Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.17291761

PERSONALIZED NANOMEDICINE DELIVERY SYSTEMS USING MACHINE LEARNING AND PATIENT-SPECIFIC DATA

ABENA NTIM ASAMOAH
The Trust Hospital, Ghana. Email: abnasamoah@gmail.com

JEFFREY B APPIAGYEI
Institute of Data Science and Informatics, University of Missouri, USA. Email: Jbazr6@umsystem.edu

FRED ASUMADU AMOFA
37 Military Hospital, Accra Ghana. Email: amofafred@gmail.com

RUTH OKAJA OTU
Department of Health Administration, Department of Biomedical Informatics and Biostatitics, University of Missouri, USA. Email: roonv7@missouri.edu

Abstract

Precision therapeutics are taking a new form due to the intersection of nanomedicine and artificial intelligence. Although effective in the delivery of drugs into the specific target, the traditional system of nanomedicine delivery is known to be characterized by problems of interpatient variation, inappropriate dosage, and unpredictability of treatment effects. This paper examines how machine learning algorithms can be implemented with patient specific data to create and optimize custom nanomedicine delivery platforms. Predictive models can be established using genomic, proteomic, and clinical data to inform the formulation of nanoparticles, predict the biodistribution of these nanoparticles, and reduce the side effects. The suggested model focuses on a data-informed pipeline that customizes the properties of nanocarriers, i.e., size, surface chemistry, and release rate, to the profile of specific patients. Case reports and new uses draw attention to the translational opportunities of this methodology in cancer, metabolic diseases, and the treatment of chronic diseases. Although each area incurs certain challenges, such as maintaining quality of the data, ethical issues, and regulatory avenues, the transformation of nanomedicine delivery through machine learning-based personalization is an essential step to precision healthcare. In this paper, the authors highlight the importance of interdisciplinary innovation in increasing the rate of clinical acceptance of personalized nanotherapeutics.

Keywords: Personalized Nanomedicine, Drug Delivery, Machine Learning, Patient-Specific Data, Predictive Modeling, Precision Healthcare, Nanocarriers.

INTRODUCTION

Nanotechnology and artificial intelligence (AI) are converging at an extremely fast rate, which is giving the healthcare sector unprecedented chances to implement more personalized treatment plans.

Nanomedicine has already shown the outstanding opportunities of increasing the efficiency of drug delivery, improving the precision of treatment, and decreasing systemic toxicity in comparison with traditional modalities (Herrmann & Rösslein, 2016).

Its clinical translation has however been blocked by the issue of interpatient variability, heterogeneous tumor microenvironment, and unpredictable pharmacokinetics (Soltani et al., 2021). These weaknesses highlight the importance of sophisticated computational

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and data-driven solutions to differentiate nanomedicine interventions to a specific patient profile.

Artificial intelligence and machine learning (ML) have emerged as critical enablers in overcoming these barriers by integrating large-scale biomedical data into predictive and adaptive therapeutic models (Adir et al., 2020; Mystridis et al., 2022).

Through the analysis of patient-specific genomic, proteomic, and clinical data, ML algorithms can optimize nanocarrier design, predict biodistribution, and anticipate therapeutic outcomes with higher accuracy than traditional empirical approaches (Das, 2023; Islam, 2023).

The development of nanoinformatics and computational modeling in recent years only reinforces this paradigm and allows conducting virtual experiments with the systems of drug delivery, which facilitates the process of preclinical validation and clinical translation (Ahmad et al., 2023; Hossain et al., 2013).

Individualized nanomedicine delivery systems especially apply to the oncology area where the heterogeneity of tumors and resistance to drugs require tailored treatment plans.

It has already been shown in the studies that combine AI with nanotechnology with progress in precision cancer medicine, where adaptive learning models are used to predict treatment response and direct nanoparticles formulation (Adir et al., 2020; Skepu et al., 2023).

Outside the field of oncology, new studies also demonstrate the use of ML-controlled nanocarrier in therapies of the lungs, kidneys, and blood plasma, which expands the range of applications of precision medicine to a variety of disease types (Ramaswamy and Keidar, 2023; Sharma et al., 2022; Islam, 2023).

Regardless of these improvements, some of the most prominent challenges can be identified: data heterogeneity, ethical issues related to the use of patient data, and the regulatory complications of AI-assisted therapeutic platforms (Svensson et al., 2023; Shao, 2023).

To manage these issues, there is a need to consider an interdisciplinary approach, involving the combination of nanotechnology, computational sciences, clinical medicine, and regulatory policy.

The combination of intelligent drug delivery systems and patient-specific information is not just a technological breakthrough, as pointed out in the recent literature, but also a clinical requirement in the development of precision healthcare (Vizirianakis, 2014; Shao, 2023).

The objective of this paper is to take an in-depth look at personalized nanomedicine delivery systems optimized with machine learning and patient-specific information.

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It will discuss the use of AI to optimize nanoparticles, incorporation of multi-omics and clinical research data, and translational opportunities of predictive modeling to support the development of personalized therapeutic approaches.

Finally, the paper emphasizes how ML-enabled nanomedicine can be used to fill the gap between innovation and precision in the laboratory and clinical environments.

Nanomedicine Delivery Systems

Nanomedicine delivery systems constitute the cornerstone of precision medicine by enabling targeted therapeutic transport, controlled release, and improved bioavailability of drugs. A wide array of nanocarriers including liposomes, polymeric nanoparticles, dendrimers, micelles, and inorganic nanostructures have been developed to enhance therapeutic efficacy while reducing systemic toxicity (Vizirianakis, 2014; Herrmann & Rösslein, 2016).

The design of these platforms is closely tied to physicochemical characteristics such as particle size, surface charge, and functionalization, which govern circulation half-life, biodistribution, and cellular uptake (Adir et al., 2020; Soltani et al., 2021).

Among the most studied systems, liposomes and polymer-based nanoparticles are particularly attractive due to their biocompatibility and ability to encapsulate diverse therapeutic agents. Liposomes have been successfully utilized for the delivery of chemotherapeutics, while polymeric carriers provide tunable release profiles and enhanced stability (Svensson, von Mentzer, & Stubelius, 2023).

Inorganic nanocarriers such as gold nanoparticles and quantum dots, though still primarily in preclinical stages, offer unique optical and imaging functionalities, allowing for theranostic applications (Sharma et al., 2022). Recent advances emphasize the convergence of nanoinformatics and artificial intelligence in tailoring nanocarriers for patient-specific conditions.

Computational approaches such as in silico vascular modeling (Hossain et al., 2013) and fluid particle dynamics (Islam, 2023) enable predictive evaluation of nanomedicine transport and distribution within heterogeneous biological systems. These computational insights, when integrated with machine learning pipelines, provide a foundation for designing adaptive nanocarriers that align with genomic, proteomic, and metabolic patient profiles (Ahmad et al., 2023; Mystridis et al., 2022).

Despite their promise, clinical translation remains a critical challenge due to biological complexity, interpatient variability, and regulatory constraints (Das, 2023; Skepu et al., 2023). However, frameworks integrating mechanistic modeling, patient-derived data, and nanoinformatics are reshaping translational pathways for nanomedicine delivery (Ramaswamy & Keidar, 2023; Shao, 2023).

This positions nanomedicine delivery systems not only as vehicles for drug transport but as intelligent platforms capable of adapting to individual patient needs, a core driver for precision healthcare (Herrmann & Rösslein, 2016).

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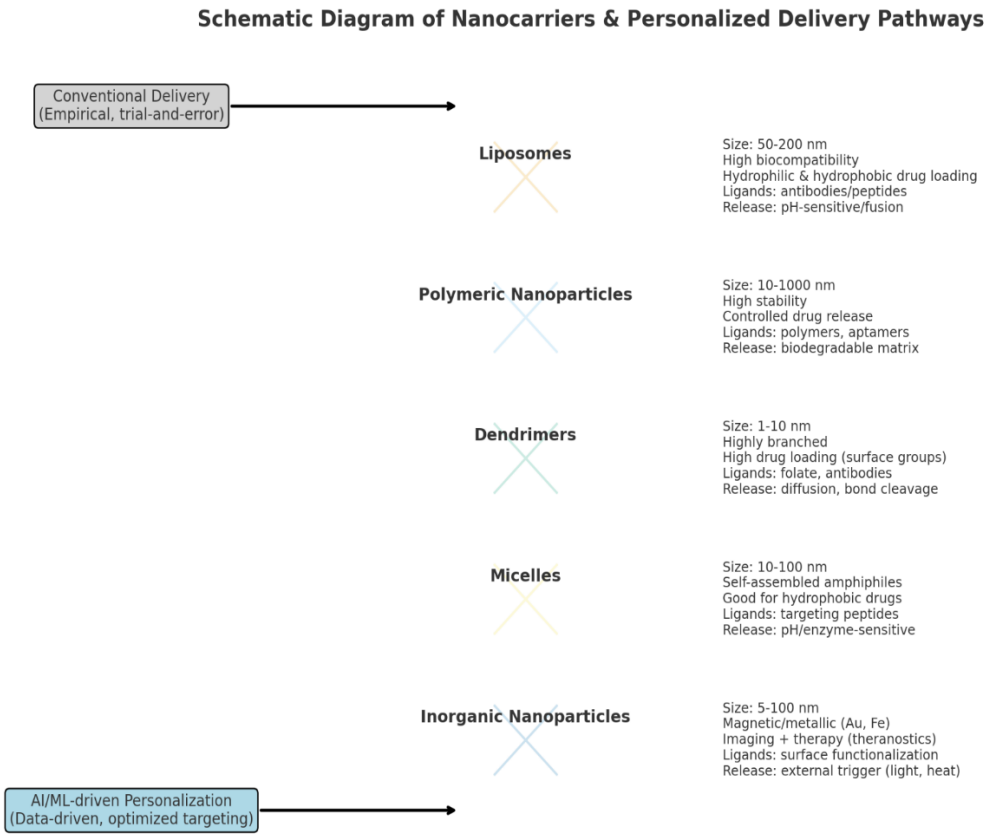

Figure 1: The schematic diagram shows the five major nanocarriers with their primary features (size, drug loading, targeting ligands, release mechanisms) alongside a comparison pathway between conventional drug delivery and AI/ML-driven personalization.

Machine Learning in Drug Delivery

The application of machine learning (ML) in drug delivery systems represents a paradigm shift from conventional trial-and-error formulations to predictive, data-driven strategies capable of tailoring therapies to individual patients. In nanomedicine, ML offers powerful tools for predicting nanoparticle interactions within biological systems, optimizing drug release kinetics, and personalizing treatment responses based on patient-specific data (Adir et al., 2020; Svensson et al., 2023). By integrating large-scale datasets derived from genomics, proteomics, medical imaging, and clinical outcomes, ML algorithms can enhance the precision, safety, and efficiency of drug delivery systems.

Predictive Modeling for Nanoparticle Behavior

ML models are increasingly being used to predict the biodistribution, clearance rates, and toxicity of nanocarriers. For example, supervised learning algorithms such as random forests and support vector machines can correlate nanoparticle physicochemical

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parameters (size, charge, hydrophobicity) with biological outcomes, enabling the design of safer and more effective nanocarriers (Skepu et al., 2023; Soltani et al., 2021).

Furthermore, unsupervised learning techniques have been employed to cluster nanoparticle behavior in heterogeneous tumor microenvironments, thereby revealing hidden patterns that inform delivery optimization (Mystridis et al., 2022).

Optimization of Drug Release Kinetics

Nanocarrier performance depends on precise control over release profiles. ML techniques, particularly neural networks, have demonstrated potential in predicting release kinetics under varying physiological conditions such as pH, enzyme activity, and blood flow dynamics (Das, 2023; Shao, 2023).

Computational fluid particle dynamics (CFPD) models, when combined with ML, enable patient-specific simulations of pulmonary or vascular delivery pathways (Islam, 2023). Such integration ensures more reliable translation from preclinical models to clinical applications (Hossain et al., 2013).

Personalization through Patient-Specific Data

The integration of patient data into ML-driven frameworks provides an avenue for real-time personalization of drug delivery. By leveraging omics data and electronic health records, ML systems can predict optimal drug dosages and delivery strategies for individual patients (Ramaswamy & Keidar, 2023; Sharma et al., 2022).

Reinforcement learning has also been explored for adaptive treatment regimens that adjust based on dynamic feedback from patient biomarkers (Ahmad et al., 2023). These adaptive systems promise to minimize toxicity while maximizing therapeutic efficacy.

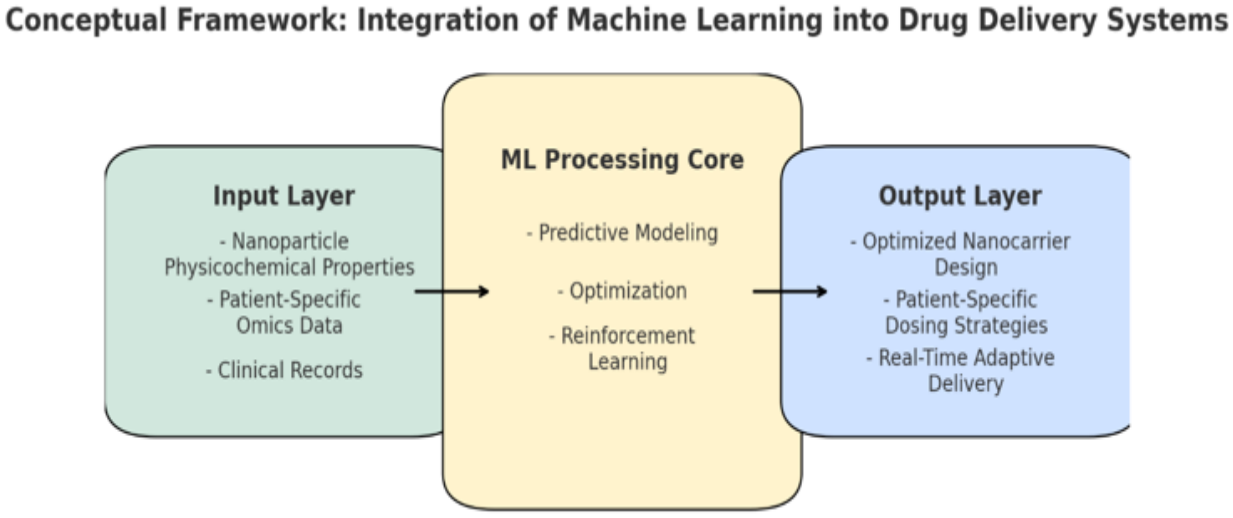

Figure 2: The framework diagram showing how machine learning integrates into drug delivery systems from inputs (data), through the ML processing core, to outputs (personalized strategies and designs).

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Table 1: Machine Learning Applications in Nanomedicine Drug Delivery

Application Area	ML Approach	Outcome	Reference
Predicting biodistribution	Random forests, SVM	Accurate mapping of nanoparticle organ accumulation and clearance	Adir et al. (2020); Soltani et al. (2021)
Release kinetics optimization	Neural networks, deep learning	Prediction of drug release under variable pH and physiological conditions	Das (2023); Shao (2023)
Tumor microenvironment modeling	Clustering, unsupervised learning	Identification of nanoparticle behavior patterns in heterogeneous tissues	Skepu et al. (2023); Mystridis et al. (2022)
Patient-specific simulation	CFPD + ML	Simulation of vascular and pulmonary drug delivery for personalized treatment	Islam (2023); Hossain et al. (2013)
Adaptive therapy regimens	Reinforcement learning	Dynamic dose adjustments based on biomarker feedback	Ramaswamy & Keidar (2023); Ahmad et al. (2023)

Collectively, these advancements demonstrate the transformative role of ML in advancing nanomedicine drug delivery toward clinically relevant precision therapies.

However, challenges remain, particularly regarding data quality, interpretability, and regulatory approval, which must be addressed to ensure safe and effective clinical translation (Vizirianakis, 2014; Herrmann & Rösslein, 2016).

Patient-Specific Data Integration

The success of personalized nanomedicine delivery systems relies heavily on the effective integration of patient-specific data into design and optimization pipelines.

This integration allows for the tailoring of nanocarrier properties such as particle size, surface charge, shape, and drug release kinetics to the biological, genetic, and clinical profile of individual patients.

Unlike conventional “one-size-fits-all” drug delivery approaches, patient-specific frameworks ensure precision, minimize adverse effects, and enhance therapeutic outcomes (Herrmann & Rösslein, 2016; Sharma et al., 2022).

Genomic, Proteomic, and Clinical Data

Patient-specific variability in gene expression, protein biomarkers, and metabolic pathways significantly impacts the therapeutic efficacy of nanocarriers (Svensson et al., 2023; Vizirianakis, 2014).

For instance, genomic alterations can influence drug resistance mechanisms, while proteomic patterns may indicate nanoparticle uptake efficiency.

Integrating these datasets into machine learning models enables the prediction of drug response and personalized treatment planning (Mystridis et al., 2022; Adir et al., 2020).

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Table 2: Categories of patient-specific data relevant to personalized nanomedicine delivery

Data Type	Key Features	Relevance to Nanomedicine Delivery	References
Genomic Data	Mutations, SNPs, expression levels	Predict drug sensitivity/resistance	Svensson et al., 2023; Sharma et al., 2022
Proteomic Data	Biomarker expression, signaling pathways	Guide nanocarrier targeting and uptake	Adir et al., 2020; Vizirianakis, 2014
Clinical Data	EHRs, comorbidities, treatment history	Optimize dosing and minimize side effects	Mystridis et al., 2022; Soltani et al., 2021
Physiological Data	Organ function, vascular flow dynamics	Model biodistribution and clearance	Hossain et al., 2013; Islam, 2023

Real-Time Physiological Monitoring

Wearable devices and biosensors are increasingly used to provide real-time patient data such as glucose levels, blood oxygen saturation, and heart rate variability. These data streams can be integrated into adaptive ML models that dynamically adjust nanomedicine dosing and release kinetics (Shao, 2023; Ramaswamy & Keidar, 2023). For example, fluid-particle dynamics combined with ML has been shown to optimize pulmonary drug delivery based on patient-specific respiratory patterns (Islam, 2023).

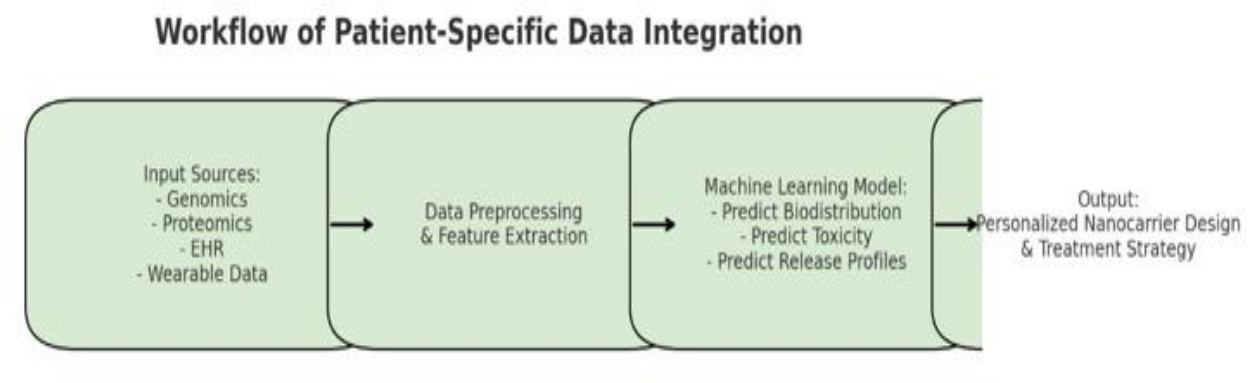

Figure 3: The schematic graph shows the workflow of patient-specific data integration, moving step by step from input sources through preprocessing, machine learning predictions, and finally to personalized nanocarrier design and treatment strategy

Computational Modeling and Nanoinformatics

Computational approaches such as nanoinformatics and in silico vascular modeling enhance prediction accuracy by simulating nanoparticle interactions within patient-specific biological environments (Soltani et al., 2021; Hossain et al., 2013). Nanomodeling frameworks further integrate these predictions with clinical and omics datasets, creating robust pipelines for decision support in personalized oncology and chronic disease management (Ahmad et al., 2023; Das, 2023).

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Table 3: Computational tools for integrating patient-specific data with nanomedicine delivery

Computational Approach	Application in Personalized Delivery	References
Nanoinformatics	Data-driven nanoparticle design and optimization	Soltani et al., 2021; Ahmad et al., 2023
In silico modeling	Predict biodistribution, vascular flow, and clearance	Hossain et al., 2013
Machine Learning	Adaptive predictions for drug release/toxicity	Adir et al., 2020; Skepu et al., 2023
Mechanistic Modeling	Integration of biological pathways into delivery frameworks	Mystridis et al., 2022; Ramaswamy & Keidar, 2023

Ethical and Translational Considerations

The use of sensitive patient-specific data necessitates stringent frameworks for data governance, ethical compliance, and transparency in algorithm design (Skepu et al., 2023).

Regulatory bodies are increasingly emphasizing explainable AI models to ensure clinical trust and facilitate safe translation of nanomedicine innovations into healthcare practice (Das, 2023; Shao, 2023).

In summary, patient-specific data integration represents the cornerstone of personalized nanomedicine delivery.

By combining multi-layered biological and clinical datasets with advanced computational models, next-generation nanotherapeutics can be precisely tailored to maximize efficacy, minimize toxicity, and advance the paradigm of precision healthcare.

Framework for Personalized Nanomedicine Delivery

The development of a patient-specific nanomedicine delivery system requires an integrated framework that combines nanocarrier design, machine learning (ML)-driven prediction models, and multimodal patient data to optimize therapeutic outcomes.

The framework proposed here follows a structured pipeline of data acquisition, computational modeling, nanocarrier optimization, validation, and clinical translation, aligning with recent advances in nanoinformatics and artificial intelligence guided therapeutics (Adir et al., 2020; Svensson et al., 2023; Soltani et al., 2021).

1. Data Acquisition and Integration

Patient-specific data forms the foundation of personalization. This includes genomic, proteomic, metabolomic, and clinical datasets, as well as imaging and real-time biosensor data.

Integrating heterogeneous datasets enhances prediction accuracy and informs nanoparticle selection (Skepu et al., 2023; Sharma et al., 2022).

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Table 4: Types of Patient-Specific Data for Nanomedicine Personalization

Data Type	Examples	Application in Nanomedicine Delivery
Genomic/Proteomic	Gene mutations, protein expression	Predicting drug sensitivity and resistance (Mystridis et al., 2022)
Clinical Records	Demographics, comorbidities, EHR data	Tailoring dosage and delivery route (Vizirianakis, 2014)
Imaging Data	MRI, CT, PET scans	Mapping biodistribution and tumor microenvironment (Hossain et al., 2013)
Real-Time Monitoring	Wearables, biosensors	Adaptive dosing and toxicity prediction (Shao, 2023)

2. Machine Learning–Based Predictive Modeling

Machine learning models are central to predicting nanoparticle behavior and patient-specific outcomes.

Algorithms such as deep learning, random forests, and support vector machines are applied to forecast:

- Drug release kinetics (Das, 2023)
- Nanoparticle biodistribution (Islam, 2023)
- Toxicity and adverse events (Ahmad et al., 2023)
- Therapeutic efficacy in specific tumor microenvironments (Ramaswamy & Keidar, 2023)

These models are strengthened by mechanistic simulations, including computational fluid dynamics and in silico vascular modeling, to bridge biological complexity with AI-driven insights (Hossain et al., 2013).

3. Nanocarrier Optimization

Personalized nanocarrier design involves tuning physicochemical properties such as size, shape, surface charge, and ligand functionalization to align with individual patient data.

For instance, ligand-based targeting can be informed by overexpressed receptors in a patient's tumor profile (Herrmann & Rösslein, 2016).

Table 5: Nanocarrier Design Parameters and Personalization Targets

Nanocarrier Property	Personalization Target	ML Integration Example
Size and Shape	Optimizing vascular permeability	Predicting optimal diameter for tumor penetration (Hossain et al., 2013)
Surface Charge	Minimizing opsonization and immune clearance	Modeling zeta potential effects on circulation (Adir et al., 2020)
Ligand Functionalization	Enhancing receptor-mediated targeting	Aligning ligands with genomic/proteomic markers (Svensson et al., 2023)
Release Kinetics	Controlling therapeutic window	Predictive ML models for drug release curves (Das, 2023)

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4. Validation and Clinical Translation

Validation occurs through a multi-tiered approach:

- In silico validation using computational modeling and nanoinformatics (Ahmad et al., 2023)
- In vitro and in vivo testing to confirm predictive outcomes (Soltani et al., 2021)
- Clinical feasibility studies focusing on safety, regulatory compliance, and patient acceptability (Shao, 2023; Vizirianakis, 2014)

Interdisciplinary collaboration between computational scientists, nanotechnologists, and clinicians is crucial for bridging laboratory advances and clinical implementation (Skepu et al., 2023).

5. Framework Overview

Bringing together these elements, the framework can be conceptualized as a closed-loop system where patient data informs ML-based predictions, which guide nanocarrier optimization, followed by iterative validation for clinical readiness.

Table 6: Proposed Framework for Personalized Nanomedicine Delivery

Stage	Key Activities	Reference(s)
Data Acquisition	Collect genomic, proteomic, clinical, imaging	Mystridis et al. (2022); Sharma et al. (2022)
Predictive Modeling	ML for release kinetics, biodistribution	Das (2023); Ramaswamy & Keidar (2023)
Nanocarrier Design	Customize size, surface, ligands	Adir et al. (2020); Svensson et al. (2023)
Validation	In silico, in vitro, in vivo testing	Soltani et al. (2021); Ahmad et al. (2023)
Clinical Translation	Safety, regulation, ethical alignment	Shao (2023); Vizirianakis (2014)

This framework demonstrates how machine learning and nanoinformatics synergize with patient-specific data to create adaptive and precise nanomedicine delivery systems. It establishes a path toward predictive, preventive, and personalized therapies, thereby advancing the clinical translation of nanomedicine into mainstream precision healthcare (Skepu et al., 2023; Svensson et al., 2023).

Challenges

1. Data availability, quality, and heterogeneity.

Personalized nanomedicine requires multimodal patient data (genomics, proteomics, imaging, EHRs) paired with high-quality nanoparticle characterization and preclinical/clinical outcome labels. Such datasets are fragmented, often small, and heterogeneously annotated, limiting model generalizability and external validation (Soltani et al., 2021; Ahmad et al., 2023). Data gaps are particularly acute for marginalized populations, increasing the risk of biased predictions and inequitable outcomes (Svensson et al., 2023).

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2. Biological complexity and multi-scale modelling.

Nanoparticle behavior is governed by multiscale biology — molecular corona formation, cellular uptake pathways, tissue transport, and whole-body pharmacokinetics. Purely data-driven ML models may miss mechanistic constraints that determine in vivo outcomes. Hybrid approaches that combine mechanistic models with ML are needed but are challenging to construct and validate (Hossain et al., 2013; Mystridis et al., 2022).

3. Interpretability and clinical trust.

Clinicians require interpretable recommendations for dosing, carrier selection, and risk tradeoffs. Black-box models impede clinical adoption; explainable AI methods must be adapted to the nanomedicine domain so that model outputs map to actionable, mechanistically plausible interventions (Adir et al., 2020; Das, 2023).

4. Standardization and nanoinformatics infrastructure.

There is no universally adopted schema for reporting nanoparticle physicochemical properties, biological assay conditions, or outcomes. Lack of standards prevents effective data pooling and meta-analysis. The nascent field of nanoinformatics must mature to provide shared ontologies, centralized databases, and interoperable pipelines (Soltani et al., 2021; Ahmad et al., 2023).

5. Translational and regulatory barriers.

Regulators currently evaluate nanotherapeutics and AI/ML systems under different frameworks. Integrated personalized nanomedicines combining adaptive algorithms with materially complex products raise novel evidence requirements for safety, reproducibility, and post-market monitoring (Svensson et al., 2023; Das, 2023). The absence of clear regulatory pathways slows clinical translation.

6. Safety, toxicity, and manufacturing reproducibility.

Patient-specific formulations increase manufacturing complexity. Ensuring batch consistency, stability, and predictable toxicity across individualized products is nontrivial. Predicting long-term nanotoxicity using in silico or preclinical surrogates remains imperfect (Herrmann & Rösslein, 2016; Das, 2023).

7. Privacy, data governance, and ethical concerns.

Integrating sensitive patient data with commercial ML pipelines raises consent, ownership, and privacy challenges. Centralized data solutions risk re-identification; federated or privacy-preserving approaches are promising but add technical and governance complexity (Adir et al., 2020; Soltani et al., 2021).

Future Directions

1. Develop hybrid mechanistic–ML frameworks (“physics-informed” ML).

Bridging mechanistic models (e.g., PK/PD, particle transport, fluid dynamics) with ML can improve extrapolation beyond training data and increase physiological plausibility.

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Examples include combining computational fluid-particle dynamics for pulmonary delivery with ML personalization (Islam, 2023) and extending in silico vascular models for systemic delivery (Hossain et al., 2013). Prioritizing hybrid frameworks will help translate predictions into clinically meaningful guidance (Mystridis et al., 2022; Ramaswamy & Keidar, 2023).

2. Invest in curated, standardized nanoinformatics resources.

Community efforts should create interoperable databases with agreed metadata standards for nanoparticle descriptors, assay protocols, and patient outcomes to enable model sharing and meta-learning. Such infrastructure is a linchpin for reproducible ML and was highlighted as critical for clinical translation (Soltani et al., 2021; Ahmad et al., 2023).

3. Federated, privacy-preserving learning for diverse cohorts.

Federated learning and differential privacy enable training across healthcare systems without centralized data pooling, reducing legal/privacy barriers while improving model robustness across populations (Adir et al., 2020). Implementing these methods will help address dataset fragmentation and bias (Svensson et al., 2023).

4. Explainable, clinically actionable ML and decision support.

Develop interpretability approaches tailored to nanomedicine (e.g., feature attributions aligned with physicochemical properties, counterfactual patient scenarios) and design human-in-the-loop workflows so clinicians can interrogate model suggestions and integrate them into decision-making (Adir et al., 2020; Das, 2023).

5. Regulatory science partnerships and adaptive evidence generation.

Early engagement with regulators to define evidence standards for combined AI-nanotherapeutic products is essential. Adaptive clinical trial designs and continuous-learning post-market surveillance paradigms can provide rigorous, real-world performance evidence while enabling iterative improvement (Svensson et al., 2023; Skepu et al., 2023).

6. Scalable, modular manufacturing platforms.

Invest in modular GMP-compatible manufacturing that supports rapid, reproducible customization (e.g., microfluidic or automated formulation platforms) to make individualized nanotherapeutics practical at scale. Coupling these platforms with digital batch records will aid quality control and regulatory compliance (Herrmann & Rösslein, 2016).

7. Clinical pilot studies in well-defined indications.

Focus early clinical translation on indications where patient stratification markedly improves benefit such as targeted oncology or pulmonary delivery using rigorous translational pipelines that move from in silico prediction to controlled, biomarker-guided trials (Sharma et al., 2022; Skepu et al., 2023; Islam, 2023).

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8. Multidisciplinary consortia and workforce development.

Realizing personalized nanomedicine requires teams spanning nanotechnology, computational modeling, clinical specialties, regulatory science, and ethics. Establishing consortia and training programs will accelerate knowledge transfer and capacity building (Vizirianakis, 2014; Adir et al., 2020).

Addressing these challenges with targeted, collaborative efforts grounded in robust nanoinformatics, hybrid modeling, privacy-aware data sharing, explainable ML, and pragmatic regulatory strategies will accelerate safe, equitable clinical translation of personalized nanomedicine by early-2020s standards (Adir et al., 2020; Soltani et al., 2021; Svensson et al., 2023).

CONCLUSION

Personalized nanomedicine delivery systems represent a pivotal frontier in advancing precision healthcare, with machine learning and patient-specific data serving as the foundation for their clinical realization. Already, the algorithmic implementation of artificial intelligence into nanotechnology has proven to be very promising in cancer medicine, allowing optimization of nanoparticles properties and treatment plans in order to lessen disparities in patient outcomes (Adir et al., 2020; Skepu et al., 2023). Computational frameworks can forecast biodistribution, reduce toxicity, and customize dosage regimens using genomic, proteomic, and clinical datasets to bridge translational gaps that have historically hindered clinical uptake of nanotherapeutics (Soltani et al., 2021; Ahmad et al., 2023).

Literature highlights the importance of machine learning solutions, alongside the use of mechanistic modeling, to design scalable and adaptive platforms able to refine drug delivery decisions, in real time (Mystridis et al., 2022; Ramaswamy and Keidar, 2023). More recent publications also emphasize that they can be used in disease-specific applications like oncology, renal cell carcinoma, pulmonary drug delivery, and further expand the applicability of such systems to diverse clinical uses (Sharma et al., 2022; Islam, 2023). Integration of nanoinformatics, computational fluid dynamics and intelligent drug systems offer other avenues of improving predictive accuracy and improving clinical translation (Hossain et al., 2013; Shao, 2023).

Even with these improvements, there are still issues in the quality of data, interpretation, regulations and ethical applications of patient information. However, nanomedicine convergence with AI automation is not only a technological change but a paradigm shift in the concept of patient-centered care (Herrmann and Rosslein, 2016; Svensson et al., 2023; Vizirianakis, 2014). Future studies should focus on interdisciplinary interactions, quality validation pipelines and sound clinical trials to help expedite the safe and effective delivery of personalized nanomedicine delivery systems. With the trend of evidence building up, the convergence of nanotechnology, machine learning, and precision medicine presents a chance to change the approach to therapy and redefine the patient outcome in the age of intelligent healthcare (Das, 2023).

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.17291761

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