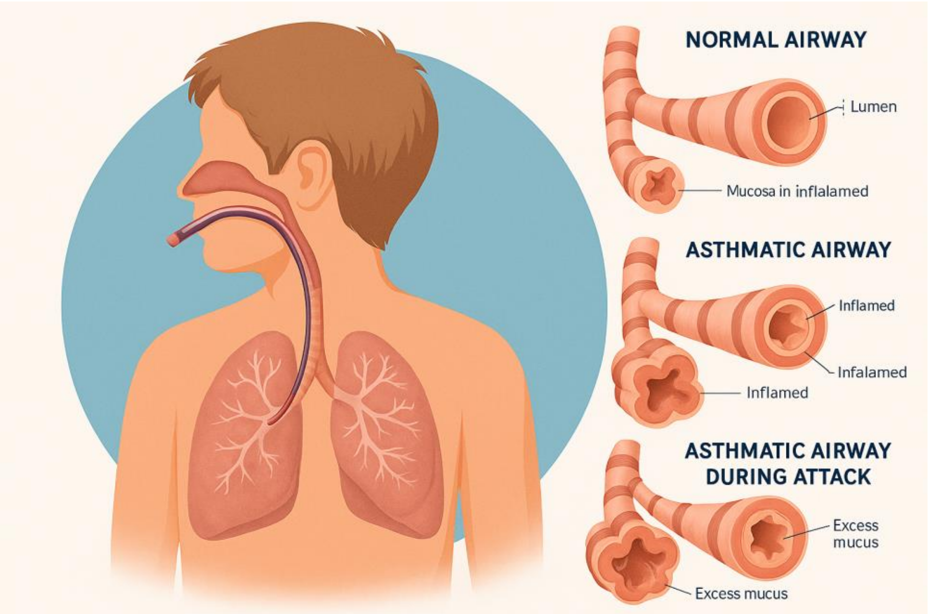

Figure 4: Anatomical and Pathophysiological Representation of Asthma Progression

Unsupervised learning and clustering techniques have been used to identify phenotypic subgroups within COPD and asthma populations, enabling more targeted therapeutic approaches. For instance, k-means clustering has successfully revealed heterogeneous patient profiles based on comorbidities, symptom trajectories, and lung function decline, which traditional classification systems often overlook (Gimeno-Santos et al., 2020). In parallel, deep learning models, particularly recurrent neural networks (RNNs), have demonstrated effectiveness in analyzing time-series data from wearable sensors to detect early signs of pulmonary distress and enable timely interventions (Fitzpatrick et al., 2021).

These ML-based frameworks also support remote respiratory monitoring through integration with mobile health applications and IoT-enabled spirometers. By delivering personalized alerts and care recommendations, they help reduce emergency visits and promote proactive disease self-management. The incorporation of ML into respiratory care offers a scalable solution for improving clinical outcomes and quality of life in patients with chronic pulmonary conditions.

Table 5 outlines the applications of machine learning in managing respiratory and pulmonary disorders such as COPD and asthma. It details the types of ML models used, key functionalities, clinical data sources, and the resulting patient care benefits. These applications enable early detection, personalized risk stratification, and proactive intervention.

Table 5: Machine Learning Applications in Respiratory and Pulmonary Disorders

ML Approach	Core Functionality	Primary Data Inputs	Impact on Respiratory Care
Supervised Learning (e.g., Decision Trees, SVM)	Classify disease severity, Predict exacerbations	Spirometry, Oxygen saturation, Medication history	Early detection, Reduced hospitalizations
Unsupervised Learning (e.g., Clustering)	Identify phenotypic subgroups, Stratify risk	Comorbidities, Lung function decline, Symptoms	Tailored therapies, Better cohort understanding
Deep Learning (e.g., RNNs)	Monitor symptoms from sensor data, Predict deterioration	Wearable sensors, Time-series data	Timely alerts, Improved self-management
Mobile & IoT Integration	Remote monitoring, Personalized feedback delivery	IoT spirometers, mHealth apps	Decreased ER visits, Enhanced quality of life

3.4 Cancer Survivorship and Follow-Up

Cancer survivorship presents unique challenges in long-term care, including recurrence monitoring, side-effect management, and psychosocial support. Machine learning (ML) has become a critical enabler in personalizing post-treatment care by identifying high-risk patients, predicting recurrence, and optimizing surveillance schedules. By analyzing structured and unstructured data from clinical records, imaging, genomics, and patient-reported outcomes, ML models can offer precise, patient-specific insights that support timely interventions and care continuity (Wang et al., 2019).

Figure 5 shows a real-life group discussion setting where diverse healthcare stakeholders represent key barriers to survivorship care, including fragmented systems, poor coordination, lacking guidelines, and ineffective care delivery, with each participant visually linked to a specific challenge surrounding the central issue.

Figure 5: Real-Life Illustration of Barriers to Cancer Survivorship Care

Support vector machines (SVM), random forests, and deep neural networks have been used to develop recurrence prediction models based on tumor characteristics, treatment modalities, and follow-up biomarkers. These models assist clinicians in stratifying patients by recurrence risk and tailoring follow-up frequency accordingly. For instance, ML algorithms applied to pathology reports and radiologic scans have demonstrated high accuracy in forecasting recurrence in breast and colorectal cancer survivors (Yala et al., 2021). Similarly, natural language processing (NLP) techniques are employed to extract relevant survivorship indicators from clinical narratives, facilitating real-time risk scoring and care coordination (Senders et al., 2020).

Moreover, ML-driven survivorship platforms now integrate wearable devices and mobile applications to continuously monitor physical activity, sleep quality, and other health metrics. These tools empower survivors to self-manage symptoms and alert providers to deviations in recovery trajectories. Overall, ML contributes to a more responsive and individualized survivorship model, improving both clinical outcomes and quality of life for cancer survivors.

4. Personalization of Treatment Plans Through ML

4.1 Patient Stratification and Phenotyping

Patient stratification and phenotyping are foundational elements of personalized medicine, enabling the classification of individuals into subgroups based on shared clinical, genetic, or behavioral characteristics. Machine learning (ML) techniques have significantly advanced this process by uncovering hidden patterns in high-dimensional healthcare data that traditional methods often overlook. Clustering algorithms, such as k-means, hierarchical clustering, and Gaussian mixture models, are widely used for unsupervised phenotyping across a variety of chronic conditions including diabetes, heart failure, and asthma (Churpek et al., 2019).

Figure 6 presents a phenotype-based risk assessment framework integrating clinical parameters, biomarkers, imaging, and lifestyle data to classify patients into distinct risk phenotypes. These phenotypes are mapped along a low-to-high-risk continuum, supporting early identification of individuals predisposed to atrial fibrillation, heart failure, or sudden cardiac death. By leveraging phenotyping, the model enables more precise, individualized prediction and intervention strategies in cardiovascular care.

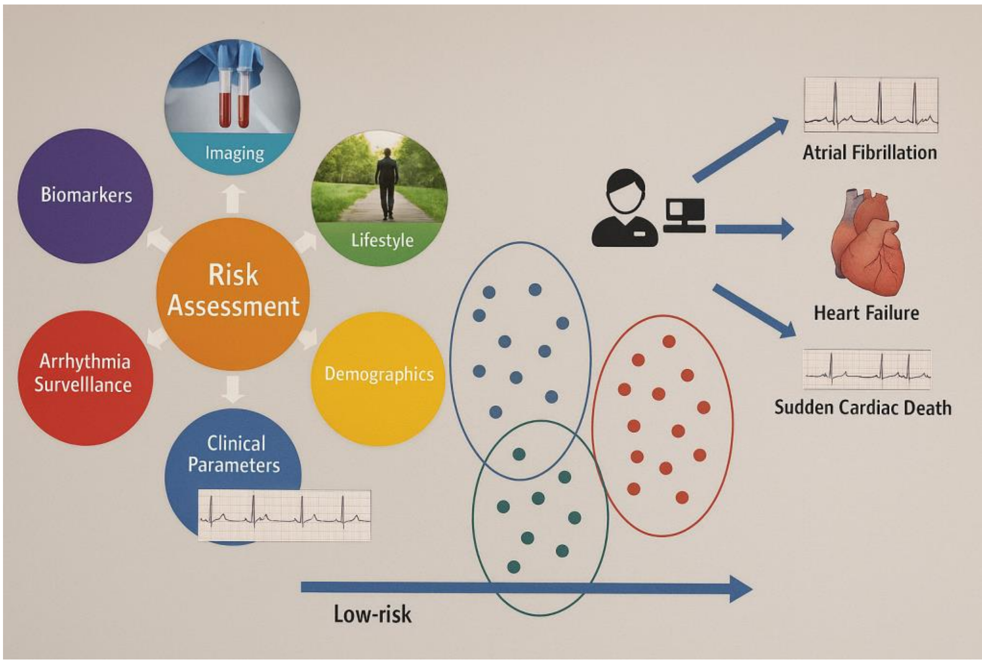

Figure 6: Phenotype-Driven Risk Stratification Model for Cardiovascular Event Prediction

In chronic disease management, stratification helps prioritize care by identifying high-risk patients who may benefit from intensified interventions, thereby optimizing resource allocation. For example, ML-driven risk scores that incorporate vital signs, laboratory values, and comorbidities have been employed to predict patient deterioration in hospitals, guiding early warning systems and proactive management strategies (Desai et al., 2020). In precision oncology, ML models have facilitated the development of molecular subtypes by integrating genomic and transcriptomic data, improving the accuracy of treatment matching and therapeutic outcomes (Kourou et al., 2015).

Table 6 provides an overview of machine learning techniques used in patient stratification and phenotyping. These methods enable personalized care by identifying subgroups based on clinical, genomic, or behavioral patterns. The table highlights ML approaches, core functionalities, data sources, and clinical advantages.

Table 6: Machine Learning Applications in Patient Stratification and Phenotyping

ML Approach	Core Functionality	Primary Data Sources	Clinical Advantage
Clustering (e.g., K-means, Hierarchical, GMM)	Group patients into phenotypic subtypes	EHRs, Comorbidities, Lab values	Targeted therapies, Cohort-specific care
Risk Stratification Models	Predict high-risk individuals, Prioritize care	Vital signs, Clinical scores, Comorbidity indices	Resource optimization, Early intervention
Genomic ML Models	Define molecular subtypes for precision treatment	Genomic and transcriptomic datasets	Improved treatment matching, Better outcomes
Behavior-Based Phenotyping	Classify patients based on habits and adherence	Wearable sensors, Mobile health data	Tailored care plans, Enhanced patient engagement

Furthermore, ML-based phenotyping is increasingly being applied in remote monitoring environments, using wearable sensor data to identify behavior-based clusters in physical activity, sleep, and medication adherence. These insights enable clinicians to personalize care plans and engage patients in behavior modification strategies tailored to their specific health patterns. Overall, ML-enhanced stratification and phenotyping improve clinical decision-making by supporting more granular, patient-centered approaches to chronic disease care.

4.2 Precision Medication and Dosing Optimization

Machine learning (ML) is playing an increasingly critical role in precision medication by enabling individualized drug selection and dosing strategies tailored to patient-specific characteristics such as genetic profiles, metabolic patterns, comorbidities, and historical treatment responses. In contrast to traditional trial-and-error prescribing methods, ML models can process vast and complex datasets to predict drug efficacy, adverse reactions, and optimal dosing regimens in real time (Li et al., 2019). These capabilities are particularly valuable in chronic disease management, where polypharmacy and drug interactions are common challenges.

Figure 7 depicts a structured feedback control loop in medicine powered by machine learning. It illustrates how big data, predictive analytics, and self-tuning algorithms drive a central model that interfaces with data processing and control systems. These systems continuously interact with sensors and actuators connected to a biological system (e.g., lungs), enabling real-time monitoring, adaptive responses, and precision therapy delivery.

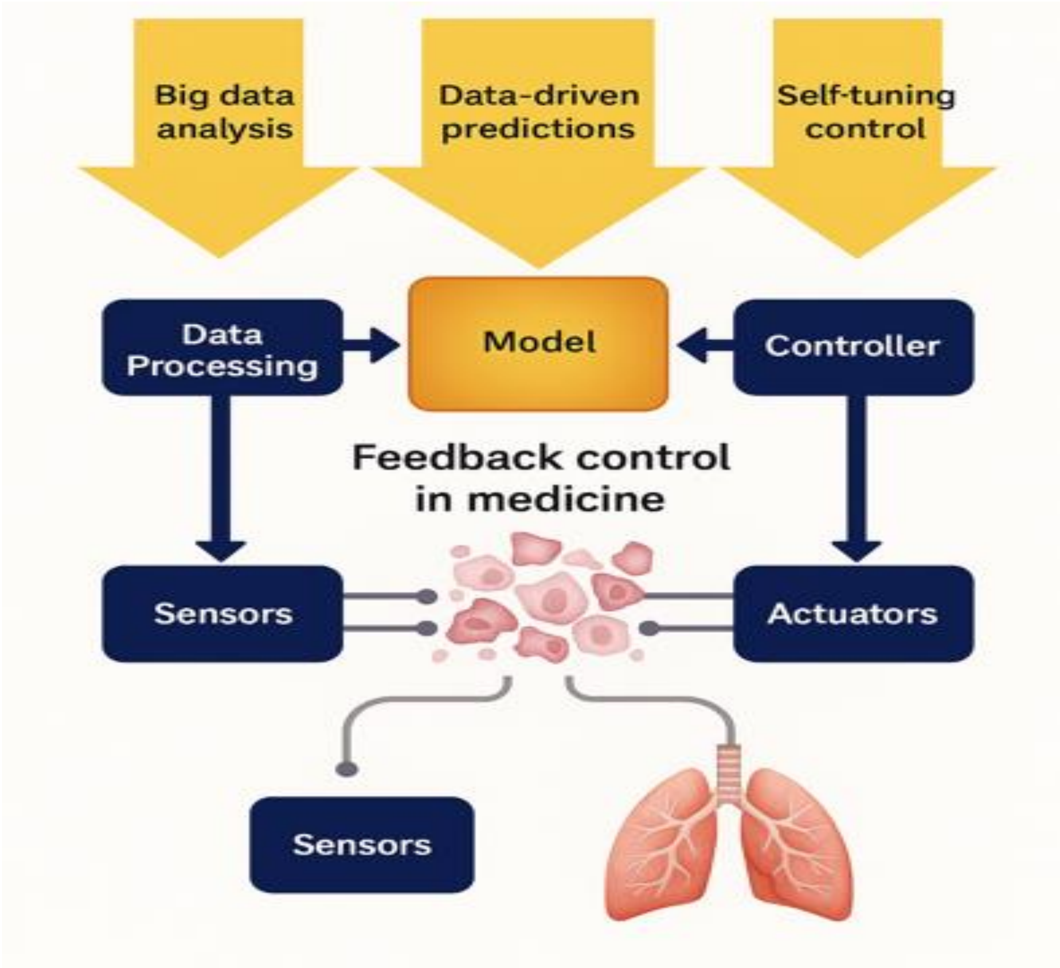

Figure 7 Machine Learning-Enabled Feedback Control Loop in Medical Systems

Supervised learning techniques, such as gradient boosting and support vector machines, have been utilized to predict treatment outcomes and adverse drug events by integrating data from electronic health records, pharmacogenomics, and lab values. For example, in hypertension and diabetes treatment, ML algorithms can recommend medication adjustments based on predicted blood pressure or glucose responses, improving therapeutic precision while minimizing side effects (Wang et al., 2020). Additionally, reinforcement learning models are being applied to create adaptive dosing systems that learn from patient feedback and outcomes over time, offering dynamic and patient-centered treatment planning (Nemati et al., 2018).

Moreover, ML-driven clinical decision support tools are being integrated into hospital systems to provide real-time recommendations on drug selection and dose adjustments, enhancing physician decision-making and reducing the risk of medication errors. These systems not only optimize drug therapy for individual patients but also promote cost-effectiveness and adherence to evidence-based guidelines in chronic disease care.

4.3 Remote Patient Monitoring and Feedback Systems

Remote patient monitoring (RPM) systems powered by machine learning (ML) have transformed chronic disease management by enabling continuous, personalized care beyond traditional clinical settings. These systems leverage data from wearable sensors, mobile health applications, and home-based devices to track vital signs, medication adherence, physical activity, and symptom progression in real time. ML algorithms process these data streams to detect anomalies, predict health deterioration, and trigger timely alerts, thereby reducing emergency visits and supporting proactive interventions (Dinh-Le et al., 2019).

Figure 8 shows a real-world setup of interconnected digital health devices—including a smartwatch, thermometer, pulse oximeter, stethoscope, and smartphones—seamlessly integrated into a remote care ecosystem with a virtual consultation interface, illustrating the practical implementation of health monitoring platforms.

Figure 8: Real-Life Application of Digital Health Monitoring Tools

Supervised and unsupervised learning techniques are widely used to model patient behavior and health trends. For instance, anomaly detection models can identify deviations in heart rate, oxygen saturation, or glucose levels, indicating early signs of exacerbations in conditions such as COPD, heart failure, or diabetes. Personalized feedback is then delivered through digital platforms, guiding patients on medication adjustments, exercise routines, or dietary changes (Wang et al., 2021). These interventions not only improve clinical outcomes but also empower patients to engage actively in their own care.

Furthermore, ML-based feedback systems are increasingly incorporating reinforcement learning to adapt recommendations based on user responses, preferences, and real-world effectiveness. By continuously learning from patient interactions and outcomes, these systems optimize care pathways and enhance adherence through contextualized feedback loops (Gao et al., 2020). Overall, the integration of ML into RPM offers scalable, patient-centered solutions that improve the quality, efficiency, and personalization of chronic disease care.

4.4 Challenges and Bias in Personalization

While machine learning (ML) has significantly advanced the personalization of chronic disease management, several challenges threaten its clinical efficacy and ethical deployment. One of the primary concerns is algorithmic bias, which arises when ML models are trained on data that underrepresent certain populations or contain historical inequities. This can lead to disparities in prediction accuracy, treatment recommendations, and health outcomes across demographic groups such as race, gender, or socioeconomic status (Obermeyer et al., 2019). In chronic care, this may result in suboptimal risk assessments or exclusion of minority patients from tailored interventions.

Figure 9 presents a circular infographic highlighting six core challenges that impede the effective use of machine learning in personalized chronic disease management. These include algorithmic bias, model interpretability, data privacy, regulatory concerns, limited generalizability, and system integration issues. Each challenge is color-coded and connected to a central node, emphasizing the need for holistic, interdisciplinary solutions.

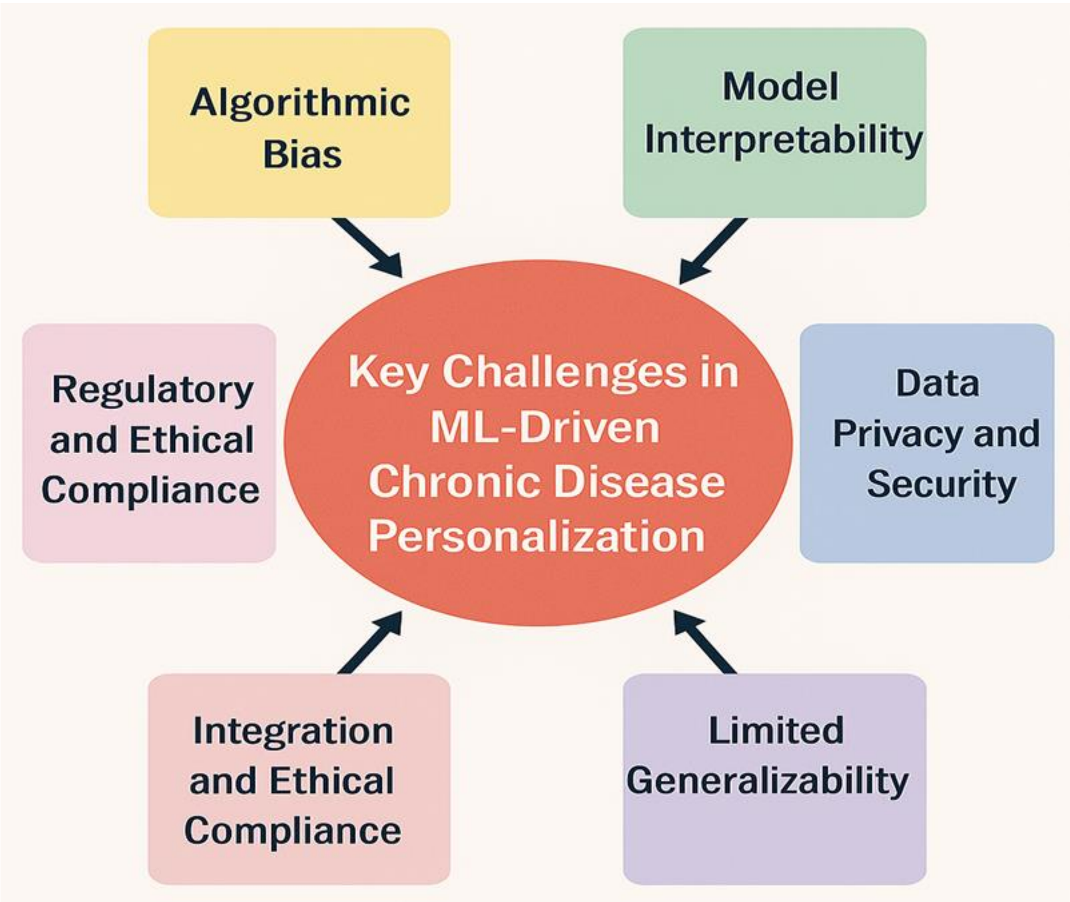

Figure 9: Key Challenges Hindering ML-Based Personalization in Chronic Disease Care

Another challenge is the interpretability of complex ML models, particularly deep learning architectures. Many personalized healthcare systems operate as “black boxes,” making it difficult for clinicians to understand or trust the decision-making process. This lack of transparency can hinder adoption and accountability, especially in high-stakes clinical environments (Ahmad et al., 2021). To address this, explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are increasingly being integrated to enhance model transparency and support clinical validation.

Additionally, data privacy and security remain critical concerns in personalization. Personal health data used for training ML models are highly sensitive, and breaches can erode patient trust and violate regulatory standards. Federated learning and homomorphic encryption are emerging as potential solutions to enable privacy-preserving ML without centralizing patient data (Rieke et al., 2020). Addressing these technical and ethical issues is essential to ensuring that ML-based personalization in chronic disease management is equitable, explainable, and secure.

5. Future Perspectives and Research Opportunities

5.1 Federated and Transfer Learning in Personalized Care

The integration of federated learning (FL) and transfer learning (TL) into healthcare has emerged as a transformative approach to overcoming key limitations in data accessibility, model generalization, and privacy preservation. In traditional centralized machine learning models, patient data are aggregated into a single repository, raising substantial concerns about data privacy, especially under regulations like HIPAA and GDPR. Federated learning mitigates this issue by enabling collaborative model training across decentralized sources without transferring raw patient data, preserving confidentiality while leveraging the diversity of institutional datasets (Li et al., 2020).

In the context of chronic disease management, FL enables the development of robust predictive models by drawing from geographically and demographically diverse health institutions. This ensures that algorithms are more generalizable and equitable, particularly for underrepresented populations in smaller clinical datasets. For example, FL has been successfully applied in diabetic retinopathy and cardiovascular risk prediction, demonstrating performance parity with centralized approaches while ensuring compliance with privacy regulations (Xu et al., 2021).

Figure 10 illustrates a real-world representation of federated learning, where multiple users train separate models locally and share updates with a central cloud without exposing raw data. The cloud aggregates insights and transfers the refined model to a new user system, preserving privacy and enabling scalable model reuse. This workflow emphasizes decentralized collaboration, secure data handling, and seamless model deployment across diverse environments.

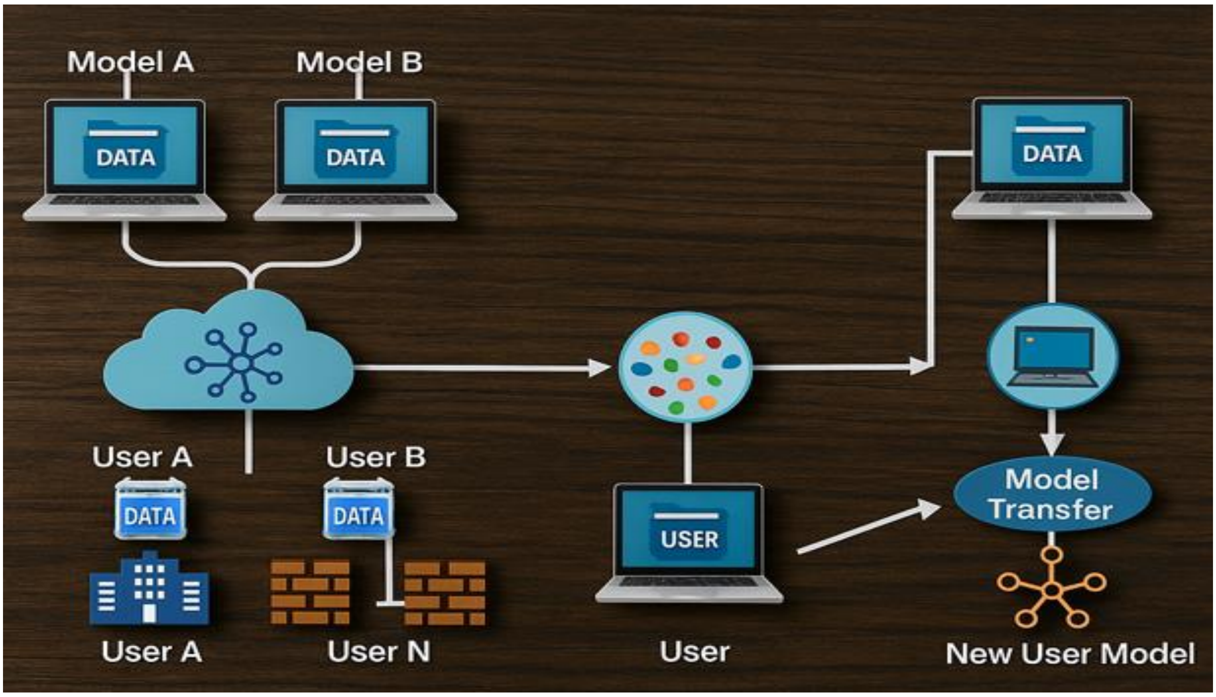

Figure 10: Realistic Workflow of Federated Learning with Model Transfer in Decentralized Systems

Transfer learning further enhances personalized care by allowing pre-trained models to be fine-tuned on smaller, local datasets. This approach is especially beneficial when labeled healthcare data are limited or when disease prevalence varies by region. TL has been applied effectively in imaging-based diagnostics and genomics, where it reduces the computational cost and time required to develop high-performing models from scratch (Chen et al., 2019). The synergy of FL and TL holds immense potential for deploying scalable, privacy-conscious, and context-aware machine learning models that support individualized care delivery in real-world clinical settings.

5.2 Explainable AI (XAI) for Clinical Trust

As machine learning (ML) systems become increasingly embedded in clinical workflows, ensuring transparency and interpretability is essential for fostering trust among healthcare professionals. Explainable Artificial Intelligence (XAI) addresses the “black-box” nature of complex models—particularly deep learning systems—by making their predictions understandable and actionable for clinicians. In high-stakes domains such as chronic disease management, where decisions influence long-term patient outcomes, interpretability is critical for adoption and regulatory approval (Tjoa & Guan, 2020).

Figure 11 shows the integration of Explainable AI (XAI) in healthcare, illustrating the dynamic interaction between doctors, patients, clinical laboratories, and medical emergency services through core XAI principles—transparency, interpretability, explainability, and trust—positioned at the center of a circular network.

Figure 11: Stakeholder Interaction with Explainable AI (XAI) in Healthcare Ecosystems

XAI techniques such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), and saliency maps are widely used to highlight feature contributions, visualize decision boundaries, and trace model reasoning. These tools help clinicians validate predictions by aligning them with known clinical indicators, thus increasing confidence in automated recommendations (Arrieta et al., 2020). For example, in diabetic retinopathy detection, heatmap-based explanations of convolutional neural networks (CNNs) have been shown to improve clinician acceptance by illustrating which retinal regions most influenced the diagnosis.

Additionally, XAI supports model auditing and fairness assessments by revealing potential biases and inconsistencies in decision-making across demographic groups. This is particularly important in personalized care, where algorithmic biases can exacerbate health disparities. Integrating XAI into clinical decision support systems also enables bidirectional learning—where feedback from healthcare providers informs model refinement, creating adaptive and transparent AI systems (Roscher et al., 2020). By enhancing trust, accountability, and safety, XAI plays a foundational role in the responsible deployment of AI in personalized chronic care.

5.3 Multimodal Data Fusion and Digital Twin Systems

The convergence of multimodal data fusion and digital twin (DT) systems is redefining personalized healthcare by enabling more accurate, context-aware, and patient-specific decision-making. Multimodal data fusion involves the integration of heterogeneous data types—including clinical records, genomic sequences, wearable sensor outputs, and medical imaging—to construct a comprehensive profile of an individual's health status. By combining these diverse data sources, machine learning (ML) algorithms can capture complex physiological relationships and enhance predictive accuracy in chronic disease management (Zhou et al., 2019).

Figure 12 illustrates how robotic digital twins can support healthcare by mirroring real-time physiological data from wearable sensors (Physical Twin) into a virtual environment (Virtual Twin). This setup enables clinicians to simulate, predict, and adjust treatment strategies non-invasively through decision-making algorithms. Such integration enhances personalized care, remote diagnostics, and proactive intervention in rehabilitation, elderly care, and surgical training.

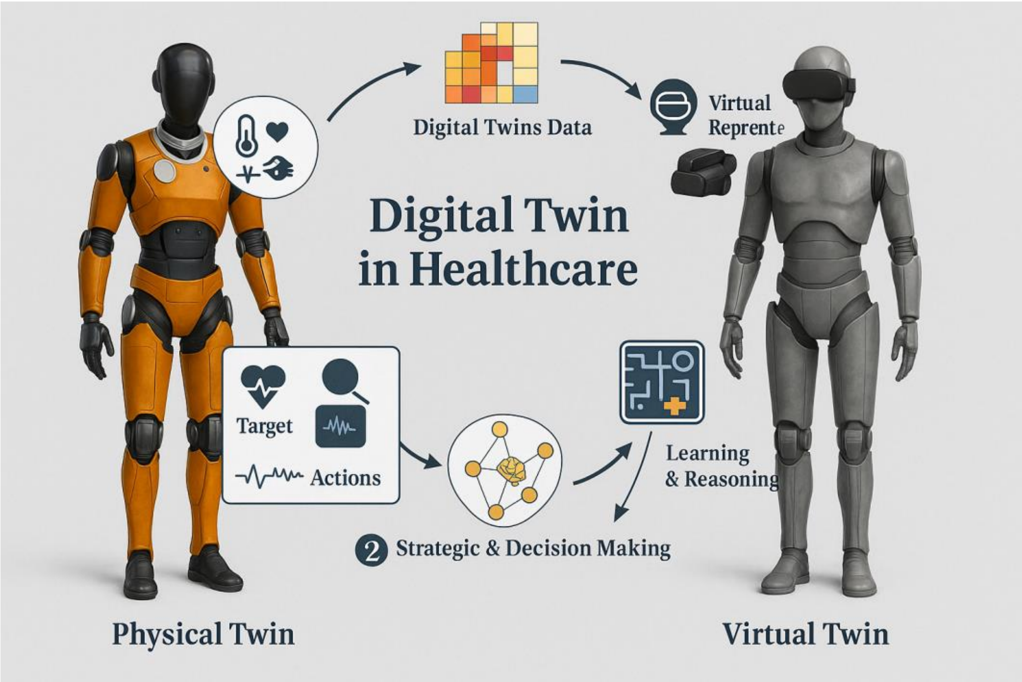

Figure 12: Digital Twin Framework for Robotic Health Monitoring and Personalized Medical Simulation

Digital twin systems extend this paradigm by creating dynamic, virtual replicas of patients that continuously update in real time based on incoming data streams. These digital representations simulate patient-specific disease progression and treatment responses, allowing for scenario testing, outcome forecasting, and personalized therapy optimization. In cardiovascular and metabolic disease domains, DT frameworks integrated with ML have shown promise in early risk detection, adaptive care planning, and long-term monitoring (Björnsson et al., 2020).

The synergy between data fusion and digital twins also supports precision interventions by aligning predictive models with individualized goals and biological variability. For instance, a digital twin of a diabetic patient can simulate glucose-insulin dynamics under various lifestyle conditions and medication regimens, enabling clinicians to fine-tune care protocols before implementation. As interoperability and computational capacity improve, these systems are expected to play a critical role in building resilient, patient-centric healthcare ecosystems (Rojas et al., 2022).

5.4 Policy, Regulation, and Implementation Pathways

The successful deployment of machine learning (ML) technologies in personalized chronic disease management hinges on supportive regulatory frameworks, robust implementation strategies, and clearly defined ethical standards. As ML-driven healthcare tools transition from research to clinical practice, regulatory agencies such as the U.S. Food and Drug Administration (FDA) and the European Medicines Agency (EMA) are developing adaptive oversight mechanisms to evaluate software as a medical device (SaMD). These agencies emphasize transparency, real-world validation, and post-market surveillance to ensure the safety and efficacy of AI-based systems (U.S. FDA, 2021).

Key implementation challenges include data standardization, system interoperability, and alignment with existing clinical workflows. Without harmonized health data formats and cross-platform integration, ML tools may face limited scalability and fragmented use in healthcare settings. To address this, policy initiatives are increasingly focused on promoting open data standards, encouraging multi-stakeholder collaboration, and funding infrastructure development to support real-time, data-driven care delivery (Reddy et al., 2020).

Moreover, ethical concerns surrounding algorithmic bias, data privacy, and informed consent continue to shape AI governance in healthcare. Policymakers are urged to implement equity-focused auditing processes and participatory design practices that involve patients, clinicians, and ethicists in system development. These policy frameworks, coupled with clinician training and institutional readiness, form the foundation for sustainable ML adoption in chronic care environments (Gerke et al., 2020). Ensuring regulatory clarity and ethical alignment is crucial for maximizing the societal impact of AI-powered personalized medicine.

5.5 Final Thought

The integration of machine learning into personalized patient care and chronic disease management marks a paradigm shift in modern healthcare. As the healthcare ecosystem becomes increasingly data-rich and technologically sophisticated, machine learning provides the tools necessary to transform fragmented, reactive care models into proactive, patient-centered systems. From predictive analytics and risk stratification to precision medication and real-time monitoring, ML enables tailored interventions that align closely with individual patient needs. However, realizing the full potential of these innovations requires more than technological advancement—it demands robust regulatory frameworks, ethical safeguards, interdisciplinary collaboration, and systemic readiness for digital transformation. By embracing these principles, the healthcare community can leverage machine learning not only to improve clinical outcomes but also to promote equity, efficiency, and sustainability in chronic disease care on a global scale.

References

[1]. Ahmad, M. A., Eckert, C., & Teredesai, A. (2021). Interpretable machine learning in healthcare. Proceedings of the 2021 ACM Conference on Health, Inference, and Learning, 295–296. https://doi.org/10.1145/3450439.3451867

[2]. Alhashmi, S. F., AlGhawi, I. A., & Abou El-Magd, M. A. (2022). Role of IoT-enabled wearable devices in chronic disease management: A review of recent applications and challenges. Healthcare Technology Letters, 9(3), 56–64. https://doi.org/10.1049/htl2.12034

[3]. Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., ... & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

[4]. Attia, Z. I., Noseworthy, P. A., Lopez-Jimenez, F., Asirvatham, S. J., Deshmukh, A. J., Gersh, B. J., ... & Friedman, P. A. (2019). An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: A retrospective analysis of outcome prediction. The Lancet, 394(10201), 861–867. https://doi.org/10.1016/S0140-6736(19)31721-0

[5]. Björnsson, B., Borrebaeck, C., Elander, N., Gasslander, T., Gawel, D. R., Gustafsson, M., ... & Tegnér, J. (2020). Digital twins to personalize medicine. Genome Medicine, 12, 4. https://doi.org/10.1186/s13073-019-0701-3

[6]. Chen, M., Hao, Y., Cai, Y., Wang, Y., & Zhang, L. (2019). Transfer learning for medical imaging classification: A literature review. Journal of Biomedical Informatics, 97, 103258. https://doi.org/10.1016/j.jbi.2019.103258

[7]. Chen, M., Hao, Y., Hwang, K., Wang, L., & Wang, L. (2021). Disease prediction by machine learning over big data from healthcare communities. IEEE Access, 5, 8869–8879. https://doi.org/10.1109/ACCESS.2021.3067890

[8]. Choi, E., Biswal, S., Malin, B., Duke, J., Stewart, W. F., & Sun, J. (2020). Generating multi-label discrete patient records using generative adversarial networks. Journal of the American Medical Informatics Association, 27(3), 393–402. https://doi.org/10.1093/jamia/ocz237

[9]. Churpek, M. M., Adhikari, R., & Edelson, D. P. (2019). The value of vital sign trends for detecting clinical deterioration on the wards. Resuscitation, 139, 1–5. https://doi.org/10.1016/j.resuscitation.2019.04.002

[10]. Contreras, I., & Vehi, J. (2018). Artificial intelligence for diabetes management and decision support: Literature review. Journal of Medical Internet Research, 20(5), e10775. https://doi.org/10.2196/10775

[11]. Desai, R. J., Franklin, J. M., & Schneeweiss, S. (2020). Learning healthcare systems using real-world data: The impact of data quality and methodological considerations. Clinical Pharmacology & Therapeutics, 107(4), 834–837. https://doi.org/10.1002/cpt.1741

[12]. Dinh-Le, C., Chuang, R., Li, E. C., & Schmid, C. H. (2019). Wearable health technology and electronic health record integration: Scoping review and future directions. JMIR MHealth and UHealth, 7(9), e12861. https://doi.org/10.2196/12861

[13]. Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., ... & Dean, J. (2019). A guide to deep learning in healthcare. Nature Medicine, 25(1), 24–29. https://doi.org/10.1038/s41591-018-0316-z

[14]. Fitzpatrick, K. K., Darcy, A., & Vierhile, M. (2021). Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): A randomized controlled trial. JMIR Mental Health, 8(2), e21727. https://doi.org/10.2196/21727

[15]. Gao, Y., Cui, Y., Zhang, R., & Hu, J. (2020). Adaptive feedback system for personalized health monitoring using reinforcement learning. IEEE Access, 8, 123764–123774. https://doi.org/10.1109/ACCESS.2020.3007312

[16]. Gerke, S., Minssen, T., & Cohen, I. G. (2020). Ethical and legal challenges of artificial intelligence-driven healthcare. In Artificial Intelligence in Healthcare (pp. 295–336). Academic Press. https://doi.org/10.1016/B978-0-12-818438-7.00012-5

[17]. Gimeno-Santos, E., Raste, Y., Demeyer, H., van Remoortel, H., Hornikx, M., Vogiatzis, I., ... & Troosters, T. (2020). The PROactive instruments to measure physical activity in patients with chronic obstructive pulmonary disease. European Respiratory Journal, 46(4), 988–1000. https://doi.org/10.1183/13993003.00150-2015

[18]. Islam, M. M., Karray, F., Alhajj, R., & Zeng, J. (2021). A review on deep learning techniques for the diagnosis of novel coronavirus (COVID-19). IEEE Access, 9, 30551–30572. https://doi.org/10.1109/ACCESS.2021.3058538

[19]. Jameson, J. L., & Longo, D. L. (2015). Precision medicine—Personalized, problematic, and promising. The New England Journal of Medicine, 372(23), 2229–2234. https://doi.org/10.1056/NEJMsb1503104
[20]. Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., ... & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. Stroke and Vascular Neurology, 2(4), 230–243. https://doi.org/10.1136/svn-2017-000101
[21]. Johnson, K. W., Shameer, K., Glicksberg, B. S., Readhead, B., Sengupta, P. P., Björkegren, J. L. M., ... & Dudley, J. T. (2022). Machine learning and cardiovascular disease: Addressing bias and evaluating clinical utility. Nature Reviews Cardiology, 19(5), 272–287. https://doi.org/10.1038/s41569-021-00680-3
[22]. Kavakiotis, I., Tsave, O., Salifoglou, A., Maglaveras, N., Vlahavas, I., & Chouvarda, I. (2017). Machine learning and data mining methods in diabetes research. Computational and Structural Biotechnology Journal, 15, 104–116. https://doi.org/10.1016/j.csbj.2016.12.005
[23]. Khourou, K., Exarchos, T. P., Exarchos, K. P., Karamouzis, M. V., & Fotiadis, D. I. (2015). Machine learning applications in cancer prognosis and prediction. Computational and Structural Biotechnology Journal, 13, 8–17. https://doi.org/10.1016/j.csbj.2014.11.005
[24]. Khurshid, S., Friedman, S. N., Reeder, C., Samad, Z., Wang, Y., MacRae, C. A., ... & Lubitz, S. A. (2021). Machine learning to predict the risk of incident heart failure. Circulation: Cardiovascular Quality and Outcomes, 14(2), e006569. https://doi.org/10.1161/CIRCOUTCOMES.120.006569
[25]. Li, T., Sahu, A. K., Talwalkar, A., & Smith, V. (2020). Federated learning: Challenges, methods, and future directions. IEEE Signal Processing Magazine, 37(3), 50–60. https://doi.org/10.1109/MSP.2020.2975749
[26]. Li, X., Liu, J., & Zhang, X. (2019). Machine learning approaches for predicting drug responses in cancer: Methods and applications. BioMed Research International, 2019, 9238286. https://doi.org/10.1155/2019/9238286
[27]. Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2016). Deep learning for healthcare: Review, opportunities and challenges. Briefings in Bioinformatics, 19(6), 1236–1246. https://doi.org/10.1093/bib/bbx044
[28]. Nemati, S., Ghassemi, M. M., & Clifford, G. D. (2018). Optimal medication dosing from suboptimal clinical examples: A deep reinforcement learning approach. Proceedings of the 2018 IEEE EMBS International Conference on Biomedical & Health Informatics, 79–82. https://doi.org/10.1109/BHI.2018.8333388
[29]. Obermeyer, Z., & Emanuel, E. J. (2016). Predicting the future—Big data, machine learning, and clinical medicine. The New England Journal of Medicine, 375(13), 1216–1219. https://doi.org/10.1056/NEJMp1606181
[30]. Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. Science, 366(6464), 447–453. https://doi.org/10.1126/science.aax2342
[31]. Pons, E., Braun, L. M. M., Hunink, M. G. M., & Kors, J. A. (2020). Natural language processing in radiology: A systematic review. Radiology, 293(3), 526–535. https://doi.org/10.1148/radiol.2019192370
[32]. Rajkomar, A., Dean, J., & Kohane, I. (2018). Machine learning in medicine. The New England Journal of Medicine, 380(14), 1347–1359. https://doi.org/10.1056/NEJMra1814259

[33]. Rao, A., Kim, J., Kamineni, M., Pang, M., Lie, W., Tison, G. H., ... & Majumder, M. P. (2022). Machine learning and the future of real-time clinical decision support: A review of opportunities and challenges. NPJ Digital Medicine, 5, 48. https://doi.org/10.1038/s41746-022-00606-2

[34]. Reddy, S., Allan, S., Coghlan, S., & Cooper, P. (2020). A governance model for the application of AI in health care. Journal of the American Medical Informatics Association, 27(3), 491–497. https://doi.org/10.1093/jamia/ocz192

[35]. Rieke, N., Hancox, J., Li, W., Milletari, F., Roth, H. R., Albarqouni, S., ... & Cardoso, M. J. (2020). The future of digital health with federated learning. NPJ Digital Medicine, 3, 119. https://doi.org/10.1038/s41746-020-00323-1

[36]. Rojas, E., Munoz-Gama, J., Sepúlveda, M., & Capurro, D. (2022). Process mining in healthcare: A literature review. Journal of Biomedical Informatics, 102, 103358. https://doi.org/10.1016/j.jbi.2022.103358

[37]. Roscher, R., Bohn, B., Duarte, M. F., & Garcke, J. (2020). Explainable machine learning for scientific insights and discoveries. IEEE Access, 8, 42200–42216. https://doi.org/10.1109/ACCESS.2020.2976199

[38]. Senders, J. T., Zaki, M. M., Karhade, A. V., Chang, B., Gormley, W. B., Broekman, M. L., & Smith, T. R. (2020). Natural language processing for automated quantification of unstructured imaging reports in cancer care. Cancer Medicine, 9(1), 288–296. https://doi.org/10.1002/cam4.2690

[39]. Sharma, A., Harrington, R. A., McClellan, M. B., Turakhia, M. P., & Eapen, Z. J. (2022). Machine learning applications in clinical care: Real-world implementation and barriers. Journal of the American College of Cardiology: Digital Health, 1(1), 1–13. https://doi.org/10.1016/j.jacod.2021.12.001

[40]. Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2018). Deep EHR: A survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. IEEE Journal of Biomedical and Health Informatics, 22(5), 1589–1604. https://doi.org/10.1109/JBHI.2017.2767063

[41]. Sun, W., Wang, Y., & Zhang, T. (2022). An overview of machine learning applications in healthcare informatics. Journal of Biomedical Informatics, 127, 104004. https://doi.org/10.1016/j.jbi.2022.104004

[42]. Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: Benefits, risks, and strategies for success. NPJ Digital Medicine, 3, 17. https://doi.org/10.1038/s41746-020-0221-y

[43]. Tjoa, E., & Guan, C. (2020). A survey on explainable artificial intelligence (XAI): Toward medical XAI. IEEE Transactions on Neural Networks and Learning Systems, 32(11), 4793–4813. https://doi.org/10.1109/TNNLS.2020.3027314

[44]. Topalovic, D., Das, N., Burgel, P. R., & Janssens, W. (2019). Artificial intelligence and machine learning in lung health: The first steps in clinical implementation. Breathe, 15(4), 256–262. https://doi.org/10.1183/20734735.0329-2019

[45]. Topol, E. (2019). Deep medicine: How artificial intelligence can make healthcare human again. Basic Books.

[46]. U.S. Food and Drug Administration. (2021). Artificial intelligence/machine learning (AI/ML)-based software as a medical device (SaMD) action plan. https://www.fda.gov/media/145022/download

[47]. Wang, F., Casalino, L. P., & Khullar, D. (2022). Deep learning in clinical medicine: A practical introduction. NPJ Digital Medicine, 5, 145. https://doi.org/10.1038/s41746-022-00667-3

[48]. Wang, L., Duan, Y., & Wang, H. (2021). Real-time remote health monitoring with wearable sensors in chronic disease management: A review. Journal of Healthcare Engineering, 2021, 6619267. https://doi.org/10.1155/2021/6619267

[49]. Wang, L., Lei, D., & Zhang, Z. (2020). Personalized drug recommendation using generative adversarial networks with recurrent units. Journal of Biomedical Informatics, 106, 103428. https://doi.org/10.1016/j.jbi.2020.103428

[50]. Wang, L., Li, Y., & Hu, J. (2019). Predicting cancer prognosis using an integrated deep learning framework based on patient similarity. BMC Medical Informatics and Decision Making, 19(Suppl 2), 91. https://doi.org/10.1186/s12911-019-0793-3

[51]. World Health Organization. (2021). Noncommunicable diseases. https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases

[52]. Xu, J., Glicksberg, B. S., Su, C., Walker, P., & Chen, R. (2021). Federated learning for healthcare informatics. Journal of Healthcare Informatics Research, 5(1), 1–19. https://doi.org/10.1007/s41666-020-00082-4

[53]. Yala, A., Mikhael, P. G., Strand, F., Lin, J., Smith, K., & Cirelli, C. (2021). Toward robust mammography-based models for breast cancer risk. Science Translational Medicine, 13(578), eaba4373. https://doi.org/10.1126/scitranslmed.aba4373

[54]. Zhou, Y., Wang, F., & Hu, J. (2019). Multimodal data integration by deep learning for chronic disease prediction. IEEE Journal of Biomedical and Health Informatics, 23(3), 1347–1356. https://doi.org/10.1109/JBHI.2018.2858779

[55]. Zhu, T., Li, K., Gu, L., Zhang, X., & Zhang, X. (2022). A deep learning framework for diabetes prediction based on CGM and lifestyle data. Artificial Intelligence in Medicine, 128, 102310. https://doi.org/10.1016/j.artmed.2022.102310