Review Article

Trends in Pharmaceutical Sciences and Technologies 2025: 11(4):293-308.

The Evolution of AI and Its Transformative Role in Pharmaceutical Nanotechnology

Mohammad Kadkhodaei[1,2];Ph.D, Maryam Monajati[1,2*];Ph.D

[1]Center for Nanotechnology in Drug Delivery, Shiraz University of Medical Sciences, Shiraz, Iran
[2]Department of Pharmaceutical Nanotechnology, School of Pharmacy, Shiraz University of Medical Sciences, Shiraz, Iran

Abstract

Artificial intelligence (AI) is transforming pharmaceutical nanotechnology by enabling rapid, intelligent, and precise solutions to challenges in drug delivery, diagnosis, and material design. By using machine learning (ML) or deep learning (DL) to simulate how nanoparticles behave, researchers can better adjust formulation details and interpret complex biological information more accurately than ever before. This review provides a thorough overview of key AI methods, including supervised, unsupervised, and combined learning approaches, as well as deep neural networks, and their applications in areas such as tumor imaging, mRNA vaccine development, and the assessment of nanomaterial safety. Selected case studies illustrate measurable progress: NanoMASK achieved correlation coefficients above 0.99 for pharmacokinetic analysis, AI-guided lipid screening identified candidates with up to 10-fold higher transfection efficiency, and optimized oral nanoformulations delivered a 6.2-fold increase in plasma drug levels. These examples highlight how AI can improve treatment effectiveness, reduce experimental workload, and accelerate translation from laboratory research to clinical implementation. Although issues such as algorithm transparency and regulatory harmonization remain, the overall impact is clear—AI is driving faster, smarter, and more reliable advances in nanomedicine toward personalized and ethically sound healthcare.

Keywords: Artificial Intelligence (AI); Machine Learning (ML); Deep Learning (DL); Nanomedicine; Targeted Drug Delivery; Predictive Modeling

Please cite this article as: Kadkhodaei M, Monajati M. The evolution of AI and its transformative role in pharmaceutical nanotechnology. Trends in Pharmaceutical Sciences and Technologies. 2025;11(4):293-308. doi: 10.30476/tips.2025.107583.1306

1. Introduction

Imagine a future where nanobots, designed and guided by artificial intelligence (AI), deliver therapeutic agents directly to target cells, minimizing side effects and maximizing therapeutic efficacy. Integrating AI with pharmaceutical nanotechnology is rapidly transforming this vision into reality, enabling researchers to create innovative solutions to some of medicine's most complicated challenges.

Since AI was first developed in the 1950s, it has evolved from early systems that used manually programmed rules to newer data-driven methods called machine learning (ML) and deep learning (DL). While initial AI systems excelled in structured tasks like chess, they struggled with the uncertainty involved in human-centered tasks such as image recognition and speech understanding. Unlike traditional AI, which followed fixed instruc-

Corresponding Author: Maryam Monajati, Department of Pharmaceutical Nanotechnology, School of Pharmacy, Shiraz University of Medical Sciences, Shiraz, Iran
E-mail: monajatim@gmail.com

Received: 16/04/2025; Accepted: 01/09/2025

tions, ML enables computers to learn patterns directly from large datasets, marking a major advancement in the field. Deep learning, a subset of ML inspired by the brain's hierarchical neural structure, processes information through multiple layers, allowing it to recognize complex patterns in data such as images and speech. Notably, computer scientist Ray Kurzweil predicts that AI will reach human-level intelligence by around 2029, emphasizing how quickly the field is advancing and its potential to greatly impact science and technology (1).

Pharmaceutical nanotechnology is a prime example of how AI is revolutionizing complex scientific fields through its ability to process and to analyze extensive and intricate datasets. Nanotechnology integrates nanoscale advancements into pharmaceutical development, enabling targeted drug delivery, improving therapeutic effectiveness, and reducing adverse effects. However, the complex interaction of nanoparticles with biological systems pose significant challenges in their design, characterization, and clinical translation (2, 3). AI addresses these obstacles by offering data-driven solutions that optimize the physicochemical properties and biological performance of nanoparticles. ML models have been used to predict correlations among nanoparticle size, charge, and surface chemistry regarding to therapeutic outcomes, thereby accelerating the development of effective drug delivery systems (4, 5). DL algorithms further enhance imaging-based nanoparticle analysis, supporting accurate organ segmentation and pharmacokinetic profiling (6, 7). Additionally, Predictive tools such as quantitative structure–activity relationship (QSAR) models assist in optimizing nanoparticle design, reducing the reliance on time-consuming experimental trials (4, 5).

Nanomedicine-specific AI milestones have emerged along two tracks. On the infrastructure side, curated datasets and standardized reporting systems such as the NCI's caNanoLab and the Nanotechnology Characterization Laboratory (NCL) provided the first AI-ready repositories for nanomedicine (8). Predictive frameworks including nano-QSAR/QSPR and machine-readable standards then connected nanoparticle descriptors to biological outcomes, laying the groundwork for reproducible, cross-study learning (9). On the development side, integration with Quality by Design (QbD) and Process Analytical Technology (PAT) approaches has aligned AI predictions with Critical Material Attributes and Critical Process Parameters, creating a bridge from algorithms to manufacturable products (8). More recently, the field has demonstrated concrete advances—from deep-learning–based imaging (7) and AI-guided lipid discovery (10) to microfluidic optimization (11)—signaling a clear transition from proof-of-concept toward clinical translation. Complementing these, the NanoMAP self-driving lab framework and ML-based corona-prediction models represent the newest frontier, where autonomous experimentation and predictive bio–nano interface mapping are beginning to close remaining translational gaps (12, 13).

In addition to design, AI has improved real-time monitoring and optimization in nanomedicine. Reinforcement learning methods adjust nanoparticle release profiles in real time to improve therapeutic accuracy. Natural language processing (NLP) tools support the extraction and analysis of data from scientific literature, accelerating the development of predictive models and comprehensive repositories for nanotechnology research (14, 15). AI models, including QSAR and physiologically based pharmacokinetic (PBPK) simulations, are used in nanotoxicology to predict toxicity, biodistribution, and clearance profiles of nanoparticles, aiding in the development of safer formulations (16, 17). Furthermore, AI is advancing personalized medicine. ML models support the development of tailored nanoparticle formulations by analyzing patient-specific genomic and proteomic data. Recent studies suggest that AI can identify optimal siRNA delivery systems for cancer therapy, potentially increasing treatment effectiveness and specificity (10, 18, 19).

Despite these achievements, several challenges remain, including data scarcity, computational demands, and model interpretability. To address these limitations, collaborative efforts are essential to develop standard-

ized datasets, enhance AI frameworks, and ensure ethical implementation. Overcoming these barriers will allow AI to bridge innovation with clinical application, positioning pharmaceutical nanotechnology as a cornerstone of precision medicine (6, 20).

2. Machine Learning and Deep Learning in Pharmaceutical Nanotechnology

ML and DL, key branches of artificial intelligence (AI), have transformed data analysis and predictive modeling by enabling systems to learn from complex datasets without explicit programming. These computational techniques are foundational to many recent advances in pharmaceutical nanotechnology, offering robust frameworks for optimizing drug delivery, nanoparticle design, diagnostics, and disease modeling.

Machine learning paradigms are typically categorized based on learning strategies. Supervised learning involves training models on labeled datasets to predict outcomes for new data, commonly used for classification and regression tasks. Unsupervised learning analyzes unlabeled data to discover hidden patterns through methods like clustering and dimensionality reduction. Reinforcement learning (RL) enables agents to learn optimal actions through trial-and-error interactions with their environment, while semi-supervised learning combines both labeled and unlabeled data to increase efficiency in scenarios where annotation is limited (21).

DL, a specialized subset of ML, employs deep neural networks (DNNs) to extract hierarchical features from raw data. These networks consist of multiple layers that progressively transform inputs into abstract representations, enabling the modeling of complex relationships. Recent advances in computational capacity—especially with the use of GPUs and backpropagation algorithms—have significantly improved the scalability and performance of DL, making it suitable for high-dimensional biomedical datasets frequently encountered in nanomedicine (22).

Additional training strategies include batch learning, which uses the entire dataset at once—ideal for stable environments—and online learning, which updates models incrementally and is better suited for dynamic systems. ML methods also differ in terms of structure: instance-based learning relies on stored examples and similarity measures, while model-based learning builds general predictive models from training data (21).

In nanomedicine, these techniques are applied across diverse tasks. Supervised learning has enabled models such as Random Forest and XGBoost to improve lipid discovery for mRNA delivery by screening virtual libraries (10), and Artificial Neural Networks (ANNs) have accurately predicted nanoparticle properties like particle size, encapsulation efficiency (EE), and polydispersity index (PDI) (23). Unsupervised methods, including UMAP, HDBSCAN, and PCA, have helped uncover critical factors in nanoparticle behavior by simplifying high-dimensional datasets and revealing polymer conformations (24, 25).

Deep learning models have demonstrated superior performance in diagnostics, outperforming conventional statistical tools in analyzing fluorescence signals for biomarker detection (26). Moreover, models such as DeepPrime have improved genome editing predictions by integrating experimental and sequence data, thereby enhancing genome engineering accuracy (27).

Hybrid and advanced techniques combine multiple ML paradigms to further enhance predictive capabilities. Integrating ANNs with Design of Experiments (DoE) has led to accurate nanoparticle optimization with fewer experimental runs (23), while sparse regression and biologically informed neural networks have allowed interpretable modeling of particle–cell interactions, bridging experimental and theoretical approaches (28).

The following table summarizes key machine learning paradigms, their associated techniques, and their applications in pharma-

Table 1. A summary of machine learning paradigms, algorithms, and their specific uses in nanomedicine.

ML Paradigm	Techniques	Applications in Nanotechnology	Data Type Used	Key Nanoparticle Features Used	Ref
Deep Learning	3D U-Net	Organ/tumor segmentation in nanomedicine PK	PET/CT imaging	Organ boundaries, intensity	(7)
	DeepBE, DeepCas9	Predicting base editing outcomes	Genomic sequencing	sgRNA sequence, base context	(29)
	DeepPrime, DeepPrime-Off	Predicting prime editing efficiencies	Genomic libraries	PBS length, RTT length	(27)
	Fully connected DNN (DNNMyo, DNNCK-MB)	Biomarker detection in POC nanodiagnostics	Fluorescence imaging	Signal intensity, emission spectrum	(26)
Supervised Learning	ANN, Backpropagation	Predicting adsorption efficiency	Adsorption datasets	Surface area, pore size	(30)
	Random Forest, XGBoost	Lipid discovery for mRNA delivery	Combinatorial assays	Lipid structure, PEG density	(10)
	SVR, Random Forest	Predicting PLGA NP drug loading	Formulation datasets	MW, ratio (LA/GA), size	(31)
	Transformer, XGBoost	Predicting NP efficacy in cancer	Molecular descriptors	Surface area, chemistry	(32)
	ANN, XGBoost, BF	Optimizing LNP vaccine bioprocess	Bioprocess datasets	Lipid type, process parameters	(23)
	ERT, Gradient Boosting	Predicting bacterial survival vs ZnO NPs	Antimicrobial assays	Particle size, doping	(33)
	SoftMax, RF	Pathogen screening (SERS)	Spectral datasets	Raman peaks, aptamer signals	(34)
	CART	Predicting ZnO NP cytotoxicity	Cytotoxicity datasets	Size, exposure dose	(17)
	Linear Regression, Bayesian	Predicting CNS NP delivery	PK datasets	Size, zeta potential	(25)
	MLP, SVR, Lasso	Predicting NP solubility (supercritical)	Solubility datasets	Solvent type, NP interactions	(35)
	ANN, TOPSIS	Optimizing oral drug delivery NPs	PK datasets	Size, bioavailability	(18)
	Gradient Boosting, RF	Predicting aerosolized nasal deposition	CFD + ML	Size distribution, airflow	(36)
	RF, SVM	NP drug delivery for cervical cancer	Genomic + PK	Release rate, ligand type	(37)
Unsupervised Learning	UMAP, HDBSCAN	Analyzing polymer conformations	Simulation data	Chain folding, encapsulation	(24)
	PCA, LDA	Classifying microbial taxa via biosynthetic NPs	Genomic + imaging	Spectral/biological signatures	(38)
	Dimensionality Reduction, Clustering	Predicting NP self-assembly	Simulation data	Monomer interactions, assembly	(39)
Hybrid Techniques	Sparse Regression, Bio-Informed NN	Modeling particle–cell interactions	Flow cytometry	Size, corona composition	(28)
	SVM, MLP	Phase behavior in nano-hybrids	Physicochemical datasets	Polymer %, solubility	(40)

Continued Table 1.

ANN, Lasso	Optimizing NP solubility and release	Release datasets	Size, drug release	(40)

Abbreviations: ML: Machine Learning; DL: Deep Learning; ANN: Artificial Neural Network; DNN: Deep Neural Network; DNNMyo: Deep Neural Network for Myoglobin detection; DNNCK-MB: Deep Neural Network for Creatine Kinase: MB detection; BF:Bootstrap Forest; ERT: Extremely Random Trees; XGBoost : Extreme Gradient Boosting; SVR :Support Vector Regression; SVM:Support Vector Machine; SMC: SoftMax Classifier; CART: Classification and Regression Trees; MLP:Multilayer Perceptron; LDA: Linear Discriminant Analysis; PCA :Principal Component Analysis; UMAP:Uniform Manifold Approximation and Projection; HDBSCAN: Hierarchical Density-Based Spatial Clustering of Applications with Noise; TOPSIS :Technique for Order of Preference by Similarity to Ideal Solution; Lasso:Least Absolute Shrinkage and Selection Operator; 3D U-Net : 3D U-Net Convolutional Neural Network Architecture ; DeepBE:Deep Base Editor; DeepCas-9variants : Deep Learning Models for Cas9 Variants; DeepPrime / DeepPrime-Off : Deep Learning Models for Prime Editing and Off-target Prediction; PET/CT : Positron Emission Tomography / Computed Tomography; ZnO: Zinc Oxide; PLGA : Poly(lactic-co-glycolic acid); SERS : Surface-Enhanced Raman Scattering; CNS : Central Nervous System; mRNA : Messenger Ribonucleic Acid

ceutical nanotechnology:

The diverse paradigms and techniques of machine learning provide a robust framework for addressing the complexities of pharmaceutical nanotechnology. By leveraging models such as supervised learning for predictive analytics, unsupervised clustering for uncovering hidden patterns, and deep learning for hierarchical representations, researchers are equipped to tackle intricate challenges. These methodologies form the backbone of AI-driven innovation and naturally transition into practical applications, as demonstrated through specific case studies in the next section.

3. Case Studies in Machine Learning: Applications to Pharmaceutical Nanotechnology

Artificial intelligence (AI) has changed pharmaceutical nanotechnology, leading to new strategies for diagnosing diseases, delivering drugs, and designing materials. This section includes a group of case studies that work together to show how machine learning (ML) and deep learning (DL) are being used to solve important problems in the field. Each example shows how AI can improve accuracy, productivity, and creativity across key domains of application (Figure 1).

3.1. Driving progress in diagnostics and imaging

AI-powered tools are changing the way imaging and diagnostics are done, making analysis more accurate and time-effective. One such advancement is NanoMASK for organ and tumor segmentation. It is incredible how well deep learning frameworks like NanoMASK can separate organs and tumors from PET/CT datasets. NanoMASK showed correlation coefficients higher than 0.997 for pharmacokinetic metrics for lipid nanoparticles. For antibody-drug conjugates, it reached DSC values of up to 90.4% for the heart and 87.2% for the liver, showing how flexible it is across different types of nanomedicine (7). This accuracy is driven by NanoMASK's 3D U-Net architecture, which integrates both anatomical CT and functional PET inputs to capture contrast patterns generated by nanoparticle distribution. Saliency mapping further showed that the model prioritizes regions where lipid nanoparticles accumulate (e.g., liver, spleen) or where antibody–drug conjugates display distinct uptake, directly linking imaging-derived nanoparticle pharmacokinetics to organ-level segmentation outcomes.

In parallel, point-of-care diagnostics have also benefited from AI, as demonstrated by the fluorescence vertical flow assay (fxVFA) platform. There is a strong link ($R^2 > 0.9$) between fxVFA and ELISA for finding biomarkers like Myoglobin and CK-MB. With a coefficient of variation below 15%, it proved reliable during blind testing, setting new standards in multiplexed diagnostics. Here, neural networks processed fluorescence intensities from 17 immunoreaction spots labeled with conjugated polymer nanoparticles. Through

Figure 1. Key application areas of artificial intelligence in pharmaceutical nanotechnology.

feature selection, the models learned which spot patterns corresponded to true biomarker concentrations, effectively filtering out noise from autofluorescence and cross-reactivity, which enabled robust and precise quantification in serum samples (26).

3.2. Optimizing nanoparticle design and delivery

Machine learning models make it possible to design and improve nanoparticle systems that are specifically tailored for drug delivery. A notable case is PEG–PLGA nanoparticles for peptide encapsulation. Using coarse-grained molecular dynamics combined with unsupervised ML (UMAP + HDBSCAN clustering), López-Rios de Castro *et al*. demonstrated that therapeutic peptides such as EEK are not randomly distributed but are preferentially solubilized in distinct microenvironments within the nanoparticle. Some peptides localize deep in the hydrophobic PLGA core, while others stabilize at the core–corona interface, depending on amphiphilicity and hydration. The ML analysis identified specific polymer conformations (e.g., extended PLGA vs extended PEG states) that create local chemical niches governing where peptides reside. This mechanistic insight shows that polymer topology and conformational clustering regulate peptide positioning, providing a rational basis for designing PEG–PLGA nanocarriers with predictable loading and release behaviors in cancer therapy (24).

Similarly, machine learning (ML) models have accelerated the discovery of ionizable lipids for mRNA delivery by integrating combinatorial chemistry with in silico prediction. From a library of 40,000 candidates, ML-guided screening identified lipid 119-23, which showed markedly enhanced biodistribution and transfection efficiency. In vivo, 119-23 LNPs achieved ten-fold higher liver transfection and twenty-fold higher spleen

transfection relative to benchmark lipids such as MC3. Moreover, 119-23 supported robust protein expression (e.g., human erythropoietin) and was further adapted into selective organ targeting (SORT) formulations to enhance lung delivery. These findings highlight how ML can uncover non-intuitive lipid structures and accelerate the development of next-generation LNPs for vaccines and systemic protein replacement therapies (10).

In addition, optimized oral nanoformulations have benefited from AI integration. In the case of posaconazole-loaded phospholipid nanoparticles, researchers combined design of experiments (DoE), artificial neural networks (ANNs), and TOPSIS to identify the optimal formulation parameters—such as total lipid content, soy oil-to-phosphatidylcholine ratio, drug concentration, and glycerol percentage—that govern encapsulation efficiency, particle size, and PDI. The trained ANN ($R^2 > 0.99$ for size and EE) learned nonlinear relationships between these formulation variables and nanoparticle performance, while TOPSIS ranked the most promising formulations against ideal targets. The optimized nanoparticles (~108 nm, EE ~74%) achieved a 6.2-fold higher AUC compared to suspension and eliminated food-dependent variability. Mechanistic studies showed that the bioavailability enhancement stemmed primarily from lymphatic transport, as blocking chylomicron pathways significantly reduced Cmax, while cellular uptake did not contribute substantially. This demonstrates how AI-driven multi-criteria optimization can rationally tune formulation parameters to improve oral bioavailability of poorly soluble antifungal drugs (18).

3.3. Enhancing understanding of nanoparticle interactions

AI tools are giving us new information about how nanoparticles behave, their toxicity, and their biological interactions. A clear example is the prediction of bacterial survival under exposure to ZnO and lanthanum-doped ZnO nanoparticles. In this study, supervised ML models (random forest, gradient boosting, and support vector regression) were trained on descriptors such as particle size, dopant concentration, exposure time, and bacterial strain type. The models achieved high accuracy ($R^2 > 0.9$) in predicting survival rates, correctly capturing that P. aeruginosa and E. coli viability dropped by up to 95%. Importantly, feature-importance analysis revealed that dopant level and nanoparticle size were the dominant predictors, linking physicochemical parameters directly to antimicrobial outcomes. This mechanistic interpretability shows how AI can guide the rational design of doped nanomaterials for targeted antibacterial applications (33). In a similar vein, cytotoxicity prediction for ZnO nanoparticles has been advanced through regression and tree-based models. In a meta-analysis of 543 data points from 26 studies, classification and regression tree (CART) analysis identified exposure concentration, primary particle size, cell morphology, and exposure duration as the most important predictors of cell viability. The model revealed a critical size threshold of 10 nm, below which ZnO nanoparticles induced markedly higher toxicity, and highlighted that concentrations ≥20 μg/mL consistently reduced viability by >50% across multiple cell types. Feature-importance ranking showed that dose and size dominated over other descriptors (e.g., zeta potential, coating), linking physicochemical parameters directly to cytotoxic outcomes. This demonstrates how ML-driven integration of heterogeneous datasets can reveal generalizable rules governing ZnO nanoparticle safety (17).

Additionally, PLGA nanoparticle optimization has benefited from machine learning approaches. In a recent meta-analysis of >200 studies, researchers built predictive models using support vector regression (SVR), random forest, logistic regression, and multilayer perceptron neural networks, with features derived

Table 2. Summary of machine learning and deep learning case studies in pharmaceutical nanotechnology.

Case Study	Application	Key Outcome	Ref
NanoMASK for Organ and Tumor Segmentation	Organ and tumor segmentation, pharmacokinetics	Correlation $R^2 > 0.997$; DSC up to 90.4% for heart segmentation	(7)
PEG-PLGA Nanoparticles for Peptide Delivery	Peptide delivery, cancer therapy design	Peptide localization tailored to tumor environments	(24)
Point-of-Care Diagnostics with fxVFA	Biomarker detection	Correlation $R^2 > 0.9$ with ELISA; <15% variation	(26)
Lipid Discovery for mRNA Delivery	Optimizing LNPs for mRNA delivery	10x liver transfection; 20x spleen transfection	(10)
Nanocomposite Design	Nanocomposite design optimization	Morphologies predicted correctly for 7/9 samples	(39)
LNP-Based mRNA Vaccines	Vaccine formulation optimization	EE 93.90%; Particle size 69.3 nm	(23)
Predicting Nano-Particle Cell Interactions	Nanoparticle-cell interactions	5x higher affinity for PSMA-expressing cells	(28)
Microbial Identification with Gold Nanoparticles	Pathogen identification	100% accuracy in microbial classification	(38)
Predicting Editing Efficiencies of Base Editors	Gene editing tool optimization	Improved editing efficiency (up to 2.7-fold)	(29)
Prime Editing System Optimization	Gene editing tool optimization	3.5x higher editing efficiency using DeepPrime	(27)
Cytotoxicity of ZnO Nanoparticles	Cytotoxicity profiling	Smaller NPs (<10 nm) are linked to higher toxicity	(17)
Optimized Oral Nanoformulations	Oral drug delivery	6.2x plasma drug level increase	(18)
PLGA Nanoparticle Optimization	Drug delivery optimization	Higher encapsulation efficiency with tailored synthesis methods	(31)
Nanoparticle Drug Delivery to the Brain	CNS drug delivery	Intranasal PLGA-CS NPs achieved the highest brain uptake	(25)
AI for Nano-Hybrid Formulations	Controlled drug release	Enhanced solubility and liquid-to-gel transitions	(40)
Pathogen Detection via SERS	Rapid screening for pathogens	100% accuracy for low-concentration pathogens	(34)
AI for Cervical Cancer	Targeted nano-drug delivery	Enhanced cytotoxicity of PLGA systems delivering curcumin and siRNA	(37)
Predicting Drug-Carriers for Cancer	Drug delivery vehicle optimization	High correlation with MD simulations (300 ns)	(32)

Continued Table 2.

Nanomedicine Solubility in SC-CO2	Drug solubility optimization	Increased solubility with pressure; temperature effects clarified	(35)
Adsorption Efficiency of Carbon Nanomaterials	Adsorption studies	98% adsorption efficiency for paracetamol	(30)
Nasal Drug Delivery Optimization	Aerosolized drug delivery	Optimized regional delivery to the brain through the olfactory bulb	(36)
Predicting Bacterial Survival Against ZnO Nanoparticles	Antibacterial nanoparticle optimization	95% bacterial mortality for P. aeruginosa and E. coli	(33)
Machine Learning-Assisted Cytotoxicity Prediction for ZnO Nanoparticles	Cytotoxicity prediction	Smaller ZnO nanoparticles (<10 nm) showed higher cytotoxicity compared to larger counterparts	(17)

Abbreviations: AI:Artificial Intelligence; ML:Machine Learning; NPs : Nanoparticles; MD simulations :Molecular Dynamics Simulations; PET/CT : Positron Emission Tomography / Computed Tomography; PSMA: Prostate-Specific Membrane Antigen ; CNS: Central Nervous System; siRNA: Small Interfering Ribonucleic Acid ; ELISA: Enzyme-Linked Immunosorbent Assay ; DSC: Dice Similarity Coefficient ; PEG-PLGA : Polyethylene Glycol–Poly(lactic-co-glycolic acid); PLGA: Poly(lactic-co-glycolic acid); PLGA-CS: Poly(lactic-co-glycolic acid)–Chitosan; LNPs: Lipid Nanoparticles; SC-CO_2: Supercritical Carbon Dioxide ; fxVFA : Fluorescence Vertical Flow Assay; SERS : Surface-Enhanced Raman Scattering; R^2 : Coefficient of Determination; EE: Encapsulation Efficiency

from polymer properties (molecular weight, lactide/glycolide ratio, PEGylation), solvents, stabilizers (PVA), and synthesis method (nanoprecipitation, emulsion, microfluidics). Feature selection with LASSO revealed that PLGA molecular weight and PEG presence were the strongest predictors of encapsulation efficiency (EE%), while the lactide:glycolide ratio dominated drug loading (DL%) outcomes. SVR achieved the lowest error for predicting size and EE% (MSE ~0.008), while logistic regression performed best for DL%. Importantly, the models captured trade-offs between size and EE%, showing that maximizing encapsulation often increases particle size. This mechanistic interpretability directly links formulation variables (polymer chemistry + processing route) to nanoparticle performance, providing a data-driven framework for rational PLGA nanocarrier design (31).

As shown in Table 2, the case studies highlight the diverse applications of machine learning and deep learning in pharmaceutical nanotechnology, demonstrating their transformative potential across various domains.

While these case studies demonstrate the transformative potential of machine learning and deep learning in pharmaceutical nanotechnology, the accompanying summary table highlights key applications and outcomes, offering a concise view of their impact. These examples also underscore critical challenges that must be addressed. These include limitations in data availability, computational resources, model interpretability, and regulatory considerations. The following section delves into these challenges, exploring the obstacles to advancing AI-driven innovations in this field.

4. Challenges in AI-Driven Nanomedicine

Incorporating artificial intelligence (AI) into nanomedicine has created transformative opportunities. However, several challenges must be overcome to realize its full potential. Figure 2 below summarizes the core challenges currently facing AI applications in nanomedicine, spanning technical, ethical, and collaborative domains.

One of the most significant obstacles is the quality and availability of data. AI models require large, high-quality datasets to function correctly. Unfortunately, the complexity and diversity of nanomaterials frequently result in sparse and inconsistent datasets, impeding the development of robust AI models. This prob-

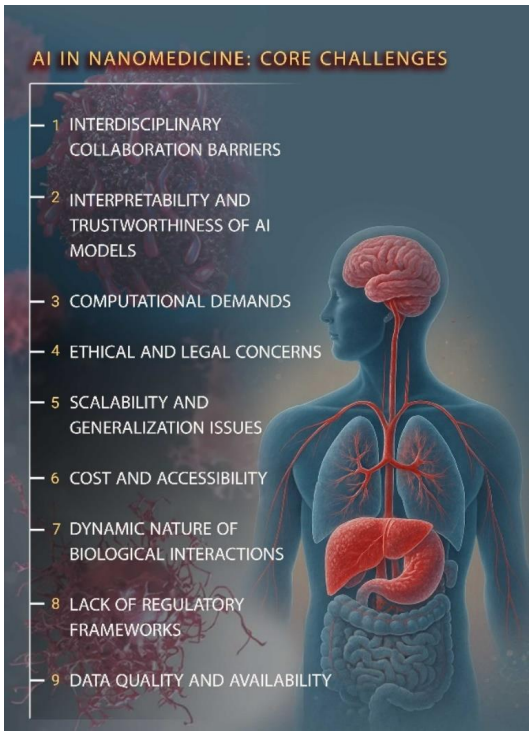

Figure 2. Core challenges in applying AI to nanomedicine.

lem is exacerbated by a lack of standardized protocols for nanomaterial characterization, which makes it difficult to compare results across experiments and limits the availability of public databases tailored for nanotechnology applications (41).

Another critical challenge is interdisciplinary collaboration. Incorporating AI into nanomedicine necessitates seamless collaboration across multiple disciplines, including computer science, materials science, and biology. However, differences in terminology, methodologies, and objectives between these disciplines frequently impede effective communication and alignment. For example, while materials scientists may concentrate on structural properties, biologists frequently prioritize cellular interactions, resulting in differences in data interpretation and model objectives (2).

The interpretability and trustworthiness of AI models are also significant challenges. Many AI models and deep learning approaches are referred to as "black boxes" with opaque decision-making mechanisms. This lack of transparency undermines trust and acceptance among researchers and clinicians, especially in drug development areas where regulatory compliance and clinical reliability are critical. To confidently integrate AI predictions into their workflows, stakeholders need clear explanations (19).

Training and deploying advanced AI models in nanomedicine requires substantial computational power, which is often unavailable in resource-constrained environments. Smaller research facilities, in particular, face limited access to high-performance computing infrastructure and cloud resources. These computational demands directly translate into high financial costs, as powerful hardware, specialized software licenses, and skilled personnel are required. Consequently, smaller laboratories and underfunded organizations encounter significant barriers to adopting AI tools. This dual challenge of computational intensity and financial inaccessibility slows innovation and creates disparities across research groups and regions. Addressing these issues will require not only investments in infrastructure but also the development of cost-efficient, scalable AI frameworks and open-source solutions to en-

sure equitable progress in the field (11, 42).

Ethical and legal concerns complicate the application of AI in nanomedicine. The handling of sensitive patient data required for AI model training raises serious privacy concerns, necessitating strong encryption and anonymization methods. Furthermore, regulatory gaps and ambiguous guidelines on liability and accountability create uncertainty for researchers and developers, slowing progress (14).

Another challenge is the scalability and generalization of AI models. Models developed for specific datasets frequently struggle to adapt to new domains or experimental conditions. Transfer learning and domain adaptation are two techniques that could improve scalability in nanomedicine but are currently underutilized. For example, models designed for one type of nanoparticle frequently fail to predict the behavior of structurally different materials (6).

The dynamic nature of biological interactions introduces an additional layer of complexity. Nanoparticles engage in evolving interactions with biological systems, including protein corona formation and cellular uptake. Modeling these dynamic processes accurately is difficult due to the scarcity of comprehensive datasets and algorithms capable of capturing these nuances. Real-time data integration is required to improve our understanding of these interactions (43).

Finally, the lack of established regulatory frameworks for evaluating and approving AI-powered nanomedicine systems creates uncertainty and slows clinical translation and commercialization. For example, the lack of consistent guidelines across regions makes global collaboration and technology deployment difficult (44).

While AI is increasingly applied in drug development and nanomedicine research, there is still no globally harmonized framework for its validation and approval. The FDA's discussion paper on AI/ML in drug and biologics development (2023) calls for a risk-based, context-of-use framework, requiring sponsors to pre-specify validation and monitoring plans (45). The FDA's discussion paper on AI in drug manufacturing (2023) emphasizes CGMP-related challenges, including data provenance, lifecycle validation of adaptive models, and inspection readiness (45). In Europe, the EMA's Reflection Paper (2024) stresses representativeness of training data, model generalisability, and post-deployment drift monitoring (46). At the legislative level, the EU AI Act (2024) classifies most health-related AI as high-risk, requiring CE-marking, conformity assessment, and post-market monitoring (47).

From a GMP perspective, key barriers remain: (i) the difficulty of ensuring data integrity and traceability across multi-site and cloud-based pipelines; (ii) lifecycle validation of adaptive/retrained models; (iii) lack of defined applicability domains and uncertainty quantification; and (iv) absence of standardized change-control pathways for iterative AI model updates. A potential solution is offered by the FDA's Predetermined Change Control Plan (PCCP, 2024), which pre-specifies model modifications and validation methods to avoid repeated submissions (48).

Practical pathways forward are already visible. AI models in nanomedicine should be aligned with Quality by Design (QbD) and Process Analytical Technology (PAT) frameworks so that predictions map directly to Critical Material Attributes (CMAs) and Critical Process Parameters (CPPs) (49). Explainable AI methods such as SHAP and LIME can provide interpretable insights into how nanoparticle features (e.g., size, charge, PEG density) influence outcomes (42). Defining applicability domains, curating datasets to NCL/ISO/ASTM standards, and embedding post-market monitoring will improve reproducibility and regulatory acceptability(8). For Europe, planning dual compliance—meeting both EMA's scientific expectations for transparency and

the EU AI Act's legal requirements for conformity assessment—will be essential.

Despite these challenges, they provide opportunities for groundbreaking progress. Addressing these barriers will improve AI integration into nanomedicine and reveal its transformative potential in drug discovery, diagnostics, and personalized therapy. The following section delves into the prospects that could reshape the nanomedicine landscape once these barriers are overcome.

5. Future Directions and Opportunitie

The AI-driven nanotechnology is anticipated to advance considerably across various domains, creating avenues for innovative concepts. The establishment of comprehensive and standardized databases for nanomaterials is essential. These databases may encompass data regarding their physicochemical characteristics, production methods, and interactions with living organisms. These databases are essential for enhancing AI models for training and predictions, as they tackle the issues of constrained data availability and quality (41). Material discovery is accelerating due to AI methodologies such as generative adversarial networks (GANs). These methods facilitate the synthesis of novel nanomaterials with tailored properties applicable in diverse domains, including electronics, biomedicine, and environmental science (14). Furthermore, employing AI to engineer novel nanomaterials facilitates the development of nanoparticles customized for particular medical applications, thereby diminishing the necessity for extensive experimental trials (6).

A promising domain is the integration of AI and microfluidics, which elucidates the use of predictive AI models alongside microfluidic systems to optimize high-throughput synthesis, reduce development costs, and enhance precision in nanomedicine fabrication (11). These systems may also facilitate the creation of dynamic disease models, such as "cancer-on-a-chip," to examine tumor microenvironments in real-time and evaluate therapeutic interventions (5).

AI-driven platforms are improving drug efficacy in the body and accelerating the identification of lead compounds in drug discovery. These developments support personalized medicine, where nanomedicines are tailored to meet each patient's specific needs, enhancing treatment effectiveness and minimizing side effects (2). Digital twin technology—virtual replicas of physical systems that are continuously updated with real or simulated data—is emerging as a promising tool for simulating nanoparticle behavior. One example is in plasmonic sensors built from nanoparticle arrays, where finite-element and boundary-element–based digital twin models can simulate how interparticle distance, particle size, substrate, and geometry affect plasmonic resonance, with experimental agreement within ~1 nm (50). Beyond sensing, digital twins are being developed for process and formulation control. For instance, a digital twin of a coaxial lamination mixer predicts mixing times that correlate with nanoparticle size and dispersity during microfluidic precipitation (51), and continuous manufacturing frameworks for virus-like particles integrate mechanistic models across unit operations to anticipate product quality (52). In formulation science, "Quality by Digital Design" approaches apply digital twins to predict particle size, drug loading, and release kinetics, enabling virtual screening before costly lab trials (53). For materials more broadly, frameworks that build multiscale digital twins of material systems (capturing structure, process history, and performance over time) suggest how such approaches could be adapted to nanoparticle systems, linking structure with functional response (54). While these are not yet full in vivo nanoparticle twins, they illustrate the core components—accurate physical modeling, multi-scale feature capture, and dynamic simulation—that will be required to simulate nanoparticle behavior in biological environ-

ments such as protein corona formation, biodistribution, and clearance.

Advancements in AI-driven nanotechnology must be made ethically and sustainably. Responsible innovation can only flourish in an environment where strong ethical norms and regulations safeguard personal information, promote equality, and increase accessibility (14). The development of eco-friendly nanomaterials is spearheaded by artificial intelligence, proving that nanotechnology can progress in ways that benefit the environment (42).

6. Conclusion

Artificial intelligence (AI) is revolutionizing pharmaceutical nanotechnology by facilitating novel diagnostics, drug delivery, and material design advancements. Machine learning (ML) and deep learning (DL) methodologies have already produced measurable outcomes—such as improving tumor segmentation accuracy to over 90% in PET/CT imaging (7), increasing oral posaconazole bioavailability by 6.2-fold with optimized nanoparticles (18), and boosting mRNA transfection efficiency by 6–10 fold through AI-guided lipid discovery (10). In nanotoxicology, ML regression and tree-based models predict ZnO nanoparticle cytotoxicity with $R^2 > 0.85$ (17), while bacterial survival against doped ZnO nanoparticles can be forecast with up to 95% accuracy (33). Similarly, ANN-based frameworks in mRNA vaccine development have achieved ~90% predictive accuracy, reducing experimental workload (23). Even in design, digital twin models now simulate nanoparticle plasmonic behavior within ~1 nm agreement of experimental results (50). Despite considerable advancements, obstacles remain. Challenges including data scarcity, model interpretability, and regulatory uncertainty still impede broad clinical application. Overcoming these will require interdisciplinary collaboration, harmonized datasets, and ethical frameworks to ensure equitable and responsible innovation.

Looking forward, innovations such as generative adversarial networks (GANs), advanced digital twin frameworks, and AI-driven microfluidic systems are poised to accelerate discovery even further. These emerging tools promise not only to personalize therapies and enhance diagnostics, but also to support the sustainable development of environmentally friendly nanomaterials. By overcoming current barriers and leveraging these capabilities, AI will continue to transform pharmaceutical nanotechnology, driving measurable improvements in patient care and global health outcomes.

Authors contributions

M. Kadkhodaei performed the literature review, data extraction, and manuscript writing. M. Monajati designed the review framework, supervised the work, and revised the manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest.

References

1. Kurzweil R. The Singularity Is Near: When Humans Transcend Biology. New York: Viking; 2005.
2. Naaz S, Asghar A. Artificial intelligence, nano-technology and genomic medicine: The future of anaesthesia. *J Anaesthesiol Clin Pharmacol*. 2022;38(1):11-7. doi:10.4103/joacp.JOACP_139_20
3. Anuoluwa Bamidele E, Olanrewaju Ijaola A, Bodunrin M, Ajiteru O, Martha Oyibo A, Makhatha E, *et al*. Discovery and prediction capabilities in metal-based nanomaterials: An overview of the application of machine learning techniques and some recent advances. *Adv Engin Inform*. 2022;52:101593.
4. Ji Z, Guo W, Wood EL, Liu J, Sakkiah S, Xu X, *et al*. Machine Learning Models for Predicting Cytotoxicity of Nanomaterials. *Chem Res Toxicol*. 2022;35(2):125-39.
5. Singh AV, Varma M, Laux P, Choudhary

S, Datusalia AK, Gupta N, *et al*. Artificial intelligence and machine learning disciplines with the potential to improve the nanotoxicology and nanomedicine fields: a comprehensive review. *Arch Toxicol.* 2023;97(4):963-79. doi:10.1007/s00204-023-03471-x
6. Kuznetsova V, Coogan A, Botov D, Gromova Y, Ushakova EV, Gun'ko YK. Expanding the Horizons of Machine Learning in Nanomaterials to Chiral Nanostructures. *Adv Mater.* 2024;36(18):e2308912. doi:10.1002/adma.202308912
7. Dhaliwal A, Ma J, Zheng M, Lyu Q, Rajora MA, Ma S, *et al*. Deep learning for automatic organ and tumor segmentation in nanomedicine pharmacokinetics. *Theranostics*. 2024;14(3):973-87. doi:10.7150/thno.90246
8. Ke W, Crist RM, Clogston JD, Stern ST, Dobrovolskaia MA, Grodzinski P, *et al*. Trends and patterns in cancer nanotechnology research: A survey of NCI's caNanoLab and nanotechnology characterization laboratory. *Adv Drug Deliv Rev.* 2022;191:114591.
9. Wyrzykowska E, Mikolajczyk A, Lynch I, Jeliazkova N, Kochev N, Sarimveis H, *et al*. Representing and describing nanomaterials in predictive nanoinformatics. *Nat Nanotechnol*. 2022;17(9):924-32.
10. Li B, Raji IO, Gordon AGR, Sun L, Raimondo TM, Oladimeji FA, *et al*. Accelerating ionizable lipid discovery for mRNA delivery using machine learning and combinatorial chemistry. *Nat Mater.* 2024;23(7):1002-8.
11. Liu L, Bi M, Wang Y, Liu J, Jiang X, Xu Z, *et al*. Artificial intelligence-powered microfluidics for nanomedicine and materials synthesis. *Nanoscale*. 2021;13(46):19352-66.
12. Hickman RJ, Bannigan P, Bao Z, Aspuru-Guzik A, Allen C. Self-driving laboratories: A paradigm shift in nanomedicine development. *Matter*. 2023;6(4):1071-81.
13. Fu X, Yang C, Su Y, Liu C, Qiu H, Yu Y, *et al*. Machine Learning Enables Comprehensive Prediction of the relative protein abundance of multiple proteins on the protein corona. *Research (Wash D C)*. 2024;7:0487.
14. Serov N, Vinogradov V. Artificial intelligence to bring nanomedicine to life. *Adv Drug Deliv Rev.* 2022;184:114194. doi:10.1016/j.addr.2022.114194
15. Hamilton S, Kingston BR. Applying artificial intelligence and computational modeling to nanomedicine. *Curr Opin Biotechnol.* 2024;85:103043. doi:10.1016/j.copbio.2023.103043
16. Chou WC, Canchola A, Zhang F, Lin Z. Machine Learning and Artificial Intelligence in Nanomedicine. *Wiley Interdiscip Rev Nanomed Nanobiotechnol.* 2025;17(4):e70027. doi: 10.1002/wnan.70027. PMID: 40813104; PMCID: PMC12353477.
17. Kantesaria R, Panda HS. A Review on AI-Based Data-Driven Models for Optimization of Nanocarriers as Drug Delivery Systems. *ACS Biomater Sci Eng*. 2026. doi: 10.1021/acsbiomaterials.5c01998. Epub ahead of print. PMID: 41668335.
18. Bayat F, Dadashzadeh S, Aboofazeli R, Torshabi M, Baghi AH, Tamiji Z, *et al*. Oral delivery of posaconazole-loaded phospholipid-based nanoformulation: Preparation and optimization using design of experiments, machine learning, and TOPSIS. *Int J Pharm*. 2024;653:123879. doi:10.1016/j.ijpharm.2024.123879
19. Rajput A, Arya D, Panshul C, Atul D, Debaprasad Gh, Ashu M. Artificial Neural Network In Pharmaceutical And Cosmeceutical Research. *Int J Pharma Sci*. 2024;2(1):410-42.
20. Abhijeet Madhukar Haval KS, Sushree Sasmita Dash. Machine learning-based enhanced drug delivery system and its applications – A systematic review. *J Angiother.* 2024;8(1):1-9.
21. Géron A. Hands-On Machine learning with scikit-learn, Keras, and TensorFlow. 2nd ed. Sebastopol, CA: O'Reilly Media; 2019.
22. Chollet F. Deep Learning with Python. 2nd ed. Shelter Island, NY: Manning Publications; 2021.
23. Maharjan R, Hada S, Lee JE, Han HK,

Kim KH, Seo HJ, *et al.* Comparative study of lipid nanoparticle-based mRNA vaccine bioprocess with machine learning and combinatorial artificial neural network-design of experiment approach. *Int J Pharm.* 2023;640:123012. doi:10.1016/j.ijpharm.2023.123012

24. López-Rios de Castro R, Ziolek RM, Ulmschneider MB, Lorenz CD. Therapeutic peptides are preferentially solubilized in specific microenvironments within PEG-PLGA polymer nanoparticles. *Nano Lett.* 2024;24(6):2011-7. doi:10.1021/acs.nanolett.3c04558
25. Yousfan A, Al Rahwanji MJ, Hanano A, Al-Obaidi H. A comprehensive study on nanoparticle drug delivery to the brain: Application of machine learning techniques. *Mol Pharm*. 2023;21(1):333-45.
26. Goncharov A, Joung HA, Ghosh R, Han GR, Ballard ZS, Maloney Q, *et al*. Deep learning-enabled multiplexed point-of-care sensor using a paper-based fluorescence vertical flow assay. *Small*. 2023;19(51):e2300617.
27. Yu G, Kim HK, Park J, Kwak H, Cheong Y, Kim D, *et al*. Prediction of efficiencies for diverse prime editing systems in multiple cell types. *Cell*. 2023;186(10):2256-72 e23.
28. Johnston ST, Faria M. Equation learning to identify nano-engineered particle-cell interactions: an interpretable machine learning approach. *Nanoscale*. 2022;14(44):16502-15.
29. Kim N, Choi S, Kim S, Song M, Seo JH, Min S, *et al*. Deep learning models to predict the editing efficiencies and outcomes of diverse base editors. *Nat Biotechnol*. 2024;42(3):484-97.
30. Prasad K, Ravi Kumar V, Kumar RS, Rajesh AS, Rai AK, Al-Ammar EA, *et al.* Predicting the adsorption efficiency using machine learning framework on a carbon-activated nanomaterial. *Adsorp Sci Technol*. 2023;2023:1-11.
31. Rezvantalab S, Mihandoost S, Rezaiee M. Machine learning assisted exploration of the influential parameters on the PLGA nanoparticles. *Sci Rep.* 2024;14(1):1114.
32. Kibria MR, Akbar RI, Nidadavolu P, Havryliuk O, Lafond S, Azimi S. Predicting efficacy of drug-carrier nanoparticle designs for cancer treatment: a machine learning-based solution. *Sci Rep.* 2023;13(1):547.
33. Navarro-Lopez DE, Perfecto-Avalos Y, Zavala A, de Luna MA, Sanchez-Martinez A, Ceballos-Sanchez O, *et al*. Unraveling the complex interactions: Machine learning approaches to predict bacterial survival against ZnO and lanthanum-doped ZnO nanoparticles. *Antibiotics (Basel)*. 2024;13(3):220.
34. Jin L, Cai X, Ren F, Yang J. An aptamer-based SERS method for rapid screening and identification of pathogens assisted by machine learning technique with robustness evaluation. *Sens Actuators B: Chem*. 2024;405.
35. Chen C. Artificial Intelligence aided pharmaceutical engineering: Development of hybrid machine learning models for prediction of nanomedicine solubility in supercritical solvent. *J Mol Liquids*. 2024;397:012001.
36. Farnoud A, Tofighian H, Baumann I, Ahookhosh K, Pourmehran O, Cui X, *et al*. Numerical and machine learning analysis of the parameters affecting the regionally delivered nasal dose of nano- and micro-sized aerosolized drugs. *Pharma (Basel).* 2023;16(1):81:124127.
37. Kour S, Biswas I, Sheoran S, Arora S, Sheela P, Duppala SK, *et al*. Artificial intelligence and nanotechnology for cervical cancer treatment: Current status and future perspectives. *J Drug Deliv Sci Technol.* 2023;83:104392.
38. Yu T, Su S, Hu J, Zhang J, Xianyu Y. A New strategy for microbial taxonomic identification through micro-biosynthetic gold nanoparticles and machine learning. *Adv Mater*. 2022;34(11): 2109365.
39. Vargo E, Dahl JC, Evans KM, Khan T, Alivisatos P, Xu T. Using machine learning to predict and understand complex self-assembly behaviors of a multicomponent nanocomposite. *Adv Mater.* 2022;34(32):2203168.
40. Barbosa RdM, Lima CC, Oliveira

FFd, Câmara GBM, Viseras C, Moura TFAdLe, *et al*. New machine learning approach for the optimization of nano-hybrid formulations. *Nanomanufacturing.* 2022;2(3):82-97.
41. Naik GG, Jagtap VA. Two heads are better than one: Unravelling the potential Impact of Artificial Intelligence in nanotechnology. *Nano Trans Med*. 2024;3.
42. Bao Z, Bufton J, Hickman RJ, Aspuru-Guzik A, Bannigan P, Allen C. Revolutionizing drug formulation development: The increasing impact of machine learning. *Adv Drug Deliv Rev*. 2023;202:115108.
43. Dutt S, Karawdeniya B, Bandara YM, Kluth P. Nanopore sensing and machine learning: future of biomarker analysis and disease detection. *Future Sci OA*. 2024;10(1):2340882.
44. Chen C, Yaari Z, Apfelbaum E, Grodzinski P, Shamay Y, Heller DA. Merging data curation and machine learning to improve nanomedicines. *Adv Drug Deliv Rev.* 2022;183:114172.
45. Administration USFaD. Using artificial intelligence and machine learning in the development of drug and biological products: discussion paper. Silver Spring, MD; 2023.
46. Agency EM. Reflection paper on the use of artificial intelligence (AI) in the medicinal product lifecycle. Amsterdam (NL); 2024.
47. Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain Union legislative acts, (2024-07-12, 2024).
48. Administration USFaD. Artificial Intelligence in Drug Manufacturing: Discussion Paper. Silver Spring, MD; 2023.
49. Villa Nova M, Lin TP, Shanehsazzadeh S, Jain K, Ng SCY, Wacker R, *et al*. Nanomedicine ex machina: Between model-informed development and artificial intelligence. *Front Digit Health*. 2022;4:799341.
50. Bonyar A, Kovacs R. Towards digital twins of plasmonic sensors: Constructing the complex numerical model of a plasmonic sensor based on hexagonally arranged gold nanoparticles. *Nanomaterials (Basel)*. 2023;13(14):2044.
51. A CSEPD. A digital twin of the coaxial lamination mixer for the systematic study of mixing performance and the prediction of precipitated nanoparticle properties. *Micromachines*. 2022;13(12):2076.
52. Hengelbrock A, Probst F, Baukmann S, Uhl A, Tschorn N, Stitz J, *et al*. Digital twin for continuous production of virus-like particles toward autonomous operation. *ACS Omega.* 2024;9(32):34990-5013.
53. Ijjeh Y, Alsarayreh N, Rifai A, Abdelnabi H, Al-Mahamid S, Alqudah DA, *et al*. Quality by digital design for accelerated sustainable nanomedicine development. *Eur J Pharm Sci.* 2025;213:107239.
54. Kalidindi SR BM, Boyce BL, Dingreville R. Digital twins for materials. *Front Mater*. 2022;9:818535.