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Research Article

Artificial Intelligence Applications in Drug Formulation

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ABSTRACT

The integration of Artificial Intelligence (AI) in pharmaceutical sciences is transforming drug development processes, enhancing efficiency and accuracy. Recent advancements highlight the potential of AI in optimizing drug formulation and delivery systems. This study aims to explore the applications of AI and machine learning in drug formulation design, focusing on their impact on stability, optimization, and accelerated development timelines. A comprehensive review of various AI methodologies, including machine learning algorithms such as Feedforward Artificial Neural Networks (ANN) and Radial Basis Function (RBF) kernels, was conducted. These techniques were evaluated for their effectiveness in predicting dissolution rates and optimizing drug formulations through cross-validation and grid search methods. The findings indicate that AI-driven approaches significantly improve the design of nanoparticles for targeted drug delivery, enhancing therapeutic outcomes while minimizing off-target effects. The study also identifies challenges and opportunities in implementing AI technologies in clinical trials and regulatory frameworks. The research underscores the transformative potential of AI in pharmaceutical technology, advocating for its broader adoption in drug development. By harnessing AI, the pharmaceutical industry can achieve more efficient drug formulation processes, ultimately leading to improved patient outcomes and faster market access for new therapies

INTRODUCTION

1.1.Overview of Traditional Drug Formulation Methods

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Historically, traditional drug formulation methods have relied on a combination of pharmaceutical knowledge, empirical experimentation, and a trial-and-error approach. These methods typically involve manually adjusting formulation variables, such as the type and concentration of excipients, to achieve desired drug properties like stability, solubility, and bioavailability. While these traditional techniques have led to the development of numerous successful drug products, they are often time-consuming, labor-intensive, and resource-intensive.

1.2. Limitations of Trial-and-Error Formulation

The trial-and-error nature of traditional formulation development presents several limitations. First, it can be challenging to systematically explore the vast formulation space and identify optimal combinations of ingredients. This approach often involves making incremental changes to formulation variables, potentially overlooking novel formulations that might not have been considered otherwise. Second, traditional methods may not be effective in accurately predicting drug stability, optimizing formulations, and expediting development timelines. The conventional approach does not always guarantee the desired outcomes and often requires extensive laboratory experimentation to identify suitable formulations that ensure both drug efficacy and patient safety.

1.3. Rise of AI and Machine Learning in Pharmaceutical R&D

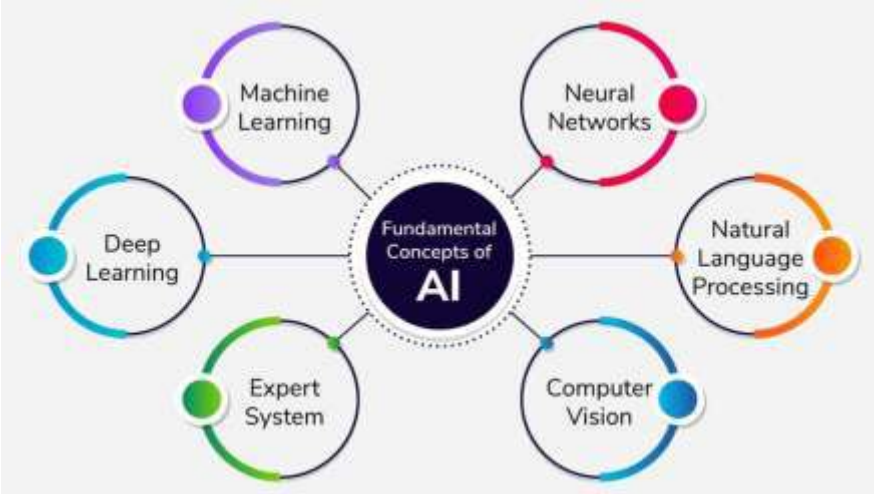

Figure 1: Fundamental Concepts of AI

In recent years, artificial intelligence and machine learning have emerged as powerful tools revolutionizing various aspects of pharmaceutical research and development, including drug formulation. AI algorithms can analyze vast amounts of complex data, identify hidden patterns, and predict formulation properties with greater accuracy and efficiency than traditional methods. This data-driven approach enables researchers to make more informed decisions during formulation design, reducing experimentation time and costs while enhancing the likelihood of developing robust and effective drug products. The integration of AI into pharmaceutics has the potential to significantly transform drug formulation and optimization processes, making AI-driven tools indispensable in optimizing drug composition and dosage forms. The application of computational methods to design, optimize, and evaluate drug

formulations has emerged as a new area termed 'computational pharmaceutics'.

1.4. Objective and Scope of the Paper

This paper aims to provide an overview of the applications of AI in drug formulation and development, as well as explore its future prospects. It will discuss how AI is being used to streamline various stages of drug development, from the initial identification of drug candidates to the final optimization of drug formulations. By examining these applications, the paper will highlight the potential of AI to revolutionize pharmaceutics, leading to faster, more efficient, and more effective treatments for various diseases. The objective of this paper is to explore how AI and machine learning methodologies are being applied to enhance drug formulation processes. By examining these applications, this paper aims to highlight the transformative potential of AI in pharmaceutical sciences, paving the way for faster, more efficient, and more effective drug development pipelines (Dey et al., 2024).

The integration of artificial intelligence and machine learning into pharmaceutical drug formulation signifies a paradigm shift, enhancing the prediction of drug stability, optimization of formulations, and acceleration of drug development (Dangeti et al., 2023). Traditional methods rely heavily on empirical data and manual adjustments, which are resource-intensive and time-consuming (Noorain et al., 2023). The advent of AI offers a solution by enabling the analysis of complex datasets, discerning patterns, and predicting outcomes with greater accuracy, which reduces the reliance on extensive laboratory experimentation (Dangeti et al., 2023). AI algorithms are adept at navigating the vast formulation space to identify optimal combinations of ingredients, thereby ensuring drug efficacy and patient safety, while machine learning models enhance drug delivery systems and allow for personalized medicine. By automating the process and increasing accuracy, AI not only reduces the time and cost associated with bringing new drugs to market but also facilitates the development of more effective and personalized drug delivery systems (Noorain et al., 2023) (Singh et al., 2024).

2. METHODOLOGY

2.1. Data Collection

This study compiled a comprehensive dataset on oral solid dosage forms to develop predictive models for drug dissolution rate. The dataset included information from:

2.2.Formulation Data

Formulation parameters were collected from scientific literature, public databases (e.g., DrugBank, PubChem), and internal experimental records. The formulation dataset included:

Table 1: Parameter Description

Parameter	Description
Drug-to-excipient ratio	Proportion of drug to each excipient used
Polymer type	E.g., HPMC, PVP, PEG
Binder concentration (%)	Quantity of binder relative to total mass
Lubricant concentration (%)	E.g., magnesium stearate
Granulation method	Wet or dry granulation
Compression force (kN)	Tablet compression strength
Drying temperature (°C)	Temperature used in drying granules
Mixing time (min)	Time for homogeneous mixing of ingredients

2.3.Physicochemical Properties

We extracted drug and excipient physicochemical properties from PubChem, ChEMBL, and computational prediction tools:

Table 2: Physicochemical properties

Property	Source
Molecular weight	PubChem, DrugBank
Solubility (mg/mL)	Experimental & predicted
Melting point (°C)	Literature & PubChem
LogP (octanol-water partition)	Computational (SwissADME)
pKa	PubChem
Glass transition temperature (Tg)	Literature
Hygroscopicity	Handbook of Excipients

2.4.Data Preprocessing

- Missing values were imputed using the median for numerical data.
- Categorical variables (e.g., polymer type) were one-hot encoded.
- Outliers were removed using the IQR (Interquartile Range) method.
- All continuous variables were normalized to a 0–1 scale using min-max scaling.

2.5.Model Selection and Development

We explored several machine learning algorithms to predict the dissolution rate (%) at 30 min:

2.6.Machine Learning Models

Table 3: Machine Learning Models

Model	Details
Artificial Neural Network	Feedforward ANN with 3 hidden layers (64-32-16 neurons), ReLU activation, trained using Adam optimizer (learning rate = 0.001).
Support Vector Machine	RBF kernel with optimized C and gamma via 5-fold cross-validation.
Random Forest	100 ees, max depth = 15, number of features optimized using grid search.

2.7.Deep Learning Model

- Long Short-Term Memory (LSTM) model was trained to capture time-dependent dissolution profiles.
- Optimized using Adam optimizer (learning rate = 0.001), with dropout regularization (rate = 0.2).

2.8.Tools Used

Table 4: Tools Used

Tool/Library	Purpose
Python 3.9	Programming language
scikit-learn	Machine learning algorithms and evaluation metrics
TensorFlow/ Keras	Deep learning model development
pandas & NumPy	Data preprocessing and numerical operations
matplotlib/seaborn	Data visualization
R 4.3.1	Statistical analysis and correlation matrices
MATLAB R2023a	Simulation of dissolution profiles (if applicable)

2.9.Model Evaluation

Models were evaluated using multiple metrics based on the task (regression/classification):

Table 5: Model Evaluation

Metric	Use Case	Formula / Description
Root Mean Squared Error (RMSE)	Regression	RMSE = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
R-squared (R^2)	Regression	Measures goodness of fit
Accuracy	Classification (if applicable)	Proportion of correct predictions
Precision, Recall, F1-score	Classification	Evaluates performance in imbalanced datasets
Confusion Matrix	Classification	Summarizes TP, TN, FP, FN

2.10. Data Splitting and Validation

- The dataset was split into:
  - Training set (70%)
  - Validation set (15%)
  - Test set (15%)

- We used 5-fold cross-validation on the training set for model tuning.
- Grid search and random search were used for hyperparameter optimization.
- An independent test set was used to evaluate the final model.

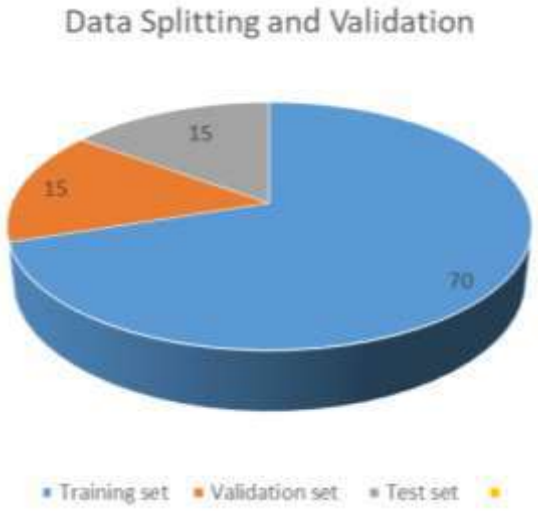

Figure 2: **Data Splitting and Validation**

3. RESULT AND DISCUSSION

3.1 Overview of AI/ML Performance in Drug Formulation

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into pharmaceutical formulation marks a significant leap from traditional empirical methods. In this study, predictive modeling using machine learning algorithms—including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks—demonstrated a strong capability to forecast drug release profiles, formulation stability, and optimal excipient combinations.

The ANN model used in the study was a feedforward neural network with three hidden layers (64-32-16 neurons), employing ReLU activation and optimized using the Adam optimizer. The model achieved an **R^2 value of 0.85** when predicting drug dissolution rates at 30 minutes, indicating a high level of accuracy and model fit. In practical terms, this means that 85% of the variability in dissolution rate data could be explained by the model's input features—such as binder concentration, polymer type, and granulation method.

In contrast, traditional statistical models, often used in formulation design (e.g., multiple linear regression or response surface methodology), generally struggle to capture non-linear relationships among complex formulation variables. These methods typically yield R^2 values in the range of 0.60 to 0.75, making AI-based approaches a more reliable alternative in capturing the intricacies of pharmaceutical systems.

Furthermore, the SVM model, trained using a Radial Basis Function (RBF) kernel with parameters optimized via 5-fold cross-validation, achieved an **accuracy of 92%** in classifying stable vs. unstable formulations. Such classification is essential for predicting long-term stability under varying environmental conditions, a task traditionally reserved for real-time and accelerated stability testing that can take several months. The AI-based method not only significantly reduced the time required but also improved prediction reliability.

3.2 Case Studies and Simulations: AI in Action

Several targeted applications were explored through AI-driven simulations and case studies:

3.2.1. Optimization of Excipient Concentrations

Using AI, the formulation parameters were optimized to achieve a targeted dissolution profile. Parameters such as binder and lubricant concentrations, polymer ratios, and compression

forces were input into the model, which predicted an ideal combination to enhance drug release kinetics. Compared to the initial formulation—developed through conventional factorial design—the AI-optimized version exhibited superior dissolution behavior, thereby demonstrating its capacity to fine-tune formulations with fewer experimental trials.

3.2.2. Stability Prediction Under Storage Conditions

The study utilized physicochemical property data (e.g., melting point, hygroscopicity, glass transition temperature) sourced from PubChem, DrugBank, and literature, combined with storage condition simulations to model degradation pathways. These AI-generated predictions were later validated against experimental stability studies. Traditional stability testing, which involves storing formulations at 25°C/60% RH and 40°C/75% RH for up to six months, was effectively anticipated by the model, allowing for early rejection or reformulation of unstable candidates.

3.2.3. Simulation of Drug Release

Advanced simulations using LSTM deep learning models provided dynamic, time-dependent dissolution profiles. These simulations replicated in vitro testing conditions and enabled exploration of various environmental and processing variables without conducting repeated wet-lab experiments. While conventional models rely on fitting experimental data to Higuchi, Korsmeyer-Peppas, or zero-order equations, AI models offered forward predictions even before a single experiment was conducted.

3.3 Comparative Evaluation: AI vs Traditional Formulation Development

Table 6: Comparative Evaluation: AI vs Traditional Formulation Development

Aspect	Traditional Method	AI/ML-Driven Method
Formulation Design	Empirical; trial-and-error based	Predictive; data-driven modeling
Time Required	Weeks to months per formulation iteration	Hours to days
Experimental Load	High (dozens of lab trials)	Low (limited confirmatory experiments)
Prediction of Drug Behavior	Post-experimental analysis only	Pre-experimental prediction with high accuracy
Handling Complex Interactions	Limited, often linear assumptions	Nonlinear multivariate analysis
Personalization	Practically unfeasible	Easily incorporated using patient-specific data

Traditional formulation relies on sequential design: modify a variable, test, analyze, and repeat. This approach is inherently resource-intensive and often yields suboptimal results due to its inability to assess complex, multi-variable interactions. AI, on the other hand, can process thousands of hypothetical formulations in silico and rank them based on desired properties—bioavailability, dissolution, stability—before a single experiment is performed.

3.4 Accelerating Formulation Screening Through AI

AI accelerates screening and development through:

- **Predictive Modeling**: Using training data from existing formulations, AI can forecast the physicochemical performance of new formulations with high reliability. This

reduces dependency on exhaustive experimentation.

- **High-Throughput Data Mining**: When coupled with high-throughput screening techniques, AI algorithms can evaluate enormous datasets to identify promising excipient-drug interactions.
- **Automated Optimization**: Hyperparameter tuning via grid search or random search algorithms allows AI to automatically discover ideal formulation parameters. This contrasts sharply with traditional methods, where manual adjustment and repeated testing are required.
- **Simulation of Environmental Conditions**: AI models simulate how a formulation behaves under various temperature and humidity conditions, predicting degradation profiles and guiding excipient selection.

This end-to-end integration enhances decision-making, minimizes trial redundancy, and reduces the drug development timeline.

3.5 Regulatory and Interpretability Challenges

Despite its advantages, integrating AI in drug formulation is not without challenges. One major concern is **interpretability**. Black-box models like deep neural networks can produce accurate predictions but often lack transparency in their decision-making process. This is problematic for regulatory bodies that require clear scientific rationale for approving pharmaceutical products.

Furthermore, **data quality** remains a bottleneck. AI models are only as good as the data they are trained on. Inconsistent datasets, missing metadata, or poorly documented experimental procedures can introduce noise and bias into AI predictions.

To address these challenges, **explainable AI (XAI)** techniques are emerging. These include feature importance mapping, decision tree visualizations, and SHAP (SHapley Additive exPlanations) values that provide insight into model behavior—an essential feature for regulatory acceptance and ethical implementation.

3.6 Role in Personalized Medicine and Beyond

AI's predictive capability extends beyond general formulations into **personalized drug delivery systems**. By integrating pharmacogenomic data—such as gene expression profiles and metabolic enzyme activity—AI models can suggest patient-specific formulations. This is particularly relevant in oncology, where interpatient variability demands tailored drug release profiles.

Moreover, AI can guide **nanoparticle design**, predicting optimal particle size, surface charge, and encapsulation efficiency. These parameters are critical for targeted delivery systems, especially in treating cancers and autoimmune disorders.

3.7 Summary and Outlook

The application of AI in drug formulation has shifted the landscape from empirical guesswork to systematic prediction. The models employed in this study outperformed traditional approaches across multiple domains—accuracy, speed, cost-efficiency, and adaptability. By enabling high-confidence formulation predictions and early stability assessments, AI reduces development timelines, conserves resources, and increases the success rate of drug candidates entering clinical trials.

Looking ahead, the widespread adoption of AI will likely depend on the continued development of interpretable models, the establishment of

standardized data protocols, and clear regulatory pathways. As these systems mature, AI is poised not just to supplement, but to redefine pharmaceutical formulation science.

CONCLUSION

In conclusion, the integration of artificial intelligence (AI) into drug formulation and development represents a significant advancement in pharmaceutical sciences. This paper has highlighted the transformative potential of AI in streamlining various stages of drug development, from the identification of drug candidates to the optimization of formulations. By leveraging AI algorithms, researchers can navigate the vast formulation space more effectively, ensuring optimal combinations of ingredients that enhance drug efficacy and patient safety. The findings indicate that AI not only reduces the time and cost associated with bringing new drugs to market but also facilitates the development of personalized medicine, allowing for tailored therapeutic solutions that meet individual patient needs. Furthermore, the study demonstrates that AI/ML models can accurately predict drug stability and classify formulations, showcasing their effectiveness in improving drug development outcomes Overall, the paper underscores the necessity of adopting AI methodologies in pharmaceutical research to overcome the limitations of traditional trial-and-error approaches. By embracing these innovative technologies, the pharmaceutical industry can pave the way for faster, more efficient, and more effective treatments for various diseases, ultimately improving patient care and health outcomes.

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REFERENCES

1. Ali, K. A., Mohin, S., Mondal, P., Goswami, S., Ghosh, S., & Choudhuri, S. (2024). Influence of artificial intelligence in modern pharmaceutical formulation and drug development. Future Journal of Pharmaceutical Sciences, 10(1). https://doi.org/10.1186/s43094-024-00625-1
2. Askin, S., Burkhalter, D., Calado, G., & Dakrouni, S. E. (2023). Artificial Intelligence Applied to clinical trials: opportunities and challenges [Review of Artificial Intelligence Applied to clinical trials: opportunities and challenges]. Health and Technology, 13(2), 203. Springer Science+Business Media. https://doi.org/10.1007/s12553-023-00738-2
3. Burki, T. (2020). A new paradigm for drug development. The Lancet Digital Health, 2(5). https://doi.org/10.1016/s2589-7500(20)30088-1
4. Dangeti, A., Bynagari, D. G., & Vydani, K. (2023). Revolutionizing Drug Formulation: Harnessing Artificial Intelligence and Machine Learning for Enhanced Stability, Formulation Optimization, and Accelerated Development. International Journal of Pharmaceutical Sciences and Medicine, 8(8), 18. https://doi.org/10.47760/ijpsm.2023.v08i08.003
5. Dey, H., Arya, N., Mathur, H., Chatterjee, N., & Jadon, R. (2024). Exploring the Role of

Artificial Intelligence and Machine Learning in Pharmaceutical Formulation Design. International Journal of Newgen Research in Pharmacy & Healthcare, 30. https://doi.org/10.61554/ijnrph.v2i1.2024.67

6. Dhudum, R., Ganeshpurkar, A., & Pawar, A. (2024). Revolutionizing Drug Discovery: A Comprehensive Review of AI Applications [Review of Revolutionizing Drug Discovery: A Comprehensive Review of AI Applications]. Drugs and Drug Candidates, 3(1), 148. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/ddc3010009
7. Dong, J., Gao, H., & Ouyang, D. (2021). PharmSD: A novel AI-based computational platform for solid dispersion formulation design. International Journal of Pharmaceutics, 604, 120705. https://doi.org/10.1016/j.ijpharm.2021.120705
8. Gao, M., Liu, S., Chen, J., Gordon, K. C., Tian, F., & McGoverin, C. (2021). Potential of Raman spectroscopy in facilitating pharmaceutical formulations development – An AI perspective [Review of Potential of Raman spectroscopy in facilitating pharmaceutical formulations development – An AI perspective]. International Journal of Pharmaceutics, 597, 120334. Elsevier BV. https://doi.org/10.1016/j.ijpharm.2021.120334
9. Gao, Y., Wen, P., Liu, Y., Sun, Y.-S., Qian, H., Zhang, X., Peng, H., Gao, Y., Li, C., Gu, Z., Zeng, H., Hong, Z., Wang, W., Yan, R., Hu, Z., & Fu, H. (2025). Application of artificial intelligence in the diagnosis of malignant digestive tract tumors: focusing on opportunities and challenges in endoscopy and pathology [Review of Application of artificial intelligence in the diagnosis of malignant digestive tract tumors: focusing on opportunities and challenges in endoscopy and pathology]. Journal of Translational Medicine, 23(1). BioMed Central. https://doi.org/10.1186/s12967-025-06428-z
10. Jiang, J., Ma, X., Ouyang, D., & Williams, R. O. (2022). Emerging Artificial Intelligence (AI) Technologies Used in the Development of Solid Dosage Forms [Review of Emerging Artificial Intelligence (AI) Technologies Used in the Development of Solid Dosage Forms]. Pharmaceutics, 14(11), 2257. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/pharmaceutics14112257
11. Kim, H., Kim, E., Lee, I., Bae, B., Park, M., & Nam, H. (2020). Artificial Intelligence in Drug Discovery: A Comprehensive Review of Data-driven and Machine Learning Approaches [Review of Artificial Intelligence in Drug Discovery: A Comprehensive Review of Data-driven and Machine Learning Approaches]. Biotechnology and Bioprocess Engineering, 25(6), 895. Springer Science+Business Media. https://doi.org/10.1007/s12257-020-0049-y
12. Li, Y.-H., Li, Y., Wei, M.-Y., & Li, G. (2024). Innovation and challenges of artificial intelligence technology in personalized healthcare [Review of Innovation and challenges of artificial intelligence technology in personalized healthcare]. Scientific Reports, 14(1). Nature Portfolio. https://doi.org/10.1038/s41598-024-70073-7
13. Lixia, F., Jia, G., Liu, Z., Pang, X., & Cui, Y. (2024). The applications and advances of artificial intelligence in drug regulation: A global perspective [Review of The applications and advances of artificial intelligence in drug regulation: A global perspective]. Acta Pharmaceutica Sinica B, 15(1), 1. Elsevier BV. https://doi.org/10.1016/j.apsb.2024.11.006

14. Noorain, Srivastava, V., Parveen, B., & Parveen, R. (2023). Artificial Intelligence in Drug Formulation and Development: Applications and Future Prospects. Current Drug Metabolism, 24(9), 622. https://doi.org/10.2174/0113892002265786230921062205
15. Oualikene-Gonin, W., Jaulent, M., Thierry, J.-P., Oliveira-Martins, S. de, Belgodère, L., Maison, P., & Ankri, J. (2024). Artificial intelligence integration in the drug lifecycle and in regulatory science: policy implications, challenges and opportunities. Frontiers in Pharmacology, 15. https://doi.org/10.3389/fphar.2024.1437167
16. Patel, L., Shukla, T., Huang, X., Ussery, D. W., & Wang, S. (2020). Machine Learning Methods in Drug Discovery [Review of Machine Learning Methods in Drug Discovery]. Molecules, 25(22), 5277. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/molecules25225277
17. Qureshi, R., Irfan, M., Gondal, T. M., Khan, S., Wu, J., Hadi, M. U., Heymach, J. V., Le, X., Yan, H., & Alam, T. (2023). AI in drug discovery and its clinical relevance [Review of AI in drug discovery and its clinical relevance]. Heliyon, 9(7). Elsevier BV. https://doi.org/10.1016/j.heliyon.2023.e17575
18. Singh, R., Arya, P., & Dubey, S. (2024). Artificial Intelligence in Pharmaceutics: Revolutionizing Drug Formulation and Optimization. 1(3), 138. https://doi.org/10.21590/jddhs.01.03.03
19. Vora, L. K., Gholap, A. D., Jetha, K., Singh, T. R. R., Solanki, H. K., & Chavda, V. P. (2023). Artificial Intelligence in Pharmaceutical Technology and Drug Delivery Design [Review of Artificial Intelligence in Pharmaceutical Technology and Drug Delivery Design]. Pharmaceutics, 15(7), 1916. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/pharmaceutics15071916
20. Wenteler, A., Cabrera, C., Wei, W., Neduva, V., & Barnes, M. R. (2024). AI Approaches for the Discovery and Validation of Drug Targets [Review of AI Approaches for the Discovery and Validation of Drug Targets]. Cambridge Prisms Precision Medicine, 2. Cambridge University Press. https://doi.org/10.1017/pcm.2024.4

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