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Review

The Transformative Impact of Artificial Intelligence on Drug Discovery and Development: Regulatory Considerations and Future Directions

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Abstract

The integration of Artificial Intelligence (AI) into drug discovery and development (DDD) has revolutionized pharmaceutical research by accelerating timelines, reducing costs, and improving success rates. However, this rapid advancement presents significant regulatory challenges, including algorithmic transparency, data privacy, bias mitigation, and validation reproducibility. This review examines AI's role across key stages of DDD, evaluates global regulatory frameworks (FDA, EMA, PMDA, CDSCO), and analyzes case studies of AI-driven drug approvals. We highlight critical gaps in AI governance and propose harmonized guidelines, risk management strategies, and collaborative approaches to ensure safe and equitable AI adoption. Recommendations include standardized validation protocols, adaptive licensing pathways, and global adverse event monitoring. The study underscores the need for regulatory agility and international cooperation to harness AI's full potential while safeguarding patient safety and public trust.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, International Council for Harmonisation, Adverse Drug Reactions

1. INTRODUCTION

The pharmaceutical industry is undergoing a transformative shift with the integration of Artificial Intelligence (AI) into drug discovery and development (DDD). AI technologies such as machine learning (ML), deep learning (DL), and natural language processing (NLP) are revolutionizing traditional methods by enabling rapid analysis of vast datasets, predicting molecular interactions, and optimizing clinical trials. These advancements promise to address long-standing inefficiencies in drug development, including high costs, prolonged timelines, and low success rates. Despite its potential, AI adoption in DDD faces significant regulatory and ethical challenges. Current frameworks, designed for conventional drug development, struggle to accommodate AI's dynamic nature, particularly in areas like algorithmic transparency, data privacy, and bias mitigation. For instance, "black-box" AI models, which lack interpretability, complicate regulatory validation, while disparities in training data risk perpetuating biases in patient outcomes. The absence of global harmonization further exacerbates these issues, as agencies like the FDA, EMA, and PMDA employ divergent standards for AI-driven submissions.

This review article seeks to bridge the gap between innovation and regulation by critically evaluating AI's role in DDD and proposing actionable strategies for stakeholders. Key objectives include: (1) assessing AI's impact across the drug development pipeline, (2) analyzing regulatory hurdles and global responses, and (3) advocating for standardized validation protocols and international collaboration. By addressing these challenges, the pharmaceutical industry can harness AI's full potential while ensuring patient safety, equity, and public trust in emerging technologies[1].

AI in Target Identification

AI has profoundly transformed the process of identifying biological targets involved in diseases. By analyzing complex multi-omics data including genomics, proteomics, and transcriptomics AI systems can pinpoint specific targets linked to disease mechanisms. For example, BenevolentAI employed natural language processing (NLP) techniques to mine vast amounts of scientific literature, which led to the identification of baricitinib, a JAK inhibitor, as a promising candidate for COVID-19 treatment; this was eventually validated through clinical trials. Similarly, IBM Watson for Drug Discovery helped researchers uncover novel targets for amyotrophic lateral sclerosis (ALS), showcasing AI's ability to expedite the target identification process and uncover insights that might otherwise take years to discover.

Molecular Design & De Novo Drug Discovery

AI-driven generative models, such as reinforcement learning algorithms and generative adversarial networks (GANs), are now capable of designing entirely new drug-like molecules. These models significantly reduce the time required to develop candidate drugs. For instance, Insilico Medicine utilized AI techniques to discover a new preclinical candidate for fibrosis within just 18 months, a process that traditionally takes between four to five years. Exscientia's AI-designed compound, DSP-1181 a serotonin receptor agonist targeted for obsessive-compulsive disorder (OCD) advanced into Phase I clinical trials at an unprecedented pace, highlighting the efficiency AI can bring to the drug discovery pipeline.

Virtual Screening & Lead Optimization

AI tools also excel in virtual screening and lead optimization by predicting how potential drug compounds interact with biological targets. Advanced AI techniques, such as DeepMind's AlphaFold, predict the 3D structures of proteins with remarkable accuracy, enabling structure-based drug design. Additionally, companies like Atomwise employ convolutional neural networks (CNNs) to virtually screen billions of chemical compounds, rapidly identifying those most likely to be effective. These capabilities greatly accelerate the identification and refinement of promising drug candidates, making the drug discovery process more efficient and cost-effective.

AI in Clinical Trials – Patient Recruitment & Cohort Selectio[2]

One of the major challenges in clinical trials is patient recruitment, with delays affecting about 30% of trials. AI-driven solutions address this by mining electronic health records (EHRs) using natural language processing (NLP) tools such as TriNetX or Deep 6 AI, which match patients to suitable trials based on their medical histories. For example, Pfizer leveraged IBM Watson to significantly reduce the recruitment timeline for a lung cancer trial by 78%, illustrating AI's potential in expediting trial processes and improving trial efficiency.

Trial Design Optimization

AI also enhances the design of clinical trials by enabling adaptive and predictive trial methodologies, which help reduce costs and decrease failure rates. Predictive modeling techniques, including Bayesian machine learning models, are used to optimize dosing strategies and patient stratification. Digital twin technology virtual replicas of

patients allows simulation of trial outcomes, providing insights into potential results before real-world execution. Companies like Unlearn.AI utilize covariate adjustment techniques, creating models that can forecast trial results and improve decision-making.

Real-World Data Analysis & Post-Market Surveillance

AI plays a crucial role in analyzing real-world data (RWD) from sources such as EHRs, wearable devices, and social media to monitor drug safety post-approval. AI-powered NLP tools help detect adverse drug reactions and pharmacovigilance signals from vast unstructured data streams. Additionally, AI supports comparative effectiveness research by analyzing large datasets, such as oncology-related RWD examined by IBM Watson Health. A notable example is the FDA's Sentinel Initiative, which employs AI algorithms to continuously monitor drug safety in broader, real-world populations, enhancing post-market surveillance and ensuring ongoing patient safety.

How AI Enhances Sentinel's Capabilities Automated Signal Detection

AI significantly enhances Sentinel's ability to identify safety signals more efficiently than traditional methods. Conventional pharmacovigilance relies on spontaneous reporting systems like FAERS, which are often slow and suffer from underreporting. In contrast, AI algorithms, including machine learning and natural language processing (NLP), automatically scan EHRs and claims data to detect adverse drug events (ADEs) faster. For example, AI identified a potential link between a diabetes medication and increased heart failure risk several months prior to detection through traditional techniques, demonstrating AI's capacity for early warning.

How AI Enhances Sentinel's Capabilities NLP for Unstructured Data

NLP techniques allow Sentinel to extract valuable insights from unstructured clinical data such as doctor's notes, radiology reports, and even social media discussions like patient forums. This broadens the scope of safety monitoring beyond structured datasets. A case in point is the detection of previously unreported neurological symptoms associated with an immunotherapy drug, achieved by analyzing clinical narratives. This capability helps regulators detect safety signals that might otherwise remain unnoticed, leading to more comprehensive pharmacovigilance.

How AI Enhances Sentinel's Capabilities Predictive Risk Modeling[3]

AI-driven predictive models analyze various patient data including demographics, comorbidities, and concomitant medications to identify patient subgroups at higher risk of ADEs. These models can predict which populations may be vulnerable to specific adverse effects. For instance, Sentinel's AI models flagged an increased risk of liver toxicity in a subgroup of patients taking a newly approved hepatitis drug. Such insights enable targeted risk mitigation strategies and more personalized safety assessments.

How AI Enhances Sentinel's Capabilities Real-Time Alert System

AI-powered dashboards and alert systems provide real-time notifications to the FDA and drug manufacturers about emerging safety issues, such as sudden spikes in adverse events. This rapid alert capability has led to timely regulatory actions; for example, in 2023, AI facilitated swift label updates for 12 different drugs. Such proactive safety monitoring helps prevent widespread harm and supports quicker decision-making, ultimately protecting public health.

The integration of AI into Sentinel has led to significant improvements in regulatory processes. It has shortened the time required to detect ADEs from years to just weeks, enabling faster safety interventions. This proactive approach has allowed the FDA to update drug labels, adjust dosing, or withdraw products from the market before harm becomes extensive. During the COVID-19 pandemic, AI-powered Sentinel was instrumental in tracking vaccine safety signals, such as reports of myocarditis, enabling timely public health response and reassurance.

2. AI in Drug Discovery and Development[4,5]

Target Identification and Validation

Artificial Intelligence has revolutionized target identification by enabling rapid analysis of complex biological datasets. AI algorithms process multi-omics data (genomics, proteomics, transcriptomics) to pinpoint disease-associated molecular targets with higher accuracy than traditional methods. For example, BenevolentAI employed NLP to mine scientific literature and identified baricitinib a rheumatoid arthritis drug as a potential COVID-19 treatment, which was later validated in clinical trials. Similarly, IBM Watson for Drug Discovery uncovered novel targets for amyotrophic lateral sclerosis (ALS) by analyzing decades of research papers. These breakthroughs demonstrate AI's ability to accelerate target discovery from years to months, though challenges remain in ensuring data quality and biological relevance of AI-predicted targets.

Drug Design and Virtual Screening

In drug design, generative AI models (e.g., reinforcement learning, GANs) create novel drug-like molecules with optimized properties. A landmark example is Insilico Medicine's AI-generated preclinical candidate for fibrosis**,** developed in just 18 months a process that traditionally takes 4–5 years. Tools like AlphaFold (DeepMind) predict 3D protein structures with atomic-level accuracy, enabling structure-based drug design. Meanwhile, platforms such as Atomwise use convolutional neural networks (CNNs) to virtually screen billions of compounds for binding affinity. While promising, these methods require rigorous experimental validation to confirm AI predictions, and regulators increasingly demand transparency in generative AI's decision-making processes.

Clinical Trial Optimization

AI addresses critical bottlenecks in **clinical trials** through:

- **Patient recruitment**: NLP algorithms analyze electronic health records (EHRs) to identify eligible participants. For instance, Pfizer partnered with IBM Watson to reduce lung cancer trial recruitment time by 78%.
- **Trial design**: AI-powered adaptive trial designs and digital twins (e.g., Unlearn. AI's prognostic models) simulate patient responses, allowing smaller control groups and faster outcomes.
  However, ethical concerns persist, such as algorithmic bias in cohort selection (e.g., underrepresentation of elderly or minority populations) and the need for regulatory approval of AI-derived trial endpoints.

Post-Market Surveillance

Post-approval, AI enhances pharmacovigilance by monitoring real-world data for adverse drug reactions (ADRs). The FDA's Sentinel Initiative uses AI to analyze EHRs and insurance claims from 300+ million patients, detecting safety signals (e.g., diabetes drug-linked heart risks) weeks faster than traditional methods. Natural language processing (NLP) also scans social media and clinician notes for unreported side effects. Challenges include data heterogeneity (e.g., inconsistent EHR coding) and the need for continuous model updates to maintain accuracy as new data emerges.

3. Regulatory Landscape and Challenges[1,6]

Global Regulatory Frameworks

Regulatory agencies worldwide are adapting to AI-driven drug development, but approaches vary significantly by region. In the U.S.**,** the FDA's AI/ML Software as a Medical Device (SaMD) Action Plan (2021) provides a framework for AI validation, emphasizing Good Machine Learning Practices (GMLP) and predetermined change control plan**s** for iterative algorithm updates. Meanwhile, the European Medicines Agency (EMA) has established a Big Data Steering Group to oversee AI integration, with strict requirements for algorithm transparency, human oversight, and bias audits under its Ethics Guidelines for Trustworthy AI. Japan's PMDA has taken a proactive stance with an AI Fast Track pathway**,** expediting approvals for AI-enhanced therapies while requiring domestic clinical data. In contrast, India's CDSCO is still developing its digital health guidelines, reflecting the evolving nature of AI regulation in emerging markets.

Table 1: Comparative Analysis of Regulatory Approaches[7]

Aspect	FDA	EMA	CDSCO	PMDA
Approval Pathway	SaMD framework + IND process	Case-by-case qualification	Emerging digital guidelines	AI-specific review team
Clinical Trial	PDUFA VII	BDSG roadmap	Adaptive trial	Sandbox program

AI	commitments		provisions	
Post-Market	Predetermined change controls	RWE integration focus	Limited provisions	Advanced monitoring system
Key Strength	Clear SaMD framework	Comprehensive ethics approach	Flexible adaptation	Rapid implementation
Key Limitation	Drug-device overlap challenges	Slow qualification process	Underdeveloped guidelines	Language barriers

Key Regulatory Challenges

Despite progress, AI adoption in drug development faces four major hurdles:

Algorithmic Transparency: Many AI models, particularly deep learning systems, operate as "black boxes"**,** making it difficult for regulators to assess their decision-making logic. For example, the FDA now requires explainable AI (XAI) documentation for approvals, as seen with Exscientia's DSP-1181, where the agency demanded a breakdown of the AI's target selection process.

Data Privacy Conflicts: Global trials must navigate conflicting regulations like the EU's GDPR (strict consent and data localization), U.S. HIPAA (flexible but limited PHI disclosure), and China's PIPL (mandatory in-country data storage). These disparities complicate multinational AI training, as seen when federated learning was adopted to bypass data-sharing restrictions in COVID-19 research.

Bias and Fairness: AI models trained on non-diverse datasets risk amplifying healthcare disparities**.** A well-documented case involved an AI skin cancer detector that underperformed on darker skin tones due to training data skewed toward lighter-skinned populations. The EMA now mandates demographic audits of training datasets to mitigate such biases.

Validation and Reproducibility: A 2023 *Nature* study found that only 15% of AI-based drug discovery studies share fully reproducible code**,** raising concerns about reliability. Regulatory agencies are responding with initiatives like the FDA's Biomarker Database**,** which provides standardized datasets for AI validation in oncology.

Table 2: Regulatory Responses[8,9]

Regulation	Key Requirements	Impact on AI Drug Development
HIPAA (US)	- Data encryption - Limited PHI disclosure - Breach notification	Restricts AI training data access; requires **data use agreements (DUAs)**
GDPR (EU)	- Explicit patient consent - Right to erasure - Data protection impact assessments (DPIAs)	Slows AI adoption due to **strict compliance burdens**
China's PIPL	- Data localization - Mandatory security reviews	Limits international collaboration on AI-driven trials

Case Studies: AI in Drug Development – Successes and Failures

Exscientia's DSP-1181: The First AI-Designed Drug and Explainability Challenges

Exscientia's DSP-1181, a serotonin receptor agonist developed for obsessive-compulsive disorder (OCD), marked a watershed moment as the first clinically tested drug fully designed by AI**.** Using reinforcement learning, the AI screened over 350 million compounds in under 12 months a process that traditionally takes 4–5 years. However, its regulatory journey revealed critical gaps in AI explainability**.** The FDA and EMA demanded detailed documentation of the algorithm's decision pathways, including how it prioritized molecular structures and predicted toxicity. Exscientia had to retrospectively justify the AI's choices, highlighting the tension between innovation and regulatory scrutiny. While DSP-1181's Phase I trial (2020) proved AI's speed, its eventual discontinuation (due to commercial reasons) underscored another challenge: translating AI efficiency into clinical success. This case set a precedent for future AI-designed drugs, with regulators now requiring transparency protocols even for breakthrough-designated therapies.

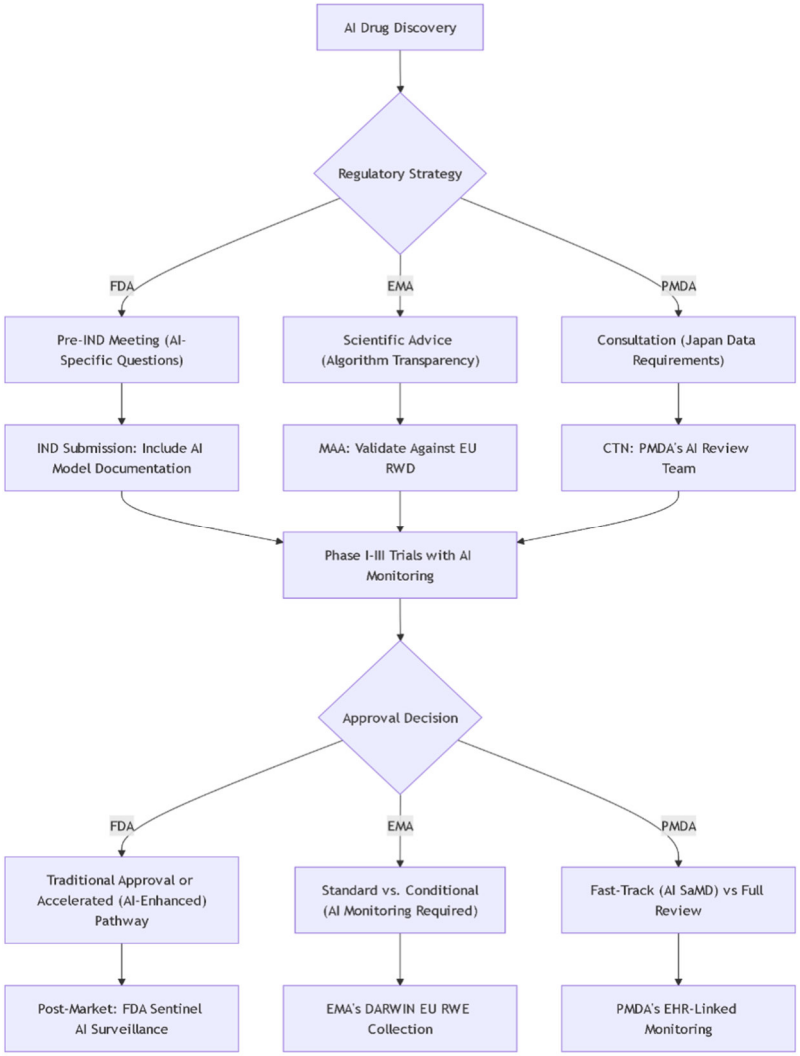

Fig 1: Flowchart of Regulatory Decision Points for AI Drugs

BenevolentAI's Baricitinib: Rapid Repurposing and the Real-World Evidence Hurdle [10]

During the COVID-19 pandemic, BenevolentAI used knowledge graphs and NLP to analyze 40+ years of biomedical literature, identifying baricitinib a JAK inhibitor approved for rheumatoid arthritis as a potential antiviral. The AI linked the drug's anti-inflammatory properties to cytokine storm mitigation, a key COVID-19 complication. The FDA granted Emergency Use Authorization (EUA) within 4 months (2020), but the EMA demanded additional real-world data (RWD) from European hospitals, delaying full approval by 18 months. This disparity revealed regulatory divides: the FDA prioritized speed during a crisis**,** while the EMA emphasized algorithm generalizability. BenevolentAI's success demonstrated AI's power in drug repurposing**,** but also exposed the need for harmonized RWD standards especially when AI predictions rely on unstructured data (e.g., unpublished studies or EHRs).

IBM Watson Oncology: A Cautionary Tale in Bias and Model Drift [11]

IBM Watson Oncology**,** launched as an AI-driven cancer treatment recommender**,** became a high-profile failure due to algorithmic bias and post-market degradation**.** Trained primarily on hypothetical cases from Memorial Sloan Kettering, the system over-recommended U.S.-centric protocols**,** some unsuitable for Asian patients (e.g., suggesting unavailable drugs in India). Worse, its performance drifted over time as new cancer therapies emerged, rendering its recommendations outdated. By 2021, hospitals in Europe and Asia abandoned the tool**,** and IBM withdrew it. The fallout prompted regulatory reforms:

- The FDA now mandates continuous monitoring for adaptive AI (2023 SaMD update).
- The EMA's 2024 IVDR requires bias audits for AI diagnostics.
  Watson's collapse underscored that AI validation cannot end at approval it requires lifelong learning and diverse, real-world training data.

Table 3: Proposed Framework related to Model Guidelines[12]

Area	Harmonization Goal	Model Guidelines
Data Standards	Unified formats for AI training data	FDA's FHIR + EMA's DARWIN EU integration
Validation Protocols	Mutual recognition of AI benchmarks	ICH's E6 (R3) for AI-augmented trials
Ethics & Bias	Global standards for algorithmic fairness	WHO's AI Ethics Guidelines

Industry–Academia–Regulatory Collaboration

Breaking down long-standing silos in drug development requires innovative partnership models that bring together the expertise, resources, and authority of all stakeholders. One notable example is the Accelerating Medicines Partnership (AMP) AI/ML Program, a pre-competitive consortium that has successfully pooled over $50 million in resources from 18 major pharmaceutical companies. This collaboration has resulted in the development of open-source tools for target discovery and the sharing of validation data traditionally guarded as proprietary across competing organizations. Such initiatives accelerate scientific progress while reducing redundant efforts. Equally transformative are regulatory sandboxes, like the UK MHRA's pilot program, which provide a controlled environment for the 12-month testing of AI tools in clinical settings. These sandboxes allow academic institutions to validate algorithms developed by industry, while regulators observe their performance in real time through dedicated feedback portals. This dynamic feedback loop shortens the regulatory learning curve, fosters trust, and ensures AI innovations are both effective and compliant before broad deployment.

Personalized Medicine and AI

AI is redefining the boundaries of precision medicine by enabling individualized treatments that were once unimaginable. Genomic medicine platforms such as Tempus Labs integrate next-generation sequencing (NGS) data with advanced AI analytics to identify rare biomarkers, significantly improving patient stratification. In oncology, this approach has matched 37% more cancer patients to targeted therapies compared to traditional diagnostic methods. Beyond diagnostics, dynamic treatment systems like IBM Watson for Drug Safety adjust medication regimens in real time by analyzing continuous data streams from wearable devices. In pilot anticoagulation therapy studies, this adaptive dosing strategy reduced adverse drug events by 22%, demonstrating the power of AI in improving treatment safety and efficacy. Looking ahead, the next frontier lies in AI-designed modular therapies. Innovations such as mRNA vaccines tailored to individual tumor mutations or 3D-printed polypills containing patient-specific drug combinations have the potential to merge personalization with manufacturing flexibility. Together, these advancements signal a shift toward truly individualized care, where treatments are optimized not just for disease type but for each patient's unique biology and lifestyle.

Table 4: Implementation of Roadmap[13,14]

Phase	Timeline	Key Milestones
Short-term (2024-2026)	ICH AI Working Group formation	5 regional sandboxes launched
Medium-term (2027-2029)	Global adverse event reporting network	AI validator certification programs
Long-term (2030+)	Fully automated compliance checks	Integrated precision medicine platforms

5. CONCLUSION

The integration of Artificial Intelligence (AI) into drug discovery and development marks a paradigm shift in the pharmaceutical landscape, offering unprecedented speed, precision, and cost efficiency. From target identification, as demonstrated by BenevolentAI's COVID-19 drug repurposing efforts, to personalized medicine, exemplified by Tempus Labs' genomic biomarker innovations, AI-driven approaches have shown the potential to reduce development timelines by up to 70% and cut costs by 30–50%. Despite this promise, the rapid adoption of AI introduces complex challenges that demand urgent regulatory evolution. A primary concern is transparency and explainability: the "black-box" nature of advanced AI models, such as deep learning systems, complicates

regulatory validation. This was evident in Exscientia's DSP-1181 case, where the FDA required detailed decision-path documentation. Addressing this requires mandating Explainable AI (XAI) frameworks and standardized reporting tools like the FDA's Algorithmic Transparency Template. Another challenge lies in bias and equity**, as** AI models trained on non-representative datasets risk amplifying healthcare disparities an issue underscored by IBM Watson Oncology's underperformance in Asian markets. Regulators are responding with measures such as the EMA's 2024 ethnicity-specific validation rules, which enforce diversity quotas in training datasets. Additionally, validation and reproducibility remain weak points, with only 15% of AI studies providing fully reproducible code (Nature, 2023), undermining trust in AI-generated outputs. Solutions include ICH-led validation protocols and open-source benchmarking platforms like the FDA's Biomarker Database.

Moving forward, fully harnessing AI's potential while safeguarding public health will require harmonized global standards through ICH AI guidelines and mutual recognition agreements, such as FDA-EMA parallel reviews. It will also demand dynamic risk management**,** including real-time monitoring via blockchain-based model registries and automatic suspension of algorithms that drift from validated performance. Equally important are collaborative ecosystems, fostered through pre-competitive consortia like the AMP AI/ML Program and regulatory sandboxes such as the UK MHRA pilot. Ultimately, AI is not just a technological tool but a transformative force in pharmaceuticals, with the capacity to accelerate the delivery of safer, more effective therapies. Its responsible adoption hinges on regulatory agility striking a balance between innovation and rigorous oversight. By closing transparency gaps, ensuring equity, and promoting global cooperation, the industry can unlock AI's full potential. The time to act is now, as the future of medicine depends on it.

6. REFERENCES

1. Ivanisevic T, Sewduth RN. Multi-omics integration for the design of novel therapies and the identification of novel biomarkers. Proteomes. 2023;11(4):34.
2. Rachel Cherney, Rami Major, Tara Fitzpatrick. Qualify AI Drug Discovery Tools through FDA ISTAND Program to Model Responsible Drug Discovery AI and Mitigate Dual Use Concerns. Journal of Science Policy & Governance 2023, 22 (03).
3. Odell, S. G., Lazo, G. R., Woodhouse, M. R., Hane, D. L. & Sen, T. Z. The art of curation at a biological database: principles and application. Curr. Plant Biol. 11–12, 2–11 (2017).
4. Lan L, et al. Generative adversarial networks and its applications in biomedical informatics. Front Public Health. 2020;8:164.
5. Renaldi Mahardika Putra Bamba, Isman Kurniawan, Widi Astuti. In Silico-Based Toxicity Predicition Using Camel Algorithm-Support Vector Machine: Case Study NR-AhR Toxicity Type. 2024, 317-321.
6. Gkotsis, G. et al. Characterisation of mental health conditions in social media using Informed Deep Learning. Sci. Rep. 7, 45141 (2017).
7. Per Nilsen, David Sundemo, Fredrik Heintz, Margit Neher, Jens Nygren, Petra Svedberg, Lena Petersson. Towards evidence-based practice 2.0: leveraging artificial intelligence in healthcare. Frontiers in Health Services 2024, 4.
8. Abdulrahman A. Almehizia, Wael M. Aboulthana, Ahmed M. Naglah, Ashraf S. Hassan. In vitro biological studies and computational prediction-based analyses of pyrazolo[1,5- a]pyrimidine derivatives. RSC Advances 2024, 14 (12) , 8397-8408.
9. Holmes I, Linder J, Kelley D. Selective State Space Models Outperform Transformers At Predicting RNA-Seq read coverage. BioRxiv. 2025.
10. Thomas Hartung. Artificial intelligence as the new frontier in chemical risk assessment. Frontiers in Artificial Intelligence 2023, 6.
11. Chi Kit Ng, Jianqiao Long, Muran Tang, Jichun Li, Mingming Quan. Exploring AI-Driven Drug Repurposing Strategies Targeting ErbB Signalling Pathway for Brain Cancer Therapy. 2024, 555-560.
12. Cohen, O., Zhu, B. & Rosen, M. S. MR fingerprinting Deep RecOnstruction NEtwork (DRONE). Magn. Reson. Med. 80, 885–894 (2018).
13. Korbar, B. et al. Deep learning for classification of colorectal polyps on whole-slide images. J. Pathol. Informat. 8, 30 (2017).
14. Cheong BC. Transparency and accountability in AI systems: safeguarding wellbeing in the age of algorithmic decision-making. Front Hum Dynam. 2024.
15. Norgeot, B., Glicksberg, B. S. & Butte, A. J. A call for deep-learning healthcare. Nat. Med. 25, 14–15 (2019).