APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN DRUG DISCOVERY AND PHARMACY PRACTICE: A REVIEW

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A thesis submitted to the Department of Pharmacy in partial fulfillment of the requirements for the degree of Bachelor of Pharmacy (B. Pharm)

School of Pharmacy BRAC
University
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Declaration

It is hereby declared that

1. The thesis submitted is my own original work while completing degree at BRAC University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. I have acknowledged all main sources of help.

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Approval

The thesis titled “Application of Artificial Intelligence in Drug Discovery and Pharmacy Practice” submitted by Mehedi Hasan (18346075) of spring 24, 2024 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of Bachelor of Pharmacy.

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Ethics Statement

The study does not involve any kind of animal and human trail.

Abstract

Artificial intelligence (AI) is revolutionizing the pharmaceutical industry, through enhancing drug discovery and improving pharmacy practice, presenting novel solutions for healthcare’s complex challenges. Reviewing everything from target identification to medication excipient and dose form prediction, the paper explains how artificial intelligence is revolutionizing the pharmaceutical industry. Artificial intelligence models have the potential to decrease animal testing by assisting in the identification of disease targets, enhancing virtual screening of drug candidates, and even supporting toxicity prediction and pharmacokinetics, AI is transforming pharmacy practice with applications in dose adjustment, adverse drug reaction monitoring, and patient compliance, thus personalizing and improving patient care. In pharmacy practice, AI enables dose optimization and adverse drug reaction detection as well as personalized medicine along with aiding in medication adherence and provision of tele-pharmacy services. Despite the wide range of benefits AI offers, algorithm bias, data privacy and regulatory questions are challenges that need to be faced for a proper adoption. Finally, the review compares its use in developed countries to expand applications in Bangladesh, underlining how AI can potentially improve efficiency and patient safety as well as outcomes on a global scale. Ultimately, the potential for AI to revolutionize pharmaceutical research, clinical practice and healthcare delivery is immense.

Keywords: Artificial Intelligence, Machine Learning, Drug Discovery, Pharmacokinetics and Pharmacodynamics, Digital Therapy, Pharmacy Practice.

Dedication

I dedicate this project to my loving and supportive parents.

Acknowledgement

First and foremost, I would like to express my gratitude to the Almighty for his endless gifts, which have been given to me in an effort to provide me with the strength and determination to complete this project. It is my genuine pleasure to offer my heartfelt appreciation to my supervisor, Mr. Asef Raj (Lecturer at BRAC University's School of Pharmacy), for his invaluable guidance and encouragement during this research. Through the course of my education and project writing, he was a true source of advice and support for me. I am quite grateful to his for his valuable comments and ideas during my study, which helped me much in completing my project work in a timely manner.

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List of Acronyms

AI	Artificial Intelligence
FDA	Food and Drug Administration
AE	Adverse event
PV	Pharmacovigilance
ML	Machine Learning
DNN	Deep neural network
ADME-T	Absorption, Distribution, Metabolism, Excretion toxicity
SAR	Structure-activity relationship
LVS	Latent vector space
Pk	Pharmacokinetics
MMAS	Morisky Medication Adherence Scales
ANNs	Artificial neural network
SVM	Support vector machines
PAT	Process analytical technology
KNN	K-nearest neighbor
XG-Boost	Extreme grading boosting
PKPD	Pharmacokinetics and pharmacodynamics
PPP	Predict Pharmacokinetic Parameters
DL	Deep learning
CNNs	Convolutional neural networks
LSTM	Long short-term memory
RNNs	Recurrent neural networks
QSAR	Quantitative structure activity relationship
PBPK	Physiologically Based Pharmacokinetic
DDIs	Drug–drug interactions
MCL	Mantle cell lymphoma

DLBCL	Diffuse large B-cell lymphoma
LDCT	Low-dose computed tomography
RNN	Recurrent neural networks
NAC	Neo-adjuvant chemotherapy
ADRs	Adverse drug reaction
NLP	Natural language processing
FAERS	FDA Adverse Event Reporting System
CDSS	Clinical decision support system
CPOE	Computerized prescriber order entry
ADEs	Adverse drug event
TDM	Therapeutic drug monitoring
PSLL	Patient Safety Learning Laboratory
CMM	Comprehensive medication management
NLP	Natural language processing
SUDs	Substance use disorders

Chapter 1

Introduction

Artificial Intelligence (AI) is a rapidly advancing field focused on creating machines that can perform tasks that typically require human intelligence. Since its inception in 1951 by Christopher Strachey and the coining of the term "AI" by John McCarthy in 1956, AI has evolved from academic research to practical applications (Davenport & Kalakota, 2019; Suleimenov et al., 2020). Initially centered on rule-based and expert systems, AI today significantly impacts healthcare, finance, and transportation. In research, AI aids in analyzing large datasets, leading to breakthroughs in genomics and drug discovery. AI plays a crucial role in improving diagnostic tools and creating personalized treatment plans in healthcare. It is essential to ensure responsible development as AI continues to progress. The rapid advancement of AI technology offers the opportunity to revolutionize healthcare services by applying it in clinical practice. Providing healthcare providers with the necessary knowledge and tools for effective implementation of AI in patient care is imperative (Esteva et al., 2017; Jordan & Mitchell, 2015; VanLEHN, 2011).

The advancement of numerous industries is aimed at meeting customer demands through various methods, with the pharmaceutical sector being crucial for saving lives. Continuous innovation and the adoption of new technologies are relied upon in this industry to address global healthcare challenges and respond to emergencies, such as the recent pandemic (Krikorian & Torreele, 2021). Extensive research and development across manufacturing, packaging, and marketing drive innovation in pharmaceuticals (V. P. Chavda et al., 2023). The focus is on developing new drugs, ranging from small molecules to biologics, with high stability and potency to cater to unmet medical needs. Significant research is required to assess the toxicity of new drugs, presenting a major concern. The industry encounters challenges that necessitate technological advancements to effectively address global healthcare needs (Vora et al., 2023).

In the healthcare sector, it is crucial to have a skilled workforce and ongoing training to address skill gaps, especially in the pharmaceutical industry. According to a report, 41% of supply chain disruptions occurred in June 2022, making it the second most significant challenges (V. Chavda, Valu, et al., 2023; Vora et al., 2023). Various factors such as pandemics, natural disasters, price fluctuations, cyberattacks, and logistical delays contribute to these challenges. These disruptions have an impact on customer satisfaction, corporate reputation, and profits. The introduction of AI holds the promise of transforming supply chain management in the pharmaceutical sector by offering innovative solutions and enhancing decision-making tools for future supply chain challenges (R. Sharma et al., 2022; Vora et al., 2023). The impact of the pandemic is waning, but it still affects clinical trials, leading pharmaceutical companies to utilize AI and virtual platforms for restart trials with minimal face-to-face interaction (Daka & Peer, 2012; Kalepu & Nekkanti, 2015; Sarpatwari et al., 2019). Challenges persist, such as the requirement for highly skilled workers, high maintenance costs, and escalating cyber threats, raising concerns about patient data security. Traditional clinical trials encounter problems like data fragmentation, resulting in extensive manual data handling and necessitating innovation in trial models. Important areas requiring attention include patient recruitment, monitoring, and retention. Effective cybersecurity measures are crucial for both office and remote settings to prevent data breaches and healthcare fraud. Enhanced technology and internal discussions are essential to address these challenges and improve trial processes (Vora et al., 2023).

This review article aims to explore the current state of AI in healthcare, its potential benefits, limitations, and challenges, its future development, application of AI in pharmacy practice in the developed countries and as well as in Bangladesh. By doing so, this review aims to contribute to a better understanding of AI's role in healthcare and facilitate its integration into clinical practice.

Chapter 2

AI for Drug Discovery

There are several ways in which AI has transformed drug research and discovery. Major breakthroughs obtained in this field with the help of AI follows as:

Target Identification: DeepMind's AlphaFold can analyze a variety of molecular data types including genetic, proteomic and clinical to identify potential therapeutic targets. AI informs the identification of new drug targets and biological pathways involved in disease, so as to enable medications that could optimize function.

Virtual Screening: By leveraging machine learning, it is able to screen through significantly larger chemical libraries and find molecules that are likely binding to a particular target. Through simulating chemical interactions and predicting binding affinities, AI helps with the prioritization of compounds for experimental testing. This minimizes time needed to identify such critical information, hence saving resources as a result.

Structure-Activity Relationship (SAR) Modeling: The Schrödinger Suitable to derive connections between a chemical composition and biological behavior in compounds. This enables researchers to optimize drug candidates by creating molecules with the desired properties, for example high potency or selectivity as well favorable pharmacokinetic profiles.

Proposing New Chemical Structures: AI algorithms like deep-chem can propose novel druglike chemical structures by combining reinforcement learning and generative image models. This way, artificial intelligence learns from chemical libraries and experimental datasets to help in the exploration of new regions of reliable drug-like chemistry.

Drug candidates have to be optimized: AI algorithms Schrödinger Suite optimize drug candidates in a multidimensional manner across efficacy, safety and pharmacokinetic profile. This allows scientists to optimize therapeutic molecules for maximum efficacy with minimal adverse events.

Drug Repurposing: Analysis of vast and varied biomedical data by AI approaches can help spot approved drugs that could be taken to treat a range of diseases. AI speeds up drug discovery by finding new uses for old drugs.

Overall, AI-driven approaches in drug research and development offer the potential to streamline and expedite the identification, optimization, and design of novel therapeutic candidates, ultimately leading to more efficient and effective medication (Shah et al., 2023; Vora et al., 2023).

2.1 Prediction of Physiochemical Properties

Secondary substance screening also entails assessment of the physicochemical properties, biological activity and toxicity of a compound. These characteristics highly influence the clinical profile of a drug candidate as an antipsychotic agent. Small molecule drugs require the best safety profiles, solubility and permeability to be able to reach their targets. Prediction of physicochemical properties helps in designing new chemical compounds to have desirable bio-pharmaceutical properties. In predicting the key descriptors, the Machine learning (ML) algorithms (Schrödinger, ACD/Labs) involve the prediction of the properties such as water solubility, membrane permeability, and lipophilicity. In lead optimization stage, absorption, distribution, metabolism and excretion toxicity or ADME-T is fine-tuned to generate models from abundance of chemical information. ML methods having molecular modeling and processing (MMP) for bioactivity properties such as oral exposure, distribution coefficient or logD, and ADME combined with various SAR analyses with the help of ChEMBL and PubChem databases (H. C. S. Chan et al., 2019).

2.2 Prediction of Bioactivity

In practice, a significant portion of medications made from natural ingredients are ineffective because they lack bioactivity. As a result, drug bioactivity assessment has emerged as a hot topic in the drug discovery process. Experiments conducted in vitro and in vivo can imitate the actions of molecules in the human body, but they are nevertheless costly as well as time-consuming. AI approaches have been successfully used to forecast pharmacological bioactivities, such as anticancer, antiviral, and antibacterial activities, because to their cost-effectiveness and time economy. In order to forecast antibiotic activity, Stokes et al. presented a directed message passing neural network. They created a molecular graph for each molecule in line with its SMILES before obtaining the feature vector based on atomic features (such as the number of bonds for each atom) (W. Chen et al., 2023). Recently, new techniques for predicting drug candidate's bioactivity have been created. In this context, Tristan et al. used a graph convolutional network to extract a signature of the drug target site by encoding discrete molecules into a continuous latent vector space (LVS). In molecular space, LVS enables gradient-based optimization, enabling predictions based on differentiable models of binding affinity and other features (H. C. S. Chan et al., 2019).

2.3 AI for Pharmacokinetics and Pharmacodynamics

Drug development has five major phases – drug discovery, pre-clinical, clinical, regulatory approval and commercialization, with PK and PD phases being significant in dosing regimens, routes of administration and safety respectively (Cui & Wang, 2019; Mager et al., 2009). Depending on historical approaches to carrying out PKPD studies, one has to undergo lengthy and costly animal trials [Figure 1] and clinical studies which may be imprecise in determining the human response (Alsultan et al., 2020; Keutzer et al., 2022). To surmount these challenges, computational models and AI have presented themselves as valid tools in rapid and efficient, yet precise, predictions of the drug's PKPD. AI combines high computing capabilities and ML with an aim to revolutionize the drug development practices with opportunities of better therapeutic outcomes and safety profiling (V. P. Chavda, Ertas, et al., 2021; Houy & Le Grand, 2018; Patel & Shah, 2022).

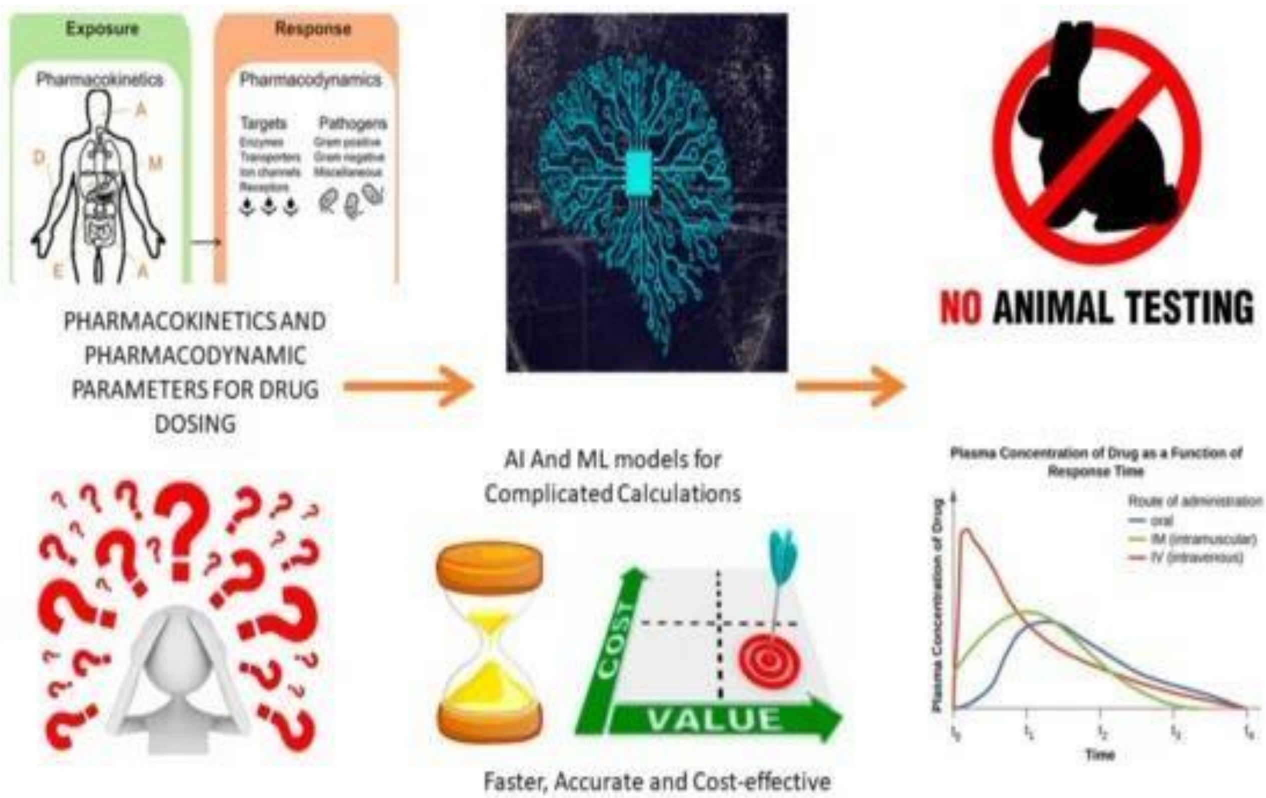

Figure 1: Role of AI in PKPD studies.

AI-Based Methods to Predict Pharmacokinetic Parameters: In the case of PPP (Predict Pharmacokinetic Parameters), the application of ML and DL models can be seen frequently in pharmacokinetic parameters prediction. As for the ADME properties' prediction, the abilities of several ML techniques have been utilized in formulating the prediction model, which includes Bayesian model, random forest, support vector machine, artificial neural network, and decision tree. Some of the DL algorithms used in the pharmacokinetics predictions area are CNNs, LSTM, and RNNs where the former is usually used to predict different pharmacokinetics parameters such as absorption, bioavailability, clearance, volume of distribution, and half-life. Quantitative structure activity relationship (QSAR) is one of the quantitative methods in which the biological activity of a molecule is predetermined based on the chemical constitution of the molecule. Pharmacokinetics is one of the fields where this method can be used with the purpose of ADME forecast of drug solubility, permeation, or metabolism (Bhattamisra et al., 2023; Daoui et al., 2021; Suresh et al., 2020; Westreich et al., 2010).

AI-Based Computational Method for PBPK: PBPK (Physiologically Based Pharmacokinetic) models are complex mathematical models for a projection of the behavior of the substances, including the drugs in the organisms. Construction of these models was traditionally data and computationally intensive. Yet, PBPK models have been evolving with the help of AI-based methods which use machine learning algorithms to define what particular features are essential for PBPK models and how the parameters of the latter should be fine-tuned. This can possibly help cut down the use of animals in the experimental process and clinical trials on human beings (Jones & Rowland-Yeo, 2013; Zhuang & Lu, 2016). To document some theories at least, pharmacokinetic parameters essential for constituting and regulating the chance and impact of a drug play a crucial role in deciding aspects like, for example, the length of exposure to the drug and the rate of drug metabolism. ADME stands for absorption, distribution, metabolism, and elimination, and these are some of the factors that are vital in the evaluation of any compound to reduce glorification. Optimization of dosing in man follows the in vivo studies in animals which in turn is backed by in vitro tests such as liver microsome tests. The allometric scaling approaches retrieve human PK parameters like the volume of distribution, organ clearance, and absorption using PC data and in vivo animal models. ADME properties in PBPK models are time-sensitive, which helps in extending the in vivo activities to humans during the later stages of drug discovery. AI and machine learning have crucial roles in working through large and detailed in vivo data and improving the evaluation of pharmacokinetic factors which contributes to the drug development (Obrezanova, 2023).

Prediction of Drug Release and Absorption Parameters: Some studies have used AI techniques (GastroPlus, PK-Sim) on specific models to predict drug release and absorption parameters. Thus, AI algorithms can process information regarding different drug delivery systems and forecast the release profiles of drugs. Due to the aspects like, how the drug interacts with its chemical and physical surroundings, properties of the dosage form, and the mechanism used to control the release of the delivery system, AI models can predict the release kinetics of the drug. AI based model can also forecast the release profile of drugs on various drug delivery systems like orally disintegrating tablets, transdermal systems, inhalers and so on (Mhatre et al., 2023).

AI models can estimate such variables as drug dissolution rate, bioavailability, and others on the basis of solubility, permeability, or formulation. These models can explain the physicochemical properties like lipophilicity and molecular weight and compare these properties with the absorption data with a view of predicting the possibility of absorption of the drug into the blood stream. In general, it is possible to highlight that AI-based models are rather effective in terms of predicting drug release and the main parameters of absorption. Using a client's data as well as other parameters, such models can determine the best way of delivering drugs, inform decisions regarding the development of drugs and even contribute to designing better drug delivery mechanisms.(Chintawar et al., 2023; Chou & Lin, 2023; Daoui et al., 2021; Jones & RowlandYeo, 2013)

Prediction of Metabolism and Excretion Parameters: Artificial Intelligence (MetaDrug, Simcyp Simulator) has been of importance in aiming at drug metabolism and excretion parameter, and thus for the pharmacokinetics of drugs. Chemical and functional properties of drugs desired from the molecular structure can also be used by AI algorithms to forecast the metabolic pathways. Through practice on data containing information on certain drugs' metabolism, AI models can learn structural properties of compounds to be related to certain metabolic stages (Tran et al., 2023). These models allow for predicting of possible metabolites and discuss major enzymes participating in the process of drug metabolism. Silico wound healing models can determine the reaction rates and enzyme–substrate binding to estimate the metabolism of a drug. Thus, instead of designating the role of interpreting metabolism impact on clearance and efficacy, AI models can predict the effects with regard to enzyme expression levels, genetic variations, drug–drug interactions at the same time. Altogether this information is useful in identifying appropriate dosing schedule for drugs and possible drug interaction (Y. Li et al., 2019). Using the AI algorithms, information on drug physicochemical characteristics like size, hydrophobicity, and charge can be used to estimate drug clearance. Since these AI models learn from datasets containing details of drug clearance pathways it is possible to predict the rate at which drugs are cleared from the body. Climbing this knowledge is essential for the designation of dosing in regimens to make the drug effective and safe (Parikh et al., 2023).

AI systems can make the prognosis of drug interactions attributed to transporters associated with the absorption, distribution, metabolism, and excretion. Thus, AI contains the potential to identify the possibility of DDI (Drug-drug interactions) or modulation of pharmacokinetics due to the transporter based on procured drug physicochemical properties and transporter profiles. This knowledge is useful in comprehending how drug molecules behave within the body and formulation of better drugs (Alsmadi & Idkaidek, 2023; Selvaraj et al., 2022; Z. Zhang & Tang, 2018).

Using the AI algorithms and incorporating the large information about metabolism and excretion of drugs, the models play an important role in the predictive nature of drug fate in the body. They help in enhancement of drug doses, in the examination of the interaction between different drugs. Also, the models allow researchers and pharmaceutical firms to categorize drug candidates by their metabolic and excretion profiles, enhancing the efficiency of drug development.

2.4 AI Tool Application in Dosage Form Designs

Drug delivery within the human body can be broken down into compartments using biological membranes and physicochemical barriers. The process of drug permeation is very important with consideration of the route of administration involved in the process. In case of orally administered drugs, the ability to penetrate the intestinal or gastric tissue barrier is very critical for distribution in the blood circulation and to the target sites (V. P. Chavda, 2019; Das et al., 2016; Siepmann & Siepmann, 2012). Drug permeation can be passive which is depends on the physicochemical property of the drug molecule or active which depends on the process of transport of the drug across the biologic membranes and the interaction of the drug with the biological system. Computers and AI systems study of PK's the drug and interactions with membranes [Figure 2]. Various forms of AI in the form of artificial neural networks contribute to simplifying the analysis and making predictions, using such databases as chemical, genome, or phenotype for improved understanding of inter-drug interaction. AI as an underlying technology (PK-Sim, Cresset's Spark) enables the setup of automated tools to enhance the information processing and the results that leads to drug delivery research. The approaches in the newer drug delivery systems concern themselves with regarding the quality attributes of the product and analyzing their effects in experimental trials for the better disposition and toxicity description (Menden et al., 2013; S.-Y.

Yang et al., 2009; Yu et al., 2004).

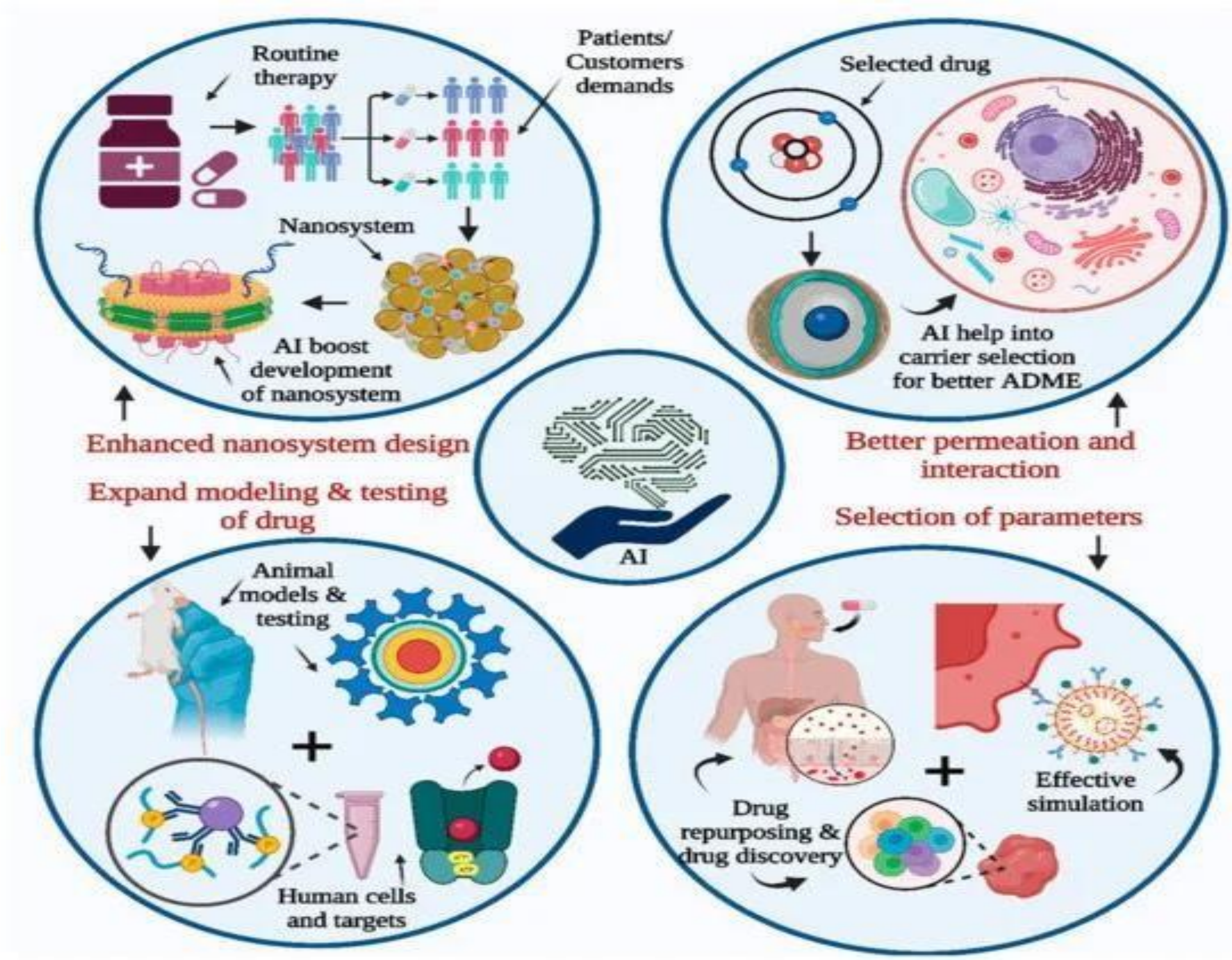

Figure 2: AI contribution to drug development and research

The advantages associated with the use of AI include the capacity in drawing information from a given number of sources coupled with indications for the selected drug delivery system to function as per the expected outcome. The molecular information, patient data, and pharmacokinetic data are described here as part of the aggregate data for consideration for the potential selection of the most suitable active pharmaceutical's counter to patient diseases or demands. The categorization of drug delivery systems is achieved by the help of AI, which means that the choice of an effective treatment depends on an accurate choice of different systems (Avdeef et al., 2005; Esch et al., 2015; S. M. Kim et al., 2017; Rafienia et al., 2010).

2.5 AI for Drug Delivery

Prediction of Dug Release through Formulations: The ability to predict drug release is beneficial for maintaining quality stability within drug manufacturing. Release studies of the drug are crucial, and they are done through in vivo and in vitro techniques, which are usually conducted and rechecked. Release controlling factors in solid oral dosage form comprises of compaction factors, geometry of the tableting mass and the drug loading ability. Such working methods include spectrophotometric analysis.

Drug release rate optimization is also a complicated process while it is quite time consuming as one has to perform the test and prepare the batches again and again (Galata et al., 2021). In drug formulation, AI contributes to the estimation of drug release, decrease of the number of runs to optimize batches and decrease of costs in pilot and production plans. In the pharmaceutical industries, it uses prediction to estimate drug release and dissolution status for selection of the right batch for further processing. In this case, AI algorithms employed by researchers include artificial neural networks (ANNs) in the determination of dissolution profiles in hydrophilic matrix sustained release tablets. For data analysis and prediction, there are other algorithms commonly used and among them are support vector machines (SVM) and regression analysis. The information used in modeling drug release is process analytical technology (PAT) data and material attributes, of which PSD is one of the parameters. It enables the selection of the right ANN models for evaluation in [Figure 3] (Han et al., 2018; Petrović et al., 2012).

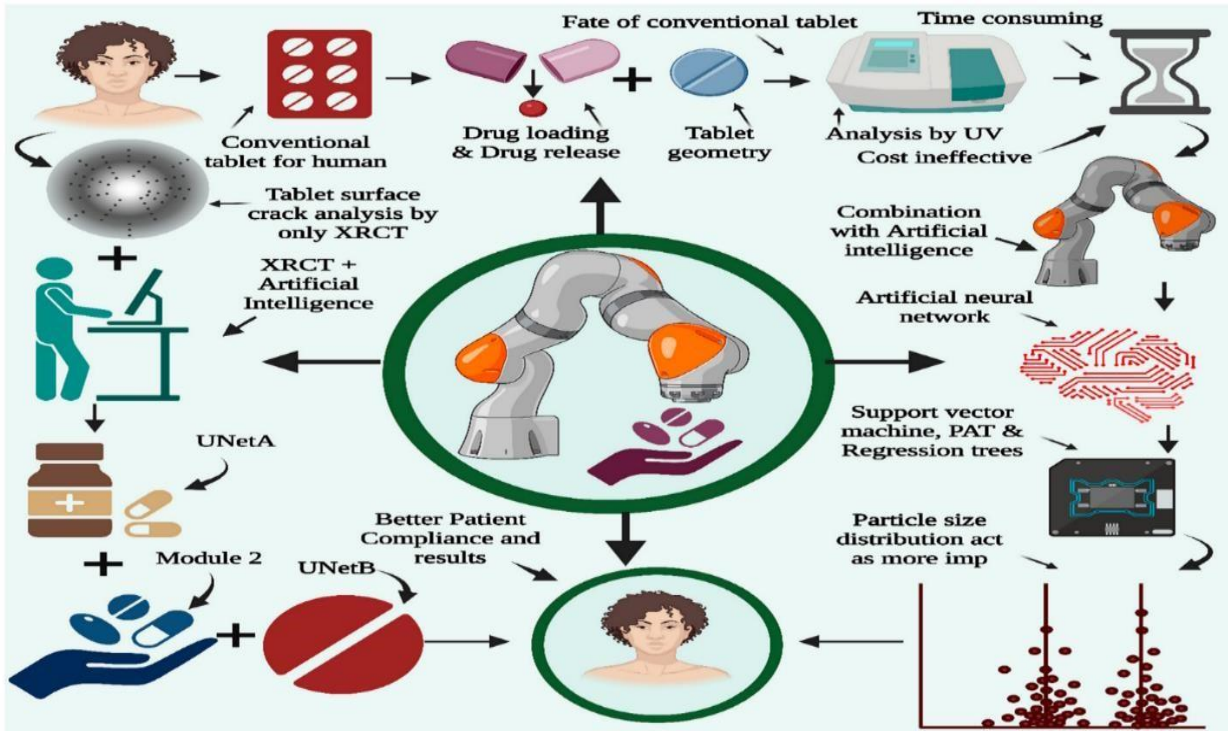

Figure 3: AI for Oral Dosage Forms.

Dissolution Rate Predictions: AI has made a tremendous contribution toward the enhancement in the prediction of the drug dissolution rates which plays an important role in bioavailability and therapeutic efficacy.

This capability of AI contributes to better formulations and dosage forms as it helps in formulating better strategies to improve solubility and absorption of the drugs (Mukhamediev et al., 2022). Scholars like Dong et al., have used AI algorithms like support vector machine (SVM), LightGBM, and extreme gradient boosting (XGBoost) in estimating dissolution rates for 50 active pharmaceuticals ingredients and 25 polymers (Sun & Lee, 2013). From the investigated machine learning algorithms, XGBoost, a scalable machine learning library was the most appropriate as it can handle large, unstructured datasets. ANNs again fared better than other algorithms by relying on the molecular computational software to deduce descriptors of active ingredients and polymers (Dong et al., 2021; Gao et al., 2021).

2.6 Drug toxicity prediction

Introducing new medications into the market is arduous in light of medication wellbeing. Unexpected toxicities are the most common cause of clinical trial attrition, and many post marketing safety problems result in unacceptable morbidity or mortality (Basile et al., 2019). Toxicological endpoints WHAT MEAN toxicology is the study of what bad things a compound does. An important step in the drug development process is evaluating toxicity, or studying which compounds are toxic to humans (Yoo et al., 2019).There are two categories of systems addressing drug safety Clinical trials assess the safety and effectiveness of a drug for its intended use before receiving FDA approval. Monitoring of drugs continues after they are released to the market. Adverse event (AE) reports play a crucial role in the pharmacovigilance (PV) process to ensure that up-to-date safety data for a drug is maintained (Basile et al., 2019). However, factors such as timely risk assessment, evaluation cost, and the desire to minimize animal testing have led to a growing preference for in silico techniques like molecular modeling and machine learning (ML) in toxicology (Vishnoi et al., 2020). DeepTox, an ensemble model, utilizes a three-layer deep neural network (DNN) to predict the toxicity of compounds. When compared against its competitors using the Tox21 dataset, DeepTox demonstrates superior performance in toxicity prediction (Yoo et al., 2019).

2.7 AI in market prediction and market analysis

The pharmaceutical industry can work by discovering and marketing mew drugs but the research and development output here has gone down because of regulations and resistance to new marketing technologies. Digital technologies help to un-complicate the market by enabling AI technologies (Tableau, Google Cloud AI) to contribute to decision making models that involves numerical data and statistic to predict the market. AI is also necessary in the aspect of market design, identifying consumer requirements, and studying the market to develop a structure for market growth. AI aids in the introduction of new products on the webpage, as the software is set to run in a certain particularized manner in a market. Such digital strategies, such as web advertising and the availability of product websites, raise general public and doctors' awareness about the drugs, and the utilization of CMRs becomes less dependent (Kalyane et al., 2020).

Chapter 3

AI in Pharmacy Practice

Artificial Intelligence (AI) is transforming the way pharmacy practice operates by enhancing efficiency, precision, and patient care. Pharmacists can utilize AI tools to manage medications and its adherence, automate prescription verification, dose recommendations and minimize errors in dispensing. Machine learning algorithms analyze patient information to anticipate potential drug interactions, optimize dosages, and offer personalized medication recommendations. AI systems also simplify administrative tasks, allowing pharmacists to dedicate more attention to clinical decision-making and patient counseling. As AI progresses, it is elevating the role of pharmacists in healthcare, leading to improved patient outcomes and more effective pharmacy operations (Chalasani et al., 2023).

3.1 Dose recommendations

There are benefits in developing an AI/ML-based dose prediction system to fit the requirements of the individual patient to derive information data from multiple sources such as safety and efficacy records, electronic health records of the patient, details of the disease, treatment history and feedback. The objective of these systems is to increase treatment efficacy, while at the same time decreasing adverse consequences. The reinforcement learning algorithms show promise for prospection and dosage adjustment in the accurate cancer treatment. The dose optimization system has been invented and it is considered as a possible innovation for improving the treatment of chronic diseases. This new tool is expected to directly contribute to the efforts of reducing the error margin consequent to chemotherapy by offering a set of suggestions for the appropriate dosage. Another fact is the patient’s response to treatment over time, which allows for dynamic calculations of the required dose to provide the necessary therapeutic and safety effect (M. Johnson et al., 2023).

3.2 Medication adherence

Approximately half of chronic disease patients do not take their prescriptions as recommended, thereby raising morbidity and mortality while making healthcare consumers lose a hundred billion

USD in a year (Brown & Bussell, 2011). While pharmacist led programmers are the most effective in enhancing medication adherence, such programmer can be compound and multiple; they engage a number of health care practitioners and their components. AI technology could be useful in implementing the multiple aspects of multifactorial therapies aimed at improving patient's drug compliance which is not a simple matter. Most AI systems encourage and check whether the patient is taking his/her medication or not. The eight technology types were classified by their technical designs and adherence monitoring functions: pillboxes or bags, bottles in which the medication is placed, smart ingesting devices, That comes in the form of blister pack technology, Computerized Medication Management System, patient self-reporting based information technology, Videobased information technology, Motion Sensors technology (Babel et al., 2021).

3.3 Adverse drug reaction (ADR) detection

AI is being used to identify and handle ADRs in pharmacy practice. This is where AI algorithms can enable pharmacists to improve patient safety by examining extensive data sets on everything from patient charts to prescriptions to test results, looking for subtle correlations of medications with side effects that might otherwise not surface. As a result, pharmacists are able to respond in a much more rapid manner and deal with the issue at hand.

It helps in monitoring the health real-time patients on their wrist watches using AI & Adaptive learning Smartwatch, Mobile applications for Medication and Symptoms. This information can be an early warning to clinicians, so they can detect ADRs and tailor treatments as needed. Meanwhile, AI-driven predictive analysis also factors in each individual patient's genetic and medical profile to determine high risk groups for ADRs, enabling more effective prescription customization by pharmacists.

For example, natural language processing (NLP) allows analyzing free text data (e. g., electronic health records, patient self-reports) to detect ADRs reducing the burden of pharmacovigilance activities. Moreover, utilizing AI algorithms to analyze massive pharmacovigilance data pools (e.g. the FDA Adverse Event Reporting System — FAERS) reveals safety signals associated with certain drugs for chemists to evaluate risks and respond proactively. (Yang et al. 2019)

3.4 Dose optimization and therapeutic drug monitoring

Dose optimization & Adverse drug event (ADE) risk prediction, for this AI has a huge role in making the patient safety and treatment process much better (Martin et al., 2022). This is where AI algorithms come in, to help healthcare providers tailor dosages and mitigate potential ADEs (H. Lee et al., 2021). Expert clinicians were outperformed for accuracy by an AI model in predicting PT/INR and warfarin dosage management, based on 19,719 hospitalized patients.

“CURATE.AI” is a new AI A novel platform, AI 'personalized' chemotherapy dose-based on patient-specific information A trial showed that the CURATE (Blasiak et al., 2022). Compared with the traditional methods, most patient responses were enhanced, and the chemotherapy dosages were decreased using AI; therefore, further randomized clinical trials are imperative.

Then there is the other end of the spectrum, Therapeutic drug monitoring (TDM) a need for agents with narrow therapeutic index where AI can predict how individual responds to a particular drug based upon their genetic and medical status. By tailoring a drug specific to each patient, prescribing the correct dose ranges obviously with higher accuracy while avoiding toxicity where possible and beginning at the right time point using AI in TDM results in improved treatment outcomes, lower healthcare costs and greater dosing accuracy (Sjövall et al., 2023). By predicting drug-drug interactions, AI further reduces adverse events. With the increasing AI technology, it will become one of the cornerstones in TDM and pharmacotherapy (Partin et al., 2023; H. Zhang et al., 2021).

3.5 Clinical decision support system (CDSS)

The aim of a clinical decision support system (CDSS) is to improve the delivery of healthcare by supplementing medical decisions with specialized clinical knowledge, patient information, and additional health data. The CDSS correlates individual patient characteristics with a computerized clinical knowledge base and then provides tailored patient assessments or recommendations to the clinician for decision-making. This technology enables pharmacists to analyze data and proactively take measures to prevent medication errors, reduce patient complications, and realize cost savings (Sutton et al., 2020).

3.6 AI in drug information and consultation

The use of AI in healthcare helps providers make better decisions and deliver higher quality care while providing more efficient and cost-effective service that is also safer for patients (Dasta, 1992). Healthcare facilities have become the new adopters of automation technologies to streamline operations. Artificial intelligence provides real-time advice to practitioners through NLP, machine learning and data analytics. AI has made it possible for patients, providers, regulators and payers to get their hands on some analysis that used to be funded only million dollar from The Gates Foundation or NIH – arguably enabling all four stakeholder groups (Alowais et al., 2023).

Artificial intelligence guides healthcare professionals to extract drug relevant information from peer-reviewed resources on which conscious decisions can be made. Simple queries are attended by virtual assistants and chatbots which will help in reducing the burden on health professionals while AI algorithms perform data analytics on patient past and present behavior and history recommending the correct dose of medicines for personalized care (Davoudi et al., 2018; L.-R. Li et al., 2021).

3.7 Computerized prescriber order entry (CPOE)

The types of healthcare errors can be classified in numerous ways. Medication errors, in fact, are the top error category proven costly and deadly—having been attributed to the deaths of at least 7000 people, according to an estimate by the Institute of Medicine. Inadequate prescribing practices, which have been shown to be associated with drug name, prescription legibility issues and misinterpretation of dose forms or abbreviations are responsible for 11 contributions. In his published research Ross said that junior doctors accounted for 4% of medication errors. CPOE or Computerized Provider Order Entry or Computerized Practitioner Order Entry: An application that allows clinicians to enter and send medication, treatment, laboratory, admission, radiology, referral, procedure orders electronically instead of using paper notes, verbal orders over the telephone or hand written fax. This procedure avoids concerns that result from the doctors noisy handwriting and errors transcribing resource for this article prescriptions. CPOE refers to these systems that select, write and store medication records electronically transmitting drug instructions to a pharmacy for fulfillment. New is also good from a patient safety perspective providing fresh opportunities to prevent the patient harming themselves - e.g. alerts for an allergy or adjusting the dose if a patient has renal disease, but at the same time they allow for dozens of new prescribing and dispensing issues which are as predicable ad infinite, but just encumber all that stands against with their potential impact (Jungreithmayr et al., 2021).

3.8 Electronic health record (EHR)

A new predictive EHR algorithm that functions as an adjunct to clinical decision support may identify when a given prescribed medication appears to deviate from the 'normal' usage by running large volumes of EHR data through AI-powered classifiers against expected medication use patterns. AI could even help determine drugs — not because it had predicted them, but simply because the model had, during every step of training, labeled that population so sharply as to effectively confirm those who were least likely to suffer side effects. Patient Safety Learning Laboratory (PSLL) that can also harness AI in EHR systems to identify, evaluate and mitigate patient safety risks. The potential of NLP and ML that are using hospital and health system pharmacies to extract and process the millions of unstructured free-text data from EHRs including medication safety, patients' medication history, side effects, drug–drug interactions, discrepancy with medications patterns and adherence assessment to improve patient care quality and premature adherence to drug evaluation. The application of this technique could assist P&T Committees in the bargaining of risk-sharing agreements as well as in making decisions (Chalasani et al., 2023).

3.9 Medication therapy management (MTM)

The CMM-Wrap program was delivered through an AI platform that incorporated population health and telemedicine for identification and prioritization of at-risk patients with subsequent AIdriven decision support for interventions. This involved the maintenance of comprehensive data repositories, reporting and custom-built Med-Risk-Scores. You had a community health tele-based brief illness management service employed by a disease therapy management provider (Kessler et al., 2021), using medical assistants and clinical pharmacists to provide care over the phoneigrants. The research concluded that this AI-based method resulted in lower overall health care expenditures and fewer hospitalizations because of the related enhancements to patient well-being.

At the time of COVID-19, a hospital from Shanghai delivers an internet pharmacy service powered by AI. Prescriptions were machine-analyzed by AI (Bu et al., 2022), then double-checked by the pharmacists. Patients at the medication pick-up site were given a "medication pick-up code" for high-risk or sensitive medications or scheduled a delivery by a third-party pharmacy, if they ordered non-urgent medication offline. In hospitals or drugstores, patients could scan QR codes for medication pick-up from a dispensing machine or pharmacist. The hospital also offered free online drug consultations by volunteer pharmacists (Edrees et al., 2022).

3.10 AI in Digital Therapy/Personalized Treatment

The combination of AI can allow for relationships to be drawn from raw data, assisting in diagnosis, disease management and mitigation. With the aid of Artificial Intelligence, computational methods derived are widely accepted techniques and have been designed to leverage the tools in different fields of medical sciences ensuring that clinicians can manage large amount of data and solve clinical problems which proved to be complicated (Holmes, 2015). Artificial Neural Networks (ANNs), evolutionary computation, fuzzy expert systems and hybrid intelligent systems among other methods are aiding healthcare workers in the manipulation of data (Fogel, 2000). ANNs, which resemble the human neural system, connect several processors (neurons) to perform a parallel computation of data (Mandal & Jana, 2019). One famous model is a feed-forward NN; it consists of an input layer, hidden layers, and output layers in multilayers there are numerical weights between the neurons (Whitley, 1994).

AI in Radiotherapy: Radiotherapy — AI: An automatic treatment planning in radiation therapy enhances the quality of the plan, improves consistency, and reduces errors. This workflow is divided into three parts namely Automated rule setting, Reasoning with prior clinical knowledge and Multicusiteria optimization (Moore, 2019).

RaySearch: Ray-Station is a next-generation system that leverages AI and machine learning to automatically implement clinical guidelines, evaluate patient anatomy, and streamline manual planning (Troulis et al., 2002). RayStation also features radiomics, that is the ability to predict outcomes / side effects from imaging biomarkers and produce patient specifically optimized radiation therapy plans (Arimura et al., 2019).

AI in Retina: The use of AI in Retina High-resulation imaging of the retina (LumineticsCore) has paved away for measuring human health on minute specifics. It reveals highly personalized information from a single snapshot of just the retina. Through the use of high-tech medical technology, a retina specialist or radiologist is able to create an individualized treatment plan and develops a healthcare system that learns and improves over time (Schmidt-Erfurth et al., 2018).

AI in Cancer: Artificial Intelligence (AI) in general is proving crucial in diagnosing and treatment of medical conditions such as lung and gastrointestinal cancers and even non-Hodgkin lymphomas (Carreras & Hamoudi, 2021). Prognostic markers, and the subclassifications of lymphomas, are put to the test using AI computational neural networks (Carreras et al., 2022). Concerning gastrointestinal oncology, AI helps in precisely predicting features of colorectal carcinoma, and in out the progression of stomach cancers, eye monitoring nocturnal helps in discovering H.pylori (Bang et al., 2020) . EE also facilitates the diagnosis of lymphomas using prognostic indicators and blood endoscopy imaging but randomization and blinding are not feasible (Z. Zhang et al., 2021). Algorithms such as Random Survival Forest and Cox Survival Regression has the capability of assessing cancer prognosis along expected lines (Y. J. Yang et al., 2020).

In lung cancer AI systems assist in screening and diagnosing pulmonary nodules and also using deep learning models they are able to estimate tumor cell volumes and predict clinical endpoints for the cancer (Arlova et al., 2022, 2022; Espinoza & Dong, 2020). Low-dose computed tomography (LDCT) imaging incorporates convolutional and recurrent neural networks (CNN and RNN) for higher accuracy in differentiating benign from malignant nodules (S. Chen, 2022). Artificial Intelligence devices in management of breast cancer enhance treatment response determination while malignant lesion recognition is facilitated by Radiologist. However, these bottlenecks include absence of public databases, blurry pictures required, dependency of ROI annotation, and the difficulty in distinguishing between malignant and benign nodules (H.-P. Chan et al., 2019).

AI in Other Chronic Diseases: AI technology and related computer aid treatments have started to penetrate other domains such as health care, particularly with respect to behavioral and cognitive therapies. Such applications can involve things like multiple-choice questions or joysticks. A newer method, this one incorporates artificial intelligence, natural language processing and many depending on user input systems and through that offer targeted treatments and medicines based on the patient's complexion (Haag et al., 1999).

Chronic diseases are accessed for treatment targeting where system in question is largely artificial intelligence which is virtual medical assistants that give guidance on text through phone applications. Diet treatment also based on the patient's microbiome is useful and practical. Conditions such as atrial fibrillation have been predicted with the help of Deep learning systems and a combination of smart watches and ECG sensors (Ellahham, 2020). In diabetes, AI methods on case-based reasoning and vector regression enhance insulin therapy, HbA1c response and treatment decision.

On a more molecular level, application of advanced methods of AI including molecular phenotyping and digital biomarkers allow for disease control on a molecular basis. It allows the people to use web-based and smartphone applications to manage diabetes with the help of advanced AI technology.

3.11 Telehealth

The use of Telehealth (telemedicine), makes it easy for patients and the doctor to share important medical information even when they are situated in separate geographical locations. Chatbots based on Natural Language Processing (NLP) further improve clinical processes by collecting patient's clinical history and second asking questions to ascertain the presence of any adverse drug events (ADE's). Developers have established adverse event monitoring systems which are conversational and comply with HIPAA but still carry out adverse drug events reporting with machine learning and natural language processing aimed at marketing to the drug industry and the FDA.

In telehealth, AI support includes the conducting of target patient screening, in pharmacovigilance activities, via portals and messaging systems to enhance efficiency. The use of mobile health applications by patients and telemonitoring and wireless monitoring devices capable of measuring usage of symptoms medication intake foods health status by the patients. Real time monitoring of patient conditions is made possible by the use of mobile gadgets such as fitbits, apple watch, insulin pumps and pacemakers creating patterns which can be analyzed by providers. Patients can also be monitored through the use of wearable technology and smart clothes which track certain physiological parameters and the management of medication regimen (MRM) (Edrees et al., 2022).

3.12 AI mental health support

AI technology has the capacity to revolutionize mental health care by providing affordable and available health services for the patients (Graham et al., 2019; J. W. Kim et al., 2019). Research shows the efficacy of internet-based cognitive therapy which makes it appropriate for treatment in refugees (Williams & Andrews, 2013). While psychiatrists practice with a hands-on approach to the patients, the use of artificial intelligence can assist in control and the prevention of diseases by helping with proper diagnostic procedures and timely treatment (Luxton, 2014). Woebot, Ginger, Mindstrong, and Moodpath are examples of mental health applications that are able to use ABC technology to screen patients for mental illnesses, provide treatment under saturation, and monitor disease progression and drug adherence (Graham et al., 2019).

AI has been declared an effective tool against various psychiatric conditions especially depression and substance use disorders (Graham et al., 2019). Use of the Woebot application for example has been associated with increased substance use, depression, and anxiety symptoms among patients with substance use disorder. But there are stumbling blocks, such as the inherent shortcomings of biased models of AI and data, which do not allow making a real diagnosis. The use of AI has limitations in that it ignores the heterogeneity of most of the mental health conditions and elements of empathy regarding caregiving often are also removed from it (Mak & Pichika, 2019). Therefore, although the ingrowth of AI in mental health is undeniably a welcome development, it should only aid the clinician in their work and should never replace a qualified diagnosis and treatments.

Chapter 4

Application of AI in pharmacy practice in the developed countries

AI has significantly impacted pharmacy practice in developed countries, enhancing various aspects of patient care, medication management, and operational efficiency. Here are some key applications:

4.1 Medication Management

Automated Dispensing Systems: AI-powered robots are good at giving out medications accurately, which makes fewer mistakes and saves time (Chapuis et al., 2010).

Inventory Management: AI can guess how much of each medication will be needed so there's never too much or too little (Albayrak Ünal et al., 2023).

4.2 Clinical Decision Support

Drug Interaction Alerts: AI can look at what drugs a patient is taking and warn if there could be a problem (Graafsma et al., 2024).

Personalized Medicine: By looking at a patient's info, like their genes, AI can suggest treatments that will work best for them (Schork, 2019).

4.3 Patient Monitoring and Adherence

Wearable devices and phone apps that use AI watch out for a patient's health info, remind them to take meds on time, and give regular updates (Jeddi & Bohr, 2020).

Tele-pharmacy Services: With the help of AI, pharmacies can give advice over video calls, renew prescriptions, and teach patients online (Georges Badr & Khiami, 2024).

4.4 Disease Management

Chronic Disease Monitoring: AI tools help keep an eye on diseases like diabetes by looking at patient data and suggesting changes to their meds quickly (Arefin, 2024).
Predictive Analytics: By using AI to predict what might happen next with a disease, pharmacists can step in early and manage things better (Subramanian et al., 2020).

4.5 Operational Efficiency

Workflow Optimization: Using AI to do boring jobs saves time so pharmacists can spend more time helping patients (Pierre et al., 2023).

Fraud Detection: AI can tell when someone's trying to get meds they shouldn't by looking at how they ask for prescriptions (Bansal et al., 2024).

4.6 Pharmacovigilance

Adverse Drug Reaction (ADR) Monitoring: Thanks to AI watching reports from patients and data from clinics, it's easier to notice any bad reactions early on (Martin et al., 2022).

Data Mining: By digging through lots of health records and other info with AI, patterns about drug safety can be found (Hauben, 2023).

4.7 Education and Training

Simulation Training: Virtual reality and other tech help pharmacy students practice in a cool way (Dai & Ke, 2022).

Continuous Learning: Using special programs with AI helps pharmacists keep up with what's new in medicines (Billiot, 2023).

4.8 AI Applications in Developed Countries

In Europe region

United Kingdom uses “Pharma-Cure” is an AI platform that helps pharmacist manage prescriptions and patient data. The system ensures accurate dispensing as well as giving clinical decision support (Raza et al., 2022). Also, “Babylon Health” is an AI-based healthcare service comprising a virtual assistant responsible for prescription management and consultations. It Includes medical consultations via telephone, teleconferencing diagnoses and managing prescription drugs (Ćirković, 2020).

Germany has “Ada Health” which is a health platform that is AI-powered in helping users manage medications as well as understand symptoms of their health. Provide personalized recommendations and healthcare assessments (Miller et al., 2020). Also, “Merck’s AI Initiatives” Uses Artificial intelligence in drug discovery, particularly in identifying new drug targets and optimizing clinical trials. These technologies reduce R&D time and improve the efficiency and safety of medicines (Blanco-González et al., 2023).

In France, “Thera-pixel” is using AI in medical imaging and diagnostics which helps identify treatment plans. Supports precision medicine (which is more targeted) thus giving rooms to personalize the treatments. Also, “Doctolib” is a digital health platform that employs artificial intelligence to manage medical appointments, consultations or even whether one has taken his/her medications. This includes integration with pharmacy services that allows better healthcare delivery (Pinar et al., 2021).

Italy has “Paginemediche” which is a telehealth platform powered by artificial intelligence offering virtual visits and drug adherence checks. Provides customized wellness recommendations while helping individuals manage chronic conditions (Lo Presti et al., 2022).

Spain’s “Savana” is a system that uses electronic health records (EHRs) analysis by applying artificial intelligence, which shows how effective a particular medicine or treatment can be. It’s a clinical decision support tools help physicians and other care providers, while this system also supports research initiatives (Hernandez Medrano et al., 2018).

In Netherlands, “Pharm-Access” is an AI-driven platform aimed at improving medication management and patient care in pharmacies it optimizes pharmacy operations while also improving data privacy measures within the organization for enhanced safety reasons (Asiki et al., 2023).

In North America

United States “IBM Watson for Drug Discovery”, it uses AI to analyze scientific literature and clinical trial data to locate potential new drug targets. This helps in recycling existing drugs as well as speeding up the process of discovering the drugs (Y. Chen et al., 2016). Also, “Pillo Health” it’s an AI-powered home health robot that can dispense medication and remind patients when they need to adhere to their medication schedule. The device records how well a person takes his or her pills and it provides help in voice-activated mode (G. Yang et al., 2020).

In Canada, “Clinical Decision Support Systems (CDSS)” Here, hospitals and pharmacies use AI systems to provide alerts on drug interactions thus personalizing medication plans. In summary, patients will be safe because few errors will occur during treatment since it will involve medication plan optimization too (Sutton et al., 2020). Again, “Tele Health” AI used here manages patients’ health records while providing them with insights on how adherence can be improved in taking prescribed medicines. Supports remote patient monitoring, virtual visits for doctors (Haleem et al., 2021).

In Pacific: Australia has “Fred IT Group” develop AI-based solutions for electronic medication management systems and prescription dispensing mechanisms. Helps pharmacies work better by enhancing workflow efficiency and reducing medication errors (Henry, 1975). Also, “HealthEngine” use Artificial Intelligence (AI) for telehealth provision on top of managing patient appointments and prescriptions. It makes healthcare accessible to more people, supports adherence to treatment regime (Jencks & Green, 1978).

In Asia

Japan's "Fujitsu's AI Pharmacy Solutions" applies machine learning to streamline pharmacy operations while improving patient care. Includes inventory management, prescription processing, and patient consultation support (Takase et al., 2022). Also, "LINE Healthcare" it is a collaboration between LINE and M3 that employs artificial intelligence to provide healthcare services like medication management as well as virtual consultations. It connects easily with common messaging platforms for accessing health services (Taylor et al., 2014).

South Korea's, "Myongji Hospital's Artificial Intelligence Project" Here, AI allows the hospital to handle patient information and optimize medication use. The AI utilization incorporates clinical decision support and predictive modelling to determine patient outcomes (D. Y. Lee et al., 2022). Also, "Medi-Bloc" is a health data platform integrating AI technology, that brings together patients' history of medication as well as their records on clinical trials. It enhances personalized medicine and offers an opportunity for remote management of patients at home (Mistry et al., 2021).

In summary, Because of AI technology in developed countries, work is improving. Medicines are managed better, patients get top-notch care, and operations run smoother all while making sure everyone stays safe. As time passes, using more advanced technology promises even more success for pharmacists and the peoples they help stay healthy in professional places like these.

Chapter 5

Application of AI in pharmacy practice in Bangladesh

While AI applications in pharmacy practice in Bangladesh are still emerging, there have been some notable initiatives and tools that are beginning to make an impact. Here are some examples:

5.1 Automated Prescription Management

Arogga is a digital pharmacy platform that leverages AI to streamline prescription management and medication delivery. Here, Patients are able import prescriptions while the system verifies the same, processes orders and ensures timely and accurate deliveries (Tabeck & Jain, 2022).

5.2 Telemedicine and Virtual Health Services

Praava Health is a healthcare service provider that uses AI-powered tools to offer telemedicine and virtual health services. Provide preliminary consultations through AI chatbots, appointment scheduling, electronic health record management (Marchand, n.d.).

Doctorola is a telehealth platform that provides virtual consultations with doctors and pharmacists. The use of artificial intelligence helps manage patients' data, provide personalized health recommendations, as well as facilitate better consultation process streamlining (Akhter & Anwar, n.d.).

5.3 Health Information Management

mPower uses AI in various mHealth initiatives to manage and analyze health information. Data analytics platforms driven by AI track disease patterns, effectively managing public health data too (J. Li & Chang, 2021).

5.4 AI in Drug Discovery and Research

Collaborative Projects: AI is frequently employed in drug discovery research collaborations between Bangladeshi universities and international institutions. By utilizing artificial intelligence to analyze extensive datasets and detect potential novel pharmaceuticals or therapeutic approaches (Chakraborty et al., 2023).

5.5 Patient Monitoring and Compliance

Digital Health Apps: Numerous digital health applications in Bangladesh employ artificial intelligence to track patients' adherence to prescription regimens. For example, send reminders, monitor drug adherence, and notify both patients and healthcare professionals of any deviations (Babel et al., 2021).

5.6 Operational Efficiency in Pharmacies

Inventory Management Systems (Automated Systems): Several pharmacies have begun deploying inventory management systems that utilize artificial intelligence. Features like, Predicting inventory needs, optimizing stock levels, and reducing waste by analyzing sales patterns and usage data (Atieh et al., 2016). **5.7 AI in Healthcare Education** eLearning Platforms: Platforms provide ongoing education and training for chemists and other healthcare professionals. Provides personalized learning experiences and up-to-date information on new drugs and treatment protocols (Gruson et al., 2013).

5.8 Pharmacovigilance

Adverse Drug Reaction Monitoring (Pharmacovigilance Tools): Artificial intelligence tools have been created to oversee and examine adverse medication responses that are reported by patients and healthcare practitioners by detecting and analyzing patterns and potential safety issues associated with drugs (Lengsavath et al., 2017).

5.9 Challenges and Future Prospects

Despite these advancements, there are still challenges to the widespread adoption of AI in pharmacy practice in Bangladesh:

Data Quality and Availability: Ensuring access to high-quality health data is crucial for effective AI applications (Parycek et al., 2023).

Infrastructure: Developing the necessary technological infrastructure to support AI initiatives requires investment (M. Sharma et al., 2022).

Regulatory Framework: Establishing a robust regulatory framework to oversee AI applications in healthcare is essential (Cath, 2018).

Training and Expertise: Building expertise in AI and training healthcare professionals to effectively use these tools is important (Dwivedi et al., 2023).

The use of AI in pharmacy practice in Bangladesh is in its nascent stages but shows significant promise. As technology and infrastructure continue to develop, and with ongoing investment and collaboration, AI has the potential to greatly enhance pharmacy practice and overall healthcare delivery in the country.

Chapter 6

Limitations of AI Tools

Although AI-based models offer advantages, they come with limitations including the requirement for extensive datasets, possible biases, and a lack of interpretability. As a result, it is important to combine AI-based models with traditional experimental approaches to guarantee the safety and effectiveness of drugs.

Lack of Transparency: AI algorithms utilize intricate processes and are often known as "black boxes" due to the difficulty in comprehending how the model reaches its predictions. This lack of transparency can make it challenging to gain regulatory approval for AI-driven pharmaceutical development tools, as demonstrating the model's accuracy and reliability can be difficult. Moreover, the lack of transparency may also result in lack of trust towards the model's predictions, especially if they contradict the expectations of clinicians or researchers (Kelly et al., 2019; Kiseleva et al., 2022).

Biases in Data: The effectiveness and accuracy of AI models depend heavily on the quality of their training data. Biased or incomplete data can lead to biased predictions. In pharmacology, the lack of diversity in clinical trial populations is a major issue. If certain demographics or disease states are underrepresented in the training data, the model's predictions may be unreliable for those groups. Inaccurate or incomplete data can also result in incorrect predictions. Ensuring that AI models are trained on trustworthy, comprehensive, an impartial data that accurately reflects the intended population is crucial for reliable clinical decision-making (Norori et al., 2021).

Limited Ability to Account for Variability: AI models trained on extensive datasets may contain biases toward typical responses, making it difficult to accurately predict reactions for individuals with atypical responses. This is particularly concerning for drugs with highly variable patient responses, such as cancer treatments (V. Chavda, Anand, et al., 2023).

Interpretation of Results: The complexity of AI models can make their outputs difficult to interpret, even for experts. This poses a challenge for clinicians and researchers trying to understand and apply the results in clinical settings or drug development. Additionally, the lack of technical expertise among some clinicians and researchers can limit the usefulness of these models. Therefore, improving the interpretability and explainability of AI models is crucial to ensure their predictions can be effectively understood and utilized (Ahmed et al., 2020; K. B. Johnson et al., 2021).

Ethical Considerations: AI implementation in drug development raises ethical issues related to patient privacy and data ownership. Protecting sensitive health information and ensuring consent for data use is crucial. Regulatory bodies are creating protocols to responsibly incorporate AI, addressing ethical concerns like animal welfare and patient safety. The FDA's discussion paper provides recommendations for AI use in drug discovery and clinical research, emphasizing validation and ethical standards. This effort aims to balance AI's potential benefits with the ethical complexities in drug development, marking a significant milestone in healthcare regulation (Norori et al., 2021).

Complex Biological Systems: AI models face limitations in replicating the complexity of biological systems, which involve intricate pathways, feedback loops, and molecular interactions. These models often simplify biological processes and rely on training data that may not capture the full complexity of these systems. Variability due to genetic differences, environmental factors, and individual differences may not be fully represented in AI models (Uddin et al., 2019). Predicting system-level behaviors is challenging due to the emergent properties of biological systems, and the integration of detailed biological knowledge is limited by incomplete understanding of specific processes and mechanisms (Quazi, 2022).

Lack of Clinical Expertise: The identification of correlations is possible with AI, but it's important to understand that despite these correlations, individual patient treatments can differ. AI algorithms generally rely on a statistical framework, which may restrict their understanding of intricate factors and the significant impact of specific parameters. The complexity of treatment decisions being influenced by individualized factors poses a challenge for AI models that primarily focus on statistical associations (Davenport & Kalakota, 2019). As a result, the capability of AI to comprehensively grasp the crucial aspects and implications of specific parameters may be constrained.

Inactive Molecules: In drug development, AI uses computational algorithms to predict how small molecules bind to target proteins, but faces challenges like representing molecular flexibility, avoiding false positives/negatives, and accounting for solvation effects and receptor flexibility. Experimental validation of compound activity is crucial to confirm predictions. Efforts are underway to improve docking algorithms, scoring functions, and molecular dynamics integration. AI tools hold significant potential and are advancing with better data availability, deep learning, and computational power. Implementing FAIR principles can enhance model accuracy by addressing data issues (Lexa & Carlson, 2012).

Despite AI's promise in PKPD studies, it cannot fully replace human involvement. AI aids in data analysis and pattern recognition, but effective PKPD studies require collaboration between AI and human experts. AI should be used with caution, balancing its potential benefits with rigorous evaluation and validation.

Chapter 8

Conclusion

The pharmacy world is changing with the help of artificial intelligence (AI). It's a game-changer for healthcare. AI can improve accuracy, efficiency, and patient results. Using AI in pharmacy covers lots of areas such as medicine, decision support, patient tracking, disease control, efficiency, drug safety, and teaching. With smart algorithms and machine learning, AI can do routine jobs, predict patient needs, manage stocks better, and tailor treatments. That means pharmacy services get sharper & faster while letting pharmacists focus on patients.AI also sifting through loads of data in real-time to find drug interactions and predicting adverse drug reactions. Also, it provides timely interventions for chronic diseases. Tele-pharmacy and AI apps give more people access to pharmacy services, particularly in remote and underserved areas, ensuring that all patients receive timely and appropriate care.

Despite these promising developments, the implementation of AI in pharmacy practice comes with challenges, including the need for substantial investment in infrastructure, data privacy concerns, and the necessity for robust training programs for healthcare professionals. A supportive regulatory framework is also essential to address ethical considerations and ensure the safe and effective use of AI technologies in healthcare.

As things keep changing, collaboration will be the key. Healthcare providers, technologists, regulators, and policymakers they all have to overcoming these challenges and fully realizing the benefits of AI's power in pharmacy practice. Welcoming AI won't just tweak how pharmacies work; it'll flip healthcare itself into a data-smart system led by what's best for patients.

Chapter 9

References

Ahmed, Z., Mohamed, K., Zeeshan, S., & Dong, X. (2020). Artificial intelligence with multifunctional machine learning platform development for better healthcare and precision medicine. *Database*, *2020*, baaa010. https://doi.org/10.1093/database/baaa010

Akhter, R., & Anwar, S. (n.d.). *A revolutionary change in health care: Doctorola Limited a view into Quiet Health Tech Revolution*.

Albayrak Ünal, Ö., Erkayman, B., & Usanmaz, B. (2023). Applications of Artificial Intelligence in Inventory Management: A Systematic Review of the Literature. *Archives of Computational Methods in Engineering*. https://doi.org/10.1007/s11831-022-09879-5

Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., Aldairem, A., Alrashed, M., Bin Saleh, K., Badreldin, H. A., Al Yami, M. S., Al Harbi, S., & Albekairy, A. M. (2023). Revolutionizing healthcare: The role of artificial intelligence in clinical practice. *BMC Medical Education*, *23*(1), 689. https://doi.org/10.1186/s12909023-04698-z

Alsmadi, M. M., & Idkaidek, N. (2023). The Analysis of Pethidine Pharmacokinetics in Newborn Saliva, Plasma, and Brain Extracellular Fluid After Prenatal Intrauterine Exposure from Pregnant Mothers Receiving Intramuscular Dose Using PBPK Modeling. *European Journal of Drug Metabolism and Pharmacokinetics*, *48*(3), 281–300. https://doi.org/10.1007/s13318-023-00823-x

Alsultan, A., Alghamdi, W. A., Alghamdi, J., Alharbi, A. F., Aljutayli, A., Albassam, A., Almazroo, O., & Alqahtani, S. (2020). Clinical pharmacology applications in clinical drug development and clinical care: A focus on Saudi Arabia. *Saudi Pharmaceutical Journal*, *28*(10), 1217–1227. https://doi.org/10.1016/j.jsps.2020.08.012

Arefin, S. (2024). Chronic Disease Management through an AI-Powered Application. *Journal of Service Science and Management*, *17*(04), 305–320. https://doi.org/10.4236/jssm.2024.174015

Arimura, H., Soufi, M., Kamezawa, H., Ninomiya, K., & Yamada, M. (2019). Radiomics with artificial intelligence for precision medicine in radiation therapy. *Journal of Radiation Research*, *60*(1), 150–157. https://doi.org/10.1093/jrr/rry077

Arlova, A., Jin, C., Wong-Rolle, A., Chen, E. S., Lisle, C., Brown, G. T., Lay, N., Choyke, P. L., Turkbey, B., Harmon, S., & Zhao, C. (2022). Artificial Intelligence-based Tumor Segmentation in Mouse Models of Lung Adenocarcinoma. *Journal of Pathology Informatics*, *13*, 100007. https://doi.org/10.1016/j.jpi.2022.100007

Asiki, G., Otieno, P., Wilunda, C., Karugu, C., Kloet, B., Teerling, J., Siteyi, A., Hendriks, M., Kyobutungi, C., & Andel, J. (2023). *Effectiveness of mobile phone text messages sent as reminders for self-monitoring of blood pressures and blood glucose at home among low income patients in Kenya: An open label randomized controlled trial*. https://doi.org/10.21203/rs.3.rs-3619421/v1

Atieh, A. M., Kaylani, H., Al-abdallat, Y., Qaderi, A., Ghoul, L., Jaradat, L., & Hdairis, I. (2016). Performance Improvement of Inventory Management System Processes by an Automated Warehouse Management System. *Procedia CIRP*, *41*, 568–572. https://doi.org/10.1016/j.procir.2015.12.122

Avdeef, A., Artursson, P., Neuhoff, S., Lazorova, L., Gråsjö, J., & Tavelin, S. (2005). Caco-2 permeability of weakly basic drugs predicted with the Double-Sink PAMPA method. *European Journal of Pharmaceutical Sciences*, *24*(4), 333–349. https://doi.org/10.1016/j.ejps.2004.11.011

Babel, A., Taneja, R., Mondello Malvestiti, F., Monaco, A., & Donde, S. (2021). Artificial Intelligence Solutions to Increase Medication Adherence in Patients With Noncommunicable Diseases. *Frontiers in Digital Health*, *3*, 669869. https://doi.org/10.3389/fdgth.2021.669869

Bang, C. S., Lee, J. J., & Baik, G. H. (2020). Artificial Intelligence for the Prediction of Helicobacter Pylori Infection in Endoscopic Images: Systematic Review and MetaAnalysis Of Diagnostic Test Accuracy. *Journal of Medical Internet Research*, *22*(9), e21983. https://doi.org/10.2196/21983

Bansal, U., Bharatwal, S., Bagiyam, D. S., & Kismawadi, E. R. (2024). Fraud Detection in the Era of AI: Harnessing Technology for a Safer Digital Economy. In M. Irfan, M. Elmogy, S. Gupta, F. Khalifa, & R. T. Dias (Eds.), *Advances in Finance, Accounting, and Economics* (pp. 143–164). IGI Global. https://doi.org/10.4018/979-8-3693-6321-8.ch006

Basile, A. O., Yahi, A., & Tatonetti, N. P. (2019). Artificial Intelligence for Drug Toxicity and Safety. *Trends in Pharmacological Sciences*, *40*(9), 624–635. https://doi.org/10.1016/j.tips.2019.07.005

Bhattamisra, S. K., Banerjee, P., Gupta, P., Mayuren, J., Patra, S., & Candasamy, M. (2023). Artificial Intelligence in Pharmaceutical and Healthcare Research. *Big Data and Cognitive Computing*, *7*(1), 10. https://doi.org/10.3390/bdcc7010010

Billiot, T. (2023). Continuous learning and advancing technologies: A framework for professional development and training in artificial intelligence. *Development and Learning in Organizations: An International Journal*, *37*(3), 28–31. https://doi.org/10.1108/DLO-042022-0064

Blanco-González, A., Cabezón, A., Seco-González, A., Conde-Torres, D., Antelo-Riveiro, P., Piñeiro, Á., & Garcia-Fandino, R. (2023). The Role of AI in Drug Discovery: Challenges, Opportunities, and Strategies. *Pharmaceuticals*, *16*(6), 891. https://doi.org/10.3390/ph16060891

Blasiak, A., Truong, A., Tan, W. J., Lester, Kumar, K. S., Tan, S. B., Teo, C. B., Tan, B. K. J., Tadeo, X., Tan, H. L., Chee, C. E., Yong, W.-P., Ho, D., & Sundar, R. (2022). PRECISE CURATE.AI: A prospective feasibility trial to dynamically modulate personalized chemotherapy dose with artificial intelligence. *Journal of Clinical Oncology*, *40*(16_suppl), 1574–1574. https://doi.org/10.1200/JCO.2022.40.16_suppl.1574

Brown, M. T., & Bussell, J. K. (2011). Medication Adherence: WHO Cares? *Mayo Clinic Proceedings*, *86*(4), 304–314. https://doi.org/10.4065/mcp.2010.0575

Bu, F., Sun, H., Li, L., Tang, F., Zhang, X., Yan, J., Ye, Z., & Huang, T. (2022). Artificial intelligence-based internet hospital pharmacy services in China: Perspective based on a case study. *Frontiers in Pharmacology*, *13*, 1027808. https://doi.org/10.3389/fphar.2022.1027808

Carreras, J., & Hamoudi, R. (2021). Artificial Neural Network Analysis of Gene Expression Data Predicted Non-Hodgkin Lymphoma Subtypes with High Accuracy. *Machine Learning and Knowledge Extraction*, *3*(3), 720–739. https://doi.org/10.3390/make3030036

Carreras, J., Nakamura, N., & Hamoudi, R. (2022). Artificial Intelligence Analysis of Gene Expression Predicted the Overall Survival of Mantle Cell Lymphoma and a Large Pan-Cancer Series. *Healthcare*, *10*(1), 155. https://doi.org/10.3390/healthcare10010155

Cath, C. (2018). Governing artificial intelligence: Ethical, legal and technical opportunities and challenges. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *376*(2133), 20180080. https://doi.org/10.1098/rsta.2018.0080

Chakraborty, S., Chopra, H., Akash, S., Chakraborty, C., & Dhama, K. (2023). Artificial intelligence (AI) is paving the way for a critical role in drug discovery, drug design, and studying drug–drug interactions – correspondence. *International Journal of Surgery*, *109*(10), 3242–3244. https://doi.org/10.1097/JS9.0000000000000564

Chalasani, S. H., Syed, J., Ramesh, M., Patil, V., & Pramod Kumar, T. M. (2023). Artificial intelligence in the field of pharmacy practice: A literature review. *Exploratory Research in Clinical and Social Pharmacy*, *12*, 100346. https://doi.org/10.1016/j.rcsop.2023.100346

Chan, H. C. S., Shan, H., Dahoun, T., Vogel, H., & Yuan, S. (2019). Advancing Drug Discovery via Artificial Intelligence. *Trends in Pharmacological Sciences*, *40*(8), 592–604. https://doi.org/10.1016/j.tips.2019.06.004

Chan, H.-P., Samala, R. K., & Hadjiiski, L. M. (2019). CAD and AI for breast cancer—Recent development and challenges. *The British Journal of Radiology*, *93*(1108), 20190580. https://doi.org/10.1259/bjr.20190580

Chapuis, C., Roustit, M., Bal, G., Schwebel, C., Pansu, P., David-Tchouda, S., Foroni, L., Calop, J., Timsit, J.-F., Allenet, B., Bosson, J.-L., & Bedouch, P. (2010). Automated drug dispensing system reduces medication errors in an intensive care setting: *Critical Care Medicine*, *38*(12), 2275–2281. https://doi.org/10.1097/CCM.0b013e3181f8569b

Chavda, V., Anand, K., & Apostolopoulos, V. (Eds.). (2023). *Bioinformatics tools for pharmaceutical drug product development*. Wiley ; Scrivener Publishing.

Chavda, V. P. (2019). Nanotherapeutics and Nanobiotechnology. In *Applications of Targeted Nano Drugs and Delivery Systems* (pp. 1–13). Elsevier. https://doi.org/10.1016/B978-0-12814029-1.00001-6

Chavda, V. P., Ertas, Y. N., Walhekar, V., Modh, D., Doshi, A., Shah, N., Anand, K., & Chhabria, M. (2021). Advanced Computational Methodologies Used in the Discovery of New Natural Anticancer Compounds. *Frontiers in Pharmacology*, *12*, 702611. https://doi.org/10.3389/fphar.2021.702611

Chavda, V. P., Sorathiya, A., Valu, D., & Marwadi, S. (2021). Role of Data Mining in Bioinformatics. In S. Balamurugan, A. Krishnan, D. Goyal, B. Chandrasekaran, & B. Pandi (Eds.), *Computation in Bioinformatics* (1st ed., pp. 69–84). Wiley. https://doi.org/10.1002/9781119654803.ch4

Chavda, V. P., Vihol, D., Patel, A., Redwan, E. M., & Uversky, V. N. (2023). Introduction to Bioinformatics, AI, and ML for Pharmaceuticals. In V. Chavda, K. Anand, & V. Apostolopoulos (Eds.), *Bioinformatics Tools for Pharmaceutical Drug Product Development* (1st ed., pp. 1–18). Wiley. https://doi.org/10.1002/9781119865728.ch1

Chavda, V., Valu, D., Parikh, P., Tiwari, N., Chhipa, A., Shukla, S., Patel, S., Balar, P., PaivaSantos, A., & Patravale, V. (2023). Conventional and Novel Diagnostic Tools for the Diagnosis of Emerging SARS-CoV-2 Variants. *Vaccines*, *11*(2), 374. https://doi.org/10.3390/vaccines11020374

Chen, S. (2022). Models of Artificial Intelligence-Assisted Diagnosis of Lung Cancer Pathology Based on Deep Learning Algorithms. *Journal of Healthcare Engineering*, *2022*, 1–12. https://doi.org/10.1155/2022/3972298

Chen, W., Liu, X., Zhang, S., & Chen, S. (2023). Artificial intelligence for drug discovery: Resources, methods, and applications. *Molecular Therapy - Nucleic Acids*, *31*, 691–702. https://doi.org/10.1016/j.omtn.2023.02.019

Chen, Y., Elenee Argentinis, J., & Weber, G. (2016). IBM Watson: How Cognitive Computing Can Be Applied to Big Data Challenges in Life Sciences Research. *Clinical Therapeutics*, *38*(4), 688–701. https://doi.org/10.1016/j.clinthera.2015.12.001

Chintawar, S., Gattani, V., Vyas, S., & Dawre, S. (2023). Role of Artificial Intelligence in Machine Learning for Diagnosis and Radiotherapy. In V. Chavda, K. Anand, & V. Apostolopoulos (Eds.), *Bioinformatics Tools for Pharmaceutical Drug Product Development* (1st ed., pp. 315–344). Wiley. https://doi.org/10.1002/9781119865728.ch14

Chou, W.-C., & Lin, Z. (2023). Machine learning and artificial intelligence in physiologically based pharmacokinetic modeling. *Toxicological Sciences*, *191*(1), 1–14. https://doi.org/10.1093/toxsci/kfac101

Ćirković, A. (2020). Evaluation of Four Artificial Intelligence–Assisted Self-Diagnosis Apps on Three Diagnoses: Two-Year Follow-Up Study. *Journal of Medical Internet Research*, *22*(12), e18097. https://doi.org/10.2196/18097

Colombo, S., Beck-Broichsitter, M., Bøtker, J. P., Malmsten, M., Rantanen, J., & Bohr, A. (2018). Transforming nanomedicine manufacturing toward Quality by Design and microfluidics. *Advanced Drug Delivery Reviews*, *128*, 115–131. https://doi.org/10.1016/j.addr.2018.04.004

Cui, P., & Wang, S. (2019). Application of microfluidic chip technology in pharmaceutical analysis: A review. *Journal of Pharmaceutical Analysis*, *9*(4), 238–247. https://doi.org/10.1016/j.jpha.2018.12.001

Dai, C.-P., & Ke, F. (2022). Educational applications of artificial intelligence in simulation-based learning: A systematic mapping review. *Computers and Education: Artificial Intelligence*, *3*, 100087. https://doi.org/10.1016/j.caeai.2022.100087

Daka, A., & Peer, D. (2012). RNAi-based nanomedicines for targeted personalized therapy. *Advanced Drug Delivery Reviews*, *64*(13), 1508–1521. https://doi.org/10.1016/j.addr.2012.08.014

Daoui, O., Elkhattabi, S., Chtita, S., Elkhalabi, R., Zgou, H., & Benjelloun, A. T. (2021). QSAR, molecular docking and ADMET properties in silico studies of novel 4,5,6,7tetrahydrobenzo[D]-thiazol-2-Yl derivatives derived from dimedone as potent anti-tumor agents through inhibition of C-Met receptor tyrosine kinase. *Heliyon*, *7*(7), e07463. https://doi.org/10.1016/j.heliyon.2021.e07463

Das, P. J., Preuss, C., & Mazumder, B. (2016). Artificial Neural Network as Helping Tool for Drug Formulation and Drug Administration Strategies. In *Artificial Neural Network for Drug Design, Delivery and Disposition* (pp. 263–276). Elsevier. https://doi.org/10.1016/B9780-12-801559-9.00013-2

Dasta, J. F. (1992). Application of artificial intelligence to pharmacy and medicine. *Hospital Pharmacy*, *27*(4), 312–315, 319–322.

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal*, *6*(2), 94–98. https://doi.org/10.7861/futurehosp.6-2-94

Davoudi, A., Malhotra, K. R., Shickel, B., Siegel, S., Williams, S., Ruppert, M., Bihorac, E., Ozrazgat-Baslanti, T., Tighe, P. J., Bihorac, A., & Rashidi, P. (2018). *The Intelligent ICU Pilot Study: Using Artificial Intelligence Technology for Autonomous Patient Monitoring* (Version 2). arXiv. https://doi.org/10.48550/ARXIV.1804.10201

Dickherber, A., Morris, S. A., & Grodzinski, P. (2015). NCI investment in nanotechnology: Achievements and challenges for the future. *WIREs Nanomedicine and Nanobiotechnology*, *7*(3), 251–265. https://doi.org/10.1002/wnan.1318

Dong, J., Gao, H., & Ouyang, D. (2021). PharmSD: A novel AI-based computational platform for solid dispersion formulation design. *International Journal of Pharmaceutics*, *604*, 120705. https://doi.org/10.1016/j.ijpharm.2021.120705

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Edrees, H., Song, W., Syrowatka, A., Simona, A., Amato, M. G., & Bates, D. W. (2022). Intelligent Telehealth in Pharmacovigilance: A Future Perspective. *Drug Safety*, *45*(5), 449–458. https://doi.org/10.1007/s40264-022-01172-5

Ellahham, S. (2020). Artificial Intelligence: The Future for Diabetes Care. *The American Journal of Medicine*, *133*(8), 895–900. https://doi.org/10.1016/j.amjmed.2020.03.033

Esch, E. W., Bahinski, A., & Huh, D. (2015). Organs-on-chips at the frontiers of drug discovery. *Nature Reviews Drug Discovery*, *14*(4), 248–260. https://doi.org/10.1038/nrd4539

Espinoza, J. L., & Dong, L. T. (2020). Artificial Intelligence Tools for Refining Lung Cancer Screening. *Journal of Clinical Medicine*, *9*(12), 3860. https://doi.org/10.3390/jcm9123860

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, *542*(7639), 115–118. https://doi.org/10.1038/nature21056

Fogel, D. B. (2000). What is evolutionary computation? *IEEE Spectrum*, *37*(2), 26–32. https://doi.org/10.1109/6.819926

Galata, D. L., Könyves, Z., Nagy, B., Novák, M., Mészáros, L. A., Szabó, E., Farkas, A., Marosi, G., & Nagy, Z. K. (2021). Real-time release testing of dissolution based on surrogate models developed by machine learning algorithms using NIR spectra, compression force and particle size distribution as input data. *International Journal of Pharmaceutics*, *597*, 120338. https://doi.org/10.1016/j.ijpharm.2021.120338

Gao, H., Su, Y., Wang, W., Xiong, W., Sun, X., Ji, Y., Yu, H., Li, H., & Ouyang, D. (2021). Integrated computer-aided formulation design: A case study of andrographolide/ cyclodextrin ternary formulation. *Asian Journal of Pharmaceutical Sciences*, *16*(4), 494–507. https://doi.org/10.1016/j.ajps.2021.03.006

Georges Badr, N., & Khiami, M. (2024). Improving access to prescription-based care through patient-centered smart pharmacy ecosystems. *ITM Web of Conferences*, *62*, 02003. https://doi.org/10.1051/itmconf/20246202003

Graafsma, J., Murphy, R. M., Van De Garde, E. M. W., Karapinar-Çarkit, F., Derijks, H. J., Hoge, R. H. L., Klopotowska, J. E., & Van Den Bemt, P. M. L. A. (2024). The use of artificial intelligence to optimize medication alerts generated by clinical decision support systems: A scoping review. *Journal of the American Medical Informatics Association*, *31*(6), 1411–1422. https://doi.org/10.1093/jamia/ocae076

Graham, S., Depp, C., Lee, E. E., Nebeker, C., Tu, X., Kim, H.-C., & Jeste, D. V. (2019). Artificial Intelligence for Mental Health and Mental Illnesses: An Overview. *Current Psychiatry Reports*, *21*(11), 116. https://doi.org/10.1007/s11920-019-1094-0

Gruson, D., Faure, G., Gouget, B., Haliassos, A., Kisikuchin, D., Reguengo, H., Topic, E., & Blaton, V. (2013). A position paper of the EFLM Committee on Education and Training and Working Group on Distance Education Programmes/E-Learning: Developing an elearning platform for the education of stakeholders in laboratory medicine. *Clinical Chemistry and Laboratory Medicine (CCLM)*, *51*(4), 775–780. https://doi.org/10.1515/cclm-2013-0095

Haag, M., Maylein, L., Leven, F., Tonshoff, B., & Haux, R. (1999). Web-based training: A new paradigm in computer-assisted instruction in medicine. *International Journal of Medical Informatics*, *53*(1), 79–90. https://doi.org/10.1016/S1386-5056(98)00118-X

Haleem, A., Javaid, M., Singh, R. P., & Suman, R. (2021). Telemedicine for healthcare: Capabilities, features, barriers, and applications. *Sensors International*, *2*, 100117. https://doi.org/10.1016/j.sintl.2021.100117

Han, R., Yang, Y., Li, X., & Ouyang, D. (2018). Predicting oral disintegrating tablet formulations by neural network techniques. *Asian Journal of Pharmaceutical Sciences*, *13*(4), 336–342. https://doi.org/10.1016/j.ajps.2018.01.003

Hassanzadeh, P., Atyabi, F., & Dinarvand, R. (2019). The significance of artificial intelligence in drug delivery system design. *Advanced Drug Delivery Reviews*, *151–152*, 169–190. https://doi.org/10.1016/j.addr.2019.05.001

Hauben, M. (2023). Artificial Intelligence and Data Mining for the Pharmacovigilance of Drug–Drug Interactions. *Clinical Therapeutics*, *45*(2), 117–133. https://doi.org/10.1016/j.clinthera.2023.01.002

Henry, E. W. (1975). Peroxidases in tobacco abscission zone tissue. III. Ultrastructural localization in thylakoids and membrane-bound bodies of chloroplasts. *Journal of Ultrastructure Research*, *52*(3), 289–299. https://doi.org/10.1016/s0022-5320(75)80069-4

Hernandez Medrano, I., Tello Guijarro, J., Belda, C., Urena, A., Salcedo, I., Espinosa-Anke, L., & Saggion, H. (2018). Savana: Re-using Electronic Health Records with Artificial Intelligence. *International Journal of Interactive Multimedia and Artificial Intelligence*, *4*(7), 8. https://doi.org/10.9781/ijimai.2017.03.001

Holmes, J. H. (Ed.). (2015). *Artificial intelligence in medicine: 15th Conference on Artificial Intelligence in Medicine, AIME 2015, Pavia, Italy, June 17-20, 2015 ; proceedings*. AIME, Cham. Springer.

Houy, N., & Le Grand, F. (2018). Optimal dynamic regimens with artificial intelligence: The case of temozolomide. *PLOS ONE*, *13*(6), e0199076. https://doi.org/10.1371/journal.pone.0199076

Jeddi, Z., & Bohr, A. (2020). Remote patient monitoring using artificial intelligence. In *Artificial*

Intelligence in Healthcare (pp. 203–234). Elsevier. https://doi.org/10.1016/B978-0-12818438-7.00009-5

Jencks, S. F., & Green, L. W. (1978). Establishing a hospital-based patient education program. *QRB. Quality Review Bulletin*, *4*(10), 8–11.

Johnson, K. B., Wei, W., Weeraratne, D., Frisse, M. E., Misulis, K., Rhee, K., Zhao, J., & Snowdon, J. L. (2021). Precision Medicine, AI, and the Future of Personalized Health Care. *Clinical and Translational Science*, *14*(1), 86–93. https://doi.org/10.1111/cts.12884

Johnson, M., Patel, M., Phipps, A., van der Schaar, M., Boulton, D., & Gibbs, M. (2023). The potential and pitfalls of artificial intelligence in clinical pharmacology. *CPT: Pharmacometrics & Systems Pharmacology*, *12*(3), 279–284. https://doi.org/10.1002/psp4.12902

Jones, H., & Rowland-Yeo, K. (2013). Basic Concepts in Physiologically Based Pharmacokinetic Modeling in Drug Discovery and Development. *CPT: Pharmacometrics & Systems Pharmacology*, *2*(8), 1–12. https://doi.org/10.1038/psp.2013.41

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255–260. https://doi.org/10.1126/science.aaa8415

Jungreithmayr, V., Meid, A. D., Implementation Team, Bittmann, J., Fabian, M., Klein, U., Kugler, S., Löpprich, M., Reinhard, O., Scholz, L., Zeeh, B., Bitz, W., Bugaj, T., Kihm, L., Kopf, S., Liemann, A., Wagenlechner, P., Zemva, J., Benkert, C., … Seidling, H. M. (2021). The impact of a computerized physician order entry system implementation on 20 different criteria of medication documentation—A before-and-after study. *BMC Medical Informatics and Decision Making*, *21*(1), 279. https://doi.org/10.1186/s12911-021-016076

Kalepu, S., & Nekkanti, V. (2015). Insoluble drug delivery strategies: Review of recent advances and business prospects. *Acta Pharmaceutica Sinica B*, *5*(5), 442–453. https://doi.org/10.1016/j.apsb.2015.07.003

Kalyane, D., Sanap, G., Paul, D., Shenoy, S., Anup, N., Polaka, S., Tambe, V., & Tekade, R. K. (2020). Artificial intelligence in the pharmaceutical sector: Current scene and future prospect. In *The Future of Pharmaceutical Product Development and Research* (pp. 73–107). Elsevier. https://doi.org/10.1016/B978-0-12-814455-8.00003-7

Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. *BMC Medicine*, *17*(1), 195. https://doi.org/10.1186/s12916-019-1426-2

Kessler, S., Desai, M., McConnell, W., Jai, E. M., Mebine, P., Nguyen, J., Kiroyan, C., Ho, D., Von Schweber, E., & Von Schweber, L. (2021). Economic and utilization outcomes of medication management at a large Medicaid plan with disease management pharmacists using a novel artificial intelligence platform from 2018 to 2019: A retrospective observational study using regression methods. *Journal of Managed Care & Specialty Pharmacy*, *27*(9), 1186–1196. https://doi.org/10.18553/jmcp.2021.21036

Keutzer, L., You, H., Farnoud, A., Nyberg, J., Wicha, S. G., Maher-Edwards, G., Vlasakakis, G., Moghaddam, G. K., Svensson, E. M., Menden, M. P., Simonsson, U. S. H., & on behalf of the UNITE4TB Consortium. (2022). Machine Learning and Pharmacometrics for Prediction of Pharmacokinetic Data: Differences, Similarities and Challenges Illustrated with Rifampicin. *Pharmaceutics*, *14*(8), 1530. https://doi.org/10.3390/pharmaceutics14081530

Kim, J. W., Jones, K. L., & D'Angelo, E. (2019). How to Prepare Prospective Psychiatrists in the Era of Artificial Intelligence. *Academic Psychiatry*, *43*(3), 337–339. https://doi.org/10.1007/s40596-019-01025-x

Kim, S. M., Yang, Y., Oh, S. J., Hong, Y., Seo, M., & Jang, M. (2017). Cancer-derived exosomes as a delivery platform of CRISPR/Cas9 confer cancer cell tropism-dependent targeting. *Journal of Controlled Release*, *266*, 8–16. https://doi.org/10.1016/j.jconrel.2017.09.013

Kiseleva, A., Kotzinos, D., & De Hert, P. (2022). Transparency of AI in Healthcare as a Multilayered System of Accountabilities: Between Legal Requirements and Technical Limitations. *Frontiers in Artificial Intelligence*, *5*, 879603. https://doi.org/10.3389/frai.2022.879603

Krikorian, G., & Torreele, E. (2021). We Cannot Win the Access to Medicines Struggle Using the Same Thinking That Causes the Chronic Access Crisis. *Health and Human Rights*, *23*(1), 119–127.

Lee, D. Y., Kim, C., Lee, S., Son, S. J., Cho, S.-M., Cho, Y. H., Lim, J., & Park, R. W. (2022). Psychosis Relapse Prediction Leveraging Electronic Health Records Data and Natural Language Processing Enrichment Methods. *Frontiers in Psychiatry*, *13*, 844442. https://doi.org/10.3389/fpsyt.2022.844442

Lee, H., Kim, H. J., Chang, H. W., Kim, D. J., Mo, J., & Kim, J.-E. (2021). Development of a system to support warfarin dose decisions using deep neural networks. *Scientific Reports*, *11*(1), 14745. https://doi.org/10.1038/s41598-021-94305-2

Lengsavath, M., Dal Pra, A., De Ferran, A.-M., Brosch, S., Härmark, L., Newbould, V., & Goncalves, S. (2017). Social Media Monitoring and Adverse Drug Reaction Reporting in Pharmacovigilance: An Overview of the Regulatory Landscape. *Therapeutic Innovation & Regulatory Science*, *51*(1), 125–131. https://doi.org/10.1177/2168479016663264

Lexa, K. W., & Carlson, H. A. (2012). Protein flexibility in docking and surface mapping. *Quarterly Reviews of Biophysics*, *45*(3), 301–343. https://doi.org/10.1017/S0033583512000066

Li, J., & Chang, X. (2021). Improving mobile health apps usage: A quantitative study on mPower data of Parkinson's disease. *Information Technology & People*, *34*(1), 399–420. https://doi.org/10.1108/ITP-07-2019-0366

Li, L.-R., Du, B., Liu, H.-Q., & Chen, C. (2021). Artificial Intelligence for Personalized Medicine in Thyroid Cancer: Current Status and Future Perspectives. *Frontiers in Oncology*, *10*, 604051. https://doi.org/10.3389/fonc.2020.604051

Li, Y., Meng, Q., Yang, M., Liu, D., Hou, X., Tang, L., Wang, X., Lyu, Y., Chen, X., Liu, K., Yu, A.-M., Zuo, Z., & Bi, H. (2019). Current trends in drug metabolism and pharmacokinetics. *Acta Pharmaceutica Sinica B*, *9*(6), 1113–1144. https://doi.org/10.1016/j.apsb.2019.10.001

Lo Presti, L., Testa, M., Maggiore, G., & Marino, V. (2022). Key drivers involved in the telemonitoring of covid-19 for self-health management: An exploratory factor analysis. *BMC Health Services Research*, *22*(1), 520. https://doi.org/10.1186/s12913-022-07828-3

Luxton, D. D. (2014). Artificial intelligence in psychological practice: Current and future applications and implications. *Professional Psychology: Research and Practice*, *45*(5), 332–339. https://doi.org/10.1037/a0034559

Mager, D. E., Woo, S., & Jusko, W. J. (2009). Scaling Pharmacodynamics from In Vitro and Preclinical Animal Studies to Humans. *Drug Metabolism and Pharmacokinetics*, *24*(1), 16–24. https://doi.org/10.2133/dmpk.24.16

Mak, K.-K., & Pichika, M. R. (2019). Artificial intelligence in drug development: Present status and future prospects. *Drug Discovery Today*, *24*(3), 773–780. https://doi.org/10.1016/j.drudis.2018.11.014

Mandal, L., & Jana, N. D. (2019). Prediction of Active Drug Molecule using Back-Propagation Neural Network. *2019 8th International Conference System Modeling and Advancement in Research Trends (SMART)*, 22–26. https://doi.org/10.1109/SMART46866.2019.9117378

Marchand, L. (n.d.). *Praava Health: Reinventing Healthcare in Bangladesh*.

Martin, G. L., Jouganous, J., Savidan, R., Bellec, A., Goehrs, C., Benkebil, M., Miremont, G., Micallef, J., Salvo, F., Pariente, A., Létinier, L., & the French Network of Pharmacovigilance Centres. (2022). Validation of Artificial Intelligence to Support the Automatic Coding of Patient Adverse Drug Reaction Reports, Using Nationwide Pharmacovigilance Data. *Drug Safety*, *45*(5), 535–548. https://doi.org/10.1007/s40264022-01153-8

Menden, M. P., Iorio, F., Garnett, M., McDermott, U., Benes, C. H., Ballester, P. J., & SaezRodriguez, J. (2013). Machine Learning Prediction of Cancer Cell Sensitivity to Drugs Based on Genomic and Chemical Properties. *PLoS ONE*, *8*(4), e61318. https://doi.org/10.1371/journal.pone.0061318

Mhatre, S., Shukla, S., Chavda, V. P., Gandikota, L., & Patravale, V. (2023). AI and ML for Development of Cell and Gene Therapy for Personalized Treatment. In V. Chavda, K. Anand, & V. Apostolopoulos (Eds.), *Bioinformatics Tools for Pharmaceutical Drug Product Development* (1st ed., pp. 371–400). Wiley. https://doi.org/10.1002/9781119865728.ch16

Miller, S., Gilbert, S., Virani, V., & Wicks, P. (2020). Patients' Utilization and Perception of an Artificial Intelligence-Based Symptom Assessment and Advice Technology in a British Primary Care Waiting Room: Exploratory Pilot Study. *JMIR Human Factors*, *7*(3), e19713.

https://doi.org/10.2196/19713
Mistry, C., Thakker, U., Gupta, R., Obaidat, M. S., Tanwar, S., Kumar, N., & Rodrigues, J. J. P. C. (2021). MedBlock: An AI-enabled and Blockchain-driven Medical Healthcare System for COVID-19. *ICC 2021 - IEEE International Conference on Communications*, 1–6. https://doi.org/10.1109/ICC42927.2021.9500397
Moore, K. L. (2019). Automated Radiotherapy Treatment Planning. *Seminars in Radiation Oncology*, *29*(3), 209–218. https://doi.org/10.1016/j.semradonc.2019.02.003
Mukhamediev, R. I., Popova, Y., Kuchin, Y., Zaitseva, E., Kalimoldayev, A., Symagulov, A., Levashenko, V., Abdoldina, F., Gopejenko, V., Yakunin, K., Muhamedijeva, E., & Yelis, M. (2022). Review of Artificial Intelligence and Machine Learning Technologies: Classification, Restrictions, Opportunities and Challenges. *Mathematics*, *10*(15), 2552. https://doi.org/10.3390/math10152552
Norori, N., Hu, Q., Aellen, F. M., Faraci, F. D., & Tzovara, A. (2021). Addressing bias in big data and AI for health care: A call for open science. *Patterns*, *2*(10), 100347. https://doi.org/10.1016/j.patter.2021.100347
Obrezanova, O. (2023). Artificial intelligence for compound pharmacokinetics prediction. *Current Opinion in Structural Biology*, *79*, 102546. https://doi.org/10.1016/j.sbi.2023.102546
Parikh, P. K., Savjani, J. K., Gajjar, A. K., & Chhabria, M. T. (2023). Bioinformatics and Cheminformatics Tools in Early Drug Discovery. In V. Chavda, K. Anand, & V. Apostolopoulos (Eds.), *Bioinformatics Tools for Pharmaceutical Drug Product Development* (1st ed., pp. 147–181). Wiley. https://doi.org/10.1002/9781119865728.ch8
Partin, A., Brettin, T. S., Zhu, Y., Narykov, O., Clyde, A., Overbeek, J., & Stevens, R. L. (2023). Deep learning methods for drug response prediction in cancer: Predominant and emerging trends. *Frontiers in Medicine*, *10*, 1086097. https://doi.org/10.3389/fmed.2023.1086097
Parycek, P., Schmid, V., & Novak, A.-S. (2023). Artificial Intelligence (AI) and Automation in Administrative Procedures: Potentials, Limitations, and Framework Conditions. *Journal of the Knowledge Economy*, *15*(2), 8390–8415. https://doi.org/10.1007/s13132-023-01433-3
Patel, V., & Shah, M. (2022). Artificial intelligence and machine learning in drug discovery and development. *Intelligent Medicine*, *2*(3), 134–140. https://doi.org/10.1016/j.imed.2021.10.001
Petrović, J., Ibrić, S., Betz, G., & Đurić, Z. (2012). Optimization of matrix tablets controlled drug release using Elman dynamic neural networks and decision trees. *International Journal of Pharmaceutics*, *428*(1–2), 57–67. https://doi.org/10.1016/j.ijpharm.2012.02.031
Pierre, K., Haneberg, A. G., Kwak, S., Peters, K. R., Hochhegger, B., Sananmuang, T., Tunlayadechanont, P., Tighe, P. J., Mancuso, A., & Forghani, R. (2023). Applications of Artificial Intelligence in the Radiology Roundtrip: Process Streamlining, Workflow Optimization, and Beyond. *Seminars in Roentgenology*, *58*(2), 158–169. https://doi.org/10.1053/j.ro.2023.02.003

Pinar, U., Anract, J., Perrot, O., Tabourin, T., Chartier-Kastler, E., Parra, J., Vaessen, C., De La Taille, A., & Roupret, M. (2021). Preliminary assessment of patient and physician satisfaction with the use of teleconsultation in urology during the COVID-19 pandemic. *World Journal of Urology*, *39*(6), 1991–1996. https://doi.org/10.1007/s00345-020-03432-4

Quazi, S. (2022). Artificial intelligence and machine learning in precision and genomic medicine. *Medical Oncology*, *39*(8), 120. https://doi.org/10.1007/s12032-022-01711-1

Rafienia, M., Amiri, M., Janmaleki, M., & Sadeghian, A. (2010). APPLICATION OF ARTIFICIAL NEURAL NETWORKS IN CONTROLLED DRUG DELIVERY SYSTEMS. *Applied Artificial Intelligence*, *24*(8), 807–820. https://doi.org/10.1080/08839514.2010.508606

Raza, M. A., Aziz, S., Noreen, M., Saeed, A., Anjum, I., Ahmed, M., & Raza, S. M. (2022). Artificial Intelligence (AI) in Pharmacy: An Overview of Innovations. *Innovations in Pharmacy*, *13*(2). https://doi.org/10.24926/iip.v13i2.4839

Sacha, G. M., & Varona, P. (2013). Artificial intelligence in nanotechnology. *Nanotechnology*, *24*(45), 452002. https://doi.org/10.1088/0957-4484/24/45/452002

Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Computer Science*, *2*(3), 160. https://doi.org/10.1007/s42979-021-00592-x

Sarker, I. H. (2022). AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. *SN Computer Science*, *3*(2), 158. https://doi.org/10.1007/s42979-022-01043-x

Sarpatwari, A., Barenie, R., Curfman, G., Darrow, J. J., & Kesselheim, A. S. (2019). The US Biosimilar Market: Stunted Growth and Possible Reforms. *Clinical Pharmacology & Therapeutics*, *105*(1), 92–100. https://doi.org/10.1002/cpt.1285

Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, *61*, 85–117. https://doi.org/10.1016/j.neunet.2014.09.003

Schmidt-Erfurth, U., Sadeghipour, A., Gerendas, B. S., Waldstein, S. M., & Bogunović, H. (2018). Artificial intelligence in retina. *Progress in Retinal and Eye Research*, *67*, 1–29. https://doi.org/10.1016/j.preteyeres.2018.07.004

Schork, N. J. (2019). Artificial Intelligence and Personalized Medicine. In D. D. Von Hoff & H. Han (Eds.), *Precision Medicine in Cancer Therapy* (Vol. 178, pp. 265–283). Springer International Publishing. https://doi.org/10.1007/978-3-030-16391-4_11

Selvaraj, C., Chandra, I., & Singh, S. K. (2022). Artificial intelligence and machine learning approaches for drug design: Challenges and opportunities for the pharmaceutical industries. *Molecular Diversity*, *26*(3), 1893–1913. https://doi.org/10.1007/s11030-02110326-z

Shah, H., Chavda, V., & Soniwala, M. M. (2023). Applications of Bioinformatics Tools in Medicinal Biology and Biotechnology. In V. Chavda, K. Anand, & V. Apostolopoulos

(Eds.), *Bioinformatics Tools for Pharmaceutical Drug Product Development* (1st ed., pp. 95–116). Wiley. https://doi.org/10.1002/9781119865728.ch6

Sharma, M., Luthra, S., Joshi, S., & Kumar, A. (2022). Implementing challenges of artificial intelligence: Evidence from public manufacturing sector of an emerging economy. *Government Information Quarterly*, *39*(4), 101624. https://doi.org/10.1016/j.giq.2021.101624

Sharma, R., Shishodia, A., Gunasekaran, A., Min, H., & Munim, Z. H. (2022). The role of artificial intelligence in supply chain management: Mapping the territory. *International Journal of Production Research*, *60*(24), 7527–7550. https://doi.org/10.1080/00207543.2022.2029611

Siepmann, J., & Siepmann, F. (2012). Modeling of diffusion-controlled drug delivery. *Journal of Controlled Release*, *161*(2), 351–362. https://doi.org/10.1016/j.jconrel.2011.10.006

Sjövall, F., Lanckohr, C., & Bracht, H. (2023). What's new in therapeutic drug monitoring of antimicrobials? *Intensive Care Medicine*, *49*(7), 857–859. https://doi.org/10.1007/s00134023-07060-5

Subramanian, M., Wojtusciszyn, A., Favre, L., Boughorbel, S., Shan, J., Letaief, K. B., Pitteloud, N., & Chouchane, L. (2020). Precision medicine in the era of artificial intelligence: Implications in chronic disease management. *Journal of Translational Medicine*, *18*(1), 472. https://doi.org/10.1186/s12967-020-02658-5

Suleimenov, I. E., Vitulyova, Y. S., Bakirov, A. S., & Gabrielyan, O. A. (2020). Artificial Intelligence: What is it? *Proceedings of the 2020 6th International Conference on Computer and Technology Applications*, 22–25. https://doi.org/10.1145/3397125.3397141

Sun, D. D., & Lee, P. I. (2013). Evolution of Supersaturation of Amorphous Pharmaceuticals: The Effect of Rate of Supersaturation Generation. *Molecular Pharmaceutics*, *10*(11), 4330–4346. https://doi.org/10.1021/mp400439q

Suresh, A., Udendhran, R., & Balamurgan, M. (2020). Hybridized neural network and decision tree based classifier for prognostic decision making in breast cancers. *Soft Computing*, *24*(11), 7947–7953. https://doi.org/10.1007/s00500-019-04066-4

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*(1), 17. https://doi.org/10.1038/s41746-020-0221-y

Tabeck, P. S., & Jain, V. (2022). Fighting Pandemic: The Mobile Application Way (a Case of the Aarogya Setu App). *Emerging Economies Cases Journal*, *4*(2), 95–102. https://doi.org/10.1177/25166042221147097

Takase, T., Masumoto, N., Shibatani, N., Matsuoka, Y., Tanaka, F., Hirabatake, M., Kashiwagi, H., Nishioka, I., Ikesue, H., Hashida, T., Koide, N., & Muroi, N. (2022). Evaluating the safety and efficiency of robotic dispensing systems. *Journal of Pharmaceutical Health Care and Sciences*, *8*(1), 24. https://doi.org/10.1186/s40780-022-00255-w

Taylor, N., Lawton, R., Moore, S., Craig, J., Slater, B., Cracknell, A., Wright, J., & Mohammed, M. A. (2014). Collaborating with front-line healthcare professionals: The clinical and cost effectiveness of a theory based approach to the implementation of a national guideline. *BMC Health Services Research*, *14*(1), 648. https://doi.org/10.1186/s12913-014-0648-4

Tran, T. T. V., Tayara, H., & Chong, K. T. (2023). Artificial Intelligence in Drug Metabolism and Excretion Prediction: Recent Advances, Challenges, and Future Perspectives. *Pharmaceutics*, *15*(4), 1260. https://doi.org/10.3390/pharmaceutics15041260

Troulis, M. J., Everett, P., Seldin, E. B., Kikinis, R., & Kaban, L. B. (2002). Development of a three-dimensional treatment planning system based on computed tomographic data. *International Journal of Oral and Maxillofacial Surgery*, *31*(4), 349–357. https://doi.org/10.1054/ijom.2002.0278

Uddin, M., Wang, Y., & Woodbury-Smith, M. (2019). Artificial intelligence for precision medicine in neurodevelopmental disorders. *Npj Digital Medicine*, *2*(1), 112. https://doi.org/10.1038/s41746-019-0191-0

VanLEHN, K. (2011). The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems. *Educational Psychologist*, *46*(4), 197–221. https://doi.org/10.1080/00461520.2011.611369

Vishnoi, S., Matre, H., Garg, P., & Pandey, S. K. (2020). Artificial intelligence and machine learning for protein toxicity prediction using proteomics data. *Chemical Biology & Drug Design*, *96*(3), 902–920. https://doi.org/10.1111/cbdd.13701

Vora, L. K., Gholap, A. D., Jetha, K., Thakur, R. R. S., Solanki, H. K., & Chavda, V. P. (2023). Artificial Intelligence in Pharmaceutical Technology and Drug Delivery Design. *Pharmaceutics*, *15*(7), 1916. https://doi.org/10.3390/pharmaceutics15071916

Westreich, D., Lessler, J., & Funk, M. J. (2010). Propensity score estimation: Neural networks, support vector machines, decision trees (CART), and meta-classifiers as alternatives to logistic regression. *Journal of Clinical Epidemiology*, *63*(8), 826–833. https://doi.org/10.1016/j.jclinepi.2009.11.020

Whitley, D. (1994). A genetic algorithm tutorial. *Statistics and Computing*, *4*(2). https://doi.org/10.1007/BF00175354

Williams, A. D., & Andrews, G. (2013). The Effectiveness of Internet Cognitive Behavioural Therapy (iCBT) for Depression in Primary Care: A Quality Assurance Study. *PLoS ONE*, *8*(2), e57447. https://doi.org/10.1371/journal.pone.0057447

Wise, J., Möller, A., Christie, D., Kalra, D., Brodsky, E., Georgieva, E., Jones, G., Smith, I., Greiffenberg, L., McCarthy, M., Arend, M., Luttringer, O., Kloss, S., & Arlington, S. (2018). The positive impacts of Real-World Data on the challenges facing the evolution of biopharma. *Drug Discovery Today*, *23*(4), 788–801. https://doi.org/10.1016/j.drudis.2018.01.034

Yang, G., Pang, Z., Jamal Deen, M., Dong, M., Zhang, Y.-T., Lovell, N., & Rahmani, A. M. (2020). Homecare Robotic Systems for Healthcare 4.0: Visions and Enabling Technologies. *IEEE Journal of Biomedical and Health Informatics*, *24*(9), 2535–2549. https://doi.org/10.1109/JBHI.2020.2990529

Yang, S.-Y., Huang, Q., Li, L.-L., Ma, C.-Y., Zhang, H., Bai, R., Teng, Q.-Z., Xiang, M.-L., & Wei, Y.-Q. (2009). An integrated scheme for feature selection and parameter setting in the support vector machine modeling and its application to the prediction of pharmacokinetic properties of drugs. *Artificial Intelligence in Medicine*, *46*(2), 155–163. https://doi.org/10.1016/j.artmed.2008.07.001

Yang, Y. J., Cho, B.-J., Lee, M.-J., Kim, J. H., Lim, H., Bang, C. S., Jeong, H. M., Hong, J. T., & Baik, G. H. (2020). Automated Classification of Colorectal Neoplasms in White-Light Colonoscopy Images via Deep Learning. *Journal of Clinical Medicine*, *9*(5), 1593. https://doi.org/10.3390/jcm9051593

Yoo, S.-R., Ha, H., Lee, M.-Y., Shin, H.-K., Han, S.-C., & Seo, C.-S. (2019). A 4-Week Repeated Oral Dose Toxicity Study of Ssanghwa-Tang in Crl:CD Sprague Dawley Rats. *EvidenceBased Complementary and Alternative Medicine: eCAM*, *2019*, 2135351. https://doi.org/10.1155/2019/2135351

Yu, L. X., Ellison, C. D., & Hussain, A. S. (2004). Predicting Human Oral Bioavailability Using in Silico Models. In R. Krishna (Ed.), *Applications of Pharmacokinetic Principles in Drug Development* (pp. 53–74). Springer US. https://doi.org/10.1007/978-1-4419-9216-1_3

Zhang, H., Chen, Y., & Li, F. (2021). Predicting Anticancer Drug Response With Deep Learning Constrained by Signaling Pathways. *Frontiers in Bioinformatics*, *1*, 639349. https://doi.org/10.3389/fbinf.2021.639349

Zhang, Z., He, T., Huang, L., Li, J., & Wang, P. (2021). Immune gene prognostic signature for disease free survival of gastric cancer: Translational research of an artificial intelligence survival predictive system. *Computational and Structural Biotechnology Journal*, *19*, 2329–2346. https://doi.org/10.1016/j.csbj.2021.04.025

Zhang, Z., & Tang, W. (2018). Drug metabolism in drug discovery and development. *Acta Pharmaceutica Sinica B*, *8*(5), 721–732. https://doi.org/10.1016/j.apsb.2018.04.003

Zhuang, X., & Lu, C. (2016). PBPK modeling and simulation in drug research and development. *Acta Pharmaceutica Sinica B*, *6*(5), 430–440. https://doi.org/10.1016/j.apsb.2016.04.004