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ARTIFICIAL INTELLIGENCE IN DRUG DISCOVERY: TRANSFORMING PHARMACOLOGY THROUGH DATA-DRIVEN INNOVATION

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ABSTRACT

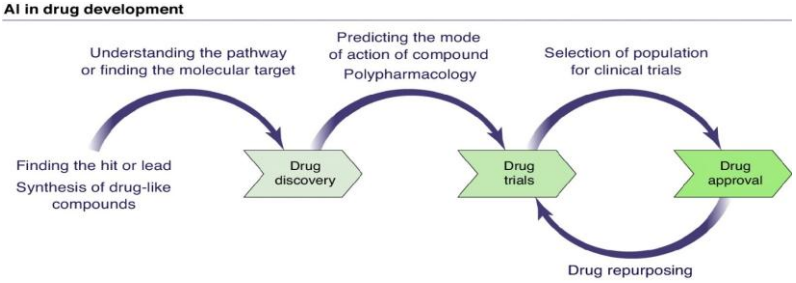
Drug development has long been a slow, expensive, and high-risk journey, but Artificial Intelligence (AI) is rapidly changing that narrative. This review explores how AI is reshaping pharmacology by making the process faster, smarter, and more personalized. From identifying potential drug candidates through advanced virtual screening tools like AtomNet and DeepDock, to improving molecular activity predictions with machine learning-driven QSAR models, AI is enhancing key stages of discovery. It's also proving valuable in drug repurposing—uncovering new uses for existing drugs using data mining, natural language processing, and network analysis, as seen in breakthroughs like baricitinib for COVID-19 and metformin for Alzheimer's. Beyond development, AI is improving drug safety through real-time pharmacovigilance, detecting adverse effects from sources like electronic health records and social media. Still, challenges such as opaque "black box" models, biased data, and regulatory uncertainty remain. Even so, innovations like explainable AI and digital twin technology are paving the way for a more transparent, efficient, and individualized approach to medicine.

KEYWORDS: Artificial Intelligence (AI), Drug Discovery, Drug Repurposing, Virtual Screening, QSAR Modeling.

INTRODUCTION

The process of drug development is inherently lengthy, expensive, and high-risk, often taking over a decade and costing billions of dollars to bring a single new therapeutic agent from the laboratory bench to the patient bedside.[1] Despite advances in biotechnology and computational chemistry, traditional drug discovery pipelines remain constrained by high attrition rates, complex biological interactions, and the need for extensive preclinical and clinical testing. Simultaneously, the biomedical sciences are generating vast quantities of data through high-throughput techniques in genomics, proteomics, transcriptomics, and chemical screening. This deluge of information presents an unprecedented opportunity to accelerate drug discovery but only if it can be meaningfully interpreted and leveraged.[2]

In this context, Artificial Intelligence (AI) and machine learning algorithms have emerged as powerful tools to extract patterns, predict outcomes, and automate decision-making in pharmacology. AI-driven approaches are now being integrated into several stages of the drug development lifecycle, including target identification, lead optimization, preclinical testing, and post-marketing surveillance, with the goal of improving efficiency, reducing cost, and enhancing predictive accuracy.[3] This review focuses on three pivotal AI applications in pharmacology: virtual screening for identifying potential drug candidates, quantitative structure–activity relationship (QSAR) modelling for predicting molecular activity, and AI-powered pharmacovigilance for real-time drug safety monitoring.



AI IN VIRTUAL SCREENING

Virtual screening is a computational technique used to evaluate large chemical libraries in order to identify compounds with a high likelihood of binding to a specific biological target. Traditionally, this process has relied on molecular docking methods and scoring functions, which attempt to estimate the binding affinity between a ligand and a target protein based on physical and chemical principles. However, these conventional approaches often struggle with limited accuracy and scalability.[4] In recent years, Artificial Intelligence (AI), particularly machine learning and deep learning, has significantly enhanced virtual screening by enabling models to learn complex, non-linear relationships from vast chemical and biological datasets.

Notable advancements in this domain include **AtomNet,** one of the first deep learning platforms to apply convolutional neural networks (CNNs) for structure-based drug screening, allowing the system to model spatial features of molecular interactions with high precision.[5] Another example is **DeepDock**, which integrates traditional docking simulations with machine learning-based binding affinity predictions, improving the identification of active compounds. Open-source platforms such as **DeepChem** and **Chemprop** further democratize access to machine learning models for chemoinformatics tasks by providing user-friendly frameworks to train predictive models on molecular descriptors and graph-based features.[6,7]

A prominent application of these technologies is Atomwise's AI-driven screening platform, which successfully identified potential inhibitors for the Ebola virus in under 24 hours an achievement that would typically take weeks using conventional methods.[8] Despite these successes, AI-based virtual screening still faces critical challenges, including overfitting to training data, poor generalizability to novel chemical scaffolds, and the dependency on high-quality, annotated datasets to ensure robust and transferable predictions.[9]

QSAR MODELS IN PHARMACOLOGY

Quantitative Structure–Activity Relationship (QSAR) modeling is a cornerstone of computational drug discovery, enabling the prediction of a compound's biological activity based on its chemical structure. Traditionally reliant on linear regression and other statistical approaches, QSAR models have been significantly enhanced through the integration of Artificial Intelligence (AI), particularly machine learning (ML) methods, which are capable of capturing non-linear relationships and managing high-dimensional datasets with improved predictive performance.[10]

Modern QSAR modelling frequently employs a variety of ML techniques, including **Support Vector Machines (SVM)**, **Random Forests (RF)**, **Artificial Neural Networks (ANN)**, and more recently, **Graph Neural Networks (GNNs)**, which operate directly on molecular graph representations to capture structural features more effectively.[9,11] These approaches have proven particularly valuable in **ADMET prediction** assessing absorption, distribution, metabolism, excretion, and toxicity profiles as well as in **toxicological screening**, which is critical during early-phase drug development to reduce failure rates in later clinical stages.

Several platforms have emerged to support AI-driven QSAR modelling, including open-source tools such as **DeepChem**, workflow-based systems like **KNIME**, and commercial software such as **AutoQSAR** by Schrödinger, which automates the model-building process.[6,12] A notable case study demonstrated the application of deep learning QSAR models to the identification of novel antimalarial compounds, achieving greater predictive accuracy than traditional linear models and expediting lead prioritization.[13]

AI APPROACHES TO DRUG REPURPOSING

Artificial Intelligence (AI) has become an essential component in modern drug repurposing strategies, offering data-driven methodologies that accelerate the identification of new therapeutic uses for existing drugs. Among these, machine learning (ML) and deep learning (DL) models both supervised and unsupervised play a crucial role in uncovering latent patterns within large-scale biomedical datasets. These models are employed to predict disease–drug associations, often by learning from molecular, phenotypic, and clinical features.[14] Supervised models leverage labeled data to train algorithms that can predict repurposing candidates, while unsupervised models cluster drugs or diseases based on similarity metrics to reveal novel associations.[15]

Natural Language Processing (NLP) represents another pivotal AI approach, allowing automated extraction of relevant information from vast amounts of unstructured textual data, such as scientific literature, electronic health records (EHRs), and clinical trial repositories. By using NLP techniques, researchers can mine co-occurrence patterns, adverse event mentions, and mechanistic insights that may not be readily accessible through traditional curation.[16]

Additionally, network-based approaches have gained prominence in drug repurposing. These methods construct and analyze disease-gene-drug interaction networks, often represented as knowledge graphs integrating heterogeneous biomedical data. Publicly available databases such as DrugBank, the Comparative Toxicogenomics Database (CTD), and PubChem provide structured information that can be leveraged to model the complex relationships among biological entities and pharmacological agents.[17,18] These graph-based frameworks enable AI systems to navigate intricate biological systems and identify repositioning candidates with a mechanistic basis.

CASE STUDIES

Artificial Intelligence (AI) has played a pivotal role in accelerating **drug repurposing**, offering a cost-effective and time-efficient strategy to identify new therapeutic uses for existing drugs. One prominent example emerged during the **COVID-19 pandemic**, where the AI platform **BenevolentAI** identified **baricitinib** a Janus kinase (JAK) inhibitor as a potential therapeutic candidate due to its dual anti-inflammatory and antiviral properties.[19] This prediction was rapidly supported by clinical trials demonstrating its efficacy in reducing disease severity when used in combination with **remdesivir**, ultimately contributing to its emergency use authorization by regulatory agencies.[20]

In oncology, AI-driven **pathway analysis and systems pharmacology** approaches have facilitated the repositioning of **thalidomide**, a drug once withdrawn due to teratogenic effects. By uncovering its immunomodulatory mechanisms, particularly in the tumor microenvironment, researchers successfully repurposed thalidomide for **multiple myeloma**, leading to the development of safer and more potent analogs such as **lenalidomid**e and **pomalidomide** collectively known as immunomodulatory imide drugs (IMiDs).[21,22]

In the field of neurology, AI-based **network pharmacology** has been utilized to investigate the potential of **metformin**, a common anti-diabetic agent, in treating **Alzheimer's disease**. By integrating multi-omics data, AI models revealed overlapping pathways involving **aging**, **neuroinflammation**, and **insulin signalling**, prompting clinical interest in metformin's neuroprotective effects. Multiple clinical trials are currently underway to assess its efficacy in delaying cognitive decline.[23,24]

For **rare diseases**, AI combined with **systems biology modelling** has enabled the repositioning of **cysteamine,** traditionally used in cystinosis, as a candidate treatment for **Batten disease** a rare, fatal paediatric neurodegenerative disorder. Through analysis of molecular networks and neuroprotective pathways, cysteamine was identified as a modulator of lysosomal function and neuronal survival, leading to preclinical validation and investigational use in this new context.[25]

AI-POWERED PHARMACOVIGILANCE

Pharmacovigilance, the science of monitoring and evaluating the safety of pharmaceutical products after they have entered the market, plays a crucial role in identifying adverse drug reactions (ADRs) that may not have been apparent during clinical trials. In recent years, Artificial Intelligence (AI) particularly Natural Language Processing (NLP) has increasingly been applied to automate the extraction of ADRs from diverse real-world data sources, including electronic health records (EHRs), clinical notes, and user-generated content on social media platforms such as Twitter and Reddit.[26,27]

AI-powered systems are capable of detecting subtle patterns and signals in large volumes of unstructured text, enabling earlier identification of potential safety concerns compared to conventional manual review or rule-based systems. One such application is IBM Watson for Drug Safety, which utilizes NLP and machine learning techniques to not only detect ADRs in near real-time but also classify their severity using AI-based scoring frameworks.[28] The benefits of integrating AI into pharmacovigilance include real-time signal detection, scalability across global datasets, and enhanced accuracy in identifying safety signals from noisy, heterogeneous sources.

However, several challenges remain. These include regulatory and ethical concerns, particularly around data privacy, as well as the difficulty of achieving the right balance between signal sensitivity and specificity to avoid both missed risks and false positives.[29] Despite these hurdles, AI continues to offer transformative potential in making pharmacovigilance more proactive, data-driven, and globally responsive.

CHALLENGES AND ETHICAL CONSIDERATIONS

Despite the promising applications of Artificial Intelligence (AI) in drug discovery, several critical limitations hinder its widespread adoption and regulatory integration. One prominent challenge is the lack of interpretability associated with many deep learning models, often referred to as "black box" systems, wherein the rationale behind a prediction or decision is not readily transparent to users or regulators.[30] This opacity complicates the validation and trustworthiness of AI-generated outputs, particularly in high-stakes settings such as drug development.

Another major concern is data bias. AI models trained on non-representative or historically biased datasets may inadvertently propagate existing disparities in healthcare outcomes, such as underrepresentation of certain populations in clinical data.[31] Furthermore, the absence of standardized validation metrics across the industry impedes reliable benchmarking and comparison of AI models, making it difficult to assess their real-world utility and reproducibility.[32]

Lastly, there are regulatory constraints, as current guidelines provided by agencies such as the U.S. Food and Drug Administration (FDA) and the European Medicines Agency (EMA) for AI-driven drug discovery tools remain limited and underdeveloped. This regulatory ambiguity creates uncertainty for developers and hinders the formal approval and deployment of AI-enabled platforms in clinical and preclinical settings.[33]

FUTURE PERSPECTIVES

The integration of Artificial Intelligence (AI) with high-dimensional omics data including genomics, proteomics, and metabolomics as well as real-world evidence (RWE)

and emerging technologies such as digital twins, is poised to fundamentally transform the landscape of personalized medicine. These AI-driven approaches enable the modelling of individual biological variability and environmental exposures, thus facilitating the development of highly tailored therapeutic interventions.[34] Digital twins, which are virtual replicas of patients constructed from real-time clinical and molecular data, further enhance predictive simulations of disease progression and treatment outcomes.[35]

As the field advances, the emergence of explainable AI (XAI) is expected to address one of the core limitations of traditional black-box models—namely, the lack of interpretability. By improving transparency, XAI fosters greater trust and accountability in AI-driven medical decision-making, which is essential for both clinical adoption and ethical deployment.[36] In parallel, regulatory bodies such as the U.S. Food and Drug Administration (FDA) and the European Medicines Agency (EMA) are actively exploring and establishing guidance frameworks to assess, validate, and monitor AI-based tools in healthcare, signalling a gradual but essential shift toward regulatory readiness for AI-integrated personalized medicine.[33,37]

CONCLUSION

Artificial Intelligence (AI) has moved beyond being just a helpful tool it's now at the heart of modern pharmacology. By making drug discovery faster, more affordable, and more precise, AI is reshaping how we find and monitor treatments. It can sift through enormous amounts of data to spot patterns that humans might miss, opening up new possibilities for targeted therapies and real-time safety monitoring. But to truly unlock its potential, we need to tackle some important hurdles. These include making AI systems more transparent and easier to understand, ensuring the data they're trained on is fair and representative, and building clearer regulatory paths to safely bring these tools into everyday use. If we get these parts right, AI could help create a future where drug development is not only more efficient, but also more personalized, ethical, and responsive to patient needs.

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