

Review Article

Clinical Research and Artificial Intelligence: How AI Is Changing Clinical Research

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Abstract

Medicine is quickly transitioning as artificial intelligence (AI) adopts the new and improved type of machine learning for better diagnosis and treatment of diseases in the various sub-specialties of practice. The enhancement of computation rate raises the potential of AI algorithms and their value for multiple domains like radiology, where some experts suppose that AI can replace radiologists. These questions are essential when determining whether specific AI applications will eventually replace doctors or only assist them in their work within specific medical specialties. This paper ponders the iridescent role of AI in clinical trials and how its drug invention process will result from innovative learning in the future. The technology engages the role of AI in clinical decision support, the latest developments in precision medicine, and the prediction of drug properties and active ingredients. The paper showcases AI contributions to remodeling clinical trial designs and model exchange and using AI to carry out the intervention. Among other things, it speaks about AI in the acquisition of the EHR, in the course of authorization of the trial, and in addressing some of the significant challenges such as data availability and perpetual vigilance. In addition, a few discussions concerning clinical AI algorithm errors and the defects of conventional trial procedures are also incorporated at the end of the paper to portray the role of AI in present clinical research more sharply.

Keywords

AI, Radiology, Technology, Clinical Trial, Clinical AI Algorithm

1. Introduction

The term AI was invented in 1955 [1]. In common practice, AI is a computational process, and the CS branch studies how to get machines to exhibit 'intelligent behavior.' Most works indicate that AI will gradually be accepted and valued as an effective solution to numerous problems concerning healthcare management. Notably, the market for artificial intelligence clinical trial solutions for patients globally is

predicted to be USD 1,969 million by 2030. Analyses predict that clinical research and development's second-fastest-growing discipline will increase at a CAGR of 22.0% between 2023 and 2030, as illustrated in Figure 1 below. Forecasts indicate that clinical research and development, the second fastest-growing discipline, will have an annual growth rate (CAGR) of 22.0% between 2023 and 2030,

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as shown in [Figure 1](#). The creation of AI-based technologies for medical purposes has positively impacted the clinical research process and will only advance further. DL, NLP, ML,

Cognitive Science, Robotic Automation, Automated Reasoning, Computational Statistics, and Neural Nature constitute eight AI sciences (overlapping [Figure 1](#)) [2].

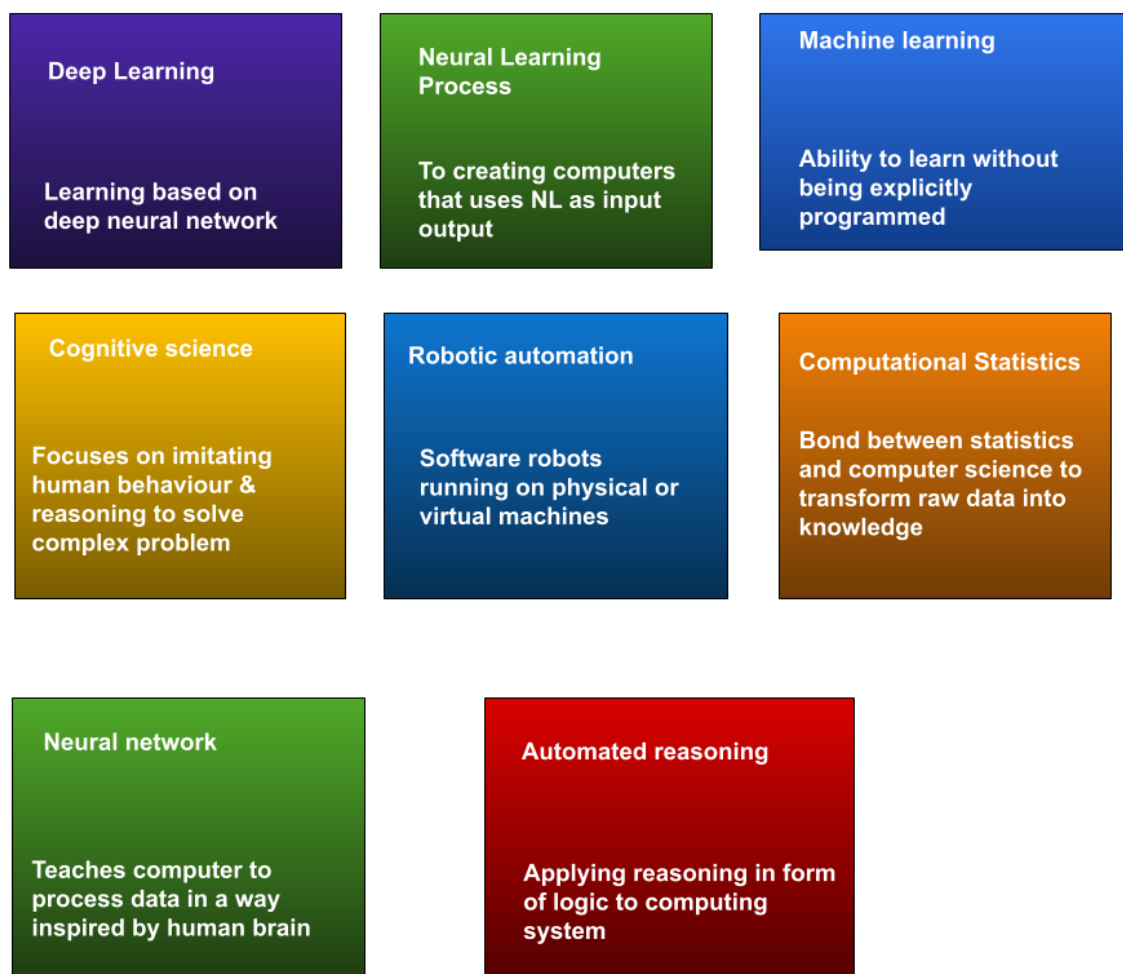


Figure 1. Science encompasses all aspects of Artificial Intelligence. [3].

Background

The most current use of AI in global healthcare is predicting new hotspots using contact tracing and aircraft passenger data to combat the coronavirus (COVID-19) pandemic. Government officials employ contact tracing as a disease control strategy to stop the spread of an illness. Touch tracing involves contacting others who have come into contact with an infected person, alerting them, and giving them quarantine instructions to prevent the disease from spreading. According to Apple Newsroom, tech behemoths like Apple and Google have teamed up to develop a contact tracking platform to leverage artificial intelligence technologies via smartphone application programming interfaces (APIs) [4]. A Canadian company creates software that reduces the likelihood of infectious disease epidemics. It correctly predicted the global spread of COVID-19 and was the first to publish a scientific

report on the virus. The business uses cutting-edge methods, including automated infectious disease surveillance, machine learning, and natural language processing (NLP). It can forecast and monitor future outbreaks by evaluating millions of articles daily from 65+ nations, as well as travel information, temperature, airline routes, climate changes, and local livestock data [5]. In [6], they discussed the application of AI in education and the current personalized learning system, smart material consumption, the pervasive uses of AI and how these have been used to benefit student needs, focusing on the context of the USA. AI is becoming an increasingly essential part of medicine today and will continue to grow in its applications to the field include patient diagnosis, drug research and discovery, improving patient-physician interactions, transcribing medical records and prescriptions, and providing remote treatment discussed in [7].

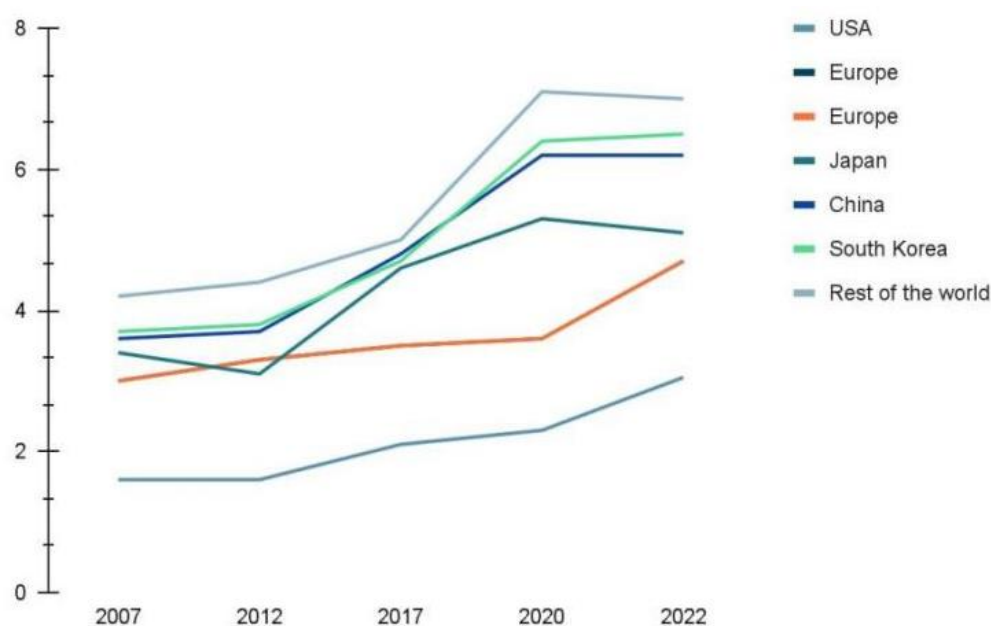


Figure 2. Global pipeline of AI bringing success in clinical trial [8].

AI has been instrumental in minimizing guesswork and exhausting manual efforts to determine the ideal clinical trial eligibility criteria. Trial Pathfinder is used in Roche, Genentech, and AstraZeneca, and Sun's lab has built AutoTrial, which uses a large language model to generate appropriate trial criteria for a description. After eligibility criteria have been defined, other tools, such as Criteria2Query, developed by Chunhua Weng's lab, assist in identifying patients to include in a study by translating criteria into actual SQL queries. Weng has also developed other tools, such as DQueST and TrialGPT, which provide helpful information to the patients by limiting the search and analyzing the compatibility of the trials. AI accelerates clinical research improvement and helps expand the patient population to include those previously left out of trials due to age, such as children and older people. AI also assists patients with complicated diseases and terminal illnesses in finding trials. Also, the number of control patients is minimized using the method of a digital twin introduced by the start-up Unlearn. Digital twins use an early dataset to create an experimental patient and forecast a result. Hereby, the density of the control group can be cut down by 20-50%, which is helpful for researchers and patients as the likelihood of receiving a placebo can also be curbed [8].

Recently, in 2020, based on deep learning, a phase I clinical trial of over 7000 drugs was carried out and advanced to the regulatory submission phase. This is 3000 drugs more than that stated success rate cutting across in 2007. Indeed, for the last 15 years, the situation has remained the same: the US maintains its leadership above 40% share in the global R&D line. IQVIA pinpointed that one biotechnological firm established in Durham, North Carolina, has its headquarters in China, and from the year 2007 to 2022, the proportion of the business increased from 2% to 15%.

This paper makes a unique and highly valuable contribution to the knowledge of how and to what extent AI is reshaping clinical trials and the entire sphere of healthcare. In doing so, it offers a broad perspective on how these innovations benefit success in trial outcomes, thereby presenting a pipeline of AI technologies in clinical trials worldwide. Note that the article focuses on the importance of the AI approach to identifying new drugs and their properties, which improves the accuracy of clinical decisions and guarantees individualized therapeutic approaches.

Moreover, the paper highlights the communication aspects that need to be embraced within clinical trials, particularly in model exchange. Such an approach implies integrating several AI tools, which results in the best possible outcomes for trial proceedings and higher accuracy. Another new theme focuses on how AI enables the redesign of clinical trials, enhancing the previous and new clinical trial paradigms for the new personalized medicine paradigm.

The paper also comprehensively explains AI's current and future possibilities in healthcare, starting with innovative clinical trials and ending with precision medicine. It underlines how AI continues to evolve in mining relevant information from Electronic Health Records (EHRs), patient triaging and drug approval, and efficacy and toxicity prediction.

At the same time, the paper is devoted to stimulating opportunities for applying AI and answering severe questions, such as the mistakes of clinical AI algorithms or classical clinical trial problems. It provides continuity regarding monitoring AI and data availability, an essential perspective for enhancing AI implementation while stressing the importance of data quality and validation.

This paper's study involves doctors researching patients from different countries worldwide. Thus, each part of the

study has a different demographic and environmental setup. The legal and ethical aspects vary according to the government in which the research is conducted. Since this is a worldwide study, each country has different legal and ethical issues. This paper's research uses AI tools like the Electrical Health Record (EHR) and many other ML and NLP-based tools.

2. Methodology

This paper uses a qualitative approach to investigate how AI changes clinical research. It focuses on systematically evaluating and analyzing the body of current literature. The technique draws on these breakthroughs' theoretical and practical implications and is similar to other research on integrating AI in healthcare and clinical settings.

3. Clinical Decision Assistance and Precision Medicine

Personalized therapy, or precise or tailored therapy, is a therapeutic strategy that individualizes treatments according to the necessities of the individual's body and characteristics. These include genetics, lifestyle, environment, and biomarkers [9]. This patient-specific approach was developed because traditional treatment methods are costly, time-consuming, and less effective. It enables clinicians to make correct decisions and administer the proper treatment.

So far, we can see that AI is emerging as a valuable technology to support precise medicine using accurate data analysis. Even in personalized treatments, it can track down patient medication response [10]. For instance, while embracing data gathered from gene expression, it has been established that AI can predict chemotherapy to chemical compounds with accuracy rates of more than 80 percent for various drugs.

Similarly, empirical studies employing EHR have demonstrated that AI can accurately anticipate antidepressant outcomes, calling for the further adoption of clinical support decision systems to improve patient anticipation. Implementing AI in the healthcare sector can enhance patient health and increase the success rate in the healthcare system [11, 12].

Although ML and genome analysis have improved treatment response and prediction, prospective and retrospective clinical research is necessary [9]. These studies require creating sets, which are nevertheless needed to provide insight into the performance of AI algorithms in real-life clinical environments and facilitate the improvement of artificial intelligence-based clinical decision support systems.

4. Predicting Drug Properties and Activities

Knowledge of drug molecules' properties and activity is crucial for their characterization within the context of the human body. ML methods have been used to predict ADME and physiochemical properties of drug-like compounds, as shown in Figure 3. ChEMBL & PubChem, for instance, boasts billions of records on the molecules, which are utilized when developing drug discovery machine learning systems. For example, Convolutional Neural Networks (CNNs) provide molecular fingerprints for molecular graphs and output solubility and biological activity. These models can also predict new features and select the molecules with the desired features. Toxicity is also indicated using machine learning, including DeepTox to measure the toxic impact of compounds or MoleculeNet to compute toxicity and other characteristics from molecular information. These advancements enhance drug discovery and facilitate the more effective discovery of promising compounds [2].

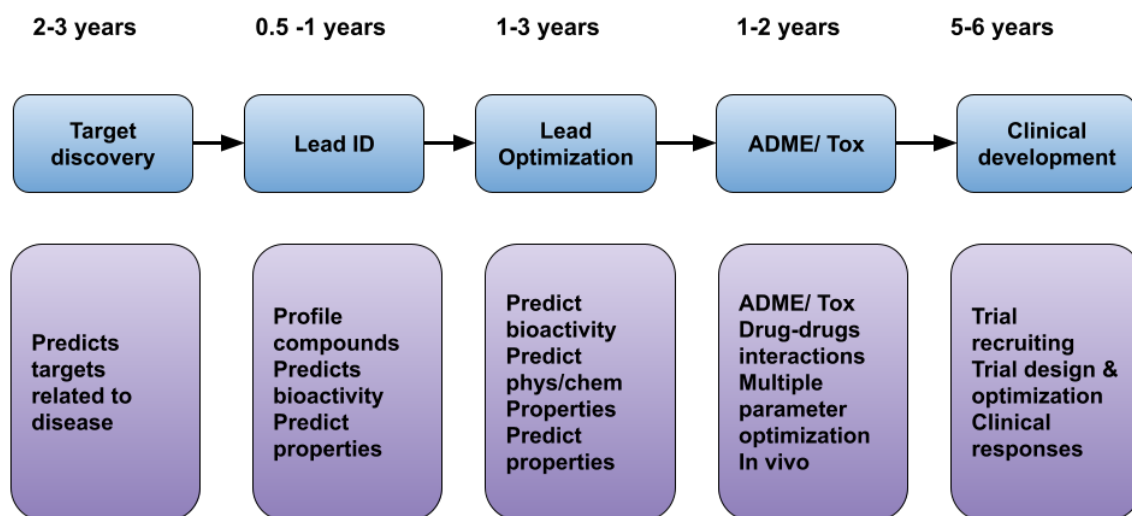


Figure 3. Potential for ML in finding and developing small molecule drugs [2].

5. Collaboration on Clinical Trials and Model Exchange

Doctors from various disciplines don the brand to help fight the coronavirus. Levels of flexibility in data, a model, and code, geographical and regional adaptation of the AI application, and interdependent collaboration become critical when applying technologies to resolve fundamental problems internationally [13].

AI requires data so that it can work effectively on how it is work is designed. Data sharing related to COVID-19 is steadily increasing across three levels: local, national, and international. These are sequences and maps data, genomic records of previous cases, proteomics, clinical, image, event, epidemics, movement, comments, medical photos, articles, and publications. Data sharing has, however, been a significant focus, and at the same time, some people have expressed their worry about data sensitivity. A lot of care should always be taken when working with or moving any sensitive information. For improving the development and distribution of such applications worldwide, some preceding works could be beneficial in conforming data, model, and code conventions. This will be international, open integrative, compatible, standardized measurements to exchange data. Hence, the cooperation and networking both within and between various groups as well as various geographical regions will be enhanced [14].

Open source advances in collaboration with various stakeholders through AI have the potential to enhance knowledge dissemination and strengthen the capacity of the national health system. For example, the Epidemic Intelligence from Open Sources (EIOS) network utilizes Open Source to identify, confirm, and assess threats in real-time public health risks [15]. International healthcare institutions, governments, interdisciplinary organizations, and research institutes distinguish themselves but strengthen their actions upon early outbreak identification. Scholars in epidemiology assert that applying international approaches and harmonized databases helps address the management of complexities and responses at global, country, and local levels. Therefore, as the dynamic pattern of the pandemic has demonstrated, trying to understand the epidemiological characteristics and risk factors in different subpopulations would require considering the hospitalization, the containment, the physical structure of the healthcare facilities, and some social implications of COVID-19 [15]. Apart from data sharing, only a few initiatives employ the transfer of trained AI models for any of the above uses. Among such future problems, specific computational requirements, design and infrastructure requirements, documentation and related issues, questions of verification and interpretation that arise, and certain legal aspects regarding ownership and secrecy were pointed out. The swap is an AI-based technology that could provide faster options for addressing the situation by switching the authorized and the

pre-trained AI models. The useful ones could include the one that can diagnose diseases from images, the one that can predict the status of a patient, the one that can distinguish between truth and falsehoods depending on patterns spread across social media, and the one that can extract knowledge graphs from massive heaps of “Scholarly articles” [16, 17].

6. Reshaping Clinical Trial Designs

AI solutions are relevant to medicine, choosing a cohort, results, adherence, and endpoints. They also allow hypotheses to be formed and revised more rapidly and accurately, thus increasing global understanding of the type of dynamic diseases [18]. For example, biomarker confirmation and protocol expansion all increase the sufficiency of cohort composition. Thus, a more significant improvement in the result is visible if the AI techniques are implemented in the design.

However, to reduce the error margin of the AI outcomes, additional cooperation is employed to develop methods for handling extensive information sets [19]. Furthermore, inside a virtual control arm, illness development might be predictable using well-engineered AI algorithms that have total access to ample quantities of high-quality data [20]. A more interesting solution may be to replace the placebo limb with the entirely fabricated limb based on the synthetic data [20]. That will likely result in several advantages: the cost, the patent and site burdens, and the time saved on CT scans. However, much time and research effort are needed to sort out and validate virtual control arms in coordination with training sets built into working CTs. Moreover, synthetic control arms may help groups of patients who want to participate in the trial but are unwilling to take the risk of being randomized between active treatment and placebo and address the issue of using the placebo control arm [17]. Building the required fundamentals and transforming the interdisciplinarity needed for such first-string technology involves a lot of dedicated work and time. Therefore, ethical issues remain another difficulty arising from the inability to effectively address privacy and misuse of health information [21].

6.1. Current Use of AI in Healthcare

An example of recent AI technology use in global healthcare contexts is contact tracing and the number of travelers by flight to predict new hot zones in the COVID-19 pandemic. Transmission control is a disease control method whereby the authorities notify individuals who have been in close contact with an infected person to self-isolate. For further improvement in this aspect, Google and Apple also brought proper exposure to developing a contact tracing platform using artificial intelligence with the help of application programming interfaces on smartphones. Users and authorities are also able to report lab results. In addition, if location services are enabled, the application can inform people

who might have been close to an infected person [22].

Moreover, the outbreak risk software is presented by a Canadian company, BlueDot, which aims to minimize contact with pathogens. BlueDot was the first company to produce a scientific paper that correctly modeled the world's COVID-19 transmission. The company uses NLP, ML, and automatic disease detection to review approximately a hundred thousand articles from sixty-five countries daily, as well as travel data, flight routes, climate, and local cattle data, to forecast future incidence [21].

6.2. Intelligent Clinical Trial

The predominantly linear and sequential character of traditional clinical trials remains the only efficient method to investigate the efficiency and reliability of new drugs. This straightforward approach based on different stages of RCTs was mainly developed to assess 'over-the-counter' medicines and has changed little in the past two decades. However, clinical development's potential productivity and outcomes may be achieved more efficiently using AI because it reduces the time required for clinical trials. It is the third of a series of papers exploring the effects of AI on the biopharma value chain [24].

In recent years, biopharma companies have been able to source many internal and external RWDs to develop various product data. However, many organizations have failed to make sense of this data due to a lack of expertise and proper tools. Predictive AI models and analytical tools can help better understand diseases, match patients and investigators, and increase creativity in clinical trials [25].

Indeed, algorithms' strong technological support makes it possible to perform tasks such as cleaning, compiling, coding, storing, and updating clinical trial data. However, improvements in electronic data capture (EDC) systems limit human mistakes and result in better system integration [25].

7. Error in Clinical AI Algorithms

AI algorithms are critical in clinical procedures within contemporary medicine since they offer aggressive treatments through intense discriminatory modes. Nevertheless, this success depends on strong QI frameworks to contain avertible failures since the basis of these models is built around continuous improvement. This means that QI entails working on cycling operation procedures to reduce mechanisms of variation and ensure constancy to support algorithmic stability in the fluidity of clinical practice.

According to AI algorithms, the correlation between patient variables and outcomes can reliably be identified. These correlation-based models have high internal validity only when held within the given conditions of the training data. Nevertheless, they may perform sub-optimally in heterogeneous clinical scenarios where patient population characteristics may change over time or across different levels of care. For

example, COVID-19 has put the feasibility of an ML algorithm developed to assess hospital admission risks from the ED data under threat. Reducing the importance of checking the respiratory rate and arrival mode [24].

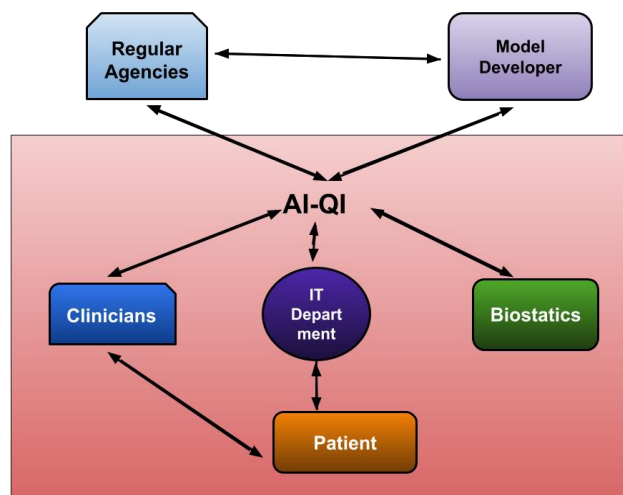


Figure 4. AI-QI is an ongoing exercise part of the participative process.

Since AI-QI is heterogeneous, it requires strict integration between doctors, hospital managers, IT experts, biostatisticians, modelers, and officials. Hospitals will need standardization as to how the shows constantly track the performance of the model, how the end-user gets a notification of the latest performance, and how the model gets updated or stopped if the performance is significantly degrading to ensure the safety and effectiveness of all AI-based algorithms applied in the hospital setting [23].

7.1. Issues with the Traditional Clinical Trial Procedure

Billions of dollars (about USD 1.5–2 billion) are spent on drug testing before introducing a new medication. The medication development process takes an average of 10 to 15 years, of which 5-7 years are required for clinical trials and another 4-6 years for research and development (R&D) [24]. Most of the money is spent on clinical studies, phase III trials being the most complicated and time-consuming. One of the most significant barriers to developing novel medications is the high failure rate of clinical studies-less than one-third of the compounds in Phase II advance to Phase III. Over one-third of Phase III compounds never receive regulatory body approval. The FDA approves just one out of every ten compounds that start clinical trials because the chances of a chemical passing through each study stage differ, as shown in Figure 5. Each failed study causes a loss of US\$0.8 to US\$1.4 billion. Surprisingly, only 10% of these costly and lengthy clinical studies succeed.

Because it is difficult for humans to collect different data sets for clinical trials and retain records of every patient taking part in the trial, AI helps resolve all these problems in the clinical trial process. AI increased the success of drug development by advancing the R&D domains. This also in-

cludes novel target identification, drug candidate selection, biometrics data analysis from wearable devices, and predicting drug effects in patients with diseases [25]. Clinical trials are the most recent field of drug research that acknowledges and permits AI's positive effects.

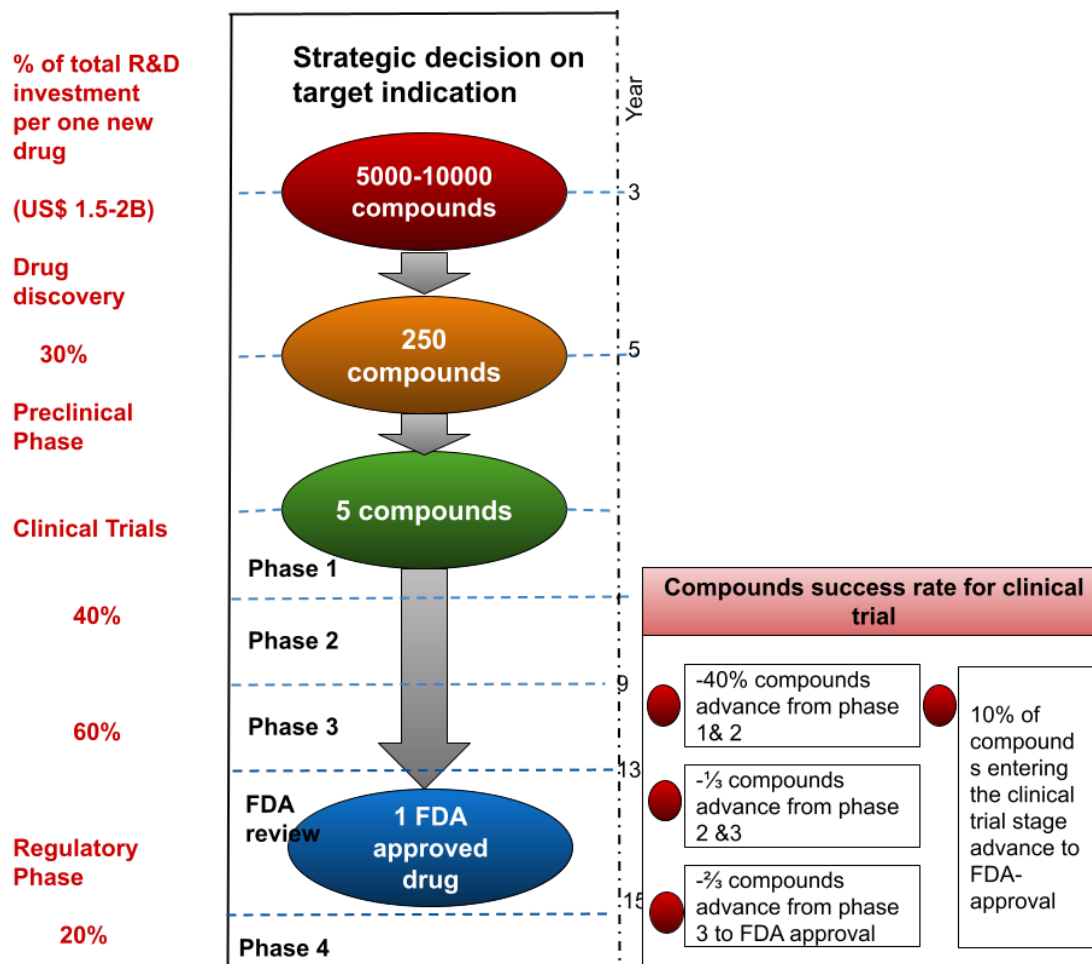


Figure 5. The drug development cycle [26].

7.2. Result

According to research, the drug development process takes a substantial amount of time and money as the drug testing phase consumes between USD 1.5–2 billion over an average period of 10 to 15 years. Most of these expenses come from Phase III clinical trials. The clinical trial failure rate is a significant problem since Phase II compounds advance to Phase III in less than one-third of cases. Still, over one-third of Phase III compounds fail to obtain regulatory approval. The failure of each research project causes a monetary loss between USD 0.8 billion and USD 1.4 billion, while just 10% of clinical trials lead to successful results.

The improvement of clinical trials and the drug development process depends heavily on AI implementation recognized by experts. Significant advancements in R&D have

become achievable through AI because it enables innovating drug candidates to analyze wearable device data and predict outcomes, boosting clinical trial performance. Modern society recognizes AI integration as a significant force that positively affects clinical research and drug development operations.

8. Challenges of Implementation

As a result of improved computing capability and easy-to-implement popular AI platforms, the rate of AI-based research and clinical applications will rise. Researchers and clinicians will likely be 1st to be involved with AI. Among all the medical departments, cardiovascular illness is the most complex and the biggest one. It is one area where AI can benefit the success rate of the patient's treatment. The current non-AI issues are distinct from the barriers linked to the AI

methodologies, and therefore, the current barriers include the following infrastructural obstacles. First, open data is less provided in some sections due to privacy issues than in others. Scientific corporate and non-corporate subjects need a data structure sufficiently protected by protection systems.

Besides, data are archived on several servers and, occasionally, on paper by conventional means. AI can only be valid if it creates an improved prognosis or predictive model. Hundreds of forecast factors in various systems don't accept AI. They require carefully made human input as AI can sometimes mix up patterns. This will be grouped with the requirement to build robust data structures. It is also important to keep legal and ethical issues equal. This means that the earlier conventional paradigm of logical or 'bite-size' learning towards medical device regularisation is no longer adequate because the AI learns from data or patterns that are input into it. Besides, the current guidelines do not state how far the unforeseen clinical consequences of AI gadgets are held responsible [26].

The Food and Drug Administration has recently unveiled a new and dynamic assessment classification for AI devices. It also discusses device changes after deployment. However, there are several general tendencies today concerning the standardization of medical AI research. Some, primarily young clinicians, are willing to accept these modifications, as documented in various surveys. Representative surveys of the present studies showed that 70% of the residents in radiology wished they had received more extensive instructions. Instead, nearly 95 percent of respondents said they would gladly take AI-related courses if provided with that [26]. It is possible to count on several pilot well-designed researched works based on synthesized big data in the foreseeable future that will predict a new medical paradigm in the middle of the following decades.

8.1. Continuous Monitoring of AI

In large, dynamic sociotechnical systems, AI will be employed and encountered in its utilization, usability, interpretability, and current capabilities that inform performability, safety, emergent behavior, and ethical concerns in that order. One more question that should be asked is about prejudice when delivering services, or, in other words, the possibility of shaping resource and priority distribution with the help of the algorithms. The study of the clinical and patient levels distinguished by interventions and outcomes and the organizational and social levels is required—the state where the patient or the practitioner, treatment options, and patients might change over time. Thus, constant supervision is needed when the algorithms are used to ensure and correct them if necessary. A similar kind of monitoring is required for Dynamic algorithms, which self-transform based on what is obtained from practice data and clinical studies. One is the ability to detect and assess what we might call 'potential' or 'hidden' problems,

for instance, an issue of approximately 0.015 between two values deduced from a chart or some improper configuration [27]. Hence, the assessment is most likely to shift to a recurrent process to ensure the continued effectiveness of the intended AI application, including those with a dynamic algorithm.

8.2. Availability of Data

Data gathering is the initial phase in creating an artificially intelligent system after issue identification and solution strategy formulation. Large amounts of high-quality data must be available to develop models that function effectively. Due to recent data breaches by large organizations and concerns about patient privacy, the topic of data gathering is cloaked in controversy. Increased computing and analytical capacity and the capacity to store enormous volumes of data are the outcomes of technological advancements. Technology like genome analysis and face recognition makes it possible to identify a person from a group of individuals. Patients and the general public are entitled to privacy and the freedom to decide what information they reveal. These days, data breaches allow patient information to end up in the hands of insurance companies, which can lead to a patient's medical insurance being denied because the insurance company believes the patient is more costly because of their genetic makeup. Due to patient privacy, data availability is constrained, which limits model training and prevents a model's full potential from being realized [26].

8.3. Major Issues That Impact Clinical Trials

The capacity of research sites to recruit and maintain a sufficient number of patients for the study is typically one of the main barriers to the success of clinical trials, notwithstanding their complexity. It has nothing to do with medical or regulatory concerns. Participant enrolment issues may result in expensive delays or the trial's early discontinuation. Approximately 55% of clinical trials are prematurely ended because they cannot attain full participation, and over 80% of studies miss their initial enrolment deadlines. Clinical trial sites fail to reach their recruiting goals for several reasons, including lack of research support, logistical challenges, and budgetary constraints. Some of the primary obstacles that affect the sites are graphically depicted in Figure 6 [28].

8.4. Effect

The graph shows that more than 60% of research fails due to stuffing and retention, 50% due to wrong patient recruitment, more than 30% due to study startup and trial complexity, and less than 20% due to physician interest, technology, and trial, access to patients, remote monitoring, decentralized trials, and ethical regulatory issues.

The issues & its impact %

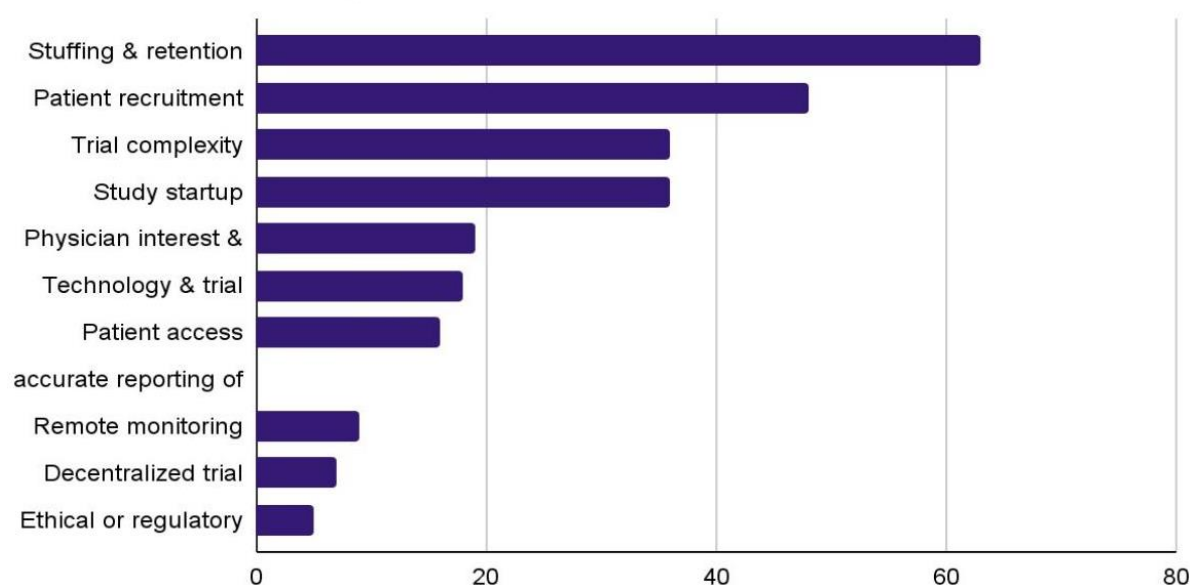


Figure 6. Significant problems that affect clinical trials and the percentage that they affect [29].

9. Applications of AI in Clinical Trials

AI is increasingly utilized to optimize clinical trial eligibility criteria, enhance participant diversity, and reduce sample size requirements. Liu et al. developed an open-source AI tool called Trial Pathfinder, which leverages electronic health record (EHR) data to simulate clinical trials by integrating data based on different inclusion criteria and analyzing the overall survival risk ratio (the difference in survival rates between patient groups) [30]. Trial pathfinder used real-world data (RWD) to simulate data from completed non-small cell lung cancer trials, revealing that specific commonly used criteria, such as laboratory test results, had little impact on the trial's effect size. If questioned for increasing these criteria, the complete potential patient enrollment doubled, and overall survival relative risk decreased by 0.05 per Patient Year analysis. This work revealed that after the treatment, only 30 percent of patients were, according to the initial inclusion criteria, and these limitations did not reduce the survival rate, but actually, vice versa. Many patients not meeting the original trial's criteria could benefit from the treatment. More recent studies have used data imaging markers (features extracted from different imaging modalities, including MRI, PET, CT, or ultrasound scans) to enhance the definition of the inclusion criteria [31, 32]. This procedure boasts very desirable qualities, such as reducing the sample size needed to a great extent while at the same time enjoying very high statistical power. AI models can also estimate clinical drug reactions, reducing the scale and enhancing trial efficacy and efficiency [33].

9.1. Mining Electronic Health Records

To improve cancer prediction, several AI models encompass all medical records, such as individuals' genetic, unstructured, and family records [34]. For example, a dataset of observed cancer-associated characteristics of an individual, age, gender, smoking history, and stage of lung cancer should be considered to model and predict survival outcomes of the disease. Furthermore, the features of the tumor's shape, including size, perimeter, concavity, fullness, length of the central axis, and the size of the minor axis, also contribute to the result [35]. For example, standard ML algorithms like SVM, C5.0, and ELM are used to predict the risk rate for cervical cancer recurrence, emphasizing pathology and medical data. They realized the four patterns that influenced recurrence proneness most. The four chief recurrence-proneness variables they reported are cell type, RT target summary, pathologic stage, and pathologic T.

However, keeping the promise may be more challenging when recording the information from electronic health records. The result could include finding the most unstructured cancer information within the NLP algorithms investigation project. For instance, the MedLEE system, which was a preprocessor that developed with an existent NLP system, was produced within a clinical research study touching on race disparity within the risks that minority women faced when they were diagnosed with breast cancer. An NLP system will thus avoid identification, and data from electronic pathology reports will be traced and filtered for primary and subsequent tumors [36]. Moreover, the EHRs can enhance the ability to locate cancer tests using NLP [30].

9.2. Patient Screening

Participating patients in clinical trials are subject to certain conditions regarding their eligibility, appropriateness, motivation, and empowerment to enroll. A patient may be disqualified due to their medical history. An eligible patient may not be in the stage of the disease or fit into a particular sub-phenotype that the treatment being tested targets, in which case the patient is not appropriate. It's possible that eligible and qualified patients aren't given enough incentives to take part, and even if they are, they do not know about a matching study or find the recruiting procedure too complicated. It is tough to get enough patients through these bottlenecks within the limited time available for recruitment, and this is the main reason why trials are delayed: Nearly one-third of all Phase III studies fail due to enrolling issues, and 86% of trials fail to fulfill recruitment deadlines [17]. A third of the trial's total duration is devoted to patient recruiting. For instance, because Phase III studies need the most significant patient cohorts, they bear 60% of the overall expenses of advancing medicine through all trial phases. Phase III studies with a 32% failure rate due to patient recruitment issues highlight one of the most serious flaws in the design of state-of-the-art clinical trials: ineffective patient recruitment methods disproportionately affect trials with the highest patient demand. Systems powered by AI and ML can aid in patient recruitment and enhance the makeup of patient cohorts [37].

9.3. Cost-Effectiveness

Only one research examined the financial effects of using AI in clinical practice. According to this study, compared to standard treatment, the use of an ML-based system for antibiotic stewardship resulted in cost savings of 25,611 USD for sepsis and 3630 USD for lower respiratory tract infections [37].

9.4. Predicting Drug Efficacy and Toxicity

The role of using AI in medicinal chemistry is to assess the performance of various potential drugs based on efficacy and toxicity. The current approach to discovering drugs is time-consuming, expensive, and sometimes somewhat unpredictable since several smaller molecules required for the compounds' synthesis need to be screened for their biological activity one by one; however, an AI, specifically ML, can learn through data and provides a more accurate analysis of datasets to make predictions about compound activities [38]. Through AI, there are proposals for new bioactive compounds that cause fewer side effects, and we can predict the activity of other compounds with high precision. It also assists in avoiding toxicity results through the examination of toxicity and non-toxicity databases of substances. Moreover, the information on AI penetration into drug-drug interactions can be gained from the known interaction data used for the crea-

tion of individualized therapy. The method involves administering, for example, various treatments dependent on one's genetic makeup to avoid side effects [39].

10. Conclusion

Healthcare and clinical trial processes are growing faster as AI is becoming associated with present medical research. AI has added value to individual therapeutic and diagnostic approaches, clinical precision, and drug prediction structure and property. Such factors affirm the management of eHealth data, promoting cooperation endeavors and optimizing clinical trials for better efficacy and clinical trial outcomes. Nonetheless, there are still restrictions regarding availability, the possibility of tracking these AI systems after that, and mistakes in the clinical AI algorithms. AI can also enhance clinical research's possible quality and outcome because AI is considered quite effective in addressing the challenges that may arise during clinical trial processes. Looking at the general trend of the incorporation of AI technology, it is expected to advance clinical trials to optimize treatment and healthcare delivery.

Abbreviations

ADME	Absorption, Distribution, Metabolism, Excretion
AI	Artificial Intelligence
APIs	Application Programming Interfaces
CAGR	Compound Annual Growth Rate
CNNs	Convolutional Neural Networks
CT	Computed Tomography
ED	Emergency Department
EDC	Electronic Data Capture
EHR	Electronic Health Record
EIOS	Epidemic Intelligence from Open Sources
ELM	Extreme Learning Machine
FDA	Food and Drug Administration
MRI	Magnetic Resonance Imaging
NLP	Natural Language Processing
PET	Positron Emission Tomography
RCTs	Randomized Controlled Trials
RT	Radiation Therapy
RWD	Real-World Data
SQL	Structured Query Language
SVM	Support Vector Machine

Author Contributions

Zomana Majid led the data collection process, searching and identifying relevant articles from PubMed, Scopus, and Google Scholar databases. She also helped to create the findings, wrote the paper, and critically assessed the final manuscript for clarity and consistency. Md Shahidul Islam was involved in editing and review of the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] Subrat Kumar Bhattamisra, et al. "Artificial Intelligence in Pharmaceutical and Healthcare Research." Big data and cognitive computing. 2023.
<https://doi.org/10.3390/bdcc7010010>
- [2] Adam Bohr, Kaveh Memarzadeh. "The rise of artificial intelligence in healthcare applications". Artificial Intelligence in Healthcare. 2020, Pages 25-60.
<https://doi.org/10.1016/B978-0-12-818438-7.00002-2>
- [3] Sudhakar P, SelvaPreethi S, and Anjali G. "Artificial Intelligence in Clinical Trials-Future Prospectives." Bioequivalence and bioavailability international journal. 2023.
<https://doi.org/10.23880/beba-16000196>
- [4] Kanadpriya Basu. Ritwik Sinha. Aihui Ong. Treena Basu. "Artificial Intelligence : How is It Changing Medical Sciences and Its Future" ? Indian J Dermatol. 2020. pp-365–370.
https://doi.org/10.4103/ijid.IJD_421_20
- [5] Bogoch L, Watts A, Thomas-Bachli A, Huber C, Kraemer MUG, Khan K. "Pneumonia of unknown etiology in Wuhan, China : Potential for international spread via commercial air travel." J Travel Med. 2020. <https://doi.org/10.1093/jtm/taaa008>
- [6] Irfan Chaudhuri, Mark Tappan and Md. Shahidul Islam, Impact of Artificial Intelligence on Education: Present Realities and Future Considerations, J. Artif. Intel., 16 (1): 1-11, 2023,
<https://doi.org/10.3923/jai.2023.1.11>
- [7] Irfan Chaudhuri and Md. Shahidul Islam, The Future of AI in Medicine: Present Realities and Future Considerations in Cardiology, Radiology and Ophthalmology, Int. J. Artificial Intelligence in Medicine (IJAIMED), 2(2), 7-26 2024,
<https://doi.org/10.5281/zenodo.14185109>
- [8] Matthew Hutson. "How AI is being used to accelerate clinical trials ?" NATURE INDEX. 2024.
<https://doi.org/10.1038/d41586-024-00753-x>
- [9] Johnson KB, Wei WQ, Weeraratne D, Frisse ME, Misulis K, Rhee K, et al. "Precision Medicine, AI, and the future of Personalized Health Care". Clin Transl Sci. 2021. pp-86–93.
<https://doi.org/10.1111/cts.12884>
- [10] Quazi S. "Artificial intelligence and machine learning in precision and genomic medicine." Med Oncol. 2022.
<https://doi.org/10.1007/s12032-022-01711-1/>
- [11] Huang C, Clayton EA et al. "Machine learning predicts individual cancer patient responses to therapeutic drugs with high accuracy." Sci Rep. 2018.
<https://doi.org/10.1038/s41598-018-34753-5>
- [12] Sheu YH, Magdamo C, Miller M, Das S, Blacker D, Smoller JW. "AI-assisted prediction of differential response to antidepressant classes using electronic health records." Digit Med. 2023. <https://doi.org/10.1038/s41746-023-00817-8>
- [13] Luengo-Oroz, M., Pham, et. Al. "Artificial intelligence cooperation to support the global response to COVID-19". Nature Machine Intelligence. 2020. pp: 295–297.
<https://doi.org/10.1038/s42256-020-0184-3>
- [14] Lip, S., Visweswaran, S., & Padmanabhan, S. "Transforming Clinical Trials with Artificial Intelligence." In Artificial Intelligence. Productivity Press. 2020. pp: 297–306.
<https://doi.org/10.4324/9780429317415-17>
- [15] Sucharitha, G., & Chary, D. V. "Predicting the effect of Covid-19 by using artificial intelligence: A case study. Materials Today: Proceedings". Research gate. 2021.
<https://doi.org/10.1016/j.matpr.2021.02.202>
- [16] Shaheen, M. Y. "Adoption of machine learning for medical diagnosis." ScienceOpen. 2021.
<https://doi.org/10.14293/S2199-1006.1.SOR-.PPHMK6.v1>
- [17] Harrer, S., Shah, P., Antony, B., & Hu, J. "Artificial intelligence for clinical trial design." Trends in Pharmacological Sciences. 2019 . pp: 577–591.
<https://doi.org/10.1016/j.tips.2019.05.005>
- [18] Delso G, Cirillo D, Kaggie JD, Valencia A, Metser U, VeitHaibach P. "How to design AI-Driven clinical trials in Nuclear Medicine". Semin Nucl Med. 2021.112–9.
<https://doi.org/10.1053/J.SEMNUCLMED.2020.09.003>
- [19] Group S-I, Cerf, French Radiology C. "Artificial intelligence and medical imaging 2018: French radiology community white paper". Diagn Interv Imaging. 2018. Pp: 727–742.
<https://doi.org/10.1016/j.diii.2018.10.003>
- [20] CS L, AY L. "How Artificial Intelligence Can Transform Randomized Controlled Trials." Translational vision science & technology. 2020. <https://doi.org/10.1167/TVST.9.2.9>
- [21] Angus, D. C. (2020). Randomized clinical trials of artificial intelligence. Jama. 2020. pp-1043-1045.
<https://doi.org/10.1001/jama.2020.1039>
- [22] Lee, E. "How do we build trust in machine learning models?" SSRN. 2021.
<http://dx.doi.org/10.2139/ssrn.3822437>
- [23] Mohammed Yousef Shaheen. "Applications of Artificial Intelligence (AI) in healthcare: A review". Scienceopen.com. 2021.
<https://doi.org/10.14293/S2199-1006.1.SOR-.PPVRY8K.v1>
- [24] Duckworth, C. et al. "Using explainable machine learning to characterize data drift and detect emergent health risks for emergency department admissions during COVID-19". Sci. Rep. 11. 2021.
<https://doi.org/10.1038/s41598-021-02481-y>
- [25] Sheela Kolluri et al. "Machine Learning and Artificial Intelligence in Pharmaceutical Research and Development: a Review." National library of medicine. 2022.
<https://doi.org/10.1208/s12248-021-00644-3>
- [26] Waymel Q, Badr S, Demondion X, Cotten A, Jacques T. "Impact of the rise of artificial intelligence in radiology: what do radiologists think?" Diagn Interv Imaging. 2019. Pp: 327–336.
<https://doi.org/10.1016/j.diii.2019.03.015>

- [27] Farah Magrabi et al. "Artificial Intelligence in Clinical Decision Support: Challenges for Evaluating AI and Practical Implications". Pubmed Central. 2019. <https://doi.org/10.1055/s-0039-1677903>
- [28] Braz. J. "Revolutionizing Medicine: Unleashing the Power of Real-World Data and AI in Advancing Clinical Trials." Pharm. Sci. 2024. <https://doi.org/10.1590/s2175-97902024e23980>
- [29] Briel M, Elger BS, McLennan S, Schandelmaier S, von Elm E, Satalkar P. "Exploring reasons for recruitment failure in clinical trials: a qualitative study with clinical trial stakeholders in Switzerland, Germany, and Canada." Trials. 2021. <http://dx.doi.org/10.1186/s13063-021-05818-0>
- [30] Zeng J, Banerjee I, Henry AS, et al. "Natural language processing to identify cancer treatments with electronic medical records. JCO Clin Cancer Info". 2021. Pp: 379–93. <https://doi.org/10.1200/CCI.20.00173>
- [31] Ezzati, A. et al. "Machine learning predictive models can improve the efficacy of clinical trials for Alzheimer's disease." J. Alzheimers Dis. 2020. Pp-55–63. <https://doi.org/10.3233/JAD-190822>
- [32] Mohan, A. et al. "A machine-learning derived Huntington's disease progression model: insights for clinical trial design." Mon. Disord. 2022. Pp-553–562. <https://doi.org/10.1002/mds.28866>
- [33] de Jong, J. et al. "Towards realizing the vision of precision medicine: AI-based prediction of clinical drug response." Brain 144. 22021. Pp-1738–1750. <https://doi.org/10.1093/brain/awab108>
- [34] Kann BH, Hosny A, Aerts HJWL. "Artificial intelligence for clinical oncology". Cancer Cell. 39, 2021. Pp: 916–927 <https://doi.org/10.1016/j.ccell.2021.04.002>
- [35] Wang S, Chen A, Yang L, et al. "Comprehensive analysis of lung cancer pathology images to discover tumor shape and boundary features that predict survival outcome." Sci Rep. 2018. <https://doi.org/10.1038/s41598-018-27707-4>
- [36] Karimi YH, Blayney DW, Kurian AW, et al. "Development and use of natural language processing for identification of distant cancer recurrence and sites of distant recurrence using unstructured electronic health record data." JCO Clin Cancer Info. 2021. Pp: 469–78. <https://doi.org/10.1200/CCI.20.00165>
- [37] Voermans AM, Mewes JC, Broyles MR, Steuten LMG. "Cost-Effectiveness Analysis of a Procalcitonin-Guided Decision Algorithm for Antibiotic Stewardship Using Real-World U.S. Hospital Data." OMICS. 2019. Pp-508-515. <https://doi.org/10.1089/omi.2019.0113>
- [38] Sant  n, E. P. Solana, R. R. Garc a, et. al. "Toxicity prediction based on artificial intelligence: A multidisciplinary overview." Wiley Interdiscip. Rev. Comput. Mol. Sci. 2021. <https://doi.org/10.1002/wcms.1516>
- [39] Jang, H. Y. Song, J. Kim, J. H. Lee, H. Kim, I. W. Moon, B. Oh, J. M. "Machine learning-based quantitative prediction of drug exposure in drug-drug interactions using drug label information." npj Digit. Med. 2022. <https://doi.org/10.1038/s41746-022-00639-0>