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Review Article

An Evidence-Based Systematic Review: The Impact of Artificial Intelligence in Pharmacology and Health Research

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ABSTRACT

Introduction: Artificial intelligence (AI) has gradually become a vital part of health care currently. AI and machine learning (ML) have made significant progress in recent years, particularly in terms of deep learning (DL) approaches in pharmacology. AI will have a significant impact on pharmacologists at all levels in the coming decade, including drug development and research, medical education, and clinical practice. AI is transforming health research, by boosting data analysis, providing diagnostic tools, predicting outcomes, and helping develop personalized treatments. AI affords early detection of diseases and creates virtual patient models to assess treatments. In this reverence, the objective of this systematic review is to evaluate the impact of AI in the field of Pharmacology and health research.

Methods: The review was performed by preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines. The studies published from 2009 to 2022 were identified using specific keywords through searches on PubMed, Google Scholar, Web of Science, Science Direct, and Cochrane review databases. The explorations retrieved 972 studies and on subsequent screening with the inclusion and exclusion criteria, 71 studies were included for this systematic review.

Results: The collective results showed that AI plays a significant role in the fields of pharmacology, research, medical education, health care diagnostics, and clinical practice, with high accuracy and efficiency.

Conclusion: AI has emerged as a powerful tool in pharmacology and healthcare, offering innovative solutions to longstanding challenges. It has revolutionized and digitally transformed the manual healthcare system into an automated version in many areas.

Keywords:
Artificial Intelligence
Machine Learning
Deep Learning
Pharmacology
Health Research

Introduction

At present, digital tools are the norm in every aspect of our lives. The widely known artificial intelligence or AI is a step in that direction. The potential of AI in the field of health care and research is remarkable and extensively rising. The importance of AI tools and technology in

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achieving important transformations such as reducing the demand-supply gap for quality healthcare services, and increasing patients' expectations about holistic healthcare delivery is now being taken into account by the medical field. Clinical pharmacology provides information and guidance on the appropriate use of medicinal products and their application to clinical practice, including drug development and research. Presently, Artificial Intelligence or Machine Learning advancements will have a significant impact on pharmacologists at various levels. Artificial intelligence (AI) is any system that can sense, reason, engage, and learn to achieve human-like responsibilities such as voice recognition, digital image reading, etc. A subfield of AI known as "machine learning" (ML) makes use of mathematical techniques to enable computer systems to continuously improve. Deep learning (DL) is a subset of machine learning in which algorithms are capable of learning for themselves by extracting important features from a vast amount of data in a sequential chain (Benbya et al., 2020; Canitza et al., 2017).

The majority of "digital natives" (patients and researchers who began using computers, tablets, and smartphones at an early age) use social media and web-based platforms to find out about healthcare and drugs (Kornegay et al., 2016). For drug-related information, predictive analytics (i.e. predicting inquiry phrases and tailored explorations) is currently accessible. AI approaches such as natural language processing (NLP) and computer vision can be used in clinical development to combine omics data, electronic health records (EHR), and biomarkers to identify and define the most appropriate subpopulation for a trial (Arnold et al., 2021). AI is utilized regularly in patient management, for example replacing diagnostic biomarkers with cost-effective non-invasive measures, matching ideal drug or drug combinations with patients' profiles, predicting drug-drug interactions, and improving treatment practices (Athreya et al., 2019; Vamathevan et al., 2019; Jiménez-Luna et al., 2021).

Advanced AI/ML systems personalized to an individual's medical and genomic background are from the perspective of clinical pharmacology. In the pharmaceutical industry, new drug research and development majorly encounter lengthy time, highly expensive, and huge manpower. (Jiménez-Luna et al., 2021; Paul et al., 2021). Finding a disease target and developing a scientific explanation might take decades and cost billions. Between the discovery of a hit chemical for a certain target and the launch of a commercial product, it takes an average of 12-14 years (Vamathevan et al., 2019; Jiménez-Luna et al., 2021; Paul et al., 2021). Furthermore, despite the rapid expansion of pharmacology data, it is still predicted to be significantly less frequent than experimental chemistry data.

In vitro, in mice, and in humans, there are just a few studies with publicly available data that examine a wide range of parameters. The mainstream of these studies was funded by pharmaceutical establishments, which see this information as a competitive advantage, rendering clinical pharmacology less susceptible to AI/ML breakthroughs (Paul et al., 2021). Human intelligence and AI technologies may merge seamlessly in the next ten years. The majority of developers in this field are expected to be working on a new artificial intelligence for medical guidance, specifically with the use of drugs. Therefore, an attempt was made in this review, to gather all the information on the impression of AI in the arena of pharmacology and health research.

Methodology & Search Strategy

The review was performed in accordance with preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines. The data collection for this systematic review was carried out independently by the researchers using different data search items; articles from 2009 to 2022 were considered [Table 1]. The whole text of each of these papers was carefully read, vetted for titles and abstracts, and then categorized according to the inclusion and exclusion criteria listed in Table 1. The data extraction process included a screening of the texts and subcategories by the authors. A total of 972 articles (abstract and title) reporting on artificial intelligence in pharmacology, and health research, were found during the initial search for this systematic review. Using primary keywords, PubMed Central, Web of Science, Scopus, and Google Scholar worldwide databases were searched.

Before the screening, 667 articles were eliminated for a variety of reasons, including duplication and a shorter period frame of 2009–2022. The decision was made to exclusively include articles covering applications of artificial intelligence in pharmacology and health research, which led to the exclusion of an additional 152

TABLE 1: Initial search strategy and criteria for the systemic review

Topic	Search terms	Inclusion and exclusion criteria
Artificial Intelligence **AND** Health care	"Artificial intelligence" OR "machine intelligence" OR "machine learning" OR "neural network" OR "multi-agent system" OR "medicine" OR "molecular medicine" OR "COVID-19"	Inclusion criteria • Articles Published 2009 – March 2022 • Articles in English language • Articles through primary research (research articles) • Articles related to Artificial intelligence use in clinical Pharmacology and health research. • Articles Indexed in PubMed Central, Web of Science and Scopus, and Google Scholar Exclusion criteria • Articles Published before 2009 • Articles not in English language • Articles not through primary research. • Without full-text versions. • Narrative reviews where no studies were conducted
AND Drug discovery	OR "drug design" OR "drug development" OR "autoencoder" OR "drug screening"	
AND Clinical Pharmacology	OR "Drug toxicity" OR "drug safety" OR "drug interaction" OR "pharmacovigilance" OR "pharmacogenomics" OR "polypharmacy"	
AND Medical Education	OR "medical college" OR "clinician" OR "medical student" OR "Medical ethics"	

articles. 139 possible articles were initially screened, and their eligibility was evaluated. 48 articles, however, were unable to be included since it was not possible to order them through the institutional library order system or directly from the authors in full text. As a result, 71 publications that matched the inclusion and exclusion criteria were evaluated and included in the systematic review [Figure 1].

Applications of Artificial intelligence in health research (Table 2):

AI is transforming the way that health research is done. AI can be used to boost data analysis, provide diagnostic tools, predict outcomes, and help develop personalized treatments. AI can help to analyze large datasets faster, enabling researchers to quickly reach conclusions that would take humans much longer. Today's healthcare "vision" includes large-scale establishments, along with the traditional interactions between patients and doctors. In these large-scale organizations, a multi-agent system (MAS) that utilizes AI is used to achieve substantial growth (Shakshuki et al., 2015). AI can also provide early detection of diseases by analyzing patterns in medical records and health data. AI is also being used to create virtual patient models to assess treatments. AI also has the potential to speed up drug discovery by automating the cycle of data gathering, testing, and analysis. AI is helping to reduce the costs and risks associated with clinical trials by providing a way to simulate trials using virtual patients. AI can also be used to provide personalized medical treatments, enabling providers to better recognize individual needs (Ngiam et al., 2019).

AI is utilized to develop institutional performance by allowing individuals to capture, share, and exploit their extensive knowledge to make optimum real-time judgments. AI-based solutions, for example, will bring specialized diagnostic skills into primary care. Images of a skin lesion could be recorded at a GP practice and submitted to a dermatology AI system for immediate analysis to accurately detect its etiology. Unsupervised (ability to discover patterns), supervised (classification and prediction), and reinforcement learning (use of

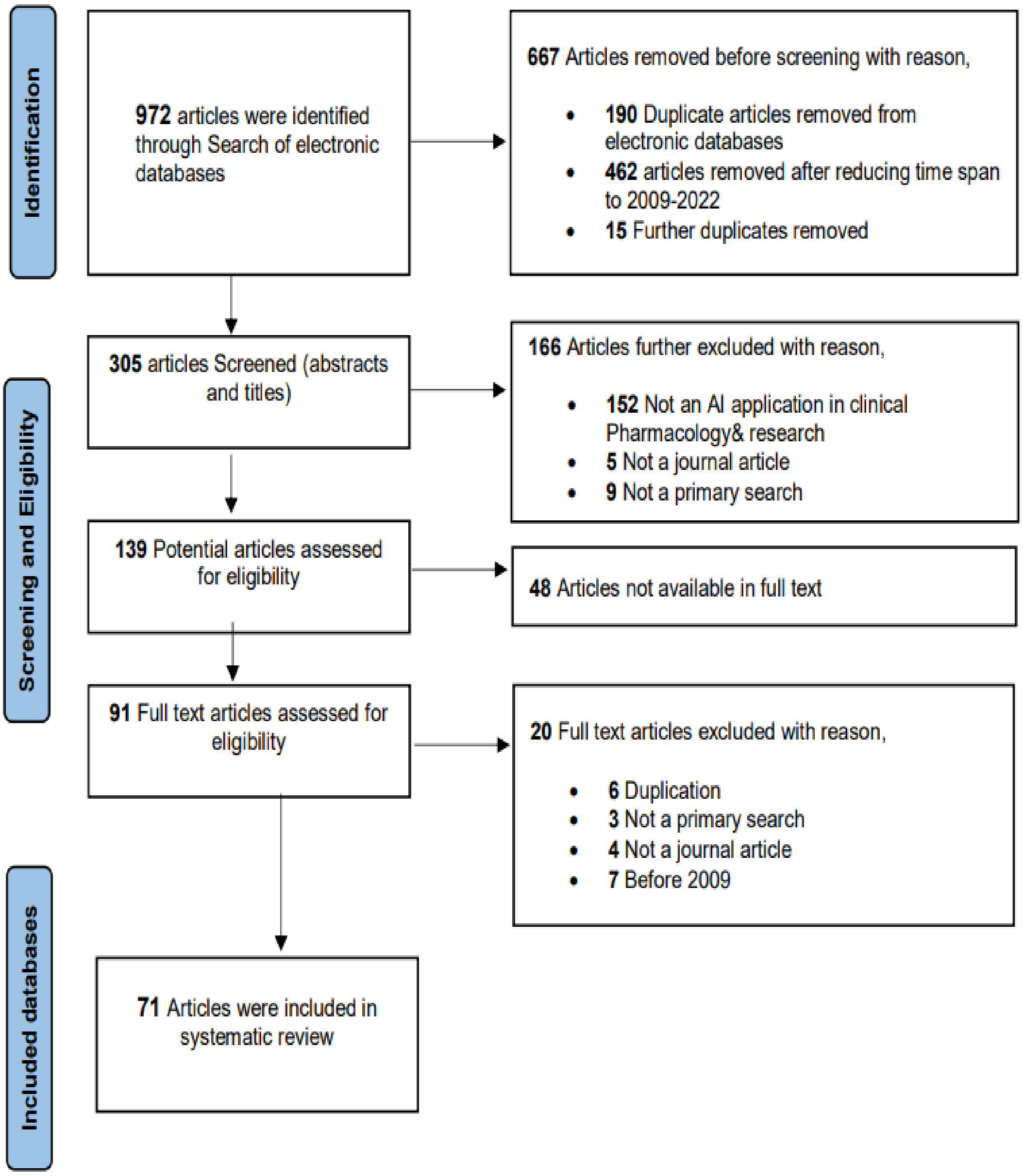

FIGURE 1

sequences of rewards and punishments for a specific problem) are examples of machine learning algorithms (Shakshuki et al., 2015; Ngiam et al., 2019; Meenakshi et al., 2017).

In medicine, artificial intelligence is categorized into two types. The first is made up of mathematical algorithms that help students learn more effectively over time. AI by providing ML algorithms and information management has promoted genetics and molecular medicine discoveries. The second type of AI application in medicine (care bots) consists of physical goods, healthcare devices, and more intricate robots that assist in treatment delivery (Yew et al., 2021; Jecker et al 2021). Another area where AI could assist is 3D printing in medicine for personalized implants and prostheses, medical models, and medical technologies that are revolutionizing healthcare and potentially disrupting many domains of traditional medicine (Dodziuk et al., 2016). It's exciting to learn about the new development of nanorobots, which are intended to address delivery challenges that arise when a medicinal agent's diffusion into a target region is difficult (Hu et al., 2020; Suhail et al., 2022).

Role of Artificial Intelligence in Pharmacology

Artificial Intelligence Approach for Drug Discovery:

TABLE 2: Applications of Artificial intelligence in Medicine

Task		Objectives	AI applications /tools (examples)	References
1.	Administrative applications	Digital consultation, chatbots for patient interaction, mental health and wellness, Telehealth, Apps for patient involvement and adherence	Electronic health records (EHRs)	Kornegay et al., 2016; Wolbrink et al., 2012
			Several ML and DL Algorithms.	Arnold et al., 2021; Athreya et al., 2019 Benbya et al., 2020; Canitza et al., 2017
2.	Medical management	Treatment effectiveness and outcome prediction	ML and DL algorithms	Arnold et al., 2021; Athreya et al., 2019; Meenakshi et al., 2017
		Personalised treatment	3D printing of treatment	Chan et al., 2019
			Magistral production of drugs	Christopoulou et al., 2020; Dandala et al., 2018; Dodziuk et al., 2016
			EHR decision support tools and learning systems	Alimadadi et al., 2020; Ampadu et al., 2016
3.	Surgical management	Preoperative	Blood marker tumour screening, Optimising image sequence, Computer assisted radiological diagnosis, Radiomic tumour marker & grading, Precise surgical planning	Zhao et al.,2021; Zhou et al., 2020
		Intraoperative	AI robotics, Malignant tissue identification, Risk detection, Workflow analysis	
		Post operative	Automated/ accurate histopathological diagnosis, Prediction of complications, Bioinformatic early warning system, Tailored follow up/ therapeutics, Predict recurrence	Lociciro et al., 2021 Jecker et al 2021; Yew et al., 2021
4.	Managing medical data & Health monitoring	Medical history details such as diagnoses, diagnostic exams, medications and treatment plans, immunization records, allergies, radiology im-ages, sensors multivariate times series (such as EEG from intensive care units), laboratory, and test results	Electronic health records (EHRs), Automated medical coding; AI-based diagnosis specificity; AI-based early detection information,	Basile et al., 2019; Benbya et al., 2020; Blais et al.,2014; Bosale et al.,2020; Cabitza et al.,2017; Chan et al.,2019;
			Deep autoencoders, Deep belief networks, Recurrent neural networks, Deep neural networks, Deep Boltzmann machine	Chaudhari et al.,2020; Chen et al.,2020
5.	Causality assessment	Causality of adverse drug reaction reports	Naranjo, Jones or Karch-Lasagna algorithms, Venulet algorithm, Bayesian network	Wilfling et al., 2020
6.	Management of COVID-19	Taxonomical classification, Detection assay, Survival prediction, Discovery of potential drug candidate, Vaccine development	CRISPR-based, Vaxign-ML, SGDormBot, an AI-powered chatbot	Chen et al., 2020; Hessler et al., 2018; Hu et al., 2020; Jecker et al., 2021; Jiménez-Luna et al., 2021; Lociciro et al., 2021; Ong et al., 2021

TABLE 3: Drug Research and Development with Artificial Intelligence

Drug development process	Outcomes	Artificial intelligence in drug development	Examples	References
Target validation	Validated target	• Benchmark compounds set design • Predicts target's role in disease • Design of in silico compound libraries • Identify novel targets • Predict draggability of targets • Predict signalling system	For generating novel drug candidates (drug discovery) • ATOMWISE • Revive Med Understanding disease mechanisms • PHENOMIC AI • Structura Biotechnology	Lake, 2019; Mak & Pichika, 2019; Smith et al., 2009 Hessler et al., 2018; Vanhaelen et al., 2020
Biological assay	Assay developed			
Compound screening				
Lead identification	Lead molecule shown effect on drug target	• Prediction of structure activity relationship (SAR) • Prediction of ADMET properties	Aggregating and synthesizing information • Arpeggio Biosciences	Bakkar et al., 2018; Jang, 2019 Jang, et al., 2019; Mak & Pichika 2019
Lead Optimisation				
Preclinical development	Clinical candidate, shown effect in an animal			
Clinical trial Phase I	Drug safe in humans			
Phase II	Drugs show effects in humans	• Drug repurposing • Selection of patient population in clinical trials to increase success rates		
Phase III	Drug show effects in large population			
Phase IV	FDA approval, manufacture, post marketing survey And observation of ADRs	• Pharmacovigilance	• biLSTM Networks • PrOCTOR is a target-based toxicity prediction software	Kompa et al., 2022 Lavan et al., 2019 Lysenko et al., 2018
	Quantitative structure activity relationship (QSAR), Target based toxicity prediction	• Open source toxicity prediction tools	• FAERS • TargeTox • PrOCTOR	Lysenko et al., 2018; Christopoulou et al., 2020
Pharmacogenomics	Pharmacogenomic analysis	• Single nucleotide polymorphisms (SNPs), DNA methylation • Drug response prediction	• Response Prediction Network (ARP Net) framework • SVM-recursive feature elimination model	Kalinin et al., 2018; Silva et al., 2021; Whirl-Carrillo et al., 2012

The link between chemical structure and physical attributes or biological activity is often modeled in medicinal chemistry. An essential step in this process is the representation used to convert a molecular structure into a format that a machine-learning system can understand. Recently, drug design and development involves the application of AI at various stages, i.e., from peptide synthesis to molecule design, virtual screening to molecular docking, quantitative structure-activity relationship to drug repositioning, protein misfolding to protein-protein interactions, and molecular pathway identification to poly-pharmacology (Gupta et al., 2021). Artificial intelligence principles have been used in the classification of active and inactive drugs, drug release monitoring, preclinical and clinical development, primary and secondary drug screening, biomarker development, pharmaceutical built-up, bioactivity and physiochemical properties identification, toxicity estimation, and pharmacodynamic identification (Zhang et al., 2017; Lake, 2019).

Artificial Intelligence in Drug Design and Drug Development:

AI is used in drug development and discovery for tasks like target validation, new drug design, drug repurposing, polypharmacological agent design, and trial design optimization to improve R&D efficiency, patient population selection, and patient safety and efficacy monitoring in clinical trials (Bakkar et al., 2018; Jang, 2019). In the drug design and development process, AI guides to development of innovative designs to create new physiologically active molecules with anticipated features, Ex- the variational autoencoder, (Hessler et al., 2018). A typical autoencoder is used to produce chemical structures (Hessler et al., 2018; Vanhaelen et al., 2020).

Further retrosynthetic planning is dominated by knowledge-based systems, such as the Substrate Product Occurrence Ratio Calculator (SPORCalc), which finds metabolically labile atom sites in prospective compounds (Smith et al., 2009). Large datasets that people can't manage unbiasedly can be mined using machine learning techniques. The use of a combination of knowledge-based and machine-learning methodologies for chemical reaction prediction has proven to be quite effective in synthesis planning (Sun et al., 2010). De novo design and retrosynthetic analysis are currently among the uses of artificial intelligence systems, which have greatly expanded in recent years.

AI can predict toxicity, provide light on new molecules to target, and simplify the metabolic routes of compounds. AI methods like computer vision and natural language processing (NLP) can be used in clinical development to identify and describe the most suitable subpopulation for a trial by combining biomarkers, genomic data, and electronic health records. To achieve realistic performance in lead optimization, pharmacology prediction, toxicology prediction, and clinical trial design from Phase 1 to Phase 3, AI applications for drug discovery and development also require domain knowledge of pharmacologists, such as ADMET, PK/PD, and dose-response analysis, among other areas (Jang, 2019; Mak et. al., 2019) [Table 3].

Drug-Target Interaction Prediction:

Since traditional screening studies are time-consuming and expensive, computational techniques for predicting drug-target interactions (DTIs) play an essential role in drug development. As the effectiveness of currently available antimicrobial drug treatment is falling, the detection of possible DTIs is a deciding stage in the drug discovery and repositioning process (Souri et al., 2022). One study proposed a deep learning architecture model that takes advantage of Convolutional Neural Networks' (CNNs') unique capacity to extract one D representations from protein sequences (amino acid sequences) and SMILES (Simplified Molecular Input Line Entry System) compound strings (D'Souza et al., 2020).

Another study used a pre-trained bidirectional encoder representation from transformers (BERT) method to extract substructure features from protein sequences and a local breadth-first search (BFS) method to learn subgraph information from molecular graphs, as well as end-to-end depiction learning of a graph neural network with an attention mechanism and an attentive bidirectional long short-term memory (BiLSTM) to predict drug-target interactions and provide target sensitivity. ChEMBL, BindingDB, PubChem, Drug Bank, Drug Central, GtopDB, and DGiDB are just a few examples of databases that give manually extracted DTIs (Souri et al., 2022; D'Souza et al., 2020; Aldahdooh et al., 2021). On unbalanced datasets, our technique achieved high AUC and recall results.

Artificial Intelligence for Drug Toxicity and Safety:

Traditionally, the most popular technique for assessing toxicity has been animal research. In vivo and in vitro research, clinical trials, and post-marketing surveillance of adverse drug reactions in real-world populations are the starting points for safety efforts during the development phase (Basile et al., 2019). Quantitative structure-activity relationships (QSAR) methods have been used to estimate a variety of medication safety outcomes, such as tissue-specific toxicity, skin/eye irritation, and 50% lethal dose (LD50) values.

Support Vector Machines (SVM) is a technique for classifying data that locates a discriminatively classifying hyperplane in an n-dimensional space (n is determined by the number of features). In a study (Basile et al., 2019), SVM beat naive Bayes, k-NN, and random forest algorithms in estimating activity value. Using QSAR, target-based activities such as toxicity can also be anticipated. Two recent open-source toxicity prediction tools for target-driven toxicity prediction, which will also assist in the production of less dangerous pharmaceutical molecules, are Targe Toxix (Lysenko et al., 2018) and PrOCTORx (Christopoulou et al., 2020). Another study used a two-stage process for entity extraction on the medication, indication, and adverse drug events, combining the BiLSTM-CRF and Attention-BiLSTM models. The issue with using clinical literature to identify ADEs is how coherently much of the specific data is provided. For identifying drugs, ADEs, and their correlations, a machine learning-based clinical

NLP system called MADEx can be used to solve this (Dandala et al., 2018; Yang et al., 2019). The FDA in the United States maintains databases called the FDA Adverse Event Reporting System (FAERS) and spontaneous reporting systems (SRS) that contain reports of adverse events (AEs), medication errors, and product quality issues that lead to AEs (Vermeer et al., 2013). The predominant data source for post-marketing drug safety mining has been self-reported Individual Case Safety Reports (ICSRs) (Ampadu et al., 2016).

Artificial Intelligence in Pharmacovigilance (PV):

Every day, pharmacovigilance gathers enormous amounts of data from all around the world, and analyzing this enormous amount of data is challenging. Herbs, conventional and alternative medicines, blood products, medical devices, herb vigilance, hemovigilance, and materiovigilance are recent additions to the artificial program's concerns (Murali et al., 2019). VigiFlow, VigiBase, VigiAccess, and VigiLyze are some of the databases utilized in the PV. Other case report analysis tools offered by PV include VigiGrade, VigiMatch, and ViGiRank. (Murali et al., 2019; Abatemarco et al., 2018).

In order to give information on adverse events, product-related issues, and consumer reports in pharmacovigilance, Individual Case Safety Reports (ICSR) are documents in a specified format that follow FDA requirements (Abatemarco et al., 2018). In ICSR processing, AI is divided into areas such as AI for decision-making and the insertion of structured and unstructured input. AI may be crucial in the development of unlisted or unique random adverse events (AEs), drug classifiers, correlation, and other applications. The exploration phase will look at how similar machine-learning approaches might be applied to other business processes such as the intake, processing, and reporting of individual safety situations after proof of concept and the choice of a suitable vendor (Kompa et al., 2020; Mockute et al., 2019).

Artificial Intelligence in Pharmacogenomics:

Pharmacogenomics (PGx) is an area of knowledge that evaluates how specific genes, alone or in combination with other loci, influence individual reactions to medication treatment (Whirl-Carrillo et al., 2012). One study described informatic and bioanalytic methodologies for combining weak signals in symptoms and main complaints with pharmacogenomic analysis of 90 single nucleotide polymorphic variants, CYP2D6 copy number, and clinical pharmacokinetic profiles to monitor drug-gene pairs and drug-drug interactions for medications with significant pharmacogenomic profiles (Silva et al., 2021; Kalinin et al., 2018).

For example, in order to determine the most effective antidepressant for an individual patient (such as Single nucleotide polymorphisms (SNPs), DNA methylation, and demographic information), an Antidepressant Response Prediction Network (ARP Net) framework was used to highlight key predictive elements from patient data such as MRI data and multi-omics data (Athreya et al., 2019). The key clinical predictors and single nucleotide polymorphisms (SNPs) that can forecast the response to early antidepressant therapy were found using the SVM-recursive feature elimination model, which is employed as a feature selection tool (Lin et al., 2020).

Artificial Intelligence in Polypharmacy:

A public health concern, polypharmacy is prevalent among the elderly and can have detrimental effects on one's health (Sirois et al., 2021). Traditional statistical methods struggle to assess if therapy is related to health outcomes due to the vast number of pharmacological combinations and use sequences.

The Artificial Intelligence research axis, according to some researchers, will develop algorithms for identifying common patterns of drug usage connected with health events while taking data location and timing into consideration (Sirois et al., 2021; Wilfling et al., 2020). Through the Health research axis, these patterns will be transformed into polypharmacy indicators helpful for doctors and public health surveillance. The Law & Ethics axis will measure the social appropriateness of AI-generated procedures and indicators developed by the health axis to make sure that they do not discriminate against any demographic group or worsen pre-existing medication inequities (Blais et al., 2014). The Quebec Integrated Chronic Disease Surveillance System (QICDSS) collects information on medication claims (generic name, dose, route, and treatment duration), physician claims (dates, ICD-9 diagnostic codes), hospitalizations (dates, ICD-9 or ICD-10 diagnostic codes, provided services), deaths (date and up to 10 causes), and sociodemographic data (age, sex, region of residence) (Müller-Staub et al., 2016).

According to some researchers, the Artificial Intelligence research axis will create algorithms for identifying typical patterns of medication use associated with health events while taking data location and temporality into account (Sirois et al., 2021; Wilfling et al., 2020). These trends will be converted into polypharmacy indicators useful for public health surveillance and clinicians through the Health research axis. To ensure that the established indicators do not discriminate against any demographic group or exacerbate already-existing medication inequities, the Law & Ethics axis will evaluate the social acceptability of AI-generated algorithms and indicators developed by the health axis (Blais et al., 2014). The Quebec Integrated Chronic Disease Surveillance System (QICDSS) includes medication claims (generic name, dose, route, and duration of treatment), physician claims (dates, diagnostic codes of International Statistical Classification of Diseases and Related Health Problems [ICD-9]), hospitalizations (dates, diagnostic codes based on ICD-9 or ICD-10, provided services), deaths (date and up to 10 causes), and sociodemographic data (age, sex, region of residence) (Müller-Staub et al., 2016).

Electronic Clinical Decision Support Systems (CDSS) have been created to address some concerns in polypharmacy. To automatically implement the guidelines and perform the rules, these systems employ patient data from the Electronic Health Record (EHR) or manually submitted by health professionals (Duke et al., 2009). RXplore (Chaudhari et al., 2020), for example, was created to answer a specific need, such as lowering ADR rates. Others, such as KALIS (Friedrichs et al., 2019), focused on polypharmacy as a whole. Some systems give alternatives and monitoring strategies in addition to simple DRP detection. This is the case with Medsafer (McDonald et al., 2022), which gives annual updates and advises deprescribing procedures for PIMs detected based on available data. This is also true of SENATOR (Lavan et al., 2019), which advocates for non-pharmaceutical alternatives.

Artificial intelligence and machine learning to fight COVID-19

The COVID-19 epidemic is being fought with the help of AI in several different methods. The prompt distribution of COVID-19 patient data, including physiological characteristics and therapeutic outcomes of COVID-19 patients, was made possible by researchers using AI and ML to generate crucial real-time data on this pandemic around the world (Alimadadi et al., 2020). Advanced machine learning algorithms can integrate and analyze massive amounts of data from COVID-19 patients to better understand viral spread patterns, improve diagnostic speed and accuracy, develop new, efficient therapeutic drugs & vaccines, and possibly identify the most vulnerable individuals based on individualized genetic and physiological characteristics (Chen et al., 2020). Additionally, AI-enabled robots are being employed in healthcare facilities to reduce human contact between healthcare professionals and infected patients. Telepresence robots, which may remotely monitor patients, distribute supplies, screen people for the virus, and promote communication between patients and their relatives, are examples of AI-enabled robots assisting with the fight against COVID-19 (Lociciro et al., 2021). It reduces psychological suffering in critically sick patients and their family members by giving regular updates to kin. In isolation chambers, a telepresence robot could thereby lessen the psychological toll of the few visits from family members (Lociciro et al., 2021).

Since the COVID-19 outbreak, cutting-edge machine-learning techniques have been applied to the taxonomic classification of COVID-19 genomes, CRISPR-based COVID-19 detection assay, survival prediction of severely ill COVID-19 patients, and the identification of potential drug candidates against COVID-19 (Ganbaatar et al., 2021). SGDormBot, an AI-driven chatbot, has been used in Singapore to mass screen migrant workers for COVID-19 based on symptoms (Chen et al., 2020). Vaxign-ML, a program based on machine learning, was recently used to undertake a reverse vaccinology study for vaccine development (Ong et al., 2021). Critical investigations are required to ascertain the true benefits and consequences of such technology integration, rather than depending merely on statistical data, as governments and healthcare organizations increasingly utilize AI-based containment and preventive measures. (Alimadadi et al., 2020; Zhao et al., 2021).

Artificial intelligence in medical education

Artificial intelligence will have an impact on all professions, including medicine and medical education. Current AI research indicates that the teacher's role is crucial for optimal AI development. In medicine, AI will not replace doctors; rather, it will augment and replace many existing functions while also generating a variety of new ones. It's vital to be aware of these changes in advance so that medical schools can begin preparing students for these new roles. Another essential technological skill that is frequently overlooked in medical education is using electronic health records (EHRs) (Masters et al., 2019).

EHRs provide a slew of benefits, including improved patient safety, but they also help with AI applications in health care. Data from electronic health records, and hence knowledge, are used by AI algorithms. EHRs not only improve patient safety, which is one of its many benefits, but they also facilitate the use of AI in healthcare. Understanding how to get accurate data into the EHR is essential because AI algorithms depend on it (Masters et al., 2019). A clinician who must comb through enormous old records can reduce their workload by using AI as a first-pass technology (Baron et al., 2021).

An examination of the literature reveals that artificial intelligence is currently used in medical education, primarily for thorough curriculum analysis. Assessment of the learning process utilizing a guided learning path: Learning & Learning Feedback Patients are not injured, and costs are decreased (Han et al., 2019). Rapid assessment, objective assessment, assessment feedback, and less teacher oversight (Chan et al., 2019). Medical data sets, EHRs, AI basics, and ethical and legal considerations must all be encompassed in the core and clinical phases of medical school (Paranjape et al., 2019). During clinical rotations and residency, applications of practical AI should take the front stage. Since digital biomarkers and treatments are developing and rely on AI, students must also obtain training in these technologies (Palanica et al., 2020). Medical professionals require multidisciplinary training in implementation science, operations, and clinical informatics to think creatively and develop technology-enabled care models.

Medical ethics considerations on artificial intelligence

Artificial intelligence will be useful in a variety of fields, including health care, medical procedures, drug discovery, and robotic surgery. Once it has been fully established within electronic systems, it will be used to reduce people's involvement in vitally harmful activities. Informed permission to use, security and openness, algorithmic equality and biases, and data confidentiality are the four main ethical problems (Keskinbora et al., 2019). The key legal issues relate to responsibility, data safety and confidentiality, cybersecurity, safety and efficacy, and academic property law. Robots and computers are representations of values because they make decisions and do actions, but the engineers who create the systems model or program how they will behave (Arnold et al., 2021).

Algorithmic methods will be necessary to ensure the safety of such systems. All AI judgments, even the simplest, are systematic because algorithms are involved, unlike human decision-making. As a result, even if activities have no legal consequences (because of a lack of adequate legal frameworks), they inexorably lead to accountability, not by the machine, but by those who built it and those who use it (Keskinbora et al., 2019). The currently murky legal relationship between AI and its users will not be resolved overnight, and progress in AI and its application in medical care will necessitate an ongoing dialogue.

To address the potential ethical and legal issues brought on by the use of artificial intelligence in healthcare, there are currently no clear rules in place. The protection of people's rights against direct or indirect subjugation requires keeping up with technology developments and putting preventative and precautionary measures in place (Arnold et al., 2021; Rodrigues et al., 2018). Concerns concerning cyber security are increased by the use of AI without human interaction. The moral visionary capacity of the physician must address concerns regarding the beneficence, autonomy, and fairness of AI as well as if its integration in healthcare has the potential to intervene, leading to nonmaleficence on the part of patients and physicians.

Limitations of Artificial intelligence

The fundamental issue with the most effective ML systems currently in use is that they operate in a statistical or model-free mode, which severely restricts their ability to perform (Khanzode et al., 2020). Such systems are unable to reason about interventions and retrospectives because they are unable to understand the context. The primary disadvantage at this time is that contemporary AI is still unable to comprehend intelligent thought and communication in a manner that is comparable to that of a person (Bosale et al., 2020). AI robots are unable to emotionally engage with teachers and students. This can hamper the personal development of the students.

Biases in AI-based algorithms can arise from a variety of sources, including biased training data as well as how the algorithms develop over time and are employed in reality (Parikh et al., 2019; Nelson et al., 2019). Starting, addressing hidden bias in AI algorithms should be seen as a patient safety issue that should be acknowledged and dealt with in advance rather than after the fact. Second, performance biases, even those that do occur, must be explicitly stated in the legal frameworks governing AI and machine learning algorithms. Third, it is crucial to involve all parties involved in healthcare in the development and deployment of AI due to the challenges posed by divergent perspectives on what uses and applications of AI are appropriate in medicine.

Another concern is that, as AI replaces most repetitive tasks with surgical robots (Hashimoto et al., 2018; Zhou et al., 2020), interruptions from AI therapists may cause humans to become sluggish as a result of its applications that make work easier. Humans have a tendency to become accustomed to these advancements, which may limit future generations. It may eventually damage human jobs, resulting in greater unemployment, dependence on programmers for creativity, a lack of personal touch, and the youthful generation becoming lethargic (Khanzode et al., 2020). It takes a lot of time and money, and the reliance on technology grows (Bosale et al., 2020). In this present review, we could not include 48 studies due to restrictions to access their full text through our institutional library, and also the latest articles beyond our study timeframe were excluded.

Conclusion

Recent years have seen tremendous advancements in artificial intelligence and machine learning (AI/ML), especially concerning deep learning (DL) methods used in pharmacology. Artificial intelligence is expected to have a major impact on pharmacologists in the next ten years, affecting them at all levels in areas such as drug research, medical education, and providing advice and information regarding the effects and proper uses of medications in humans, in addition to using that knowledge in clinical practice. A community and regulatory drive for open data sharing that increases the amount of preclinical and clinical pharmacology data available to the ML community is necessary to accelerate AI/ML developments in this discipline. The major goal is to strike a careful, mutually beneficial balance between the human skills and judgments of primary care physicians with training and the efficient deployment of automation and artificial intelligence. But there's concern in the medical industry that AI may eventually supplant humans entirely, which could limit the benefits otherwise. Innovative AI-powered IT facility delivery models; value-added healthcare services for medical decision-making; patient data protection; and health monitoring features are suggested areas for further research.

Conflict of Interest

None to Declare

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None

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