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Review paper

Artificial Intelligence in Precision Pharmacotherapy

Optimizing Drug Selection and Dosing in Chronic Diseases

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ABSTRACT

Chronic disease is one of the major causes of death worldwide which generally not vaccine preventable are also don't resolve spontaneously. The world health organization identifies four main types of chronic diseases including cardiovascular diseases (CVD, primarily heart disease and stroke), Cancer, chronic respiratory diseases and diabetes which are responsible for the majority of related deaths, while they can be treated, are seldom healed with medicine or other medical treatment. Chronic disease care is becoming increasingly confined, which frequently results in suboptimal therapeutic efficacy and adverse medication reactions. Pharmacotherapy involve in management and treatment of chronic diseases mainly associate with the dose and drug selection for the authorized treatment that significantly impact on outcomes. Artificial intelligence and machine learning are shifting pharmacotherapy from a reactive, standardize model to proactive personalized and data driven. Different AI driven software's and technical platform along with their superiority in management of chronic diseases has elaborate in this review article. This article looks at the use of Artificial intelligence to optimize medicine selection and dosing for complicated, long-term illness. Apart from their promising outcomes, concern about mainly data privacy, model interpretability and also ethical regulatory barriers remain. This study explores the challenges emphasizing the significant importance of transparent, explainable AI in ensuring efficacy and safety in clinical practices. The use of AI in precision pharmacology has the potential to greatly improve therapeutic results, patient compliance and healthcare resource use for chronic conditions.

1. Introduction

Pharmacotherapy often known as drug therapy, is the mainly use of pharmaceutical substances to treat, manage or prevent illness and medical problems. It comprises a wide spectrum of therapeutic approaches from over-the-counter medicines to complicated prescription pharmaceuticals, all of which aim to improve patient outcomes and quality of life. Pharmacotherapy is the foundation of modern healthcare, providing a wide range of pharmacological substances to addresses a variety of health issues [1]. Chronic diseases are health conditions that last longer than 3 months and may necessitate ongoing care because of significant decline in health (Fig. 1). Years or even lifetime may pass before chronic illness resolved. These illness or condition typically develop as people ages and also manageable but infrequently curable [2].

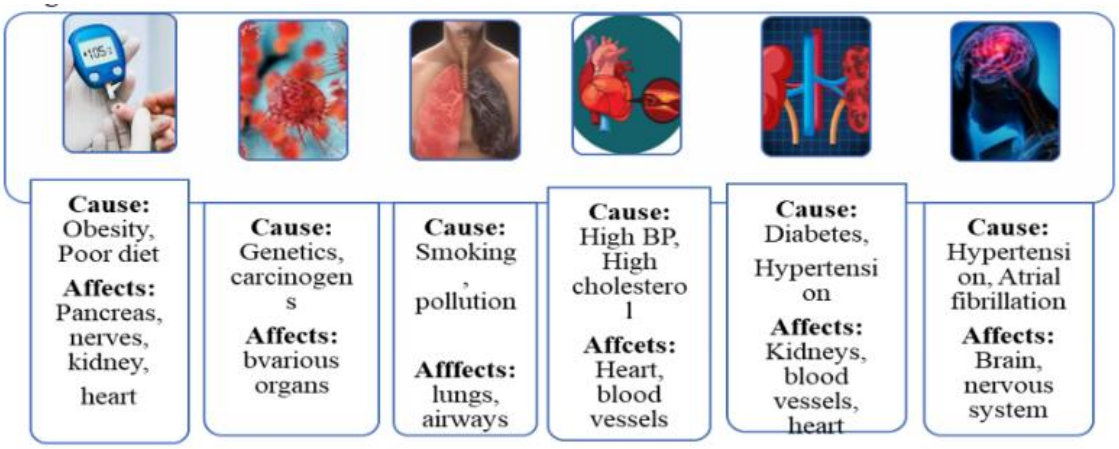

Fig. 1 Chronic diseases and their impact on body

The main cause of early mortality and disability are chronic illness. Living with chronic illness. They are generally not vaccine preventable, do not resolve spontaneously and while they can be treated or healed by medical treatments. Chronic disease especially cardiovascular disease (CVD), Stroke, arthritis, obesity, COPD, asthma and kidney diseases, type 2 diabetes, cancer cause more than half of all deaths worldwide [3]. About 3 million deaths from CVD occur annually in both India and China. One million tobacco related deaths occur annually in China and 700,000 in India. There is 1 in 5 adults in the world now smokers and 1 in 10 classified as overweight or obese, future prospects regarding CVD and type 2 diabetes are grim [4]. Cancer is the one of the most cause of death in past 20 years due to various reasons which influence on the rate of causing factors. Complex global healthcare concerns and more diverse prompted new integrated approaches to healthcare, with growing emphasis on the patient perspective. Handling patient provider interaction and patient education, in particular are becoming increasingly important in delivering better outcomes and increased quality of life. Chronicity is relative term that has altered as advanced in medicines translate from bench to bedside and the focus of care shifts from dealing with acute or fatal diseases to long term management of chronic conditions [5].

Because chronic diseases diminish work productivity, investor returns in developing countries will be affected, which in turn will likely affect the growth of countries within the organization for Economic Cooperation and development [6].

Traditional pharmacokinetic (pK) and pharmacodynamics (PD) models have been used to guide dosing techniques, especially in drug research and specialized care settings. Population PK models predict average rug concentration time profiles and variability across defined cohort, whereas PD models describe dose response interactions. Although these approaches help to make initial dose recommendations, they are often based on established assumptions about compartmental distribution and clearance kinetics. Their routine use in outpatient chronic disease treatment I still limited because to complexity, resource restrictions and the requirement for specialized skills [7]. Combined impact shows integrating both improves outcomes such as tailored medicines selection combined with pharmacokinetic based dosing minimize adverse responses, increases adherence and saves healthcare costs in chronic management. Population modeling and TDM enable proactive adjustments, particularly for polypharmacy in diseases such as hypertension. This technique promotes long term control and improved quality of life. In chronic disease management, the overall result of treatment is depends upon the selection of appropriate drug and dosing for therapy [8]. Optimized dosing and drug selection centers on achieving a steady state where therapeutic effects are sustained while long term toxicities are minimized. Because of patients having chronic disorders remain on therapy for extended periods, the focus then shifted from a maximum tolerance dose toward a precision dosing model that considers individual biological variability and lifelong adherence [9].

The ideal characteristics of pharmacotherapy for chronic disorders focus on balancing long-term effectiveness with patient safety and lifestyle integration. Since chronic conditions require medication for extended periods, often a lifetime the pharmacological profile must minimize the burden of treatment while maximizing health outcomes. The current pharmacotherapy system for chronic conditions like diabetes and hypertension is complex environment with a wide range of pharmaceutical agents, treatment recommendations, and clinical procedures [10]. Oral antidiabetic medicines, insulin, diuretics, beta blockers, angiotensin converting enzyme inhibitors, angiotensin II receptor blockers and calcium channel blockers are only a few of the kinds of drugs that are commonly used in current pharmacotherapy procedures. But even the defined

treatment recommendations, there are still a number of issues with the present system. For many patients, adherence to medication regimens is still subpar, which results in poor diseases control and higher risk of complications [11].

Dose and drug selection are crucial in controlling chronic diseases such as diabetes, hypertension and cardiovascular disorders because they optimize efficacy, safety and patient adherence. Drug selection choosing the proper drug requires considering individual criteria such as patient genetics, age and pharmacogenomics to match therapies that maximize benefits while minimizes side effects. For example, genetic variants can influence the selection of anti-hypertensive or antidiabetic for better outcomes in chronic situations [12]. Evidence based recommendations and clinical pharmacology principles guarantee that selections fit with long term illness management. Dose selection involves optimization tailors' regimens based on pharmacokinetics (absorption, distributions, metabolism, and excretion), with therapeutic drug monitoring (TDM) being used for tight therapeutic windows. Simpler schedules, such as once daily dosage, enhance adherence in chronic patients over more frequent ones [13]. Adjustments take into consideration individual variables such as organ function and drug interactions to avoid toxicity or sub therapeutic levels. Hence optimized drug and dosing selection plays crucial role in the chronic disease therapy.

2. Conventional Methods

Conventional drug and dose selection procedures are standard, rule-based strategies used in medications safety and efficacy. These methods generally based on physical experimentation, animal testing and basic statistical protocols rather than sophisticated computer modeling or artificial intelligence. Drug selection is screening enormous libraries of chemical compounds to find interaction with biological target of selected drug candidate. While the usual method for dosage selection typically follows a "more is better" mindset, with computational designs such as the 3+3 model increasing doses until a maximum Tolerated Dosage (MTD) is attained. While these approaches have established the foundation for modern medicines, they often exhibit slow progress, high cost and the potential to administer doses that exceed the patient's necessary toxicity

2.1 Conventional methods for dose selection as listed below

a. Clinical guidelines
b. Stepwise therapy
c. Physician expertise
d. RCT data (randomized controlled trials)

Chronic disease management has traditionally relied on standardized clinical guidelines, physician's expertise and periodic patient monitoring to guide drug selection and dose titration (Fig. 2). Conditions such as diabetes mellitus, hypertension, chronic obstructive pulmonary disease, cancer and heart failure are typically managed using structure treatment algorithms derived from randomized controlled trails and large cohort studies [14]. While these approaches have significantly improved morbidity and mortality outcomes, they are largely population based and rely on episodic assessment rather than continuous individualized optimization. Guideline based drug selection. Drug selection in chronic disease care is generally guided by evidence based clinical guidelines created by professional organizations. As shown in these guidelines use data from RCTs and meta-analyses to prescribe first line, second line and adjunctive therapy based on illness severity, concomitant diseases, and broad risk stratification criteria, anti-hypertensive therapy for example, frequently uses a stepwise escalation strategy, starting with approved first line medicines and processing based on blood pressure response and tolerance [15]. Although guideline directed therapy standardizes care and decreases unnecessary variance, its structure is fundamentally rigid. Recommendations are typically based on average treatment effects reported in diverse populations, which may not account for individual heterogeneity in pharmacokinetics, pharmacodynamics, hereditary variables or behavioral determinates.

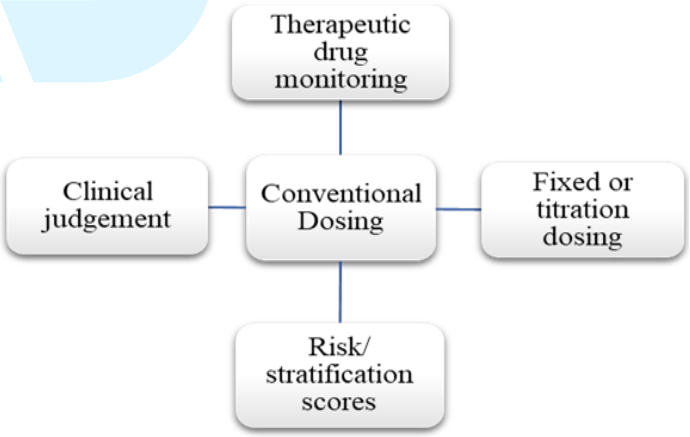

Fig. 2 Convectional methods in drug selection in treatment of chronic diseases

2.2 Conventional methods for drug selection listed below

a. Therapeutic Drug monitoring
b. Fixed or titration dosing
c. Risk/ stratification scores
d. Clinical judgments

Drug selection decisions are often based on categorical risk grouping rather than continuous, multidimensional patient specific data. In traditional

practice, dose optimization is often carried out using a start low, go slow titration paradigm. Initial dose is determined using conventional reference ranges, followed by gradual modifications at predetermined intervals based on clinical response, laboratory data, or symptom reporting (Fig. 3) [16]. In diabetes care, for example, mediation doses are titrated based on periodic glycated hemoglobin (HbA1c) readings or self-monitored glucose values, which are typically measured weeks to months apart. Therapeutic drug monitoring (TDM) is used for certain drugs that have limited therapeutic indices. Plasma medication concentrations are tested intermittently to guide adjustments; however, this monitoring is limited to certain drug classes and is not commonly used in the majority of chronic diseases therapy [17].

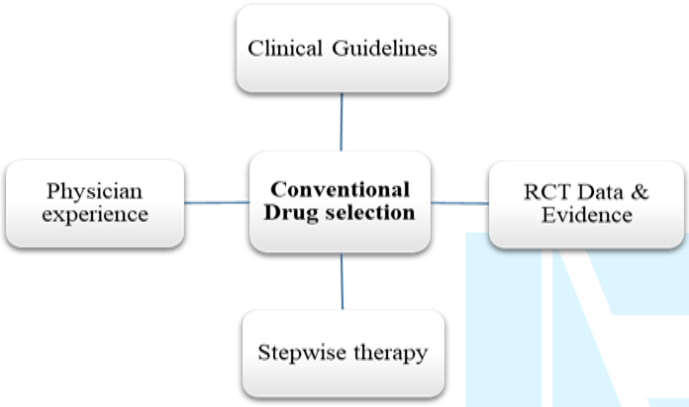

Fig. 3 Convectional methods in dosing in treatment of chronic diseases

Convectional care frequently employs validated risk scoring systems to estimated diseases progression or adverse event probability. Importantly, conventional methods are don't directly optimize drug selection or dosing at the individual level. Monitoring and data utilization monitoring in convectional chronic care I primarily episodic, taking place during planned clinic visits. Data sources often include laboratory findings, vital signs, medications lists and patient reported symptoms recorded in electronic health records [18]. Although HER systems collective extensive longitudinal data, this data typically used descriptively rather than analytically for predictive dose adjustments. As a result, therapy changes are reactive to observed outcomes rather than proactive optimization [19].

2.3 Challenges in treatment and management of chronic diseases:

Managing chronic diseases involves complex challenges in dosing and drug selection due to patient variability and treatment demands. Challenges associated with the one of the leading diseases in world as mentioned in below Table 1.

Table 1 Challenges associate with chronic disease management

Disease	Challenges
Diabetes Mellitus (Type 1&2)	In the real time trend, causes of inconsistent insulin adjustments due to manual blood sugar checks. Changes in patient diet or activity variation results from error and trial for oral med used to treat patient.
Heart attack	Aggressive lipid management limits Evolving consensus on beta blockers used in treatment Critical balance between dissolving clots and avoiding fatal bleeding.
Alzheimer's	Patient heterogeneity Comorbidities Slow titration and tolerability Adverse effects and safety
Chronic Kidney Disease	Pharmacokinetic alternation Drug-drug interaction Impaired renal clearance
COPD/ Asthma	Inhaler technique errors High inter patient variability Overuse and underuse

2.3.1 Dosing challenges

Manual Pharmacokinetic calculations struggle with inter patient variability leading to trial-and-error adjustment and frequent under or toxic overdosing (adverse effect), such in accuracies are particularly dangerous for drugs with narrow therapeutic indices, were precise concentration control crucial. The inability to rapidly analyze complex, patient specific data means that optimal, personalized care is delayed. Examples: management of Vancomycin, a potent antibiotic with a narrow therapeutic window. Because its clearance depends heavily on a patient's renal function and body mass, manual calculations often miss the mark, resulting in nephrotoxicity or treatment failure [26]. No real time predictive modeling means delayed detection changes in drug clearance from inflammation, increasing toxicity risks in CKD or heart failure can creates a dangerous lag, as traditional biomarkers like serum creatinine often

only reflects damage 24-48 hours after it occurs. Inflammation significantly alters drug clearance by down regulating metabolic enzymes and transporters, which without immediate detection, leads to drug accumulation and acute toxicity. Examples: Digoxin frequently used in heart failure but has a very narrow safety margin. Toxicity manifest as dangerous arrhythmias, nausea and visual disturbances. Real time modeling could predict these shifts by integrating heart failure severity and inflammatory markers like C reactive protein [27]. Labor intensive therapeutic drug monitoring requires repeated lab tests and clinician interpretation, staining resources without automated pattern recognition is currently addressing several critical resources and efficiency Constraints. Tacrolimus an immunosuppressant used to prevent organ transplant rejection. Automated extraction allows for faster, more accurate adjustments with less frequent hospital visit [28].

2.3.2 Drug selection challenges

Polypharmacy decisions depend on static guidelines and memory heightening interaction oversights diabetes patients. These decisions are increasing recognized as a balance between static clinical guidelines and the mitigation of interaction oversights caused by human memory [29]. A common example of this decision-making tension involves treating diabetic patient for routine infection. Integrated pharmacogenomics into patient simulations eliminated trail error prescribing, which frequently results in serious adverse effects or treatment failure. Clinicians for example, can avoid regimens that are genetically predisposed to failure by mimicking a patient's CYP2C19 metabolism before to administering antidepressants. This tailored method directly targets the fundamental cause of non-adherence by ensuring that the medication is both comfortable and effective from the first dosage, lowering the 50% dropout rate seen in mismatched regimens [30]. When data driven insights are unavailable, doctors frequently resort to general regimens that disregard the physiological feedback loops of many diseases. For example, a doctor may administer Thiazide diuretics for hypertension without understanding their lower efficiency at low GFR, or fail to modify SGLT2 inhibitors, which while cardio rental protective, necessitate precise monitoring of first creatinine rise. The lack of computer monitored drug disease interactions cause therapeutic inertia, in which the fear of worsening on condition precludes the optimization of another [31].

3. Advantages of AI in Chronic Disease Management

AI can detect chronic diseases including cardiovascular diseases, diabetes, cancer, and infectious diseases early on, according to multiple studies. AI can benefit public health by detecting chronic diseases with optimized dosing and drug selection leading to more effective interventions. AI advantages are shown in (Fig. 4) by examining data from various sources. AI algorithm provides through summary of person's health and anticipates future ailments. This enables healthcare practitioners to create personalized interventions and medicines to enhancement patient health and slow disease progression [32].

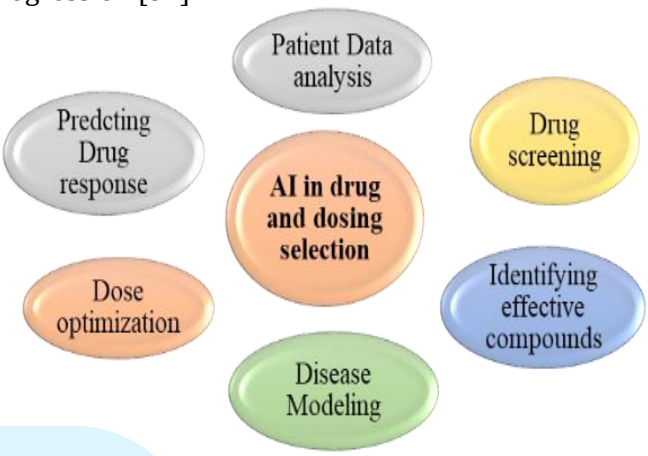

Fig. 4 Advantages of AI in chronic disease management

AI can guide blood pressure and volume strategies for end stage kidney disease by learning from previous responses. Artificial neural networks can forecast session specific results and make individualized modification to reduce hypotension and maximum fluid evacuation maintaining patient trust necessitates strong cyber security and regulatory compliance. The ethical implications include algorithmic bias, transparency and informed consent. Biased data and black box AI algorithms can exacerbate disparities and erode trust between patients and doctors. Transparency and informed consent are key considerations [33]. The implementation issues are equally considerable. Adoption is hampered by a lack of digital health literacy, particularly among the elderly and low-income groups, as well as unequal access to cellphones and internet connectivity. Integrating AI into clinical workflows and EHRa poses technological and logistical obstacles, necessitating interdisciplinary collaboration training for healthcare staff. Accurate models may fail if alerts are ignored or escalation paths are unclear. This highlights the need of process fit and human oversight [34].

There are significant gaps in evidence for long term effectiveness, standardized outcomes measures and external validation across varied groups. Although monitoring and predicted technologies have shown practically and patient reported advantages, clinical outcomes are still variables and limited in generalizability due to signal center or narrow cohorts. Large scale, prospective validation with

standardized outcomes is urgently required. Although engagement focused AI improves PROs in the short term, problems such as variable retention and insufficient external validation warrant additional investigation. Physician led innovation enables AI technologies to addresses clinical difficulties including optimizing chronic illness monitoring and tailoring treatment plans by combining domain and evaluation [35]. Collaboration among clinicians and researchers is crucial for aligning AI development with patient centered care priorities.

Using AI in treatment of chronic disease by overcoming different conventional strategies or methods including treatment process in various chronic diseases are mentioned in below Table 2.

Table 2 AI overcome challenges associate with conventional methods in chronic disease management

Chronic Disease	Conventional Methods	Treatment Process	AI overcomes challenges	Reference
Type 2 Diabetes	Medications (metformin), Diet/exercise	Diagnose via HbA1c , monitoring glucose quarterly, titrate insulin	AI apps predict glucose trends via wearable, optimizing dosing improves adherence with reminders.	[20]
Hypertension	ACE inhibitors, Lifestyle changes	Monitoring and measurement of BP repeatedly.	AI analyzes BP data continuously, suggests precise dose adjustments, detects non adherence early.	[21]
COPD/ Asthma	Bronchodilators, pulmonary rehab	Assess lung function, use of inhaler and monitor exacerbations.	AI powered spirometers forecast exacerbations, personalized rehab plans, reduce hospital visit	[22]
Rheumatoid Arthritis	DMARDs, physical therapy	Confirm via blood tests , start methotrexate , monitor liver function monthly add biologics if active	AI imaging tracks joint inflammation, predicts flares, customizes biologics to minimize side effects.	[23]
Cardiovascular diseases	Statins, angioplasty	Risk score calculation, start high intensity statin, coronary imaging if symptomatic, PCI if blocked	AI ECG analysis prevents events, optimizes statin dosing via genetic data, and enhances lifestyle tracking.	[24]
Cancer	Chemotherapy, immunotherapy, radiation	Stage via biopsy/imaging, select targeted therapy based on genetics, monitor tumor markers/response scans.	AI analyzes tumor genomics for drug matching, predicts resistance, and personalizes chemo dosing to reduce toxicity.	[25]

3.1 AI software's used in management of chronic diseases

There are several AI software's used in various chronic diseases like cancer, diabetes, heart disease shown in Table 3 below. Alzheimer's, chronic kidney disease, COPD / Asthma. Mainly in treatment of diabetes mellitus DreMed Adviser Pro as well as Glooko software's were used to insulin dose and remote monitoring [36]. Whether as in management of heart diseases Idoven and PMcardio computerized models were used for ECG analysis for detection 23 cardiac patterns and detection of blood biomarkers [37]. Software's such as Ella AI and VGG16 can analysis early detection via MRI and Measure biomarkers in Alzheimer's condition [38]. AI/ML for diseases management and monitoring as well as video-based physiotherapy with adaptive algorithms has done by XpertHaler and Kaia COPD app respectively in COPD therapy [40]. In chronic kidney diseases, Roche AI algorithm can predict kidney function and urine biomarkers ACR NGAL, KIM-1 decline risk [39]. Whether in cancer treatment software used are Tempus PathAI Genetic mutation, MSI, TMB. Histopathogical biomarkers. EGFR, ALK, PD-L1 detected by using this software [41].

Table 3 AI software's used in chronic disease management

Chronic Diseases	AI Software	Primary use case	Examples
Diabetes	DreaMed Adviser Pro	Analyses CGM data for insulin dose optimization	Used by clinicians in the US and Israel to adjust insulin for 10000+ patients, reducing A1C by 0.5-1%
Diabetes	Glooko	Consolidates data for pattern identification and remote monitoring.	Deployed in 50+ counties; partnered for diabetes data insights in Europe.
Heart Diseases	Idoven	ECG analysis for detection 23 cardiac patterns involve electrical biomarkers.	Analyzed 1M+ ECGs for NHS UK trails, improving arrhythmia detection by 20%
Heart Diseases	PMcardio	Diagnoses 38 cardiovascular conditions from ECGs. Detect blood biomarkers like troponin, natriuretic peptide.	Adopted in 100+ countries; used in Ukraine for wartime cardiac triage.
Alzheimer's	Ella AI	Measure biomarker such as p-tau217 and medical reports.	Singapore pilot with 500 elderly users, cutting caregiver time by 30%
Alzheimer's	VGG16- based models	Early detection via MRI hippocampus analysis	Tested in India hospital on 1000 MRIs, achieving 92% accuracy pre symptoms
Chronic Kidney Diseases	Roche AI algorithm	Predicts kidney function and urine biomarkers ACR NGAL, KIM-1. decline risk	Integrated in Roche's cobas systems; EU clinics predict progression 2 years early.
COPD/Asthma	XpertHaler	AI/ML for diseases management and monitoring	India deployment tracks inhalers for 5000 patients, alerting on exacerbation.
COPD/Asthma	Kaia COPD app	Video based physiotherapy with adaptive algorithms.	US/EU users; reduced hospital readmissions by 40 % in trials.
Cancer	Tempus PathAI	Genetic mutation, MSI, TMB. Histopathological biomarkers.	EGFR, ALK, PD-L1 detected by using this software.

Some important and widely used software with the case studies are mentioned below:
Case studies:

3.1.1 DreaMed Advisor pro

Patient profile: Adolescent and young adults with type 1 diabetes struggle with glucose management. Manual adjustment of infrequent insulin therapy fails to address insulin need to patients, which leads to higher risk of hypoglycemia and hyperglycemia.

Clinical Application and evaluation mentioned in below Fig. 5.

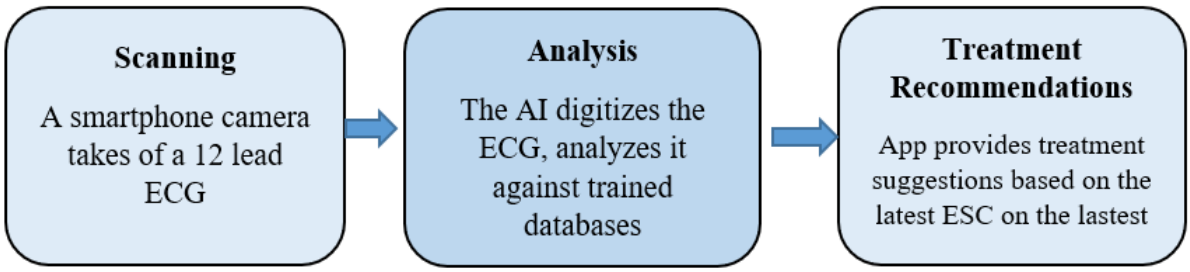

Fig. 5 Clinical Application and evaluation

This case study shows that AI can predominate over conventional methods. It reduces the gap between raw data and collection and actionable treatment steps. Showing remote capabilities that crucial for patients with limited access to specialists.

3.1.2 PMcardio

Research shows that PMcardio provides diagnostic accuracy comparable to cardiologist, allowing efficient and faster treatment in management of heart diseases.

A study in 2023 shows that PMcardio showed high diagnostic accuracy, AF (Atrial fibrillation) detection with almost 97% sensitivity and 99%

specificity also major ECG abnormalities with around 86% sensitivity and 92% specificity.

In another case of heart attack involved STEMI detection, An AI EGC model used by PMcardio significantly improved ST segment elevation myocardial infraction detection (STEMI). It was shown to reduce false activations and improve specificity to 81%.

This software works on following manner (Fig. 6)

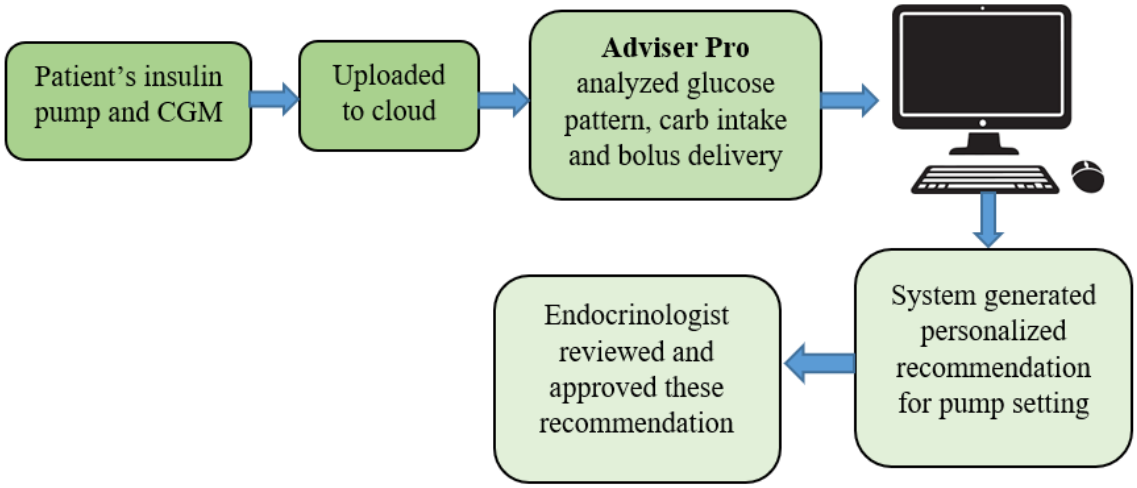

Fig. 6 Stepwise working procedure software

PMcardio is certified as class II (b) medical device under EU MDR.

3.1.3 Roche AI algorithm

Large scale validation studies supporting the Roche Kidney Klinrisk Algorithm's clinical value shows that how well it can predict the course of CKD9 Chronic Kidney Disease) in variety of patient demographics (Fig. 7).

A 2023 study involving 4 million US adults showed the Klinrisk model was more than 80% accurate in predicting CKD progression over a five-year period. In study of around 170,000 patients, the model effectively categorized individuals into low, moderate, and high-risk groups.

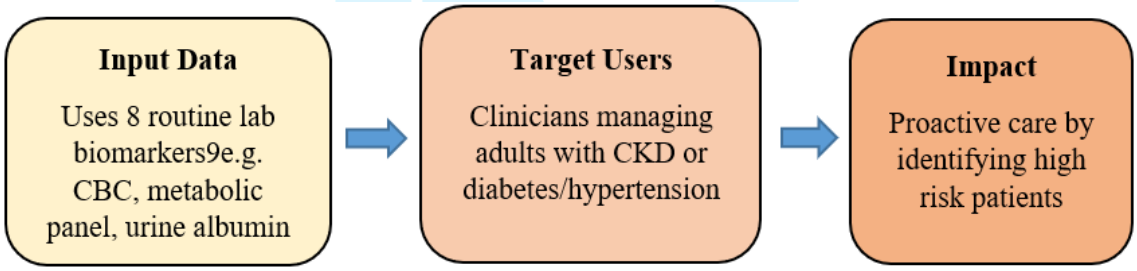

Fig. 7 Roche AI algorithm predicting CKD

4. Application of AI in Management of Chronic Diseases

True personalization beyond Rule based medicine which involves Traditional dosing often relies on – Population averages, Guideline thresholds, linear pK models. AI can integrate: Age, weight renal function. Genetic markers, lifestyle data and real time biomarkers. Example: In chronic kidney disease, renal clearance fluctuates dynamically. AI models can continuously adjusted dosing rather than relying on static creatinine cutoffs. Dynamic Real time dose adjustments has chronic disease evolve over time. AI systems can continuously learn from new patient data, Adapt dosing I near real time, Detect subtle trends before clinical deterioration, Responsiveness to temporal variability. Example: In diabetes mellitus, AI driven insulin algorithm already adjust doses based on continues glucose monitor data- something manual titration cannot match in speed [42]. Improved Safety through pattern detection. AI excels at identifying early toxicity signals, rare adverse event combinations, Subclinical organ stress Example: Detecting early nephrotoxicity trends. Identifying hypotension risk patterns in hypertension treatment. Better management of Polypharmacy. Chronic disease patients often take multiple medications. AI can Model complex drug-drug interactions, simulated metabolic pathways competition, Predict cumulative Toxicity. Also it can reduce Trial and Error titration. Traditional dose titration can take weeks to months, multiple clinic visits.AI may predicts optimal dosing

earlier, shorten stabilization time, reduce adverse titration events [43]. This can improve patient comfort adherence, healthcare efficiency. The monitoring and prediction stack includes risk stratification, screening and patient assistance. Explainable AI stratifies exacerbation risk based on smoking history, BMI, and system characteristics. Adding explainable AI to pulmonologist PFT interpretation improved diagnosis accuracy in specialist settings, but some subsets performed worse, highlighting the importance of monitoring. CT deep learning offers accurate staging and prognosis for chronic obstructive pulmonary disease (COPD). Scalability in resource limited settings in region with: few specialist, limited pharmacology expertise [44]. AI decision support can: Assist general practitioners, standardize care quality, and reduce variation between providers. It doesn't replaced specialist but can extend their reach. Integration of genomics and precision medicines. AI can integrate; pharmacogenomics markers, enzyme polymorphism, transporter differences traditional statistical models struggle when variables explode combinatorial. Reduction in human cognitive load information overload, alert fatigue, time constraints involve AI can Pre analyzes large datasets, provide ranked dosing options, and highlight risk flags. This supports, rather than replace [45].

In Continuous learning System unlike static guidelines, AI systems can: Update with new clinical trial data, incorporate post market surveillance, adapt to new drug approvals. Potentially faster than waiting for guideline revisions. Long term outcome optimization instead of optimizing only a lab value, AI can optimize: Hospitalization risk, cardiovascular outcomes, mortality probability, and cost effectiveness. It can simulated future trajectories rather than reacting to present labs [46].

Overall look of applications of AI in the various parts of prevention, control and management/treatment involved in chronic diseases mainly focuses on drug selection and dosing range of medication with suitable software along with their significant use are mentioned in below (Fig. 8).

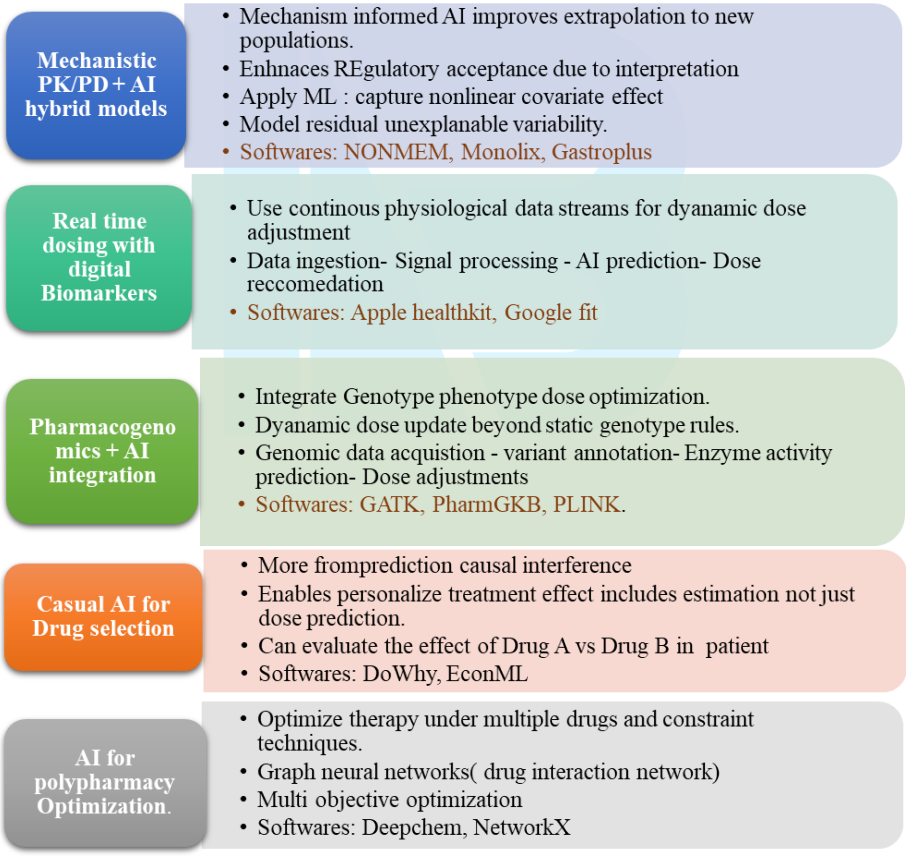

Fig. 8 Application of AI software's in pharmacotherapy

4.1 AI in Pharmacotherapy

AI in chronic disease pharmacotherapy revolutionizes long term care by making it proactive and personalized. By continuously analyzing data from wearables and electronic health records, AI can determine the most effective drug combinations and precise dosage for conditions such as diabetes and hypertension, as well other chronic diseases moving beyond the conventional trial and error approach. Additionally, AL addresses medication non adherence with smart monitoring systems and predictive alerts that intervene before doses are missed. This technology enables clinicians to detect early signs of diseases progression, minimize risk related to

polypharmacy, and adjust treatments in real time, ultimately enhancing patient's quality of life.

4.2 AI in Precision/ personalized pharmacotherapy

AI helps to tailor medications to genetics, biomarkers and patient response. Software used in personalized pharmacotherapy listed below:
Tempus AI: uses Ai and genomic data for personalized cancer pharmacotherapy and chronic disease treatment.
Deep Genomics: Applies AI to drug discovery and personalized therapeutics.
Nant Health: AI guided precision medicine, especially in oncology.

4.3 AI in adverse effect monitoring

AI algorithms continuously analyze electronic health records, lab results to detect early signals and effect patterns effective before even noticeable by humans. By automating the simultaneous analysis of thousands of variables, AI enhances the patient safety in chronic diseases treatment care also supports regulatory agencies and pharmaceutical companies in monitoring the long-term safety of medications in real world. Most used software's in Pharmacovigilance are as below.
ArisGlobalLifeSphere MultiVigilance: Uses NLP and machine learning to automate case processing.
Veeva Vault Safety Suite: Streamline adverse event reporting
VigiMatch: can identify duplicate safety reports within the global VigiBase database.

4.4 AI in managing drug-drug/ drug- food interaction

Patients with chronic conditions as type 2 diabetes, hypertension and chronic kidney diseases often require multiple medications for long term periods, increasing the risk of adverse interaction and inappropriate dosing for treatment. AI systems analyze patient specific factors as age, body weight, kidney and liver function, medical history, laboratory values and concurrent medications to predict potential drug-drug interactions. For example, AI can identified harmful combinations, adjust dosing according to renal function and reduces toxicity risk in patients with impaired organ function. AI also supports drug selection by considering disease severity, comorbidities, interaction burden, lifestyle and even genetic factors to personalized therapy. In chronic disease management, this leads to safer prescribing, individualized dosing, also fewer adverse drug events, improved treatment associate adherence and better long-term patient outcomes while assisting healthcare professionals in making evidence-based decisions. Example of AI software used is Lexi comp: Drug dosing, interaction analysis and chronic medication management.

4.5 Medication Optimization

Useful in chronic polypharmacy (patients taking multiple drugs long term)
Medi Span Clinical APIs: AI enhanced drug interaction checks and dosing guidance.
Micromedex: Evidence based medication decision support.
Medtronic Diabetes: AI driven insulin delivery optimization.

4.6 AI for medication Adherence

Long term treatment often fails because patients stop medicines
Ai Cure: Uses computer vision and AI to monitor medication adherence
Proteus Digital Health: Smart medication tracking for chronic diseases.

5. Challenges Associate with Use of AI

The reliability and accuracy of AI technologies having practical issues including data quality problems, data messiness or biases in process data sets, despite the technology's amazing advantages in data processing and pattern recognition. Therefore, it's imperative to guarantee their accuracy and stability in real world applications. Important process to ensure data accuracy and dependability in the data processing phase include outlier discovery and management, duplicate data identification and merging and imputation of missing values. Biased or unrepresentative data in which AI dosing models depend on historical datasets. If certain populations are underrepresented, recommendations may be less accurate, potentially unsafe, systematically biased. Poor data quality in real world settings**.** Chronic disease management relies heavily on patient reported adherence, wearable data, and electronic health records (EHRs). Also, it can misinterpret missing data as clinical stability. Over fitting and generalization problems**.** Al models may perform well in controlled situations but fail when patients change medications, comorbidities evolve, new drug formulations enter the market, or guidelines alter [47]. Clinical risks include the possibility that AI will optimize for restricted measures such as hbA1c levels, blood pressure objectives, and inflammatory markers. However, this does not apply to long term safety, quality of life, or polypharmacy interactions. Ethical and legal concerns: chronic illness optimization necessitates ongoing monitoring, longitudinal health data. This increases the risk of data breaches, secondary abuse and re identification. Clinical judgment has been reduced. Individual patient

assessments have been reduced, and recommendations are encouraged to be accepted passively. Human clinical reasoning continuous to be crucial in difficult patients (advanced chronic kidney disease with renal clearance).

Regulatory and validation barriers: unlike static pharmaceuticals, AI systems learn and update and their behavior may change over time. Regulatory challenges include continues learning algorithms and post market surveillance criteria. This demonstrates deployment or lead to a poorly managed implementation. Cost and accessibility disparities AI based dosing systems require digital infrastructure, complex HER integration, and technical maintenance which increase costs and creates two types of treatment quality [48].

Patient search and Autonomy issues. Patients may distrust algorithm driven care, feel reduced data points, resist machine adjusted doing. Chronic disease management requires long term therapeutic relationships.

6. Future Scope

AI is poised to revolutionize chronic illness management by optimizing drug selection and administration, for disease such as diabetes, hypertension, heart failure and cancer, AI algorithms will combine massive datasets from pharmacogenomics, electronic health records (EHRs), wearable, and real time biomarkers to predict individual drug reactions with unparalleled accuracy. Machine learning models, such as deep neural networks and reinforcement learning, will analyzes genetic variations, lifestyle factors, and physiological dynamics to recommend not only the best drug but also the precise dose reactions, which currently affects up to 30% of chronic patients. Future application includes polypharmacy optimization in Multimorbidity older patients, in which AI simulated drug- drug interactions using virtual PK/PD modeling to prioritize regimens that balance efficacy, safety and cost. NLP will use unstructured clinical notes and patient report outcomes to refine predictions, while federated learning allows for collaborative model training across hospitals without data privacy issue. In oncology, AI will pioneer patient specific dosage for chemotherapies by combining tumor genetics, micro biome data, and imaging, expediting drug discovery through generative AI, which creates novel compounds customized to chronic disease subtypes [49].

The use of digital twins in pharmacotherapy, where virtual patient models dynamically simulated medication response using real time clinical, biochemical and behavioral data, will be one of the most revolutionary advancements. By reducing adverse medication reactions and enhancing long term results. Furthermore, by allowing individualized treatment impact estimation instead of depending o population level connections, the incorporation of causal inference frameworks into AI systems will revolutionize drug selection. This is especially important when managing complicated chronic diseases.

Real time adaptive dosing via wearable integration on edge AI enables preemptive changes, such as treating beta blockers in heart failure based on heart rate variability or diuretics in CKD with hydration sensors, saving hospitalizations by 255. Predictive analytics can forecast disease development and switch diabetic kidney disease treatments from metformin to SGLT2 inhibitors. Federated learning across global datasets allows for privacy preserving models that enhance dosing algorithms for privacy preserving models that enhance doing algorithms for are genetic variants, reducing adverse outcomes in conditions such as hypertension and rheumatoid arthritis. Although challenges like as algorithmic bias, legal obstacles, and interoperability remain, developments in explainable AI and block chain protected data transmission provide fair, transparent implementation. By 2030, AI might reduce chronic care costs by 20-30 %, increases adherence with app based nudges and extend quality adjusted life years, making optimal therapy acceptable to billions of people globally. In the coming decade, AI driven digital twins virtual patient models integrating multi omics data (genomics, proteomics, metabolomics) will stimulates real time disease progression, predicting optimal drug combinations with unprecedented accuracy [50]. From a regulatory point of view, new lifecycle-based approval models that include post deployment surveillance, model drift detection, and periodic revalidation will be required as AI based dosing tools advance. Adaptive algorithms that change over time will require the expansion of current software as a medical device (SaMD) framework.

Quantum enhanced AI will accelerate pharmacokinetics simulations, forecasting individualized response to novel therapies, such as CRISPR edited biologics. AI could reduce chronic disease mortality through proactive, patient specific regimens, bridging the gap curative pharmacotherapy while slashing healthcare costs [51].

7. Conclusion

Artificial intelligence is transforming chronic disease management by enabling optimized drug and dosing selection tailored to individual patient characteristics. Traditionally, prescribing focuses heavily on standardized guidelines and population averages, which may fail to account for inter patient diversity in genetics, metabolism, and organ function and adherence habits. AI powered models can effectively predict therapy responses and disease progression by

merging genomic data, electronic health records, real world evidence, and patient reported outcomes. This shift from population- based prescribing to customized treatment procedures improves clinical results while reducing the trial-and-error approaches that are frequent in chronic disease management. AI algorithms help clinicians identify ideal medication combinations, change doses dynamically, and anticipate complications before they occur clinically. Machine learning approaches also enables continuous learning from large datasets, allowing treatment suggestions to change as new information becomes available. Despite its potential, incorporating AI into every day. Apart from its promise, incorporating AI into normal treatment necessitate high quality data, transparent algorithms, regulatory supervision, and physician involvement to ensure dependability and ethical use. To avoid expanding healthcare disparities, data bias must be addressed and appropriate access ensured. Overall, AI powered drug optimization and selection mark a paradigm shift in chronic disease therapy. Artificial intelligence increases treatment precision, long term outcomes and the sustainability of chronic care management systems by enabling evidence based, tailored therapy decision.

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Conflict of Interest

The authors declare no competing interest.

References

1. Deb, T., Das, A., Ojha, B., & Das, P. (2024). Ensuring safe and effective pharmacotherapy: The role of "community pharmacology" in attaining "health for all" from the Indian perspective. Journal of family medicine and primary care, 13(12), 5465–5471. https://doi.org/10.4103/jfmpc.jfmpc_1226_24.
2. Hacker, K. (2024). The burden of chronic disease. Mayo Clinic Proceedings: Innovations, Quality & Outcomes, 8(1), 112-119. https://doi.org/10.1016/j.mayocpiqo.2023.08.005.
3. Global Burden of Disease Collaborative Network, Global Burden of Disease Study 2021 (GBD 2021) Results (2024, Institute for Health Metrics and Evaluation – IHME) https://vizhub.healthdata.org/gbd-resuls.
4. Derek Yach et al., Global Chronic Diseases.Science307, 317-317(2005).DOI: https://10.1126/science.1108656.
5. Ferlay J, Ervik M, Lam F, Colombet M, Mery L, Piñeros M, et al. Global Cancer Observatory: Cancer Today. Lyon: International Agency for Research on Cancer; 2020 (https://gco.iarc.fr/today. accessed February 2021).
6. Alleynea, G., Evansb, T., Irwinc, A., Jhad, P., & Veillarde, J. Enhancing Human Capital and Boosting Productivity by Tackling Non-Communicable Diseases.2018
7. Gettman, D. Integrating Pharmacokinetics/Pharmacodynamics (PK/PD) with Artificial Intelligence to Advance Predictive Modeling of Therapeutic Windows.
8. Religioni, U., Barrios-Rodríguez, R., Requena, P., Borowska, M., & Ostrowski, J. (2025). Enhancing Therapy Adherence: Impact on Clinical Outcomes, Healthcare Costs, and Patient Quality of Life. Medicina (Kaunas, Lithuania), 61(1), 153. https://doi.org/10.3390/medicina61010153.
9. Minichmayr, I. K., Dreesen, E., Centanni, M., Wang, Z., Hoffert, Y., Friberg, L. E., et al. (2024). Model-informed precision dosing: state of the art and future perspectives. Advanced drug delivery reviews, 215, 115421.
10. Moke, E. G., Demaki, W. E., Daubry, T. M. E., Ataikiru, O. M., Agbonifo-Chijiokwu, E., Ofulue, O.et al. (2023). Coexistence of hypertension with diabetes mellitus and its pharmacotherapy. Scientia Africana, 22(2), 135-154.
11. Gao, M., Lin, W., Ma, T., Luo, Y., Xie, H., Cheng, X., & Bai, Y. (2022). The Impact of Different Antihypertensive Drugs on Cardiovascular Risk in Isolated Systolic Hypertension with Type 2 Diabetes Patients. Journal of clinical medicine, 11(21), 6486. https://doi.org/10.3390/jcm11216486.
12. Pagès-Puigdemont, N., Mangues, M. A., Masip, M., Gabriele, G., Fernández-Maldonado, L.,et al.(2016). Patients' Perspective of Medication Adherence in Chronic Conditions: A Qualitative Study. Advances in therapy, 33(10), 1740–1754. https://doi.org/10.1007/s12325-016-0394-6.
13. Coleman, C. I., Limone, B., Sobieraj, D. M., Lee, S., Roberts, M. S., Kaur, et al..,(2012). Dosing frequency and medication adherence in chronic disease. Journal of managed care pharmacy, 18(7), 527-539.
14. Hisashige A. (2012). The effectiveness and efficiency of disease management programs for patients with chronic diseases. Global journal of health science, 5(2), 27–48. https://doi.org/10.5539/gjhs.v5n2p27.
15. Dizet, S., Haffen, E., & Javelot, H. (2025). Adherence to evidence-based treatment guidelines for depression: a systematic review. BMC psychiatry, 25(1), 825. https://doi.org/10.1186/s12888-025-07192-6.
16. Caffrey, A. R., & Borrelli, E. P. (2021). The art and science of drug titration. Therapeutic advances in drug safety, 11, 2042098620958910. https://doi.org/10.1177/2042098620958910.
17. Sherwani, S. I., Khan, H. A., Ekhzaimy, A., Masood, A., & Sakharkar, M. K. (2016). Significance of HbA1c Test in Diagnosis and Prognosis of Diabetic Patients. Biomarker insights, 11, 95–104. https://doi.org/10.4137/BMI.S38440.
18. Wang, W., Ferrari, D., Haddon-Hill, G., & Curcin, V. (2023). Electronic health records as source of research data. Machine Learning for Brain Disorders, 331-354.
19. Bennett, C. C., Doub, T. W., & Selove, R. (2012). EHRs connect research and practice: Where predictive modeling, artificial intelligence, and clinical decision

support intersect. Health Policy and Technology, 1(2), 105-114.
20. Daly, A. B., Boughton, C. K., Nwokolo, M., Hartnell, S., Wilinska, M. E., Cezar, A.,et al,.(2023). Fully automated closed-loop insulin delivery in adults with type 2 diabetes: an open-label, single-center, randomized crossover trial. Nature medicine, 29(1), 203-208.
21. Malviya, R., Kaushik, N., Rai, T., Saraswathy, M. P., & Awasthi, R. (2025). Machine Learning in Healthcare: Advances and Future Prospects. Apple Academic Press.
22. Topalovic, M., Das, N., Burgel, P. R., Daenen, M., Derom, E., Haenebalcke, C.,et al,.(2019). Artificial intelligence outperforms pulmonologists in the interpretation of pulmonary function tests. European Respiratory Journal, 53(4).
23. Momtazmanesh, S., Nowroozi, A., & Rezaei, N. (2022). Artificial intelligence in rheumatoid arthritis: current status and future perspectives: a state-of-the-art review. Rheumatology and therapy, 9(5), 1249-1304.
24. Nasser, A., Michalczak, M., Żądło, A., & Tokarek, T. (2025). AI-Powered Precision: Revolutionizing Atrial Fibrillation Detection with Electrocardiograms. Journal of Clinical Medicine, 14(14), 4924. https://doi.org/10.3390/jcm14144924.
25. Li, J., Hu, J., Yang, Y., Zhang, H., Liu, Y., Fang, Y., Qu, L., Lin, A., Luo, P.,et al.. (2025). Drug resistance in cancer: molecular mechanisms and emerging treatment strategies. Molecular biomedicine, 6(1), 111. https://doi.org/10.1186/s43556-025-00352-w.
26. Matsuki, Y., Kozima, Y., Yanagi, M., Sako, K. I., Watanabe, T., Yasuno, N.,et al,.(2025). Vancomycin dosing design method considering risk factors for nephrotoxicity. Journal of pharmaceutical health care and sciences, 11(1), 14. https://doi.org/10.1186/s40780-025-00416-7.
27. Patocka, J., Nepovimova, E., Wu, W., & Kuca, K. (2020). Digoxin: Pharmacology and toxicology—A review. Environmental toxicology and pharmacology, 79, 103400.
28. Bansal, Shyam Bihari,*. Therapeutic Drug Monitoring of Tacrolimus in Kidney Transplantation. Indian Journal of Transplantation 14(1):p 8-14, Jan–Mar 2020. | DOI: https://10.4103/ijot.ijot_4_20.
29. Wojtczak, D., Kasznicki, J., & Drzewoski, J. (2017). Pros and cons of polypharmacy in elderly patients with diabetes. Clinical Diabetology, 6(1), 34-38.
30. Pirmohamed, M. (2023). Pharmacogenomics: current status and future perspectives. Nature Reviews Genetics, 24(6), 350-362.
31. Gu W, Shao Q, Jiang L. Predicting Pharmacokinetics of Drugs in Patients with Heart Failure and Optimizing Their Dosing Strategies Using a Physiologically Based Pharmacokinetic Model. Pharmaceutics. 2025; 17(11):1394. https://doi.org/10.3390/pharmaceutics17111394.
32. Alum, E. U., & Ugwu, O. P. C. (2025). Artificial intelligence in personalized medicine: transforming diagnosis and treatment. Discover Applied Sciences, 7(3), 193.
33. Harishbhai Tilala, M., Kumar Chenchala, P., Choppadandi, A., Kaur, J., Naguri, S., Saoji,et al,.(2024). Ethical Considerations in the Use of Artificial Intelligence and Machine Learning in Health Care: A Comprehensive Review. Cureus, 16(6), e62443. https://doi.org/10.7759/cureus.62443.
34. Tong, L., Shi, W., Isgut, M., Zhong, Y., Lais, P., Gloster, L.,et al.,(2023). Integrating multi-omics data with EHR for precision medicine using advanced artificial intelligence. IEEE Reviews in Biomedical Engineering, 17, 80-97.
35. Vasey, B., Novak, A., Ather, S., Ibrahim, M., & McCulloch, P. (2023). DECIDE-AI: a new reporting guideline and its relevance to artificial intelligence studies in radiology. Clinical Radiology, 78(2), 130-136.
36. Mennella, C., Maniscalco, U., De Pietro, G., & Esposito, M. (2024). Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. Heliyon, 10(4).
37. De Guio, F., Rienstra, M., Lillo-Castellano, J. M., Toribio-Fernández, R., Lizcano, C.,et al,.(2025). Enhanced detection of atrial fibrillation in single-lead electrocardiograms using a Cloud-based artificial intelligence platform. Heart Rhythm, 22(7), 1667-1674.
38. Ul Rehman, S., Tarek, N., Magdy, C., Kamel, M., Abdelhalim, M., Melek, A.,et al,. (2024). AI-based tool for early detection of Alzheimer's disease. Heliyon, 10(8), e29375. https://doi.org/10.1016/j.heliyon.2024.e29375.
39. ILYAS, G. (2025). Predicting Chronic Kidney Disease: A Machine Learning Approach to Early Detection and Risk Assessment.
40. Niraula, P., Upreti, M., Kadariya, S., Poudel, B., Kadariya, S., & Kunwar, S. (2025). AI/ML driven prediction of COPD exacerbations and readmissions: a systematic review and meta-analysis. Frontiers in Digital Health, 7, 1641356.
41. Plass, M., Olteanu, G. E., Dacic, S., Kern, I., Zacharias, M., Popper, H., Fukuoka, J., Ishijima, S., Kargl, et al,.(2025). Comparative performance of PD-L1 scoring by pathologists and AI algorithms. Histopathology, 87(1), 90–100. https://doi.org/10.1111/his.15432'
42. Nelson, J. (2024). AI-assisted chronic disease management: Real-time interventions.
43. Ngcobo N. N. (2025). Silent Dangers in Elderly Pharmacotherapy: The Interplay of Polypharmacy, Multimorbidity, and Drug Interactions. Journal of evaluation in clinical practice, 31(7), e70283. https://doi.org/10.1111/jep.70283.
44. Du, Y., Yang, P., Liu, Y., Deng, C., & Li, X. (2025). Artificial intelligence in chronic disease self-management: current applications and future directions. Frontiers in Public Health, 13, 1689911.
45. Zack, M., Stupichev, D. N., Moore, A. J., Slobodchikov, I. D., Sokolov, D. G., Trifonov, I. F., & Gobbs, A. (2025). Artificial Intelligence and Multi-Omics in Pharmacogenomics: A New Era of Precision Medicine. Mayo Clinic proceedings. Digital health, 3(3), 100246. https://doi.org/10.1016/j.mcpdig.2025.100246.
46. Chen, E., Prakash, S., Janapa Reddi, V., Kim, D., & Rajpurkar, P. (2025). A framework for integrating artificial intelligence for clinical care with continuous therapeutic monitoring. Nature biomedical engineering, 9(4), 445-454.
47. Johnson, K. B., Wei, W. Q., Weeraratne, D., Frisse, M. E., Misulis, K., Rhee, K.,et al. (2021). Precision medicine,

AI, and the future of personalized health care. Clinical and translational science, 14(1), 86-93.
48. Mennella, C., Maniscalco, U., De Pietro, G., & Esposito, M. (2024). Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. Heliyon, 10(4). https://doi.org/10.1016/j.heliyon.2024.e26297.
49. Bringhurst, K., Jones, T., Runko, G., Jabbari, M., Zipparro, N., Nghi Vo, G., Ullah, A.,et al.(2025). Artificial Intelligence in the Management of Polypharmacy Among Older Adults: A Scoping Review. Cureus, 17(8), e90867. https://doi.org/10.7759/cureus.90867.
50. Cate, M. (2025). Integration of AI and Predictive Analytics to Optimize SGLT2 Inhibitor Prescription in High-Risk Patients.
51. Braga, D. M., & Rawal, B. (2025). Harnessing AI and Quantum Computing for Revolutionizing Drug Discovery and Approval Processes: Case Example for Collagen Toxicity. JMIR bioinformatics and biotechnology, 6, e69800. https://doi.org/10.2196/69800.