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In Silico Approaches for Rational Drug Design and Potential Enzyme Inhibitors Discovery: A Mini-Review

Morteza Sadeghi[1], Marzieh Karami[2], Mehran Miroliaei[3], Mustafa Ghanadian[4]

1. Department of Biochemistry, Sanandaj Branch, Islamic Azad University, Sanandaj, Iran
2. Department of Nursing, Sanandaj Branch, Islamic Azad University, Sanandaj, Iran
3. Department of Cell and Molecular Biology & Microbiology, University of Isfahan, Isfahan, Iran
4. Department of Pharmacognosy, Isfahan University of Medical Sciences, Isfahan, Iran

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Abstract

The field of drug design has undergone remarkable advancements with the advent of *in silico* methods, which utilize computational approaches that accelerate the discovery and development of novel therapeutics. This review provides an overview of two essential techniques in this domain: molecular docking and molecular dynamics simulation. Molecular docking plays a central role in drug design by predicting the binding interactions between a small molecule (ligand) and its target protein (receptor). By leveraging algorithms and scoring functions, molecular docking enables researchers to evaluate the binding affinity and selectivity of potential drug candidates. Through the exploration of various conformations and orientations, molecular docking facilitates the identification of lead compounds for further optimization. In tandem with molecular docking, molecular dynamics simulation has emerged as a powerful tool for studying the dynamic behavior of biomolecular systems over time. By employing physical principles alongside computational algorithms, molecular dynamics simulations provide insights into the conformational changes, flexibility, and stability of protein-ligand complexes. These simulations not only elucidate binding mechanisms but also reveal critical structural features that influence drug-target interactions. This mini-review highlights the applications of molecular docking and molecular dynamics simulation in drug design, emphasizing their utility in lead identification, optimization, and virtual screening. Collectively, the integration of *in silico* methods—particularly molecular docking and molecular dynamics simulation—has transformed the field of drug design, enabling researchers to significantly accelerate the identification of novel drug candidates while optimizing their therapeutic properties. As computational technologies continue to evolve, these techniques hold immense promise for facilitating the discovery and development of safer, more effective drugs.

Keywords: Drug design, Molecular Docking, Molecular Dynamics Simulations, *In Silico*

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Introduction

The development of novel pharmaceutical substances is an arduous and highly intricate endeavor in contemporary scientific inquiry. Such a pursuit necessitates the collaborative efforts of numerous entities, including but not limited to academic researchers, regulatory authorities, biotechnology companies, the pharmaceutical industry, and both public and private sectors. The development of new drugs represents a multifaceted and interdisciplinary process, wherein its complexity stems from the diverse range of disciplines required

Corresponding Author: **Morteza Sadeghi**, Department of Biochemistry, Sanandaj Branch, Islamic Azad University, Sanandaj, Iran
Email: m.sadeghi@iausdj.ac.ir

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for progress (1-3). This effort has not only improved human health by providing better medicines but has also driven advances in scientific research (4, 5). This phenomenon has spurred the refinement and construction of more intricate and precise tools and methodologies, aimed at discovering and optimizing novel active compounds, as well as deepening our comprehension of their specific targets.

Following the culmination of the Human Genome Project, it was anticipated that a substantial influx of novel drug targets would be swiftly discovered. Nevertheless, the approximately 30,000 genes identified within the human genome failed to present themselves as a direct reservoir for drug development (6). This limitation arises from the fact that it is the proteins encoded by these genes, rather than the genes themselves, that serve as the conventional focal points for pharmacological interventions. The proteome, which encompasses a substantially larger and more complex repertoire than the genome, proves to be markedly intricate (7, 8). Proteins undergo post-translational modifications, form associations with other molecules and prosthetic groups, and participate in the creation of multimeric complexes. Furthermore, many of these proteins possess functions that remain elusive or insufficiently characterized, and their correlation with diseases frequently exhibits complexity, defying precise definition. It quickly became evident that indiscriminate expression, purification, and *in vitro* evaluation of hundreds or even thousands of proteins against libraries containing hundreds of thousands or even millions of compounds could not be construed as a rational and efficient methodology (9-11).

Over time, the strategies and methodologies employed in the realm of drug design have evolved dramatically, capitalizing on and driving forward new technological breakthroughs to overcome the diverse impediments encountered throughout the process. In earlier decades, up until the 1990s, lead discovery and the synthesis of drug-like molecules were among the primary challenges (12, 13). However, the advent of combinatorial chemistry, gene technology, and high-throughput screening assays prompted a shift in focus toward addressing the inadequate absorption, distribution, metabolism, and excretion (ADME) properties exhibited by novel therapeutics.

Presently, the landscape of drug development appears exceptionally promising, owing to the exponential growth of information derived from genomic and proteomic investigations (14, 15). This vast wealth of knowledge not only facilitates the identification of new drug targets but also supports the application of rational combinatorial chemistry to generate extensive compound libraries. Additionally, the creation of genetically modified animal models has emerged as an invaluable tool for the design and evaluation of novel drugs. These developments are further complemented by the prospect of employing ultra-high-throughput screening techniques to analyze vast collections of compounds (16-19). Nonetheless, despite these notable advancements, the long-anticipated era of revolutionary drug design remains elusive.

A diverse range of computational methodologies can be employed at various stages of the drug design continuum. During the early phases, the primary objective is to narrow down the pool of potential ligands, while in the later stages, particularly during lead optimization, the emphasis shifts toward minimizing experimental costs and reducing time consumption (20, 21). Despite the seeming simplicity of this concept, it has been pursued through numerous approaches, of which only a handful have yielded notable successes. The limited success in achieving desired outcomes has underscored the need for a thorough re-examination of the fundamental principles underlying the process.

Recent scholarly works have highlighted the necessity of refining certain hypotheses employed in the enrichment steps, thereby encouraging a critical evaluation of existing practices.

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While some drug developers have pursued alternative experimental approaches to address these challenges, others have concentrated their efforts on enhancing computational protocols (22). These advancements encompass a range of strategies, including but not limited to incorporating protein flexibility into docking algorithms, conducting exhaustive explorations of ligand conformations within binding sites, refining and validating the stability of resulting complexes, and accurately estimating binding free energies (23, 24). Unsurprisingly, molecular dynamics (MD) simulations have emerged as a cornerstone of these endeavors, aimed at refining docking methodologies. It is precisely these simulations that constitute the primary focus of the present review.

Our primary focus lies in articulating protocols and methodologies, rather than delving into the underlying theoretical foundations of these techniques. Our goal is to provide the reader with a practical and concise overview of the potential benefits that can be realized through the integration of docking and MD simulations in the rational design of innovative pharmaceutical compounds.

The initial segment, entitled "Drug Design through In Silico Methods," offers a succinct introduction to the utilization of computational strategies within the drug design process. Within the subsequent section, titled "Drug Design by Ligand-Based Methods," we explore diverse strategies for incorporating receptor flexibility into the docking procedure. Moving forward, the section labeled "Role of MD Simulation in Drug Design" scrutinizes the applications of MD simulations for optimizing and validating protein-ligand complexes. Lastly, the concluding section, "MD Simulation Methods and Techniques," elucidates how docking a small molecule into its protein target can be achieved exclusively through MD simulations.

Drug Design through *in silico* Methods

Enzymes have garnered substantial scholarly and pharmaceutical interest, as evidenced by the extensive body of published research, resolved crystalline structures, and the discovery of small-molecule inhibitors targeting various components of the human genome. The remarkable progress achieved in this domain owes much to the utilization of computational methodologies, which have provided invaluable insights into the structural attributes of both enzymes and ligands, crucial for promoting favorable interactions and achieving desired inhibitory effects (25).

To effectively design enzyme inhibitors, it is essential to thoroughly understand their structure, how they recognize and bind substrates, their conformational dynamics and reactions, how they release products, and the distinctions between their active and inactive states. Within the realm of computer-aided drug design, two primary methodologies are commonly recognized, namely "ligand-based drug design" and "structure-based drug design" (Figure 1).

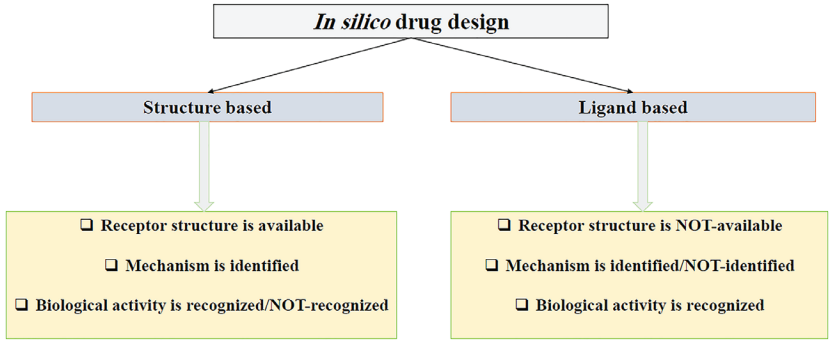

Figure 1. *In silico* drug design based on structure and ligand.

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The latter strategy relies on comprehensive structural data derived from biological targets and encompasses *in silico* techniques such as molecular docking, structure-based virtual screening, and MD simulation (26, 27). Conversely, in cases where specific target information is unavailable, the former approach, "ligand-based drug design," hinges upon the knowledge of ligands that are known to interact with a particular target. The methodologies employed within this approach include ligand-based virtual screening, similarity searching, quantitative structure-activity relationship (QSAR) modeling, and pharmacophore generation (28, 29).

Notably, over recent years, a substantial body of research has reported significant advancements in utilizing computer-aided drug design to facilitate the discovery and development of novel therapeutic agents.

Drug Design by Ligand-Based Methods

QSAR modeling involves establishing a complex mathematical framework, wherein a detailed interplay is established between experimentally determined biological activity and meticulously quantified chemical attributes. These attributes, commonly referred to as descriptors, intricately delineate the intrinsic nature of the scrutinized molecule within a well-defined set of structurally similar compounds (30). The primary objective of QSAR modeling is to leverage the insights gained from a relatively small dataset, encompassing both structural and activity-related aspects, to enable the judicious selection of optimal lead compounds for further investigation. In doing so, this methodology streamlines the drug development process while simultaneously mitigating time and cost constraints (31).

Classical 2D-QSAR models establish correlations between various physicochemical parameters, including steric, hydrophobic, and electronic properties of compounds, and their corresponding biological activities. In contrast, more advanced 3D-QSAR models incorporate quantum chemical parameters into their analysis. One of the pioneering approaches in generating 3D-QSAR models is comparative molecular field analysis (CoMFA). This technique characterizes molecules based on their electrostatic and steric fields and subsequently correlates these characteristics with biological activity using partial least squares regression (32, 33). A summary of recent QSAR studies that provide valuable insights into the design of potent enzyme inhibitors is presented in Table 1.

Applications of Molecular Docking in Drug Design

Molecular docking has revolutionized drug discovery and development by enabling the virtual screening of large chemical libraries to identify potential drug candidates with high binding affinity and specificity for target enzymes (34, 35). This computational technique plays a pivotal role in accelerating the drug design process, reducing both the time and costs associated with experimental screening.

Table 1. QSAR methods and type of their descriptors.

QSAR methods	Type of descriptors
2D	Fragment-based
	Electrostatic chemical
	Geometrical
	Topological
	Constitutional
3D	CoMSIA
	CoMFA
	CoMMA
	GRIND

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Virtual screening using molecular docking involves generating multiple conformations of small-molecule ligands that could potentially bind to the active site of the target enzyme. These ligands are then docked into the receptor's binding pocket, and their binding conformations and affinities are assessed using scoring functions. Scoring functions estimate binding free energy by considering factors such as steric complementarity, electrostatic interactions, hydrogen bonding, hydrophobic effects, and desolvation energies (36, 37). The ligands are ranked based on their predicted binding energies or scores, enabling researchers to prioritize the most promising candidates for further experimental validation. One of the key advantages of molecular docking is its ability to explore structure-activity relationships (SAR) and predict modifications that enhance binding interactions. By analyzing the interactions between ligands and the target enzyme, researchers can identify the key molecular features responsible for binding affinity and selectivity (38). This information guides the rational design and optimization of lead compounds, improving their potency and pharmacokinetic properties (Figure 2).

In the drug discovery process, molecular docking is often integrated with complementary computational techniques such as MD simulations, quantum mechanics calculations, and homology modeling (39). MD simulations provide valuable insights into the dynamic behavior of the ligand-receptor complex, capturing conformational changes and exploring the flexibility of both the protein and ligand during binding. Quantum mechanics calculations offer precise descriptions of molecular interactions, particularly in systems involving metal ions or covalent bonding. Homology modeling enables the construction of three-dimensional models of target enzymes when experimental structures are unavailable, thereby facilitating docking studies across a wide range of proteins (40).

Molecular docking has been successfully employed across various therapeutic areas, including cancer, infectious diseases, neurological disorders, and metabolic disorders. In cancer research, for instance, molecular docking has facilitated the discovery of small-

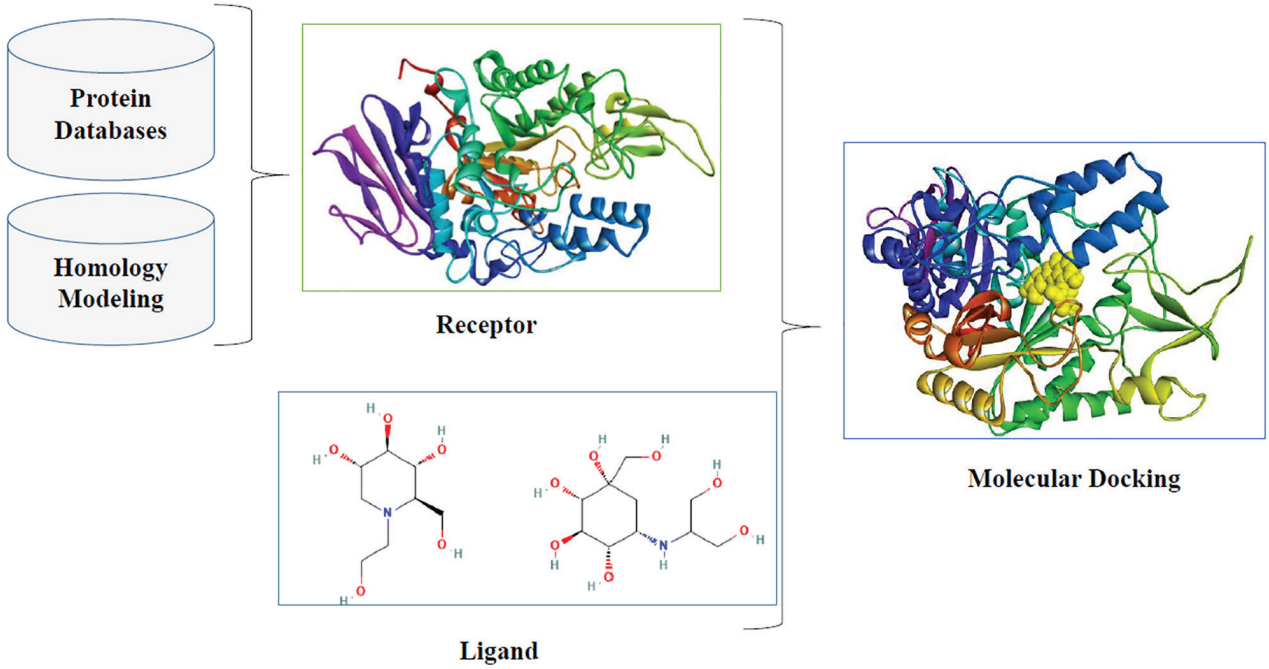

Figure 2. Applications of Molecular Docking in Drug Design

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molecule inhibitors that selectively target oncogenic proteins or enzymes involved in tumor growth pathways (41). These inhibitors can disrupt critical protein-protein interactions or interfere with enzymatic activity, thereby inhibiting tumor progression. Similarly, molecular docking in infectious disease research has aided the identification of potential drugs targeting essential enzymes in pathogens, such as proteases and polymerases, which are crucial for their survival and replication (42, 43). Furthermore, molecular docking enables the exploration of drug repurposing opportunities by screening existing approved drugs or compounds against new targets. This strategy significantly reduces the time and cost required for developing new drugs, as repurposed drugs have already undergone extensive safety testing. Despite its numerous advantages, molecular docking faces several challenges (44). Accurate prediction of binding affinities remains a significant hurdle due to the limitations of current scoring functions, which are often empirical and rely on simplified representations of molecular interactions. Capturing protein flexibility and accounting for solvent effects further complicate the process. Protein conformational changes upon ligand binding, the presence of water molecules within the active site, and explicit consideration of solvation effects demand sophisticated algorithms and computationally intensive approaches (45).

Enzyme Inhibitor Design

Enzyme inhibitors are molecules that selectively bind to specific enzymes and modulate their activity, making them valuable therapeutic agents for a wide range of diseases. The design and development of effective enzyme inhibitors necessitate a deep understanding of their binding modes and interaction patterns within the active site of the target enzyme (46). Molecular docking, a key computational tool, plays a crucial role in elucidating these molecular interactions and assists in optimizing inhibitor potency, selectivity, and pharmacokinetic properties.

The active site of an enzyme is the region where substrates bind and undergo chemical reactions. It typically contains specific amino acid residues that facilitate substrate recognition and catalysis (47). When designing enzyme inhibitors, researchers aim to develop molecules that can efficiently bind to the active site and disrupt or regulate enzymatic function. Molecular docking techniques provide valuable insights into inhibitor binding modes by predicting how inhibitors interact with active site residues.

During a molecular docking simulation, the three-dimensional structure of the target enzyme serves as the receptor, while potential inhibitor molecules function as ligands (48). The ligands are systematically docked into the active site, exploring a range of conformations and orientations. By considering factors such as steric complementarity, electrostatic interactions, hydrogen bonding, hydrophobic effects, and other molecular interactions, docking algorithms evaluate the fitness of each ligand within the active site (49). Through scoring functions, the ligands are ranked based on their predicted binding affinity or energy. Molecular docking offers several critical insights for enzyme inhibitor design. Firstly, it reveals the binding modes and key interactions between the inhibitor and active site residues. This information helps researchers identify the specific molecular features required for optimal binding and guides the modification of lead compounds to improve their potency and selectivity. For example, if a specific residue forms a critical hydrogen bond with the inhibitor, modifications to the inhibitor's chemical structure can enhance this interaction. Furthermore, molecular docking can predict the pharmacokinetic properties of enzyme inhibitors (50). This includes assessing factors such as solubility, permeability through cell membranes, metabolism, and the potential for drug-drug interactions. By considering these properties during the design phase, researchers

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can prioritize compounds with favorable pharmacokinetic profiles, thereby increasing the likelihood of successful translation into therapeutic interventions.

Molecular docking is particularly valuable in the design of enzyme inhibitors for diseases such as cancer, infectious diseases, and metabolic disorders (51). In cancer research, for instance, molecular docking has proven instrumental in identifying small-molecule inhibitors that target specific enzymes involved in aberrant signaling pathways or tumor growth. These inhibitors can disrupt critical protein-protein interactions or interfere with enzymatic activities essential for cancer cell survival and proliferation (52). In the context of infectious diseases, molecular docking aids in the discovery of enzyme inhibitors that selectively target crucial enzymes in pathogens. By inhibiting these enzymes, the replication and survival of pathogens can be disrupted, offering potential treatments for various infections. Examples include the development of protease inhibitors for HIV/AIDS therapy and polymerase inhibitors for antiviral drugs targeting the hepatitis C virus (53), α-glucosidase and α-amylase inhibitors for antidiabetic drugs (54), and acetylcholinesterase and butyrylcholinesterase inhibitors for Alzheimer's disease (55) (Figure 3).

Moreover, molecular docking facilitates the exploration of enzyme inhibitors as potential therapies for metabolic disorders such as diabetes and hypercholesterolemia. By designing inhibitors that target specific enzymes involved in metabolic pathways, it becomes possible to regulate the abnormal biochemical processes associated with these diseases. While molecular docking has significantly advanced the design and optimization of enzyme inhibitors, some challenges remain. Accurate prediction of binding affinity and energy remains a complex area of research due to the intricacies of molecular interactions and the limitations of current scoring functions. Incorporating protein flexibility, accounting for solvent effects, and accurately representing conformational changes upon ligand binding continue to pose challenges in computational modeling. Nevertheless, advancements in

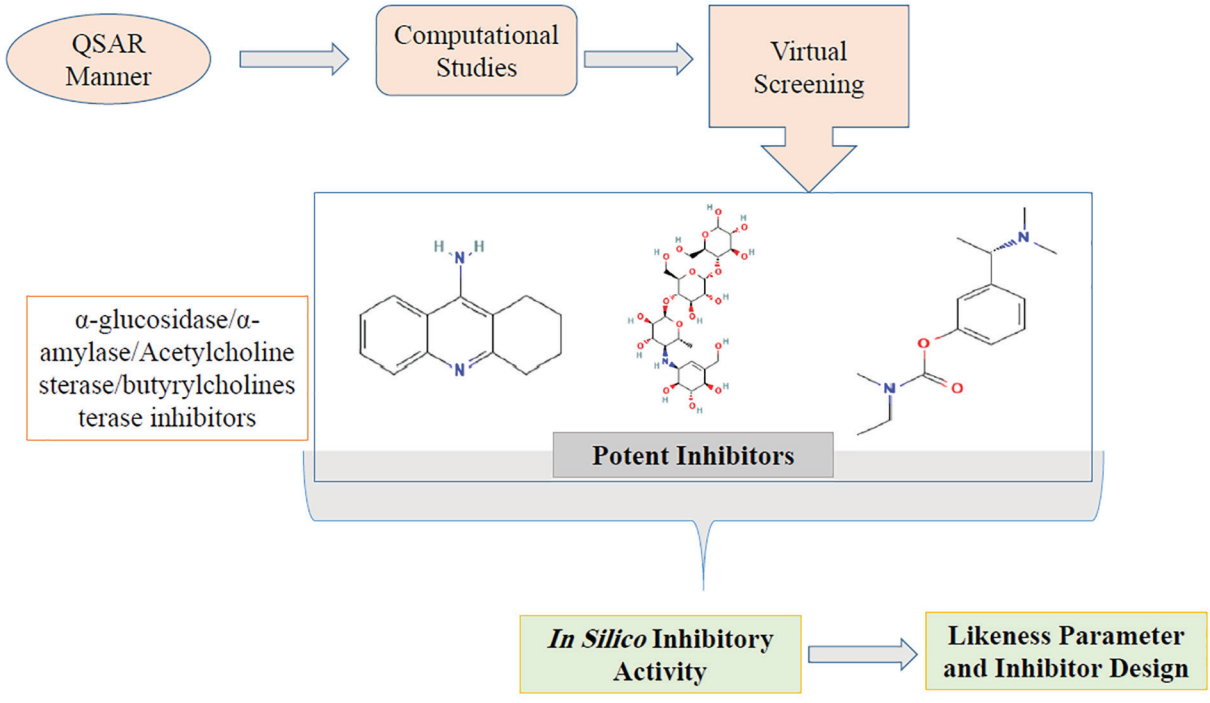

Figure 3. Application of *in silico* manner in enzyme inhibitor design.

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algorithms, force fields, and scoring functions are steadily improving the accuracy and reliability of molecular docking predictions.

Methods of Molecular Docking

One widely used technique in molecular docking is rigid docking, which assumes that both the protein and ligand maintain fixed conformations throughout the binding process (56). Rigid docking algorithms typically generate numerous ligand conformations or poses within the protein's binding site and evaluate them using scoring functions that estimate the binding affinity (57). While rigid docking offers a computationally efficient approach for screening ligands against a protein target, it does not sufficiently account for conformational changes in either the protein or the ligand.

To address the limitations of rigid docking, flexible docking techniques have been developed. Flexible docking allows for limited conformational flexibility in either the protein or the ligand during the binding process. This flexibility can be introduced by permitting the protein or ligand to undergo conformational changes, such as side-chain rotations or backbone movements (58). By incorporating flexibility, flexible docking methods capture a broader spectrum of ligand-protein interactions and potentially improve the accuracy of binding predictions. Induced-fit docking is another notable strategy in molecular docking that explicitly accounts for conformational changes in the protein upon ligand binding (59). Unlike rigid and flexible docking approaches, induced-fit docking models the dynamic nature of the protein by allowing its structure to adapt to the presence of the ligand. This adaptation may involve local rearrangements, loop closures, or global conformational changes in the protein (60). Induced-fit docking methods often employ iterative optimization algorithms to explore the conformational space of both the protein and the ligand, resulting in a more accurate representation of the ligand-protein complex (Figure 4).

Additionally, fragment-based docking is a technique that involves decomposing ligands into smaller molecular fragments for efficient screening against the protein target. This approach leverages the observation that small molecular fragments can often bind to proteins with high affinity and specificity. Fragment-based docking algorithms reconstruct these fragments within the binding site to generate larger, more complete ligands (61). By exploring

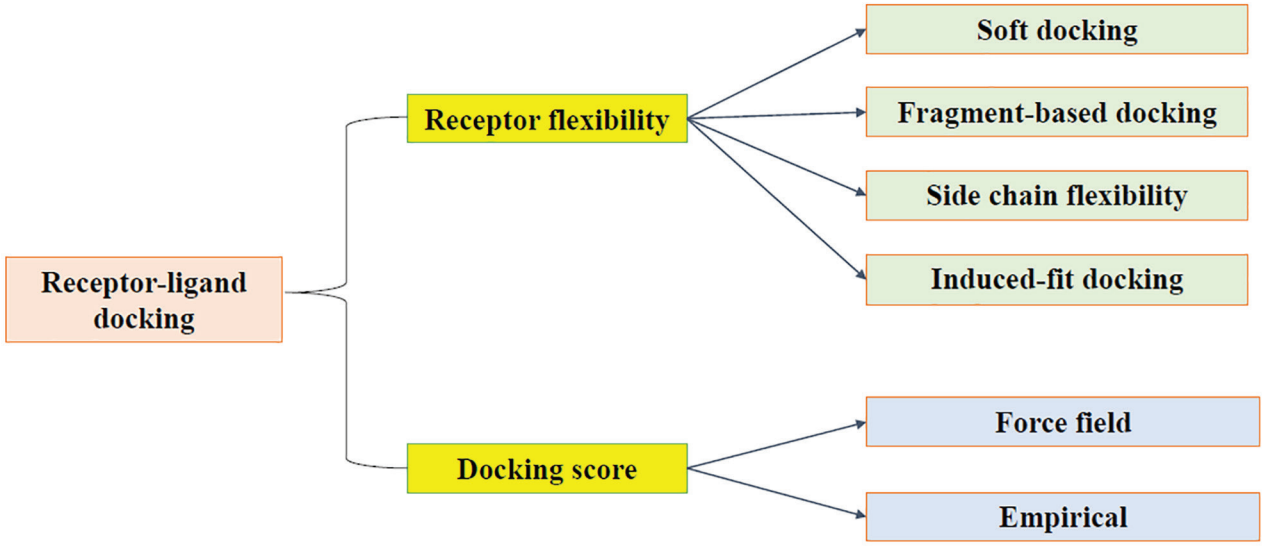

Figure 4. Type of molecular docking methods.

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a reduced chemical space, fragment-based docking methods can efficiently sample a diverse array of ligand conformations and identify potential hits for further optimization. It is worth noting that the selection of an appropriate molecular docking strategy depends on various factors, including the structural characteristics of the protein target, the nature of the ligands, and the specific research objectives (62). Researchers frequently employ a combination of docking techniques or integrate docking with other computational methods to enhance the accuracy and reliability of their predictions. The continuous development of novel algorithms and software tools in molecular docking has greatly contributed to advancing our understanding of ligand-protein interactions and facilitates the rational design of new therapeutic agents (63).

Molecular Docking Challenges and Future Directions

Molecular docking has emerged as a powerful tool in the field of drug discovery and enzyme inhibitor design, aiding in the identification and optimization of potential drug candidates (64). However, despite its successes, several challenges persist, driving continued research efforts.

One of the primary challenges is the development of more accurate scoring functions. Scoring functions play a pivotal role in molecular docking by evaluating the binding affinity between a ligand (small molecule) and a target protein. These functions enable researchers to prioritize and rank potential ligands based on their predicted binding affinities (65). However, current scoring functions often struggle to reliably predict these affinities, leading to inaccuracies in the ranking and selection of compounds. This can result in wasted resources and effort during the experimental validation of poorly ranked candidates (66). Consequently, there is an ongoing need for the refinement of scoring functions to better capture the intricacies of ligand-protein interactions. Another challenge lies in accurately accounting for protein flexibility during the molecular docking process. Proteins are dynamic entities that undergo conformational changes upon ligand binding. Traditional molecular docking methods typically assume rigid protein structures, overlooking the dynamic nature of proteins (67). This oversimplification can lead to inaccurate predictions, as it fails to account for the induced-fit phenomenon, where ligand binding triggers structural adaptations in the protein. Incorporating protein flexibility into docking simulations is therefore essential for accurately modeling and predicting ligand-protein interactions (68). Additionally, considering solvent effects is critical for reliable molecular docking. In a cellular environment, proteins and ligands exist in a solvent medium, such as water, which profoundly influences their interactions. Solvent molecules can form hydrogen bonds, modulate electrostatic interactions, and mediate hydrophobic effects. However, many traditional docking approaches simplify the system by treating the solvent implicitly or ignoring it altogether. This simplification overlooks the complex interplay between the ligand, protein, and solvent, potentially leading to inaccurate predictions (69). Incorporating solvent effects into docking simulations is therefore crucial for generating more realistic and reliable predictions.

To address these challenges, the integration of machine learning (ML) approaches and advanced simulation techniques has gained considerable attention. ML algorithms can effectively learn from large datasets of experimentally determined ligand-protein complexes to develop scoring functions with enhanced predictive capabilities. These algorithms can identify key molecular descriptors and capture complex, non-linear relationships between these descriptors and binding affinities (70, 71). By training on diverse chemical libraries and experimental data, ML models can offer more accurate predictions of binding affinities, overcoming the limitations of traditional scoring functions. Advanced simulation techniques, such

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as MD simulations, have also been employed to address protein flexibility and solvent effects in molecular docking. MD simulations model the motion of atoms over time, enabling the study of conformational changes in proteins and the dynamic behavior of ligands within a solvent environment. Integrating MD simulations into the docking process allows researchers to explore ligand binding pathways, identify key residues involved in binding, and develop a comprehensive understanding of ligand-protein interactions (72).

Role of ML and Artificial Intelligence (AI) in Improving Docking Predictions

Emerging trends in molecular connectivity are being profoundly influenced by advancements in ML and AI, which are transforming the fields of chemistry and molecular biology. Neural networks and other ML models are increasingly used to predict molecular properties such as solubility, reactivity, and binding affinity based on known connections and historical data (73). AI can rapidly analyze and process data from high-throughput screening experiments, identifying potential molecular interactions and connectivity patterns that may not be immediately obvious. Moreover, AI models can accelerate molecular simulations by predicting their outcomes with greater speed and reduced computational requirements, leveraging knowledge gained from previous simulation data. ML also enhances the accuracy of force fields used in simulations, enabling a more precise representation of molecular forces and interactions (74). As AI and ML techniques continue to evolve, their integration into molecular docking is expected to substantially improve prediction accuracy, reduce computational costs, and advance the rational design of novel therapeutic agents.

Role of MD Simulation in Drug Design

MD simulation is a powerful computational technique widely employed in various scientific disciplines, particularly in the fields of chemistry, physics, and biology. It involves simulating the behavior of atoms and molecules in a virtual environment, allowing researchers to gain valuable insights into the intricate dynamics and interactions that govern their behavior (75, 76).

At its core, MD simulation models the movement of atoms and molecules by numerically solving Newton's equations of motion, incorporating interatomic forces derived from empirical potential energy functions. These functions capture the physical and chemical properties of the system under investigation, providing a mathematical representation of how atoms and molecules interact with one another (77, 78). In the realm of drug design, MD simulation serves as an indispensable tool for understanding the dynamic behavior of biomolecules, such as proteins and nucleic acids. Proteins, for instance, exhibit complex movements and structural fluctuations that are crucial to their proper functioning. By subjecting these biomolecules to MD simulation, scientists can observe and analyze their conformational changes, flexibility, and interactions with ligands or other molecules (79, 80).

One of the most significant applications of MD simulation in drug design is the prediction of ligand-receptor interactions. Ligands are small molecules, including drug candidates, that bind to specific protein receptors, influencing their activity and modulating biological processes. MD simulation enables researchers to explore the binding process in detail, unveiling the molecular mechanisms underlying ligand recognition and binding affinity (81, 82). This knowledge can inform the discovery and optimization of novel drug candidates by providing insights into their interactions with target proteins. Moreover, MD simulation facilitates the study of drug molecules in different environments, such as lipid membranes or aqueous solutions, offering a more realistic representation of their behavior in biological systems (83). These simulations can elucidate factors influencing drug permeability, solubility, stability, and transport across cell membranes, thereby aiding in the design of drug delivery systems and the optimization

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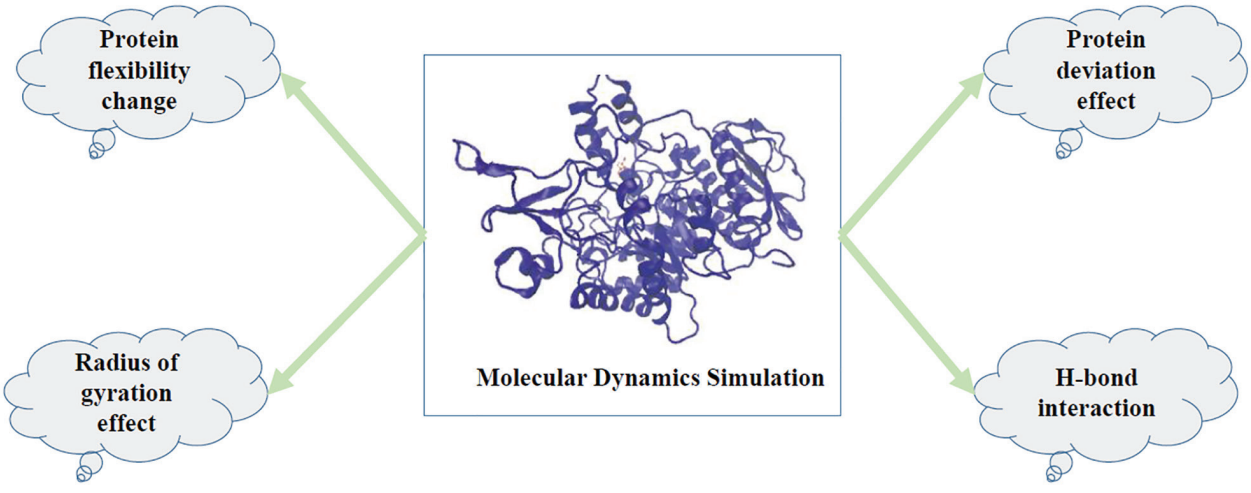

Figure 5. Use of MD simulation in drug design and biomedicine.

of drug formulations. Advancements in computer hardware and simulation algorithms have significantly enhanced the accuracy and efficiency of MD simulations (84). High-performance computing clusters and specialized software packages now enable researchers to simulate increasingly larger systems over longer timescales, capturing more realistic dynamics in complex biological systems (Figure 5).

MD Simulation Methods and Techniques

In the field of MD simulations, force fields play a crucial role in accurately representing the interactions between atoms within a biomolecular system (85). A force field is a mathematical model that parameterizes the potential energy functions governing the behavior of atoms and molecules. It provides a set of equations that describe bond lengths, angles, dihedral angles, and non-bonded interactions (86). Force fields are specifically designed to capture the complex interplay of forces, such as electrostatic, van der Waals, and bonded interactions, with the goal of accurately reproducing experimental data and theoretical predictions.

Several widely used force fields for biomolecular simulations include CHARMM (Chemistry at HARvard Macromolecular Mechanics), AMBER (Assisted Model Building with Energy Refinement), and GROMOS (Groningen Molecular Simulation) (87). CHARMM, for instance, combines quantum chemical calculations with empirical parameters to model the behavior of diverse biomolecules, including lipids, proteins, nucleic acids, carbohydrates, and small organic molecules. AMBER, in contrast, is designed for a broad range of systems, from small organic molecules to large biomolecular complexes, and incorporates both classical and semi-empirical potentials. Meanwhile, GROMOS focuses primarily on biomolecular simulations and employs a generalized treatment of molecular mechanics parameters (88, 89). By utilizing these force fields, researchers can simulate the behavior of complex biomolecular systems over time, gaining insights into their structure, dynamics, and function (Figure 6). Integration algorithms are essential to MD simulations, as they enable the numerical solution of the equations of motion. These algorithms govern how a system's positions and velocities evolve over time. One commonly used integration algorithm is the Verlet algorithm, which relies on Taylor series expansions to approximate the positions and velocities of atoms at discrete time steps. The Verlet algorithm is widely recognized for its simplicity and computational efficiency, as it effectively conserves energy by accurately

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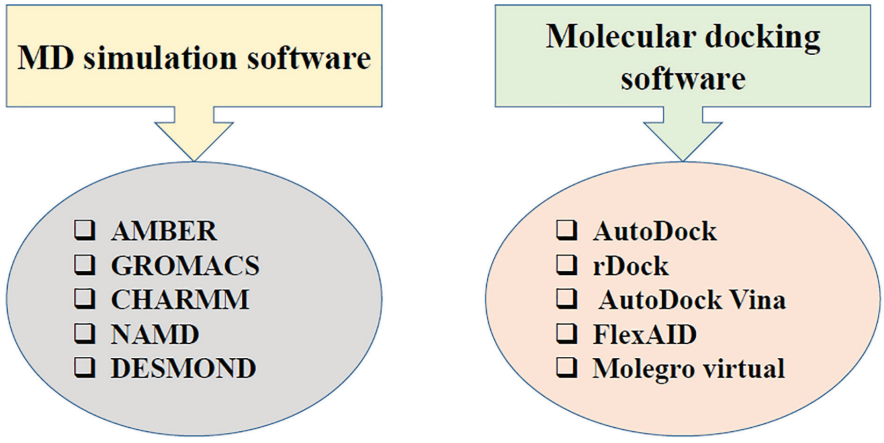

Figure 6. General MD simulation and molecular docking software.

accounting for changes in both potential and kinetic energy. Another widely adopted algorithm is the Leapfrog algorithm, a modified version of the Verlet algorithm. The Leapfrog algorithm updates positions and velocities at half-time steps relative to one another, resulting in improved stability and accuracy compared to the standard Verlet algorithm (90, 91). Integration algorithms play a crucial role in maintaining the stability and accuracy of MD simulations, ensuring that the simulated system evolves in a physically meaningful manner while adhering to constraints such as bond lengths, angles, and dihedral angles. Moreover, these algorithms enable researchers to investigate various dynamic processes, including protein folding, ligand binding, and conformational changes (92).

Molecular docking has played a pivotal role in drug discovery by helping researchers identify new drugs and enzyme inhibitors. The following are a few notable case studies and examples:

Imatinib (Gleevec) for Chronic Myeloid Leukemia

Imatinib is one of the first success stories of a drug developed using a structure-based drug design approach, which includes molecular docking. This technique was instrumental in identifying compounds capable of inhibiting the BCR-ABL kinase, a protein that, when mutated, drives chronic myeloid leukemia (CML). As a highly specific inhibitor of BCR-ABL, Imatinib revolutionized CML treatment, significantly improving survival rates (93).

Oseltamivir (Tamiflu) for Influenza

Influenza neuraminidase is a key target for antiviral drugs, and molecular docking has been extensively utilized in the design of its inhibitors, including Oseltamivir. By leveraging the crystal structure of neuraminidase, researchers applied docking techniques to develop a novel scaffold for potent inhibitors. This process led to the development of Oseltamivir, a widely used antiviral drug that effectively alleviates influenza symptoms and reduces transmission (94).

HIV Protease Inhibitors

Molecular docking played a crucial role in the development of Saquinavir, the first HIV protease inhibitor to gain regulatory approval. Docking simulations guided the design of molecules that fit precisely into the active site of the HIV protease enzyme. As a result, Saquinavir became a cornerstone of antiretroviral therapy, significantly advancing HIV management (95).

SARS-CoV-2 Main Protease Inhibitors

The COVID-19 pandemic accelerated the search for inhibitors targeting the SARS-CoV-2 main protease (Mpro). Molecular docking was widely employed in virtual screening campaigns to identify potential inhibitors both from existing drug libraries and newly designed compounds. This

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approach facilitated the identification of several promising lead compounds, including repurposed drugs, thereby expediting the drug development process for COVID-19 treatments (96).

Conclusion

In conclusion, molecular docking is a powerful tool in drug discovery and development, enabling virtual screening, lead optimization, and structure-activity relationship analysis. By aiding in the identification of potential drug candidates with high affinity and specificity for target enzymes, molecular docking accelerates the drug design process, substantially reducing both the time and costs associated with experimental screening. As computational methodologies continue to advance, tackling challenges such as enhancing scoring function accuracy and better incorporating protein flexibility, molecular docking is poised to play an increasingly significant role in the discovery of novel therapeutics.

Conflict of Interests

The authors declare no conflict of interest.

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Ethics approval and Consent to Participate

As the research did not involve human subjects, informed consent was not required.

Code of Ethices

As this study is a review, it does not involve any ethical considerations.

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References

1 Siemons M, Koplin TJ, Simon U. Advances in high throughput screening of gas sensing materials. Appl Surf Sci. 2007;254(3):669-76.
2 Johnson JE, Olson AJ. Icosahedral virus structures and the protein data bank. JBC. 2021;296(2):e100554.
3 Pan S-Y, Zhou S-F, Gao S-H, Yu Z-L, Zhang S-F, Tang M-K, et al. New perspectives on how to discover drugs from herbal medicines: CAM′ S outstanding contribution to modern therapeutics. eCAM. 2013;2013(1):627375.
4 Aldewachi H, Al-Zidan RN, Conner MT, Salman MM. High-throughput screening platforms in the discovery of novel drugs for neurodegenerative diseases. Bioeng. 2021;8(2):30.
5 Blay V, Tolani B, Ho SP, Arkin MR. High-throughput screening: today's biochemical and cell-based approaches. Drug Discov Today. 2020;25(10):1807-21.
6 Alonso H, Bliznyuk AA, Gready JE. Combining docking and molecular dynamic simulations in drug design. Med Res Rev. 2006;26(5):531-68.
7 Hamzeh-Mivehroud M, Alizadeh AA, Morris MB, Church WB, Dastmalchi S. Phage display as a technology delivering on the promise of peptide drug discovery. Drug Discov Today. 2013;18(23-24):1144-57.
8 Tiwari V. Post-translational modification of ESKAPE pathogens as a potential target in drug discovery. Drug Discov Today. 2019;24(3):814-22.
9 Zhang H, He J, Hu G, Zhu F, Jiang H, Gao J, et al. Dynamics of post-translational modification inspires drug design in the kinase family. J Med Chem. 2021;64(20):15111-25.
10 Zhai L-h, Chen K-f, Hao B-b, Tan M-j. Proteomic characterization of post-translational modifications in drug discovery. Acta Pharmacol Sin. 2022;43(12):3112-29.
11 Trott O, Olson AJ. AutoDock Vina: improving the speed and accuracy of docking with a new scoring function, efficient optimization, and multithreading. J Comput Chem. 2010;31(2):455-61.
12 Li W, Chang ST-L, Ward FR, Cate JH. Selective inhibition of human translation termination by a drug-like compound. Nat Commun. 2020;11(1):4941.
13 Wei W, Cherukupalli S, Jing L, Liu X, Zhan P. Fsp3: A new parameter for drug-likeness. Drug Discov Today. 2020;25(10):1839-45.
14 Eastman P, Behara PK, Dotson DL, Galvelis R, Herr JE, Horton JT, et al. Spice, a dataset of drug-like molecules and peptides for training machine learning potentials. Sci Data. 2023;10(1):11.
15 Morris GM, Huey R, Lindstrom W, Sanner MF, Belew RK, Goodsell DS, et al. AutoDock4 and AutoDockTools4: Automated docking with

[DOI: 10.18502/jabs.v15i1.17550]

selective receptor flexibility. J Comput Chem. 2009;30(16):2785-91.
16 Judson R, Kavlock R, Martin M, Reif D, Houck K, Knudsen T, et al. Perspectives on validation of high-throughput assays supporting 21st century toxicity testing. Altex. 2013;30(1):51.
17 Miller TW, Amason JD, Garcin ED, Lamy L, Dranchak PK, Macarthur R, et al. Quantitative high-throughput screening assays for the discovery and development of SIRPα-CD47 interaction inhibitors. PLoS One. 2019;14(7):e0218897.
18 Sadeghi M, Miroliaei M, Ghanadian M. Inhibitory effect of flavonoid glycosides on digestive enzymes: In silico, in vitro, and in vivo studies. Int J Biol Macromol. 2022;217:714-30.
19 Dallakyan S, Olson AJ. Small-molecule library screening by docking with PyRx. Chemical biology: methods and protocols. 2015:18(3)243-50.
20 Barrett JS, Goyal RK, Gobburu J, Baran S, Varshney J. An AI Approach to Generating MIDD Assets Across the Drug Development Continuum. The AAPS Journal. 2023;25(4):70.
21 Zheng F, Zhan C-G. Computational modeling of solvent effects on protein-ligand interactions using fully polarizable continuum model and rational drug design. Communications in Computational Physics. 2013;13(1):31-60.
22 Ingber DE. Human organs-on-chips for disease modelling, drug development and personalized medicine. Nat Rev Genet. 2022;23(8):467-91.
23 Harmalkar A, Gray JJ. Advances to tackle backbone flexibility in protein docking. Curr Opin Struct Biol. 2021;67:178-86.
24 Jakhar R, Dangi M, Khichi A, Chhillar AK. Relevance of molecular docking studies in drug designing. Curr Bioinform. 2020;15(4):270-8.
25 Sadeghi M, Sheikhi M, Miroliaei M. Control of eriocitrin release from pH-sensitive gelatin-based microgels to inhibit α-glucosidase: an experimental and computational study. Food & Function. 2022;13(19):10055-10068.
26 Sharma V, Wakode S, Kumar H. Structure-and ligand-based drug design: Concepts, approaches, and challenges. Chemoinformatics and bioinformatics in the pharmaceutical sciences. 2021;21(2):27-53.
27 Babu S, Nagarajan SK, Sathish S, Negi VS, Sohn H, Madhavan T. Identification of potent and selective JAK1 lead compounds through ligand-based drug design approaches. Front pharmacol. 2022;13:837369.
28 Vázquez J, López M, Gibert E, Herrero E, Luque FJ. Merging ligand-based and structure-based methods in drug discovery: An overview of combined virtual screening approaches. Molecules. 2020;25(20):4723.
29 Aminu KS, Uzairu A, Abechi SE, Shallangwa GA, Umar AB. Ligand-based drug design, molecular docking and pharmacokinetic studies of some series of 1, 4-dihydropyridines derivatives as human intestinal maltase-glucoamylase inhibitor. Chemical Data Collections. 2022;41:100911.
30 Hirpara KS, Patel UD. Quantitative structure–activity relationship (QSAR) models for color and COD removal for some dyes subjected to electrochemical oxidation. Environ Technol. 2022;4(1):1-12.
31 Liu Y, Cheng Z, Liu S, Tan Y, Yuan T, Yu X, et al. Quantitative structure activity relationship (QSAR) modelling of the degradability rate constant of volatile organic compounds (VOCs) by OH radicals in atmosphere. Sci Total Environ. 2020;729:138871.
32 Hadni H, Elhallaoui M. 2D and 3D-QSAR, molecular docking and ADMET properties in silico studies of azaaurones as antimalarial agents. New Journal of Chemistry. 2020;44(16):6553-65.
33 Das S, Amin S, Jha T. Insight into the structural requirement of aryl sulphonamide based gelatinases (MMP-2 and MMP-9) inhibitors–Part I: 2D-QSAR, 3D-QSAR topomer CoMFA and Naïve Bayes studies–First report of 3D-QSAR Topomer CoMFA analysis for MMP-9 inhibitors and jointly inhibitors of gelatinases together. SAR and QSAR in Environmental Research. 2021;32(8):655-87.
34 Fatullayeva PA, Mejidov AA, Safronenko MG, Nikolayevich Khrustalev V, Yalcin B, Sadeghian N, et al. ((E)-N′(3, 5-di-tert-butil-2-hedroxybenzilidene)-2-hydroxybenzohydrazide (H3sahz) 2 Copper (II) Complex: Synthesis, Crystal Structures, in silico Evaluations, and Enzymatic Inhibition. ChemistrySelect. 2023;8(15):e202300319.
35 Gök Y, Taslimi P, Şen B, Bal S, Aktaş A, Aygün M, et al. Design, Synthesis, Characterization, Crystal Structure, In silico Studies, and Inhibitory Properties of the PEPPSI Type Pd (II) NHC Complexes Bearing Chloro/Fluorobenzyl Group. Bioorg Chem. 2023:106513.
36 Sadeghi M, Shakouri Khomartash M, Taslimi P. The Potential of C-Glycosylflavonoids as α-Glucosidase Inhibitors Determined by Virtual Screening, Molecular Docking, Molecular Dynamics, and IC50 Studies. ChemistrySelect. 2023;8(20):e202300847.
37 Sanginabadi F, Gheibi N, Divsalar A, Saboury AA, Yaghmaei P, Sadeghi M. Exploring the Potential of ω3 Derivatives as Tyrosinase Inhibitors: A Comprehensive Study Combining Experimental, Computational, and Biological Approaches. ChemistrySelect.

[DOI: 10.18502/jabs.v15i1.17550]

2023;8(22):e202300373.
38 Tokalı FS, Taslimi P, Sadeghi M, Şenol H. Synthesis and Evaluation of Quinazolin-4 (3H)-one Derivatives as Multitarget Metabolic Enzyme Inhibitors: A Biochemistry-Oriented Drug Design. ChemistrySelect. 2023;8(25):e202301158.
39 Olawale F, Iwaloye O, Olofinsan K, Ogunyemi OM, Gyebi GA, Ibrahim IM. Homology modelling, vHTS, pharmacophore, molecular docking and molecular dynamics studies for the identification of natural compound-derived inhibitor of MRP3 in acute leukaemia treatment. Chemical Papers. 2022;76(6):3729-57.
40 Watanabe C, Watanabe H, Okiyama Y, Takaya D, Fukuzawa K, Tanaka S, et al. Development of an automated fragment molecular orbital (FMO) calculation protocol toward construction of quantum mechanical calculation database for large biomolecules. Chem-Bio Informatics Journal. 2019;19:5-18.
41 Arjmand B, Hamidpour SK, Alavi-Moghadam S, Yavari H, Shahbazbadr A, Tavirani MR, et al. Molecular docking as a therapeutic approach for targeting cancer stem cell metabolic processes. Front pharmacol. 2022;13:768556.
42 Elhady SS, Eltamany EE, Shaaban AE, Bagalagel AA, Muhammad YA, El-Sayed NM, et al. Jaceidin flavonoid isolated from Chiliadenus montanus attenuates tumor progression in mice via VEGF inhibition: In Vivo and in silico studies. Plants. 2020;9(8):1031.
43 Ye L, Xu Y, Wang L, Zhang C, Hu P, Tong Sa, et al. Downregulation of CYP2E1 is associated with poor prognosis and tumor progression of gliomas. Cancer Medicine. 2021;10(22):8100-13.
44 Li T, Guo R, Zong Q, Ling G. Application of molecular docking in elaborating molecular mechanisms and interactions of supramolecular cyclodextrin. Carbohydr Polym. 2022;276:118644.
45 Hussain M, Jabeen N, Amanullah A, Baig AA, Aziz B, Shabbir S, et al. Molecular docking between human TMPRSS2 and SARS-CoV-2 spike protein: conformation and intermolecular interactions. AIMS microbiology. 2020;6(3):350.
46 Khan I, Rehman W, Rahim F, Hussain R, Khan S, Fazil S, et al. Synthesis, In Vitro α-Glucosidase Inhibitory Activity and Molecular Docking Study of New Benzotriazole-Based Bis-Schiff Base Derivatives. Pharmaceuticals. 2023;16(1):17.
47 Munir A, Khushal A, Saeed K, Sadiq A, Ullah R, Ali G, et al. Synthesis, in-vitro, in-vivo anti-inflammatory activities and molecular docking studies of acyl and salicylic acid hydrazide derivatives. Bioorganic chemistry. 2020;104:104168.
48 Soltani S, Koubaa I, Dhouib I, Khemakhem B, Marchand P, Allouche N. New specific α-glucosidase inhibitor flavonoid from Thymelaea tartonraira leaves: Structure elucidation, biological and molecular docking studies. Chem Biodiversity. 2023;20(3):e202200944.
49 Menteşe E, Emirik M, Sökmen BB. Design, molecular docking and synthesis of novel 5, 6-dichloro-2-methyl-1H-benzimidazole derivatives as potential urease enzyme inhibitors. Bioorganic Chemistry. 2019;86:151-8.
50 Türkeş C. Investigation of potential paraoxonase-I inhibitors by kinetic and molecular docking studies: chemotherapeutic drugs. Protein and peptide letters. 2019;26(6):392-402.
51 Demir Y, Türkeş C, Beydemir Ş. Molecular docking studies and inhibition properties of some antineoplastic agents against paraoxonase-I. Anti-Cancer Agents in Medicinal Chemistry (Formerly Current Medicinal Chemistry-Anti-Cancer Agents). 2020;20(7):887-96.
52 Mascarenhas AMS, de Almeida RBM, de Araujo Neto MF, Mendes GO, da Cruz JN, Dos Santos CBR, et al. Pharmacophore-based virtual screening and molecular docking to identify promising dual inhibitors of human acetylcholinesterase and butyrylcholinesterase. J Biomol Struct. Dyn. 2021;39(16):6021-30.
53 Elfiky AA, Mahdy SM, Elshemey WM. Quantitative structure-activity relationship and molecular docking revealed a potency of anti-hepatitis C virus drugs against human corona viruses. Journal of medical virology. 2017;89(6):1040-7.
54 Jhong CH, Riyaphan J, Lin SH, Chia YC, Weng CF. S creening alpha-glucosidase and alpha-amylase inhibitors from natural compounds by molecular docking in silico. Biofactors. 2015;41(4):242-51.
55 Khan Y, Rehman W, Hussain R, Khan S, Malik A, Khan M, et al. New biologically potent benzimidazole-based-triazole derivatives as acetylcholinesterase and butyrylcholinesterase inhibitors along with molecular docking study. J Heterocycl Chem. 2022;59(12):2225-39.
56 Cao Q, Huang Y, Zhu Q-F, Song M, Xiong S, Manyande A, et al. The mechanism of chlorogenic acid inhibits lipid oxidation: An investigation using multi-spectroscopic methods and molecular docking. Food Chemistry. 2020;333:127528.
57 Sadeghi M, Zarei MA. Molecular docking studies of some flavone analogues as α-Glucosidase inhibitors. Journal of Medicinal Plants. 2020;19(75):55-64.

[DOI: 10.18502/jabs.v15i1.17550]

58 Fan Y, He Q, Gan C, Wen Z, Yi J. Investigation of binding interaction between bovine α-lactalbumin and procyanidin B2 by spectroscopic methods and molecular docking. Food Chemistry. 2022;384:132509.
59 Miller EB, Murphy RB, Sindhikara D, Borrelli KW, Grisewood MJ, Ranalli F, et al. Reliable and accurate solution to the induced fit docking problem for protein–ligand binding. J Chem Theory Comput. 2021;17(4):2630-9.
60 Allegra M, Tutone M, Tesoriere L, Attanzio A, Culletta G, Almerico AM. Evaluation of the IKKβ binding of indicaxanthin by induced-fit docking, binding pose metadynamics, and molecular dynamics. Front pharmacol. 2021;12:701568.
61 Alzain AA, Elbadwi FA, Alsamani FO. Discovery of novel TMPRSS2 inhibitors for COVID-19 using in silico fragment-based drug design, molecular docking, molecular dynamics, and quantum mechanics studies. Informatics in Medicine Unlocked. 2022;29:100870.
62 Zhou H, Cao H, Skolnick J. FRAGSITE: A fragment-based approach for virtual ligand screening. J Chem Inf Model. 2021;61(4):2074-89.
63 Erlanson DA, Davis BJ, Jahnke W. Fragment-based drug discovery: advancing fragments in the absence of crystal structures. Cell Chem Biol. 2019;26(1):9-15.
64 Saikia S, Bordoloi M. Molecular docking: challenges, advances and its use in drug discovery perspective. Curr Drug Targets. 2019;20(5):501-21.
65 Crampon K, Giorkallos A, Deldossi M, Baud S, Steffenel LA. Machine-learning methods for ligand–protein molecular docking. Drug Discov Today. 2022;27(1):151-64.
66 Li J, Fu A, Zhang L. An overview of scoring functions used for protein–ligand interactions in molecular docking. Interdisciplinary Sciences: Computational Life Sciences. 2019;11:320-8.
67 Singh S, Baker QB, Singh DB. Molecular docking and molecular dynamics simulation. Bioinformatics: Elsevier; 2022. p. 291-304.
68 Stanzione F, Giangreco I, Cole JC. Use of molecular docking computational tools in drug discovery. Progress in Medicinal Chemistry. 2021;60:273-343.
69 Vakser IA. Challenges in protein docking. Current opinion in structural biology. 2020;64:160-5.
70 Menchaca TM, Juárez-Portilla C, Zepeda RC. Past, present, and future of molecular docking. Drug Discovery and Development-New Advances: IntechOpen; 2020;11(3);11-21.
71 Torres PH, Sodero AC, Jofily P, Silva-Jr FP. Key topics in molecular docking for drug design. Int J Mol Sci. 2019;20(18):4574.
72 Rosell M, Fernández-Recio J. Docking approaches for modeling multi-molecular assemblies. Curr Opin Struct Biol. 2020;64:59-65.
73 Khamis MA, Gomaa W, Ahmed WF. Machine learning in computational docking. Artificial intelligence in medicine. 2015;63(3):135-52.
74 Gupta R, Srivastava D, Sahu M, Tiwari S, Ambasta RK, Kumar P. Artificial intelligence to deep learning: machine intelligence approach for drug discovery. Mol Divers. 2021;25:1315-60.
75 Sadeghi M, Miroliaei M, Taslimi P, Moradi M. In silico analysis of the molecular interaction and bioavailability properties between some alkaloids and human serum albumin. Structural Chemistry. 2022;33(4);1-14.
76 Zhang Q, Petersen HH, Ostergaard H, Ruf W, Olson AJ. Molecular dynamics simulations and functional characterization of the interactions of the PAR2 ectodomain with factor VIIa. Proteins: Structure, Function, and Bioinformatics. 2009;77(3):559-69.
77 Venable RM, Kramer A, Pastor RW. Molecular dynamics simulations of membrane permeability. Chem Rev. 2019;119(9):5954-97.
78 Xia J, Flynn W, Gallicchio E, Uplinger K, Armstrong JD, Forli S, et al. Massive-scale binding free energy simulations of HIV integrase complexes using asynchronous replica exchange framework implemented on the IBM WCG distributed network. J Chem Inf Model. 2019;59(4):1382-97.
79 Lazim R, Suh D, Choi S. Advances in molecular dynamics simulations and enhanced sampling methods for the study of protein systems. Int J Mol Sci. 2020;21(17):6339.
80 Sadeghi M, Miroliaei M, Ghanadian M, Szumny A, Rahimmalek M. Exploring the inhibitory properties of biflavonoids on α-glucosidase; computational and experimental approaches. Int J Biol Macromol. 2023;253:127380.
81 Santos LH, Ferreira RS, Caffarena ER. Integrating molecular docking and molecular dynamics simulations. Docking screens for drug discovery. 2019;17:13-34.
82 Gümüş A, Sadeghian N, Sadeghi M, Taslimi P, Gümüş S. Novel triazole bridged quinoline-anthracene derivatives: synthesis, characterization, molecular docking, evaluation of electronic and enzyme inhibitory properties. J Biomol Struct Dyn. 2023;21:1-16.
83 Evangelista Falcon W, Ellingson SR, Smith JC, Baudry J. Ensemble docking in drug discovery:

[DOI: 10.18502/jabs.v15i1.17550]

how many protein configurations from molecular dynamics simulations are needed to reproduce known ligand binding? The Journal of Physical Chemistry B. 2019;123(25):5189-95.
84 Joshi SY, Deshmukh SA. A review of advancements in coarse-grained molecular dynamics simulations. Molecular Simulation. 2021;47(10-11):786-803.
85 Sadeghi M, Miroliaei M, Fateminasab F, Moradi M. Screening cyclooxygenase-2 inhibitors from Allium sativum L. compounds: in silico approach. J Mol Model. 2022;28(1):1-12.
86 Sadeghi M, Khomartash MS, Gorgani-Firuzjaee S, Vahidi M, Khiavi FM, Taslimi P. α-glucosidase inhibitory, antioxidant activity, and GC/MS analysis of Descurainia sophia methanolic extract: in vitro, in vivo, and in silico studies. Arab J Chem. 2022:104055.
87 Moradi S, Nowroozi A, Shahlaei M. Shedding light on the structural properties of lipid bilayers using molecular dynamics simulation: a review study. RSC advances. 2019;9(8):4644-58.
88 Salo-Ahen OM, Alanko I, Bhadane R, Bonvin AM, Honorato RV, Hossain S, et al. Molecular dynamics simulations in drug discovery and pharmaceutical development. Processes. 2020;9(1):71.
89 Dey D, Hossain R, Biswas P, Paul P, Islam MA, Ema TI, et al. Amentoflavone derivatives significantly act towards the main protease (3CLPRO/MPRO) of SARS-CoV-2: in silico admet profiling, molecular docking, molecular dynamics simulation, network pharmacology. Molecular diversity. 2023;27(2):857-71.
90 Kadupitiya J, Fox G, Jadhao V. Recurrent neural networks based integrators for molecular dynamics simulations. Bulletin of the American Physical Society. 2020;65(4):213-219.
91 Grønbech-Jensen N. Complete set of stochastic Verlet-type thermostats for correct Langevin simulations. Molecular Physics. 2020;118(8):e1662506.
92 Sokolov IO, Barkoutsos PK, Moeller L, Suchsland P, Mazzola G, Tavernelli I. Microcanonical and finite-temperature ab initio molecular dynamics simulations on quantum computers. Phys Rev Res. 2021;3(1):013125.
93 Henkes M, van der Kuip H, Aulitzky WE. Therapeutic options for chronic myeloid leukemia: focus on imatinib (Glivec®, Gleevec™). Therapeutics and clinical risk management. 2008;4(1):163-87.
94 Ward P, Small I, Smith J, Suter P, Dutkowski R. Oseltamivir (Tamiflu®) and its potential for use in the event of an influenza pandemic. J Antimicrob Chemother. 2005;55(1):i5-i21.
95 Tong J, Wu Y, Bai M, Zhan P. 3D-QSAR and molecular docking studies on HIV protease inhibitors. J Mol Struct. 2017;1129:17-22.
96 Cherrak SA, Merzouk H, Mokhtari-Soulimane N. Potential bioactive glycosylated flavonoids as SARS-CoV-2 main protease inhibitors: A molecular docking and simulation studies. Plos one. 2020;15(10):e0240653.

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