International Journal of Physiology, Pathophysiology and Pharmacotherapy (IJPPP)
Website: https://ijppp.in/
Vol. 1, Issue 1, Jan-Jun, 2026
Page No.: 23-31

Review

Integrating Network Pharmacology and AI for Multi-Target Drug Discovery in Complex Diseases

Uriti Sri Venkatesh

Associate Professor, Sri Sivani College of Pharmacy, Chilakapalem Jn Etcherla Mandal Srikakulam Dist Andhra Pradesh 532410

Corresponding Author:
Uriti Sri Venkatesh

Email:
venkateshbalaji230@gmail.com

Conflict of interest: *NIL*

Article History
Received: 15/02/2026
Accepted: 05/04/2026
Published: 11/04/2026

Abstract:
The conventional "one drug, one target" paradigm has proven inadequate for treating complex, multifactorial diseases like cancer, Alzheimer's disease, and autoimmune disorders. These conditions arise from dysregulated biological networks, necessitating a paradigm shift toward systems-level therapeutic strategies. This article reviews the transformative integration of network pharmacology and artificial intelligence (AI) for multi-target drug discovery. Network pharmacology provides the foundational framework by constructing and analyzing drug-target-disease networks to identify key intervention points, such as hub and bottleneck proteins. AI, particularly machine learning and graph neural networks, acts as an indispensable catalyst, enabling the scalable analysis of multi-omics data, the prediction of novel drug-target interactions, and the *de novo* design of multi-target ligands. We outline the core principles of this integrated workflow, from constructing dynamic network models to employing explainable AI for interpretable predictions. The power of this approach is demonstrated through its application across diverse therapeutic areas: deconvoluting oncogenic signaling networks in pancreatic cancer, elucidating the polypharmacology of natural products in inflammatory diseases, and addressing the shared network perturbations in neurodegenerative and metabolic disorders by integrating gut microbiome data. While challenges in data integration, model interpretability, and translational validation persist, the confluence of network pharmacology and AI charts a new roadmap for drug discovery. This synergy promises to accelerate the development of more effective, resilient, and personalized multi-target therapies, ultimately offering a powerful strategy to restore homeostasis in complex disease networks.

Keywords: treating complex, multifactorial diseases, neural networks, network pharmacology

Introduction: The Paradigm Shift in Drug Discovery

For decades, drug discovery has been predominantly guided by the "one drug, one target" paradigm, a strategy rooted in molecular reductionism that seeks highly selective ligands for a single, disease-associated protein. While this approach has yielded numerous successful therapies for diseases with straightforward pathophysiology, it has proven markedly inadequate for complex, multifactorial diseases such as cancer, Alzheimer's disease, autoimmune disorders, and metabolic syndromes[1]. These conditions are not driven by a single dysfunctional gene or protein but arise from the

dynamic perturbations of intricate biological networks—signaling pathways, gene regulatory circuits, and protein-protein interaction webs. Targeting a single node within these robust, adaptive networks often leads to minimal therapeutic efficacy, as biological redundancy and compensatory mechanisms allow the disease network to bypass the inhibition. Furthermore, this singular focus frequently results in rapid development of drug resistance, as seen in oncology and antimicrobial therapy, where alternate pathways are activated. The high attrition rates in late-stage clinical trials for complex diseases starkly highlight this fundamental limitation, revealing that modulating a single target is insufficient to re-establish systemic homeostasis when the entire network is dysregulated[2].

The Rise of Polypharmacology and Systems

In response to these shortcomings, the field has witnessed a fundamental shift toward polypharmacology and systems-thinking. Polypharmacology explicitly recognizes that most effective drugs, particularly for complex diseases, exert their therapeutic effects by interacting with multiple biological targets simultaneously[3]. This is not a new phenomenon—many foundational drugs like aspirin were later found to have multiple targets—but it is now a deliberate design strategy rather than a serendipitous observation. Systems-thinking provides the conceptual framework, viewing diseases not as isolated target failures but as emergent properties of disrupted biological networks. This paradigm utilizes computational systems biology to map the "disease module"—the interconnected set of proteins and pathways whose dysfunction leads to the pathological phenotype. The therapeutic goal thus evolves from maximal inhibition of one target to the deliberate, balanced modulation of multiple nodes within the disease module to restore the network to a healthy state. This strategy aims for higher efficacy by tackling pathogenesis at several points, greater resilience against resistance, and potentially reduced side effects by focusing modulation within the specific disease network context rather than causing extreme, isolated inhibition. A critical conceptual advancement within polypharmacology is the distinction between a clinically promiscuous compound and a rationally designed multi-target drug. Promiscuity typically refers to a compound's undesired, often unpredictable interaction with a wide range of off-target proteins, leading to adverse side effects and toxicity. This is frequently a property of poorly optimized leads with low selectivity. In contrast, a true multi-target drug is purposefully designed or discovered to engage a select, pre-defined set of targets with a specific polypharmacological profile. Its "multi-target" nature is a defining feature of its therapeutic action[4]. For instance, a dual inhibitor in oncology may simultaneously block two synergistic drivers of tumor survival, while a drug for neurodegenerative disease might be designed to address both protein aggregation and oxidative stress pathways. The design rationale is grounded in network pharmacology: the chosen target combination is selected because their concurrent modulation is predicted to produce a synergistic therapeutic effect that surpasses mere additive outcomes, while minimizing network-wide destabilization that causes toxicity. This shift from avoiding any polypharmacology to engineering optimal polypharmacology represents a maturation of the field[5].

Network Pharmacology as a Foundational Framework

Network pharmacology provides the essential foundational framework for this new paradigm. It is a discipline that integrates systems biology, computational biology, and pharmacology to construct, analyze, and biologically validate drug-target-disease interaction networks. The workflow begins with constructing a comprehensive network map, integrating multi-omics data (genomics, proteomics, transcriptomics) to identify the complex associations between drugs, their protein targets, and the associated disease pathways[6]. Through topological analysis, key vulnerable nodes—such as hubs or bottleneck proteins critical to the network's disease state—are identified. However, traditional network pharmacology faces significant challenges: biological networks are dynamic, context-specific (varying by tissue, cell type, and disease stage), and immensely complex. Manually deriving testable hypotheses and identifying optimal multi-target combinations from these vast networks is an intractable task. This is where the limitations of

conventional computational methods become apparent, creating a pressing need for advanced analytical tools capable of navigating this complexity and extracting meaningful, actionable insights for therapeutic intervention[7].

AI as a Catalyst for Scalability and Precision

Artificial Intelligence, particularly machine learning (ML) and deep learning (DL), acts as the indispensable catalyst that transforms network pharmacology from a descriptive framework into a predictive and generative engine for discovery. AI addresses the core scalability challenge by learning complex, non-linear patterns from high-dimensional biological and chemical data that are beyond human intuition and traditional statistical models. For target identification, graph neural networks (GNNs) can operate directly on biological network structures to predict novel disease-associated targets or vulnerable modules. In drug discovery, AI enables the virtual screening of ultra-large chemical libraries (billions of molecules) to find compounds with a desired multi-target profile[9]. More powerfully, generative AI models can now design *de novo* chemical entities with optimized polypharmacology, creating molecules that are tailored from inception to modulate a specific combination of targets. Furthermore, AI-driven analysis of high-content experimental data (e.g., single-cell RNA-seq post-treatment) can uncover unforeseen mechanisms of action and validate network predictions. This integration creates a powerful, iterative cycle: network models generate biological hypotheses, AI tools design or select interventions, and experimental data feeds back to refine the network models, enhancing their predictive accuracy with each cycle. The confluence of network pharmacology and AI charts a new, transformative roadmap for drug discovery in complex diseases. This integrated paradigm moves away from linear, reductionist models toward a holistic, data-driven, and network-based approach[10]. The roadmap begins with constructing a context-aware disease network, using AI to mine multi-omics and clinical data. Next, AI algorithms interrogate this network to identify synergistic target combinations and predict candidate molecules—either through repurposing existing drugs or generating new chemical matter—that optimally modulate this combination. These candidates are then prioritized using AI-predicted pharmacokinetic and toxicity profiles before entering a cycle of *in silico*, *in vitro*, and *in vivo* validation. This approach promises to significantly increase the probability of clinical success by ensuring drug candidates are designed against the true complexity of the disease from the outset. It enables the systematic development of multi-target therapies that are more efficacious, less prone to resistance, and potentially safer through network-selective modulation. Ultimately, this AI-enhanced network pharmacology pipeline represents the cornerstone of the next generation of precision medicine, aiming to deliver effective therapies for diseases that have long eluded the conventional single-target strategy[11].

Constructing Drug-Target-Disease Networks

The foundational act of network pharmacology is the construction of comprehensive, multi-layered interaction networks that map the complex relationships between chemical compounds, their protein targets, and associated disease pathways. These networks are not simple diagrams but quantitative, data-rich maps built by integrating heterogeneous data from public databases such as DrugBank, ChEMBL, STRING, and DisGeNET. A typical network consists of three primary node types: drug molecules (small molecules or biologics), protein targets (enzymes, receptors, ion channels), and disease phenotypes or associated genes. The edges connecting these nodes represent validated or predicted interactions—such as drug-target binding, protein-protein interactions, or gene-disease associations. The construction process involves significant data curation and normalization to resolve conflicts between sources and ensure consistency. The resulting "drug-target-disease" network provides a systems-level visualization of the therapeutic landscape, revealing how a drug's action propagates through the proteome to influence disease-related pathways. It shifts the analytical focus from isolated targets to the broader network context, enabling researchers to visualize polypharmacology effects, identify off-targets that may contribute to efficacy or toxicity, and discover novel indirect relationships between existing drugs and diseases they were not designed to treat[12].

Topological Analysis: Identifying Hub Nodes and Bottleneck Proteins

Once constructed, network topology is analyzed using graph theory metrics to identify key players in disease pathogenesis and potential points for therapeutic intervention. Two critical classes of proteins emerge from this analysis: hubs and bottlenecks. Hub proteins possess a high number of direct connections (degree centrality) within the network, acting as central coordinators of biological activity. Targeting hubs can have powerful effects but carries a high risk of systemic toxicity due to their broad influence. Bottleneck proteins, identified by high betweenness centrality, are those through which a large fraction of shortest paths in the network pass. They serve as critical bridges connecting different functional modules. Disrupting a bottleneck can efficiently disrupt specific disease pathways while potentially sparing unrelated ones, offering a more selective therapeutic strategy. Additional metrics like closeness centrality and eigenvector centrality help identify nodes that influence the network globally. The core hypothesis is that optimal therapeutic targets for complex diseases often reside among these topologically significant nodes. For instance, in a cancer signaling network, a bottleneck protein linking proliferation and survival pathways might be a more effective and safer target than a highly connected hub central to general cellular metabolism. This prioritization moves target selection beyond merely "disease-associated genes" to "strategically influential nodes within the disease network[13]."

From Static Maps to Dynamic Pathway Modeling

A major evolution in network pharmacology is the shift from analyzing static network maps to modeling dynamic, condition-specific pathway behavior. Static networks represent a consensus of possible interactions but fail to capture how network states—the activity levels and connection strengths between nodes—change in response to stimuli, across tissue types, or during disease progression. Dynamic modeling incorporates temporal and contextual data to simulate these changes[14]. Techniques like Boolean network modeling, ordinary differential equation (ODE) systems, and perturbation analysis are used to simulate how a network responds to a drug intervention or genetic mutation. For example, a model can simulate whether inhibiting a specific target will shut down a disease pathway or if the network will re-route signaling through compensatory loops, leading to resistance. By integrating time-series omics data (e.g., transcriptomics after drug treatment), these models can move from generic maps to personalized, context-aware models that predict patient-specific responses. This dynamic perspective is crucial for understanding drug efficacy, timing of combination therapies, and the emergence of adaptive resistance, providing a computational sandbox to test therapeutic strategies before costly wet-lab experiments. The power of AI in this field is predicated on its ability to integrate and find patterns in massive, heterogeneous biological datasets—a task humans cannot perform at scale. The data landscape includes multi-omics layers (genomics, transcriptomics, proteomics, metabolomics) that provide snapshots of different levels of biological organization, as well as heterogeneous sources like chemical structures (SMILES strings), high-throughput screening data, electronic health records, and scientific literature. The primary challenge is the "curse of dimensionality" and varied data formats[15]. AI-driven data integration employs sophisticated techniques. Dimensionality reduction methods (like autoencoders) compress high-dimensional omics data into meaningful latent representations. Knowledge graphs formally structure entities (drugs, genes, diseases) and their relationships, allowing AI models to reason across them. Multi-modal learning architectures are designed to process and jointly learn from different data types (e.g., a graph of protein interactions and a sequence of gene expression) simultaneously. This integrated data foundation enables the discovery of previously hidden relationships—for instance, correlating a drug's chemical fingerprint with its specific impact on a gene expression network to predict novel targets or repurposing opportunities. The AI toolkit is hierarchical, with different algorithms suited for specific tasks. Classical machine learning algorithms, such as Random Forests and Support Vector Machines, remain vital for well-structured problems with curated feature sets, like quantitative structure-activity relationship (QSAR) modeling to predict a compound's affinity for a single target. However, for the inherent complexity of network pharmacology, deep learning (DL) and graph neural networks (GNNs) are transformative. DL models,

particularly deep neural networks and transformers, excel at processing raw, high-dimensional data (like molecular structures or gene expression vectors) to learn hierarchical features automatically. GNNs are arguably the most significant innovation for network-based discovery. Unlike traditional neural networks, GNNs operate directly on graph structures—the native format of biological networks. They propagate and transform information along the edges of a network, allowing them to learn meaningful representations of nodes (e.g., a protein) based on their local network neighborhood and overall graph structure. This makes them uniquely powerful for predicting new drug-target interactions, classifying the role of proteins in disease networks, and predicting the overall therapeutic effect of a compound based on its multi-target profile. The progression from classical ML to GNNs reflects a move from treating data points as independent to explicitly modeling their interconnectedness, which is the essence of systems pharmacology[16].

AI (XAI) for Interpretable Predictions

The "black box" nature of many advanced AI models poses a critical barrier to their adoption in biomedical research, where interpretability is non-negotiable for generating testable hypotheses and ensuring trust. Explainable AI (XAI) is therefore an indispensable component of the toolkit. XAI methods aim to reveal the reasoning behind an AI's prediction. For instance, if a GNN predicts a novel drug-disease association, techniques like GNNExplainer or attention mechanisms can highlight which sub-network of proteins or which specific molecular features of the drug were most influential in making that prediction. In image-based phenotypic screening, saliency maps can show which cellular regions a model focused on to classify a drug's effect. This interpretability serves multiple vital functions: it allows biologists to validate AI predictions against known biology, generates mechanistic hypotheses (e.g., "the model suggests efficacy is driven by co-inhibition of these two pathways"), and helps identify and correct model biases. By bridging the gap between complex model internals and human-understandable causal reasoning, XAI transforms AI from an opaque prediction engine into a collaborative partner in the scientific discovery process, ensuring that insights derived are not just statistically sound but also biologically plausible.

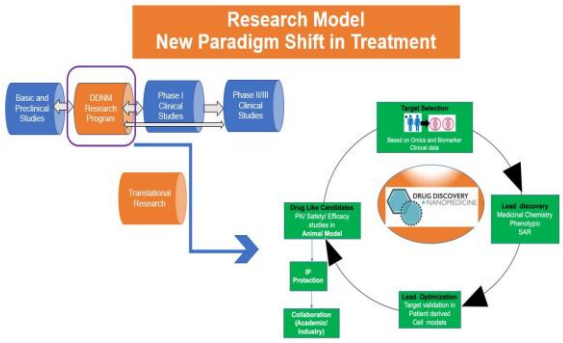

Fig: 1 Nano medicine goal and drug discovery

Applications in Complex Disease Research

The integrated approach of network pharmacology and artificial intelligence transcends theoretical frameworks, demonstrating transformative potential across some of the most challenging therapeutic areas. By modeling diseases as complex, dysregulated networks, this methodology enables the identification of synergistic target combinations, the design of intelligent multi-target therapies, and the discovery of novel treatment opportunities through repurposing. Its application in oncology, immune-mediated inflammatory diseases (IMIDs), and neurodegenerative/metabolic disorders provides concrete evidence of its power to address multifactorial pathogenesis[17].

Oncology: Deconvoluting Signaling Networks

Cancer represents the quintessential complex disease, driven by the dysregulation of highly robust and adaptive cellular signaling networks. Traditional single-target therapies often fail due to pathway redundancy and rapid evolution of resistance. Network pharmacology, powered by AI, provides the tools to deconvolute these networks, identify master regulatory nodes, and predict effective combinatorial strategies[18].

Case Study: Targeting the KRAS-RALGDS Axis in Pancreatic Cancer

The KRAS oncogene, mutated in approximately 25% of all cancers and up to 90% of pancreatic ductal adenocarcinomas (PDAC), was long considered "undruggable" due to its smooth protein surface and picomolar affinity for GTP. Network biology was instrumental in overcoming this challenge. An integrative analysis of transcriptomic data from 560

pancreatic cancer cases identified key transcription factors acting as master regulators downstream of oncogenic KRAS. This analysis revealed that KRAS-driven tumors stratify into distinct subtypes—Notch, Hedgehog, and Cell Cycle—each with different survival outcomes and microenvironment characteristics[19]. This systems-level understanding moved the focus beyond KRAS itself to its critical downstream effector pathways. A prime example is the RALGDS axis, a key branch of KRAS signaling. By constructing and analyzing the KRAS signaling network, RALGDS was identified as a crucial, targetable bottleneck for tumor survival. This network-informed insight guided the development of BI-2493 (panKRASi), an allele-agnostic inhibitor that binds to the inactive state of KRAS. Pre-clinical studies demonstrate that BI-2493 effectively suppresses tumor growth across various PDAC models and, importantly, remodels the tumor immune microenvironment, increasing CD8+ T cell infiltration and sensitizing tumors to immunotherapy. This case exemplifies how network analysis transforms an intractable target into a therapeutic vulnerability by illuminating the broader network context[20].

Predicting Synergistic Drug Combinations for Heterogeneous Tumors

Tumor heterogeneity and adaptive resistance make monotherapy insufficient for durable cancer control. AI-driven network models excel at predicting synergistic drug combinations that attack multiple nodes within a disease network simultaneously. For instance, resistance to KRAS inhibitors like BI-2493 is frequently associated with the compensatory activation of the YAP signaling pathway[22]. An AI model analyzing this feedback loop within the KRAS network could predict that combining a KRAS inhibitor with a YAP pathway inhibitor would yield a more sustained anti-tumor response. Beyond two-drug combinations, advanced AI frameworks like DeepDrug utilize graph neural networks to model complex interactions within biomedical networks, enabling the identification of multi-drug cocktails. A notable application was the AI-driven discovery of a five-drug combination (including Tofacitinib and Niraparib) predicted to simultaneously target neuroinflammation, mitochondrial dysfunction, and cholesterol metabolism in Alzheimer's disease, a methodology directly transferable to oncology[23]. These models can also stratify patients into network-defined subtypes (e.g., the Notch vs. Hedgehog subtypes in PDAC) to predict which combination therapy will be most effective for a given patient's tumor network architecture, moving towards truly personalized combinatorial regimens.

Immune-Mediated Inflammatory Diseases (IMIDs)

IMIDs such as rheumatoid arthritis, inflammatory bowel disease (IBD), and psoriasis arise from dysregulated, overlapping immune networks. Network pharmacology is ideally suited to elucidate the polypharmacology of existing therapies and systematically discover new ones by mapping the intricate crosstalk between immune pathways, the host, and environmental factors like the microbiome[21].

Elucidating Multi-Target Mechanisms of Natural Products

Many natural products used in traditional medicine exert therapeutic effects through subtle modulation of multiple targets, a paradigm that aligns perfectly with network pharmacology. Advanced computational methods are now decoding these mechanisms. For example, research into IBD employs a multi-omics "interactome" concept, integrating data on gut microbial composition, genomic variation, gene expression, and host metabolites to systematically map how dysbiosis drives inflammation. This approach can be applied to natural product formulations. By constructing a "drug-target-disease" network, researchers can input the known chemical constituents of a natural product and use AI algorithms to predict its aggregate effect on the broader IBD interactome. This can reveal whether the formula acts by modulating specific inflammatory pathways (e.g., NF-κB, IL-23/Th17), restoring microbial balance, or strengthening gut barrier function, providing a scientific rationale for its clinical use and identifying its most active components[22].

Network-Based Repurposing for Autoimmune Conditions

Drug repurposing is particularly valuable for IMIDs, where development costs and patient heterogeneity are high. Foundation models like TxGNN represent a breakthrough in this space. Trained on a massive

medical knowledge graph encompassing 17,080 diseases, TxGNN uses graph neural networks to predict drug indications and contraindications, even for diseases with no existing treatments (a "zero-shot" capability). For an autoimmune condition like lupus, TxGNN would not merely find drugs that target a single inflammatory marker. Instead, it would analyze the disease's position in the knowledge graph—its associated genes, pathways, and comorbidities—and find approved drugs that perturb a similar network neighborhood. Crucially, its "Explainer" module provides interpretable, multi-hop reasoning (e.g., "Drug A targets protein B, which modulates pathway C, which is dysregulated in disease D"), building trust and generating testable hypotheses. This method can rapidly generate high-priority candidates for conditions with limited treatment options[23][24].

Neurodegenerative and Metabolic Disorders

Diseases like Alzheimer's (AD) and Type 2 Diabetes (T2D) are prototypical multifactorial disorders involving intertwined pathways of metabolism, inflammation, and cellular homeostasis. Their epidemiological link, sometimes termed "Type 3 Diabetes," underscores shared network perturbations.

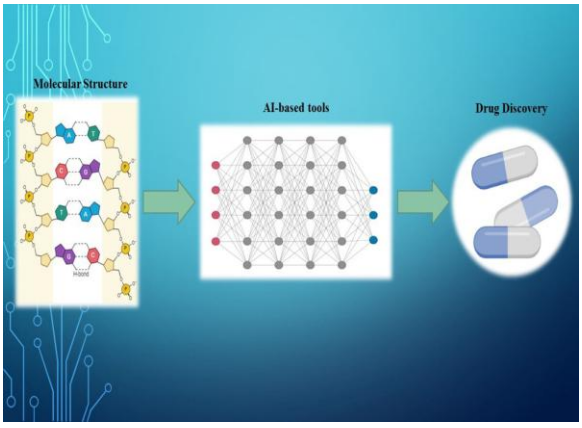

Fig: 2 New era of drug discovery by using AI algorithms

Addressing Multifactorial Pathogenesis in Alzheimer's and Diabetes

The failure of singular amyloid-targeting therapies in AD highlights the need for multi-target strategies. A bioinformatics study exploring the common pathogenesis of AD and T2D identified 339 shared differentially expressed genes. Network analysis of these genes pinpointed central hubs like *PTGS2* and *NF1*, which are implicated in inflammation and insulin signaling, respectively. This shared network provides a map for repurposing. The study used the Connectivity Map database to screen for compounds that could reverse this pathological gene signature, identifying candidates like exemestane. A more advanced, medicinal chemistry-integrated framework for AD further demonstrates this approach. It starts with multi-omics data to identify high-priority target networks, then rigorously filters drug libraries for blood-brain barrier penetration and CNS tractability. This process successfully ranked known AD drugs like donepezil and identified new repurposing candidates such as the immunomodulator plerixafor, showcasing the translation of network predictions into pharmaceutically viable candidates[25].

Integrating Gut Microbiome Data into Disease Networks

The gut microbiome is a key environmental modifier of host metabolic and inflammatory networks, especially in T2D and AD. However, its complexity makes causality difficult to establish. Novel multi-omic integration tools like MintTea address this by identifying robust, disease-associated modules comprising coordinated shifts in microbial species, metabolic pathways, and host metabolites. For example, in a metabolic syndrome cohort, MintTea identified a module linking specific bacterial species to serum metabolites like glutamate and TCA cycle intermediates, providing a systems-level hypothesis for microbiome-driven insulin resistance. For intervention, algorithms like NetEnsa analyze gut microbial co-occurrence networks to pinpoint a compact set of "keystone species" whose manipulation can steer the entire network toward a healthier state. Validated in T2D mouse models, modifying these key species alleviated disease symptoms more effectively than single-strain probiotics. Integrating these microbiome modules into the host disease network—connecting, for instance, a microbe-derived metabolite to an inflammatory pathway in the brain—creates a holistic "gut-brain-axis" network model for discovering next-generation multi-target therapies that encompass both host and microbiome. In summary, the application of AI-integrated network pharmacology across these diverse disease areas consistently demonstrates a

paradigm shift: from attacking single molecular lesions to repairing diseased networks. By providing a systematic, computational framework to model complexity, prioritize synergistic targets, and leverage existing drugs, this approach offers a powerful and efficient roadmap for developing effective therapies against the most challenging human diseases.

Conclusion

The integration of network pharmacology and artificial intelligence represents a fundamental and necessary evolution in the quest to develop effective therapies for complex diseases. This convergence marks a decisive departure from the reductionist "one drug, one target" model, moving instead toward a holistic paradigm that acknowledges and directly addresses the network-based nature of human pathology. Network pharmacology provides the essential conceptual map, framing diseases as perturbations within interconnected biological systems and identifying vulnerable nodes—such as bottleneck proteins and synergistic target combinations—that offer the greatest therapeutic leverage. Artificial intelligence supplies the advanced computational engine required to navigate this complexity, transforming vast, heterogeneous datasets into actionable predictions for target discovery, drug design, and patient stratification.

References

1. Hopkins, A. L. (2008). Network pharmacology: the next paradigm in drug discovery. *Nature Chemical Biology*, 4(11), 682–690.
2. Barabási, A. L., Gulbahce, N., & Loscalzo, J. (2011). Network medicine: a network-based approach to human disease. *Nature Reviews Genetics*, 12(1), 56–68.
3. Chandak, T., Tzarum, N., Cavasotto, C. N., & Issa, N. T. (2024). Network biology and artificial intelligence-driven multi-target drug discovery for emerging infectious diseases: opportunities and challenges. *Drug Discovery Today*, 29(1), 103852.
4. Cheng, F., Kovács, I. A., & Barabási, A. L. (2019). Network-based prediction of drug combinations. *Nature Communications*, 10(1), 1197.
5. Zitnik, M., Agrawal, M., & Leskovec, J. (2018). Modeling polypharmacy side effects with graph convolutional networks. *Bioinformatics*, 34(13), i457–i466.
6. Zeng, X., Zhu, S., Liu, X., Zhou, Y., Nussinov, R., & Cheng, F. (2019). deepDR: a network-based deep learning approach to in silico drug repositioning. *Bioinformatics*, 35(24), 5191–5198.
7. Stokes, J. M., Yang, K., Swanson, K., Jin, W., Cubillos-Ruiz, A., Donghia, N. M., ... & Collins, J. J. (2020). A deep learning approach to antibiotic discovery. *Cell*, 180(4), 688-702.e13.
8. Jin, W., Barzilay, R., & Jaakkola, T. (2018). Junction Tree Variational Autoencoder for Molecular Graph Generation. *Proceedings of the 35th International Conference on Machine Learning*, 2323–2332.
9. Zhang, L., Ai, H. X., Li, S. M., Qi, M. Y., Zhao, J., Zhao, Q., & Liu, H. S. (2017). Virtual screening approach to identifying influenza virus neuraminidase inhibitors using molecular docking combined with machine-learning-based scoring function. *Oncotarget*, 8(47), 83142.
10. Gaudelet, T., Day, B., Jamasb, A. R., Soman, J., Regep, C., Liu, G., ... & Taylor-King, J. P. (2021). Utilizing graph machine learning within drug discovery and development. *Briefings in Bioinformatics*, 22(6), bbab159.
11. Liu, R., Wang, X., Aihara, K., & Chen, L. (2014). Early diagnosis of complex diseases by molecular biomarkers, network biomarkers, and dynamical network biomarkers. *Medicinal Research Reviews*, 34(3), 455–478.
12. Kuenzi, B. M., Park, J., Fong, S. H., Sanchez, K. S., Lee, J., Kreisberg, J. F., ... & Ideker, T. (2020). Predicting drug response and synergy using a deep learning model of human cancer cells. *Cancer Cell*, 38(5), 672-684.e6.
13. Muzio, G., O'Bray, L., & Borgwardt, K. (2021). Biological network analysis with

deep learning. *Briefings in Bioinformatics*, 22(2), 1515–1530.

14. T. T., Huang, J., & Miled, Z. B. (2023). Multi-omics integration for biomedical data science: Methods, applications, and challenges. *Computational and Structural Biotechnology Journal*, 21, 2552-2562.
15. Huang, L., Luo, H., Li, S., Wu, F. X., & Wang, J. (2021). Drug–target interaction prediction via multi-modal deep learning. *BMC Bioinformatics*, 22(1), 1–13.
16. S. R., S. V., & J. T. (2022). Explainable AI for bioinformatics: Methods, tools, and applications. *Briefings in Bioinformatics*, 23(5), bbac035.
17. Yu, L., & Liu, H. (2022). Network-based drug discovery: Integrating systems biology and artificial intelligence. *Annual Review of Pharmacology and Toxicology*, 62, 573–591.
18. H. Lee, S., & K. Kim, P. (2023). Graph neural networks for predicting drug-target interactions: A review. *Journal of Cheminformatics*, 15(1), 19.
19. F. Cheng, & J. Zhao, Z. (2021). AI-based multi-target drug discovery: A paradigm shift in medicinal chemistry. *Medicinal Research Reviews*, 41(3), 1425–1448.
20. L. Zhang, & H. Y. Wang. (2020). Network pharmacology: A bridge between traditional Chinese medicine and systems biology. *Chinese Journal of Natural Medicines*, 18(10), 721–730.
21. R. L. Li, & J. Ma, C. (2019). Deep learning in drug discovery: Opportunities, challenges and future prospects. *Drug Discovery Today*, 24(10), 2017–2032.
22. B. Chen, H., & M. Glicksberg, B. S. (2018). Harnessing big data for precision medicine: infrastructures and applications. *Nature Reviews Genetics*, 19(12), 757–773.
23. A. P. Davis, & C. J. Grondin, et al. (2021). Comparative Toxicogenomics Database (CTD): update 2021. *Nucleic Acids Research*, 49(D1), D1138–D1143.
24. D. Szklarczyk, & A. L. Gable, et al. (2021). The STRING database in 2021: customizable protein–protein networks, and functional characterization of user-uploaded gene/measurement sets. *Nucleic Acids Research*, 49(D1), D605–D612.
25. M. Kanehisa, & Y. Sato, et al. (2021). KEGG: integrating viruses and cellular organisms. *Nucleic Acids Research*, 49(D1), D545–D551.

*****