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Review Article

Review on Artificial Intelligence

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ABSTRACT

Artificial intelligence (AI) has many potential uses and consequences in the fields of management, education, and learning; this study sought to assess those uses and consequences. A narrative approach and assessment framework, identified through preliminary analysis, were used to examine AI's role in education. The study effectively achieved its objectives by employing a qualitative methodology, utilizing literature reviews as the primary research design and approach. AI is a discipline dedicated to innovations and advancements that have led to the creation of machines, computers, and other systems capable of demonstrating human-like intelligence. Cognitive talents, learning capacities, flexibility, and decision-making capacities are all part of this. The research shows that academic institutions, in particular, have used AI in many ways in the education sector. Initially emerging from computing and related technologies, AI evolved into online and web-based intelligent educational platforms. Over time, its integration with embedded computing systems and other technological advancements has managed to development of humanoid robots and web-based chatbots, which can function autonomously or together with educators in delivering instruction. These AI-powered tools have enabled instructors to efficiently manage directorial responsibilities such as grading and assessment while also improving the quality of their teaching. Moreover, AI-driven systems equipped with machine learning capabilities have enhanced curriculum personalization, tailoring content to meet individual student needs. This customization has fostered greater student engagement and retention, ultimately enriching the learning experience and elevating the overall quality of education..

INTRODUCTION

Various sectors are endeavouring to improve their innovations to satisfy the demands and expectations of their clients through diverse techniques. The pharmaceutical sector is essential for safeguarding lives. Constant innovation and the application of new technology are the cornerstones in the fight against medical crises like the current epidemic and other worldwide

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healthcare issues. [1] Innovation in the pharmaceutical sector is primarily based on research and development in multiple areas, including production technology, packaging challenges, and consumer-focused marketing methods. Innovative pharmaceutical technologies, encompassing tiny pharmacological agents and biologics, are preferred for their superior stability and effectiveness in addressing unmet medical requirements. Additional inquiry and inspection are urgently needed to address the significant issue of rising toxicity levels associated with innovative drugs. Making medicinal compounds that are both highly effective and suitable for use in healthcare is one of the primary goals. To address the world's growing need for medical and healthcare services, the pharmaceutical industry must overcome a number of obstacles that necessitate new technologies. [3-5] Training healthcare professionals on an ongoing basis is essential so that they may better participate in the day-to-day operations of the healthcare sector, which is a constant demand for skilled workers. Recognising skill gaps in the workplace is essential for the pharmaceutical sector. While recognising that delivering sufficient training poses considerable difficulties, it is crucial to adequately rectify the identified shortcomings through suitable corrective actions. June 2022 was the month in which 41% of supply chain disruptions occurred, according to data supplied by specific authorities. According to the data, supply chain disruption is now the second biggest challenge. To bolster company resilience, numerous pharmaceutical companies are forecasting improvements in their supply networks and creative solutions to these issues. The emergence of COVID-19 has profoundly impacted global operations, including ongoing clinical research. Supply chain disruptions are exacerbated by pandemics, natural disasters, price volatility, cyberattacks, logistical setbacks, and product deficiencies. The epidemic's effect on transport has affected international enterprises and the supply chain network. Delays in price fluctuations result from suppliers' decisions over price updates, arising from uncertainty about whether to implement innovative or current prices for goods or materials. Cross-border commercial collaboration across nations generates additional issues, including increased criminal activity and uneven access to essential resources for production and operations. Modifications to the footprint are necessary to meet patient needs and ensure compliance. Complications with cold chain preservation rendered a substantial proportion of COVID-19 vaccinations produced by the pharmaceutical industry useless during the pandemic. Insufficient innovation and inaccurate forecasting in commercial and industrial operations are the principal reasons leading to supply chain disruptions due to delayed responses. Disruptions in the pharmaceutical supply chain significantly impact consumer satisfaction, corporate reputation, and prospective revenues [6-9]. The management of supply chain activities within the pharmaceutical business is set for a substantial revolution owing to the adoption of AI (Figure 1). To devise efficient solutions for diverse supply chain difficulties, it consolidates different AI research initiatives from previous decades. The report goes on to propose future lines of inquiry that might enhance supply chain management decision-making resources [10,11]. Although pandemic's impact is diminishing, clinical trials remain partially influenced. Many pharmaceutical businesses are eager to utilise emerging technology, such as AI and virtual platforms. Figure 1 illustrates that these novel technologies may facilitate the recommencement or recreation of clinical research with reduced face-to-face interaction [12–18]. The primary issue at present is the exorbitant expense of maintenance and the necessity for highly qualified labour. Cybersecurity issues and data breaches are the fourth significant barrier to identifying a technology-driven solution. The 21st century has witnessed a rise in cyberattacks targeting patient data, prompting heightened concern among pharmaceutical companies on the security of patient information and private medical records, which are especially vulnerable to cybersecurity risks. Conventional clinical trials encounter numerous substantial obstacles, such as data fragmentation and the involvement of disparate systems. These challenges generally emerge from the fragmented data produced during the trials, requiring substantial human data conversion operations for both documentation and systems. The trial models' deficiency in inventiveness necessitates the re-execution of the current task. Key elements of the healthcare sector requiring focused attention in relation to clinical trials include patient recruitment, enrolment, monitoring, retention, and medical adherence. Patient enrolment is hindered by the protracted travel to trial locations, and many site visits prompt patients to re-register in same atmosphere. The use of AI in design study facilitates both the optimisation and enhancement of the labour required for creating a patient-centric design. AI decreases the number of data workers required for clinical studies by employing methods to gather the extensive data generated by those experiments. Wearable sensors and gadgets allow for remote collection of vital signs and other essential data; AI algorithms that make use of this data offer real-time insights throughout the research; this meets the patient's need for regular in-person contact. [19].

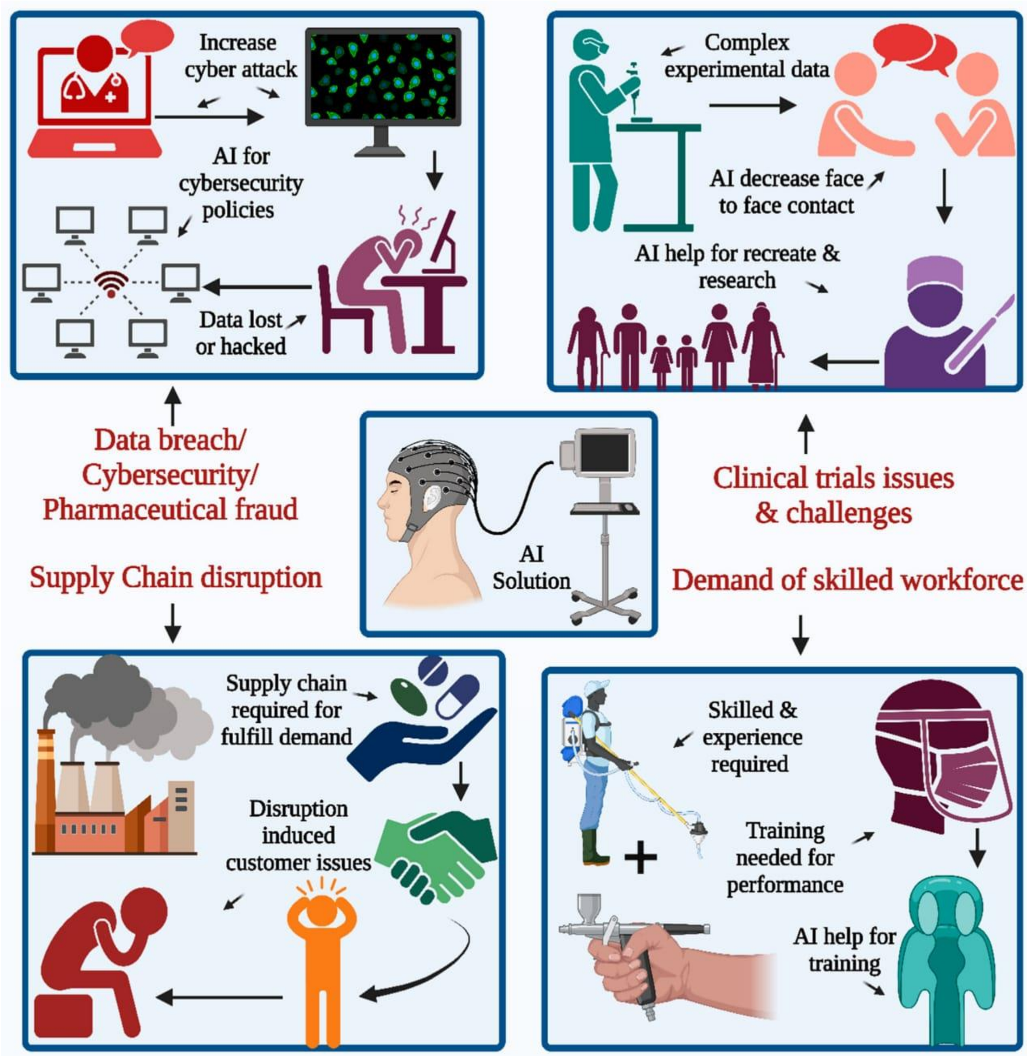

Figure 1: Illustration on potential use of AI

Any industry relies on a skilled workforce to make the most of their knowledge, skills, and abilities in product development; Figure 1 shows one potential way AI could be used to address complications in Pharma industry. The second one has to do with supply chain interruptions and problems with conducting clinical trials. Concerns about security and data breaches have grown in recent years, and the frequency of cyberattacks is on the rise.

History

- Maturation of AI began between 1943 and 1952. Warren McCulloch and Walter Pits in 1943 shown first study in what is now known as artificial intelligence, proposing an artificial neuron model. A later rule for changing the strength of neuronal connections, now called Hebbian learning, was introduced by Donald Hebb in 1949. In his 1950 publication Computing Machinery and Intelligence, English mathematician Alan Turing established the groundwork for machine learning by proposing the Turing test to find out if a computer could display intelligence comparable to that of a human. Herbert A. Simon and Allen Newell's groundbreaking artificial intelligence program, Logic Theorist, was established in 1955. It proved 38 out of 52 mathematical theorems and discovered improved proofs for a few more. Officially created by John McCarthy at the 1956 Dartmouth Conference, the phrase "artificial intelligence" marked the beginning of AI as an area of study.

- Research into algorithms to solve mathematical problems peaked between 1956 and 1974, sometimes referred to as the "golden years" of artificial intelligence. The first chatbot, ELIZA, was built by Joseph Weizenbaum in 1966. In 1972, Japan developed WABOT-1, first humanoid robot, continuing advancement of artificial intelligence. The first AI winter, which occurred between 1974 to 1980, was marked by a sharp drop in government support for AI research, which dampened interest and slowed development. The rise of expert systems that could mimic human decision-making sparked a new wave of interest in AI from 1980 to 1987.
- The inaugural national conference of the American Organisation of AI was held at Stanford University in 1980. This expansion, however, was brief, since funding came to a standstill during the second AI winter (1987–1993) owing to excessive expenditure and ineffective outcomes. Between 1993 and 2011, AI saw a renaissance thanks to the advent of intelligent agents.
- After defeating Garry Kasparov, the global chess champion, in 1997, IBM's Deep Blue created history. In 2002, the Roomba vacuum cleaner made its way into homes with the help of artificial intelligence. Businesses began to use AI in 2006, with platforms like Twitter, Facebook, and Netflix using AI to provide customers with more tailored experiences.
- The epoch of deep learning, big data, and artificial common intelligence began in 2011 and continues to evolve. IBM’s Watson won Jeopardy! 2011 by solving complex questions and riddles, demonstrating an advanced understanding of natural language. In 2012, Google launched Google Now, an AI-driven feature that predicted user needs. the chatbot Eugene Goostman in 2014, won a race in the Turing test. By 2018, IBM’s Project Debater showcased AI’s ability to engage in sophisticated debates, while Google’s Duplex demonstrated an AI-powered virtual assistant that seamlessly made phone appointments, fooling humans into believing they were speaking to a person. These advancements highlight the continuous growth of AI, shaping industries and everyday life [20-25].

Classification

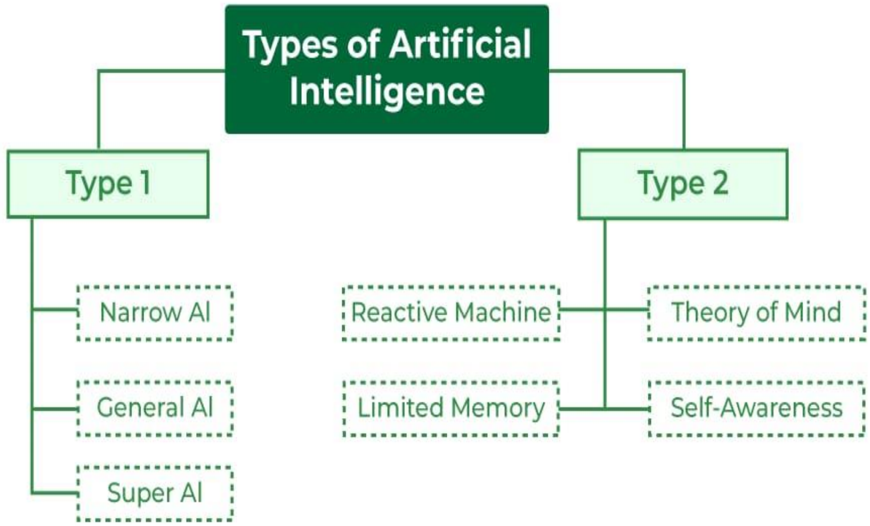

Figure 2: Types of AI

AI can be classified in two different categories: Type 1 and Type 2 (Figure 2) [26,27].

Type 1 classification categorizes AI based on its ability. The first category, Narrow Intelligence (ANI) or Weak AI, is designed to perform specific tasks as facial credit, steering a car, playing chess, or supervision traffic signals. These AI systems operate within a limited scope and cannot perform tasks beyond their programmed capabilities. The second category, General Intelligence (AGI) or Strong AI, denotes to AI that can achieve all intellectual tasks that a human can, demonstrating the ability to adapt to unfamiliar tasks and replicate human cognitive functions. The third and most advanced category, Super Intelligence (ASI), surpasses human intelligence and has capabilities far beyond human abilities, such as excelling in fields like mathematics, space exploration, and artistic creativity. Type 2 classification categorizes AI based on its functionality. The first type, Reactive Machines, are considered for precise applications but lack memory, meaning they cannot use past experiences to influence future decisions. The chess program from IBM is an example of a reactive machine; it can identify the pieces on the board and make predictions about future moves without remembering previous games. Second, there's Limited Memory AI, which can draw on prior experiences to influence decision-making but can't keep that data indefinitely. This kind finds widespread application in driverless cars, as the system uses the data collected to guide its actions. Finally, there's Theory of Mind AI, which posits that human desires, goals, and ideas influence their choices. The public does not have access to this AI just yet because it is in its infancy. Last but not least, there's self-awareness AI, which describes computer programs that can think for themselves. Like Theory of Mind AI, self-aware AI remains theoretical and does not yet exist in practical applications. These classifications help in understanding the capabilities and limitations of AI, guiding future research and advancements in field.

Tools of AI

AI has revolutionized the pharmacy and healthcare sectors by introducing robotic technologies that enhance efficiency, safety, and patient care. The Robot Pharmacy at UCSF Medical Centre is an example of a cutting-edge innovation that uses robotic technology to prepare and monitor drugs. In comparison to human chemists, the technology has demonstrated superior accuracy and efficiency by correctly preparing 350,000 doses of medication. Robots like this can make dangerous chemotherapy meds, as well as other injectable and oral pharmaceuticals, freeing up chemists and nurses to work more closely with doctors and patients [28]. The MEDi Robot, which stands for "Medicine and Engineering Designing Intelligence," is another noteworthy innovation; it is a pain management robot created to assist youngsters who are undergoing medical treatments. The University of Calgary professor Tanya Beran oversaw the development of this AI-powered robot, which aims to ease children's anxiety before a medical treatment by establishing rapport and explaining the process. Although MEDi does not possess cognitive abilities such as reasoning or planning, it is programmed to exhibit AI-like behavior to comfort and guide young patients [29,30]. The Japan Science and Technology Agency, Kyoto University, the Advanced Telecommunications Research Institute International (ATR), Hiroshi Ishiguro of Osaka University, and another Japanese institution worked together to create Erica, a humanoid care robot with a mixed-race face, the ability to mimic human expressions and speech, and the ability to speak Japanese. While it cannot walk independently, Erica can engage in natural conversations, express emotions, and even share personal preferences, such as a fondness for animated films and a desire to visit Southeast Asia. Ishiguro designed Erica's facial features based on an average of 30 beautiful women, making it one of the most visually appealing and intelligent androids developed so far [31,32]. Another remarkable AI-powered robotic innovation is the TUG Robot, designed by Aethon for hospital logistics. All around the hospital, these self-governing robots carry food, specimens, medicine, and other heavy items like trash and linens. One version of the TUG robot is a base platform that can hold racks, bins, and carts for conveying different medical supplies; the other is a fixed and secured cart for delivering sensitive products. This flexibility makes the TUG robot a highly efficient and valuable asset in healthcare settings [33]. The integration of AI-powered robots in pharmacy and healthcare has significantly enhanced operational efficiency, patient safety, and overall medical service delivery, marking a new era in the profession.

Role of AI in Pharma industry

Drug Discovery

Applying AI to drug development progression can improve prospects of developing multiple therapeutic molecules from chemical space, which are currently hindered by inadequate technology [34, 35]. Predicting different parameters, like log P or log D, is impacted by the quantitative structure-activity relationship. This is done to facilitate generation through computations, forecast outcomes, and evaluate the important molecule's pharmacokinetics, biological safety, efficacy, and adverse effects [36,37]. Because of their three-dimensional distribution and properties, molecules must be delocalised in order to traverse the enormous expanse. If you want to prove that your molecules have bioactivity, you should compile all the prior information you can find on their selectivity and placement in databases like PubChem, ChemBank, DrugBank, and ChemDB. The goal of virtual screening is to improve analysis, speed elimination, and selection using a variety of in silico techniques [34]. Drug design algorithms reevaluate the properties in terms of chemistry, physics, and toxicology when selecting a lead compound to produce binding and activity [38]. Biological activity and effectiveness can be enhanced by a variety of physicochemical features [39]. With the use of AI-driven QSAR techniques, QSAR is built with the future use of the drug candidate in mind [40-42]. It could take a decade to control the newly discovered biological activity if traditional approaches for establishing statistical differences are followed [43]. A number of parameters influence the binding to target receptors during the development of new medications, including the drug's solubility, partition coefficient, degree of ionisation, and intrinsic permeability [44]. The Simplified Molecular Input Line Entry System (SMILES) and other molecular descriptors are used by algorithms to forecast binding characteristics [45]. In order to determine six physicochemical parameters, the Estimation Program Interface Suite often makes use of a quantitative structure-property relationship (QSPR) [46]. The ADMET predictor and ALGOPS software have used deep learning and neural networks to predict the lipophilicity and solubility of different substances [47]. A large number of undirected graphs are employed for solubility prediction [48]. These factors can be used to forecast the occurrence of a new chemical entity: mass, refractivity, volume, total surface area, sum of indices, solubility index, rotatable bonds, hydrogen count, and log P [49].

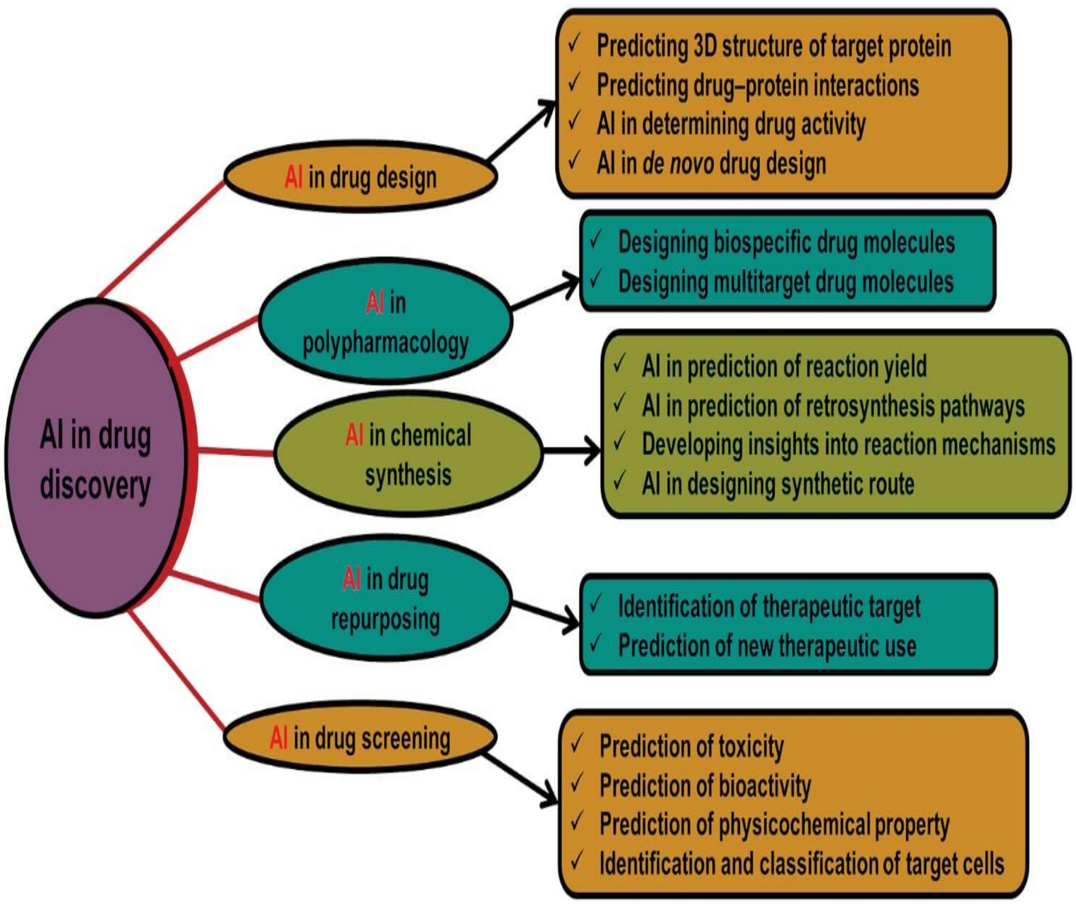

Figure 3: AI in drug discovery

AI in Extrapolation of Bioactivity and Toxicity

Effectiveness relies on how well it binds to the specific receptor or protein of interest. The idea behind interaction based on resemblance is that the target and drug will work together to target the same thing [50]. The similarity ensemble technique and Chem Mapper are both capable of predicting the target-drug interaction [51]. Additionally, the substructure and connectivity, or both, might be considered [50]. Deep learning methodologies have demonstrated enhanced efficacy as they operate independently of the three-dimensional protein structure [51]. Prediction of interactions between Deep Affinity, proteins, and medicinal compounds constitutes the methodologies [52]. In order to prevent negative results, the prediction is crucial. Preclinical studies evaluate toxicity and possible improvement areas after in vitro testing, which are typical forms of initial study. To cut costs, you can use any number of web-based solutions [46]. The National Institutes of Health, the Environmental Protection Agency, and the USFDA are collaborating on the Tox21 Data Challenge to evaluate computational methods for pharmacological toxicity assessment. A novel algorithm named Deep Tox detected static and dynamic information inside chemical descriptors and outperformed all current approaches, while eToxPred was utilised to evaluate the toxicity of tiny chemicals. Using the guilt-by-association principle, TargeTox is able to forecast the harmful effects of pharmaceuticals on specific biological targets [53]. To better anticipate how novel chemicals will behave, a scoring function is useful. The toxicity of a medicine could be predicted with high accuracy by PrOCTOR, leading to its failure in clinical trials. Adverse drug events were also detected [54]. Through the prediction of protein structures, AI can offer feedback by combining computation, geometry, and assessment with structure-based drug discovery [55]. To understand its efficiency and effectiveness, the probability is crucial [55]. Various computer methods can handle problems related to QSPR [56]. With the use of rule-based selection systems, decision-support tools can generate positive feedback based on the properties and regulation of the amount of extra ingredients [57]. As product efficiency and quality become more complex, industrial systems are endeavouring to impart human expertise to robots [58]. The integration of technologies in manufacturing can enhance the pharmaceutical sector. Chemical Assembly employs an innovative platform to facilitate automation [58].

AI in Clinical Trials

Clinical trials require a lot of period and money and are most tedious part of drug discovery. No matter how much effort and money goes into clinical studies, the success rate for those that get FDA approval is really low [59—61]. Numerous bottlenecks exist in clinical trials, which can result in study failure. The bottlenecks encompass a limited number of volunteers, attrition during the trial, adverse effects of the experimental treatment, and conflicting data. Should such a failure transpire during the latter stages of clinical trials, specifically phase III and phase IV, the sponsor must endure a significantly elevated financial burden [62]. Clinical trials that incur substantial expenses also influence the therapeutic costs for patients. Consequently, biopharmaceutical companies incorporate the R&D expenses of unsuccessful studies into the pricing of approved medications to sustain profitability [63]. Designing the trial, recruiting and selecting patients, selecting study sites, monitoring participants, and analysing data are all parts of carrying out clinical trials. Patient recruitment and selection is the most challenging of these processes; as a result, phase-III trials are prematurely ended in 30% of cases and 80% of studies go over their enrolment timelines. Keeping track of trials in a global study involving multiple centres is expensive and time-consuming. Another problem with clinical trials is the huge amount of time it takes to collect and analyse data, which can be quite lengthy from the "last subject's last visit" to when data is submitted to regulatory agencies. Fortunately, digitalisation and artificial intelligence have changed these challenges.

Clinical Trial Strategy, Patient Documentation, Recruitment and Registration

AI models improve superiority of trial designs, optimise patient range by reducing populace variability, and allow for prognostic and predictive enrichment, according to the FDA. The development of clinical trials is only one of several areas where Bayesian nonparametric models (BNMs) have shown to be an invaluable tool. Using a nonparametric methodology, this model is both flexible and effective. Through the use of this idea, finite sets of limited parameters can be used in conjunction with sets of parameters having infinite dimensions. The time needed for clustering and trial design is decreased with this strategy. Some examples of popular Bayesian Nonparametric Models (BNMs) are the Dirichlet process mixing model and the MCMC approach. Clinical trial design makes extensive use of Bayesian Network Models (BNMs) for a variety of purposes, such as dose selection in cancer patient trials, immuno-oncology, and cell treatment. Erroneous dose determination and the identification of future target populations are two potential outcomes of patient variability, which adds difficulty to dosage selection [64]. Adaptive dose selection is implemented across many populations using a Bayesian nonparametric methodology. This allows for the collection of data from varied populations while taking their diversity into consideration. By providing accurate optimal dose selection, these models help to decrease inaccuracy [66]. Dirichlet is used by other designs like modified toxicity probability interval (mTPI) designs. This algorithm automatically sorts people into similar groups based on new data and uses prior approximation to calculate the dosage [67]. Patients' medical records provide crucial information for establishing compliance with inclusion or exclusion criteria, making participant selection the most important component of the experiment. Gathering patient data or conducting new tests would be both time-intensive and expensive. AI enables the integration of patient data through electronic medical records (EMR), encompassing omics data and many other patient information dispersed across several sites, custodians, and formats. An effective method for patient identification and characterisation can be facilitated by this research that makes use of computer vision technologies, as optical character recognition (OCR) and natural language processing (NLP). [65]

Monitoring Trial, Patient Obedience and Endpoint Detection

Another challenge with clinical trials is participant monitoring; however, this can be accomplished with the use of wearable gadgets powered by artificial intelligence. Individualised, real-time, and energy-efficient monitoring is provided here [65]. Recent developments in artificial intelligence have enabled risk-based monitoring (RBM) to emerge as a viable, low-cost replacement for more conventional methods of monitoring. Potential benefits of an upgraded RBM version include reduced trial-site expenses and enhanced data monitoring efficiency and quality. AI-assisted "smart monitoring" employs data visualisation and predictive analysis to enhance data quality verification and trial site performance. Accurate data collection and the effectiveness of the experiment depend on patients following the trial's compliance protocols. Video surveillance and wearable sensors autonomously and continuously collect patient data, enhancing the efficiency of monitoring patient adherence in the trial [65]. AI-enabled medical image-based endpoints and illness detection are far more efficient than manual interpretation, offering cost-effectiveness and speed. Recent advancements indicate that AI has the potential to revolutionise traditional clinical trials, making them more cost-effective, safer, and expedited.

AI used in pharmaceutical industry

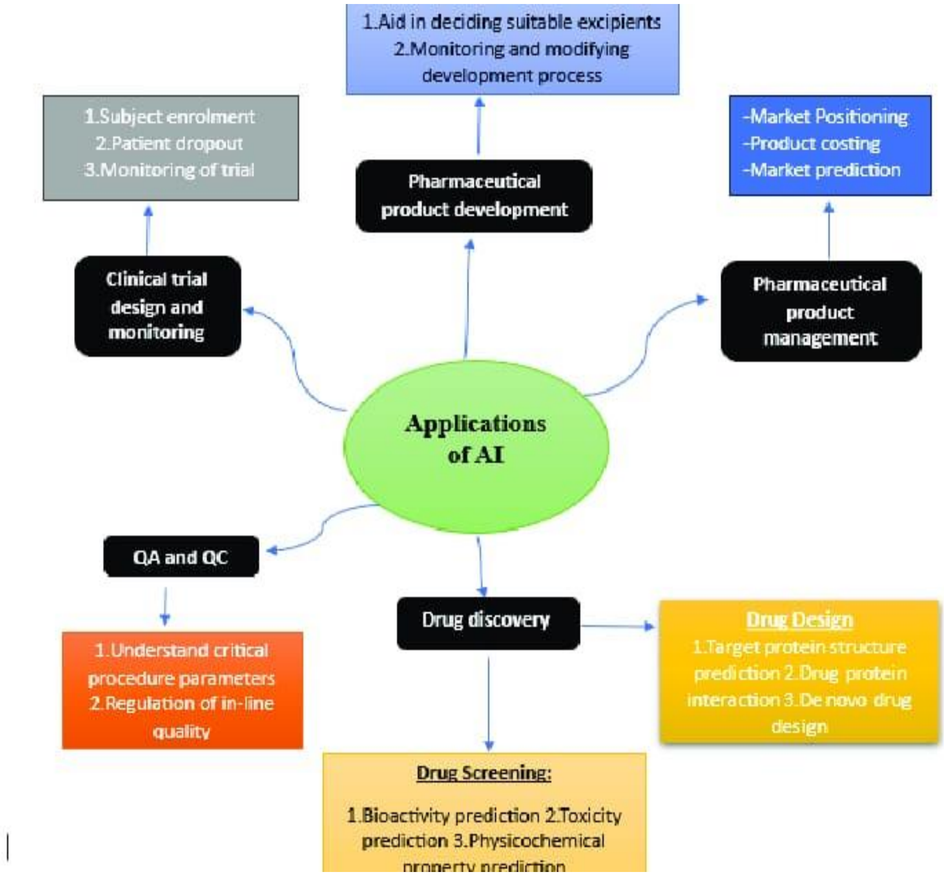

Figure 4: AI Application in pharmaceutical industry

Topmost 10 Pharma Companies Utilising AI [65-68]

This is the Fourth Industrial Revolution, characterised by the dominance of AI globally. AI will have the greatest effect on the healthcare and pharmaceutical industries. Using AI and ML for drug discovery, clinical research, disease diagnostics, new medicine creation, forecasting, and data analysis, we will take a look at the top 10 pharmaceutical companies of 2019 that utilised these technologies.

1. Pfizer

Pfizer and IBM Watson have established a partnership to develop new pharmaceuticals. A partnership to speed up immuno-oncology drug discovery was announced in December 2016 by Pfizer and IBM. Pfizer began working with an AI company in May of 2018. Pfizer has joined the Machine Learning for Pharmaceutical Discovery and Synthesis Consortium, which was launched by the Massachusetts Institute of Technology. Pfizer and XtalPi, a Chinese tech startup, have established a partnership to improve the drug discovery process and increase the molecular stability of an organic compound.

2. Roche

Retinal thickening and possible blindness are symptoms of diabetic macular oedema, a disease associated with diabetes for which Roche has created machine learning diagnostic methods. Ophthalmologists can benefit from more tailored treatment plans thanks to AI algorithms developed by Roche using its large clinical trial database, which can estimate disease prevalence, progression risk, and therapy response.

3. Novartis

Upon assuming the role of CEO at Novartis, Vasant Narasimhan initiated transformative measures for integration of AI into company, establishing a global benchmark for others. Novartis successfully deciphered cancer pathology images with artificial intelligence. Novartis collaborated with the tech startup PathAI to develop a method for cancer diagnosis.

4. Johnson & Johnson

AI analysis of data from a recent real-world trial by Johnson & Johnson found that XARELTO® (rivaroxaban) significantly reduced strokes, stroke severity, and stroke-related mortality compared to warfarin in newly diagnosed patients with nonvalvular atrial fibrillation (NVAF). According to the study, XARELTO® reduced the risk of experiencing the most severe strokes and reduced the overall number of strokes by 18% compared to warfarin.

5. MSD (Merck & Co., Inc., Kenilworth, New Jersey, USA)

The 'Velocity Health' venture brings together Merck and Wayra UK, a subsidiary of Telefonica, a Spanish telecommunications firm. When it comes to healthcare, the Velocity Health programs put an emphasis on prevention, particularly in the areas of diabetes and cancer.

6. Sanofi

Recursion Pharmaceuticals has collaborated with Sanofi Genzyme, the global specialised care division of Sanofi, to deploy its therapeutic repurposing technology aimed at discovering new applications for Sanofi's clinical-stage medications in various genetic disorders.

7. AbbVie

Abbvie is employing AI in a discreet manner. It does, however, possess a trusted project concomitant with Atomwise. In September 2016, AiCure and AbbVie collaborated to utilise an AI-driven patient monitoring tool to enhance adherence in a phase 2 schizophrenia trial conducted by AbbVie.

8. GlaxoSmithKline (GSK)

GSK has created an internal AI division and is utilising AI for drug disambiguation. Originally, it was titled "Medicines Discovered Using Artificial Intelligence." Eventually, it became known as the "In silico Drug Discovery Unit."

9. Amgen

Amgen has invested in GNS Healthcare, a precision medicine firm. Machine Learning for Pharmaceutical Discovery & Synthesis Consortium, which Amgen joined in May 2018, was announced by MIT. Owkin is a machine learning firm that focusses on medical research; Amgen is one of their collaborators.

10. Gilead Sciences

In April 2019, Gilead publicly announced the application of AI in pharmaceutical development. This month, Gilead and the clandestine firm Insitro established a strategic alliance. The collaboration will focus on NASH, or nonalcoholic steatohepatitis. Pharmaceutical Technology monitors current job openings from pharmaceutical businesses that include AI or related technologies.

Future Scope of AI

- AI in data analysis.
- AI in cybersecurity.
- AI in scientific research.
- AI in transportation.
- AI in healthcare.
- AI in domestic environments.
- AI in scientific research, among others.
- The domain of science is experiencing substantial progress in AI. AI can manage and process substantial volumes of data more rapidly than human cognition. This makes it optimal for research involving sources with substantial data volumes. In this domain, AI is already advancing significantly [66].

- **AI in Cybersecurity**

AI is also contributing to the field of cybersecurity. The threat posed by hackers is increasing as an increasing number of enterprises transition their data to cloud computing and IT networks.

- **AI in data analysis**

AI and Machine Learning provide significant advantages in data analysis. Iteration enhances AI algorithms, hence improving their accuracy and precision correspondingly. Data analysts can manage and process extensive datasets with the assistance of AI.

- **AI in Transportation**

AI has been utilised in the transportation sector for numerous years. Autopilot has been utilised to navigate aircraft in flight since 1912. An autopilot system governs a vehicle's trajectory, however its application extends beyond aircraft. Autopilot is utilised by vessels and spacecraft to aid in maintaining their trajectory.

- **AI in residential settings**

AI has established a distinctive role in households as Smart Home Assistants. Two prominent smart home devices that enable various tasks with voice commands are the Amazon Echo and Google Home.

- **AI in Healthcare**

The medical business is now employing this technology due of its advantages. Medical professionals and researchers are reaping numerous advantages from AI.

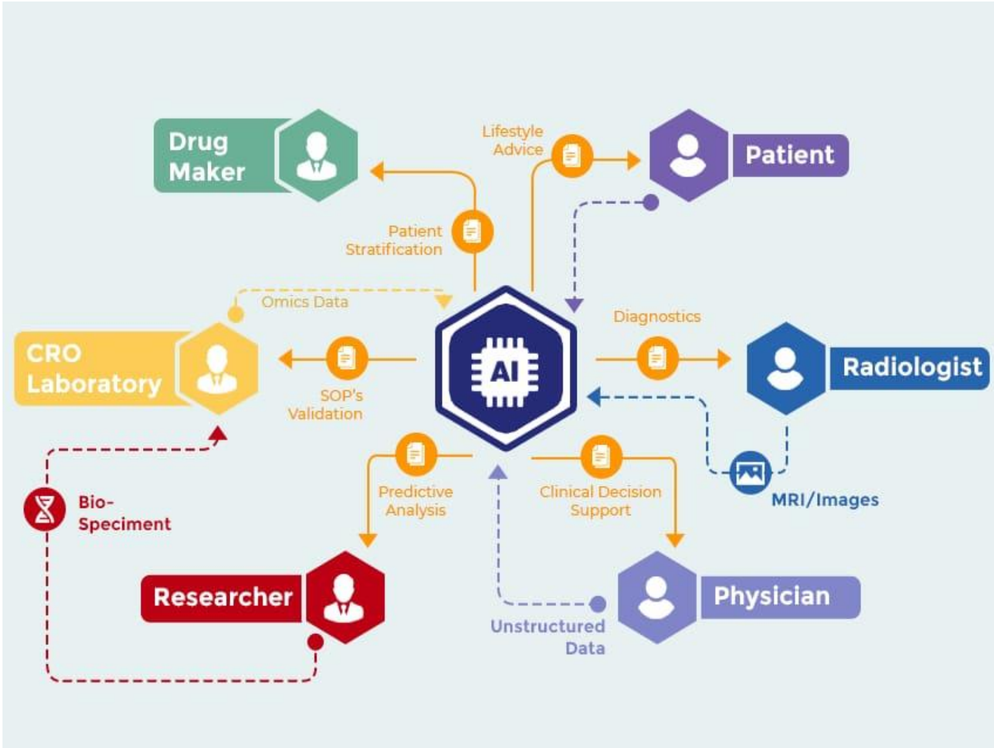

Figure 5: Future scope of artificial intelligence

ADVANTAGES [68]

- AI is now accessible to the pharmaceutical sector to tackle concerns that were earlier elsewhere the scope of basic data analysis.
- AI can execute particular jobs with more precision, hence decreasing costs and enhancing productivity.
- AI provides actionable insights that can significantly enhance clinical trial results.
- A thorough comprehension of market dynamics, consumer performance, and their interconnections.
- It aids the industry in identifying candidates for clinical trials and enables corporations in detecting efficacy and safety concerns with drugs at a significantly earlier stage.
- Antivirus detection systems are enhanced by it, and it facilitates the development of novel AI algorithms.
- It also facilitates the selection of patients for clinical trials inside the industry.
- If AI were meticulously designed, it would commit fewer errors than humans. They would be exceptionally rapid, precise, and accurate.
- In future, robotic surgery will exceed human capabilities in precision across many surgical procedures.
- AI can now comprehend and analyse extensive biological data using deep learning and normal language processing, thereby transforming drug discovery process.

DISADVANTAGES [68]

- AI generally lacks the human element as it is unable to engage in independent reasoning and can solely adhere to directives.
- The subsequent generation can be significantly compromised by it.
- Initially, mass destruction can be managed.
- Unemployment will ensue if robots replace humans in all occupations.

- May incur significant expenses for construction, maintenance, and reconstruction.
- Improper operation of machinery can rapidly result in damage. A multitude of individuals harbour apprehensions that, at the absolute least.
- It has been partially documented that humans get reliant on AI and experience a decline in cognitive abilities due to cellphones and other technologies.
- AI possesses the potential to surpass human capabilities and subjugate them as automatons.

CONCLUSION

AI could enhance global healthcare by identifying a pharmacological foundation for drug research and development, utilising technologies such as artificial neural networks (ANN), computational fluid dynamics (CFD), and robotics, in response to contemporary challenges and promising prospects. AI insights could be utilised to more accurately characterise patients and forecast outcomes. Empirical evidence was utilised to get these conclusions. Consequently, AI has generated appealing opportunities for pharmaceutical businesses developing a new generation of computational gadgets capable of informing clinicians about the effects of genetic variations that modify DNA within a cell. We must advance while being aware of and understanding the implications of each new technological advancement. Given that we are, in my view, experiencing an era of AI enlightenment, we ought to embrace this transformation, utilise AI to facilitate it, and strive to cultivate a superior society.

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