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Artificial Intelligence in Personalized Drug Delivery: Current Advances and Future Perspectives- *A Comprehensive Review*

[1]Ms Sonali Arora, [2]Mr. Sachin Sharma, [3]Prof. (Dr). Ravi Jayant, [4]Ms Gunjan,[5]Ms Swati Sharma

[1]Assistant Professor, Sunder Deep Pharmacy College, SDGI Global University, Ghaziabad, Uttar Pradesh, India
Sonaliarora131290@gmail.com
[2]Assistant Professor, Department of Pharmaceutics, ITS College of Pharmacy, Muradnagar, Ghaziabad sachinsharma25665@its.edu.in
[3]Professor, Department of Pharmaceutics NKBR College of Pharmacy and Research Centre, Meerut jayantbpharm@gmail.com
[4]Assistant Professor, Department of Pharmaceutics, ITS College of Pharmacy, Muradnagar, Ghaziabad
gunjanchaudhary25661@its.edu.in
[5] Associate Professor, Department of Pharmacology, Neelkanth College of Pharmacy, Meerut

ABSTRACT

Artificial intelligence (AI) is reshaping the trajectory of drug delivery science, moving the field away from empirical trial-and-error formulation toward predictive, data-driven design of patient-specific therapeutics [1,2,3]. This review synthesizes current advances in the application of machine learning (ML), deep learning (DL), reinforcement learning (RL), and generative models across four major domains of personalized drug delivery: (i) nanoparticle and lipid nanoparticle (LNP) design, (ii) individualized dosing and pharmacokinetic/pharmacodynamic (PK/PD) modeling, (iii) three-dimensional (3D) printed patient-specific dosage forms, and (iv) closed-loop, sensor-integrated delivery systems. Representative case studies, including the AI-Guided Ionizable Lipid Engineering (AGILE) platform for mRNA-LNP vaccines [33,35,36], random-forest-based prediction of encapsulation efficiency in polymeric nanoparticles [11,16], and reinforcement-learning-driven closed-loop insulin delivery [38,42], illustrate how AI models are already improving formulation efficiency, dose precision, and therapeutic outcomes. We further examine the emerging role of generative AI and digital twins in simulating patient-specific responses [50,51,52,63], and we critically discuss persistent challenges, including data scarcity and heterogeneity, model interpretability, regulatory uncertainty, and ethical considerations surrounding algorithmic bias and data privacy [43,44,45,46,47,48,49]. The review concludes with a forward-looking perspective on the convergence of AI, nanomedicine, wearable biosensing, and precision pharmacology, and outlines the translational steps required to move AI-enabled personalized drug delivery from proof-of-concept research into routine clinical practice.

Keywords: artificial intelligence; machine learning; deep learning; personalized medicine; drug delivery; nanomedicine; lipid nanoparticles; 3D printing; precision dosing; digital twin

1. Introduction

Drug delivery science has traditionally relied on iterative, empirically driven formulation development, in which candidate carriers, excipients, and dosing regimens are optimized through repeated rounds of laboratory experimentation [3,9]. While this approach has produced numerous clinically successful therapies, it is slow, resource-intensive, and poorly suited to the growing recognition that patients differ substantially in their genetic makeup, physiology, disease biology, and treatment response [6,8]. Personalized medicine seeks to address this variability by tailoring therapeutic interventions, including the dose, route, timing, and carrier system, to the individual patient [58,59]. Realizing this vision at scale requires computational tools capable of integrating heterogeneous patient data and predicting formulation and dosing outcomes far more rapidly than conventional experimentation allows.

Artificial intelligence, encompassing machine learning, deep learning, natural language processing, and generative modeling, has emerged as the leading candidate to fill this gap [1,2,4]. Enabled by the convergence of large biomedical datasets, affordable computing power, and increasingly sophisticated neural network architectures, AI models can now learn complex, nonlinear relationships between formulation parameters (e.g., nanoparticle size, surface charge, lipid composition) and pharmaceutically relevant outcomes (e.g., encapsulation efficiency, cellular uptake, in vivo biodistribution) [11,13,16,17]. Bibliometric analyses indicate that publications applying AI to drug delivery remained sparse before 2018 but have since grown exponentially, exceeding several hundred per year by the mid-2020s (Figure 1) [7].

This review provides a structured synthesis of current advances in AI-enabled personalized drug delivery. Section 2 introduces the principal AI methodologies used in the field. Section 3 examines applications in nanoparticle and lipid-nanoparticle carrier design. Section 4 discusses AI-guided individualized dosing and pharmacokinetic modeling. Section 5 covers AI-integrated 3D printing of patient-specific dosage forms. Section 6 reviews closed-loop and wearable-sensor-integrated delivery systems. Section 7 discusses generative AI and digital twin technologies as an emerging frontier.

Section 8 critically appraises the technical, regulatory, and ethical challenges to clinical translation, and Section 9 offers a forward-looking perspective on the field.

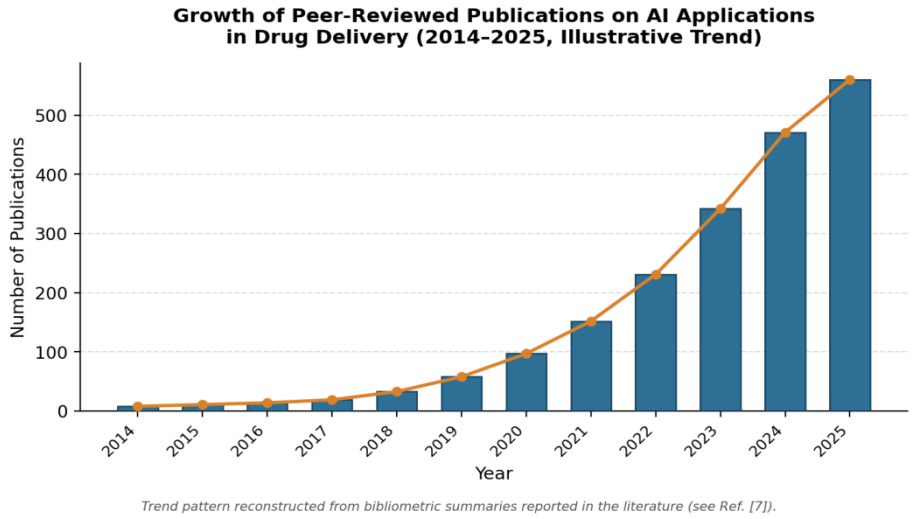


Figure 1. *Illustrative trend in the growth of peer-reviewed publications applying artificial intelligence to drug delivery research between 2014 and 2025, reconstructed from bibliometric patterns reported in the literature [7].*

2. Overview of AI Methodologies Applied to Drug Delivery

AI is not a single technology but a family of computational methods with distinct strengths and limitations. Table 1 summarizes the principal categories of AI techniques currently applied across the personalized drug delivery pipeline, together with representative use cases identified in the reviewed literature [17]. Classical supervised learning methods such as random forests and gradient-boosted trees remain the most widely used approach for structured, tabular formulation data because of their robustness to noise, ability to model nonlinear interactions, and relative interpretability compared with deep architectures [17,11]. Deep learning methods, including convolutional and graph neural networks, are increasingly favored when the input data are high-dimensional or structurally complex, such as molecular graphs, microscopy images, or genomic sequences [36,56]. Reinforcement learning is particularly well suited to sequential decision problems such as real-time dose titration, where an agent must continually adapt its policy to patient feedback [38,42]. Generative models, including generative adversarial networks (GANs) and variational autoencoders (VAEs), extend AI's role beyond prediction to de novo design, enabling the proposal of previously unexplored lipid structures, polymers, or molecular candidates with desired properties [37,56,69].

Table 1. *Principal categories of artificial intelligence techniques applied to personalized drug delivery research.*

AI Technique	Description	Representative Application	Ref.
Supervised learning (regression/ classification)	Learns a mapping from labeled input features to a known output (e.g., formulation parameters → encapsulation efficiency).	Random forest prediction of PLGA nanoparticle drug loading and encapsulation efficiency.	11,16
Deep neural networks / CNNs	Multi-layer networks that automatically extract hierarchical features from complex, high-dimensional data such as molecular structures or images.	Message-passing neural networks predicting ionizable lipid activity for mRNA-LNP delivery (LOUNN).	36
Reinforcement learning (RL)	An agent learns an optimal sequential policy through reward-based interaction with an environment.	Closed-loop insulin dosing that continuously adjusts infusion rates based on glucose feedback.	38,42
Generative models (GAN/VAE/diffusion)	Learn the underlying data distribution to generate novel candidate structures or synthetic data.	GAN-based generation of novel ionizable lipid structures with tailored encapsulation properties.	37,43

AI Technique	Description	Representative Application	Ref.
Graph neural networks	Operate directly on molecular graphs to model structure–activity/structure–property relationships.	Prediction of RNA–LNP binding affinity and nanoparticle–cell interactions.	37,17
Natural language processing (NLP)	Extracts structured knowledge from unstructured text such as electronic health records or scientific literature.	Mining of EHRs and literature to support pharmacovigilance and dose individualization.	20,23
Digital twins / generative simulation	Dynamic, data-driven virtual representations of a patient or manufacturing process, continuously updated with new data.	Patient-specific digital twins simulating individualized PK/PD response to guide dosing.	50,51,52

3. AI in Nanoparticle and Lipid Nanoparticle Carrier Design

Nanoparticle-based delivery systems, including polymeric nanoparticles, liposomes, solid lipid nanoparticles, and ionizable lipid nanoparticles (LNPs), depend on a large combinatorial parameter space encompassing size, surface charge, composition, and preparation method [16,17]. Because exhaustive experimental screening of this space is impractical, AI has become an important tool for narrowing candidate formulations before wet-lab validation [13]. Ensemble tree-based methods, particularly random forest and gradient boosting, remain the most common approach for predicting critical quality attributes such as particle size, polydispersity index, drug loading, and encapsulation efficiency from formulation and process parameters [11,15,16]. In a representative example, a random forest model trained on more than 300 literature-derived PLGA nanoparticle formulations achieved R^2 values of 0.93 and 0.96 for drug loading and encapsulation efficiency, respectively, demonstrating that ML can meaningfully guide formulation design even from moderately sized, heterogeneous datasets [11].

The design of ionizable lipid nanoparticles for mRNA delivery has become one of the most visible success stories for AI in this domain, propelled by the clinical importance of LNP-based mRNA vaccines [36,39]. The AI-Guided Ionizable Lipid Engineering (AGILE) platform combines self-supervised pretraining on a large virtual lipid library with supervised fine-tuning on experimental data, enabling rapid in silico screening and revealing cell-type-specific preferences among candidate ionizable lipids [33,35]. A related deep-learning strategy, lipid optimization using neural networks (LOUNN), applied a directed message-passing neural network to more than 9,000 LNP activity measurements and successfully extrapolated predictions to lipid structures divergent from its training set, illustrating the generalization capacity of graph-based deep learning models in this space [36]. Complementary work has applied random forest regression to 213 experimentally characterized LNP formulations to identify which ionizable lipid structural features most strongly drive mRNA expression efficiency [35], while systematic reviews describe the use of generative adversarial networks for de novo lipid design and graph neural networks for predicting RNA–LNP binding affinity [37].

Beyond LNPs, perturbation-theory machine learning (PTML) approaches have been used to predict the probability that a given drug–nanoparticle pair will form an effective drug-decorated nanoparticle complex, achieving area-under-the-curve values above 0.96 across datasets spanning hundreds of thousands of candidate combinations for both anti-glioblastoma and antimalarial applications [10,12]. Machine-learning-augmented molecular dynamics has also been used to reduce the substantial computational cost associated with predicting the in vivo therapeutic efficacy of drug-carrier nanoparticle designs for cancer treatment [13]. Collectively, these studies demonstrate that AI models can serve both a predictive role, ranking or filtering candidate nanoparticle designs prior to synthesis, and a generative role, proposing novel carrier structures optimized for a specified therapeutic objective [17].

Table 2. *Representative AI-driven studies in nanoparticle and lipid nanoparticle formulation design for drug and mRNA delivery.*

Platform / Study	AI Method	Delivery System	Reported Outcome	Ref.
AGILE platform	Deep learning (self-supervised + supervised neural network)	Ionizable lipid nanoparticles for mRNA delivery	Rapid in silico screening of lipid libraries; identified cell-type-specific LNP preferences	33,35
LOUNN	Directed message-passing neural network	Ionizable lipids for pulmonary gene therapy	Trained on >9,000 LNP activity measurements; extrapolated to novel lipid structures	36

Platform / Study	AI Method	Delivery System	Reported Outcome	Ref.
PTML – glioblastoma DDNPs	Bagging ensemble / decision trees	Drug-decorated nanoparticles (anti-glioblastoma)	AUROC 0.96 across 855,129 drug–nanoparticle complexes	10
PTML – antimalarial DDNPs	Random forest classifier	Drug-decorated nanoparticles (antimalarial)	Mean AUC 0.992 (10-fold cross-validation) across ~250,000 examples	12
PLGA microfluidic dataset	Random forest regression	PLGA nanoparticles (microfluidic preparation)	R^2 = 0.93 (drug loading) and 0.96 (encapsulation efficiency)	11
Rational LNP design	Random forest regression (213 LNP formulations)	mRNA vaccine LNPs	Identified ionizable lipid composition features driving mRNA expression efficiency	35
Cancer nanocarrier MD-ML hybrid	ML-augmented molecular dynamics	Drug-carrier nanoparticles for cancer therapy	Reduced computational cost of efficacy prediction versus full MD simulation	13

4. AI-Guided Personalized Dosing and Pharmacokinetic/Pharmacodynamic Modeling

Model-informed precision dosing (MIPD) uses pharmacokinetic/pharmacodynamic (PK/PD) models together with patient-specific covariates, such as body weight, renal function, and genotype, to individualize drug dosing [18,21]. Classical population pharmacokinetic modeling has long supported this goal, but AI/ML methods are increasingly used as complementary tools that can capture complex, nonlinear covariate relationships that traditional compartmental models struggle to represent [18,22]. In pediatric populations, where interindividual PK/PD variability is compounded by growth and organ maturation, AI models trained on pharmacokinetic datasets have been shown to model drug clearance in neonates and infants more reliably than conventional allometric scaling methods [20]. Reinforcement learning frameworks have similarly been applied to optimize antibiotic dosing in critically ill pediatric patients by continuously adjusting infusion rates in response to patient-specific physiological data [20].

A well-known clinical example is the use of machine learning to individualize warfarin dosing, integrating clinical variables such as age, weight, and height with pharmacogenomic markers including CYP2C9 and VKORC1 genotypes to generate a more precise initial dose recommendation than conventional trial-and-error titration [24]. In geriatric populations, machine-learning-based clinical decision-support systems assist prescribers in balancing polypharmacy risk by simulating cumulative drug–drug interaction burden and adverse event probability [20]. More broadly, AI-based PK/PD modeling has been described as a means of integrating real-world data from electronic health records, genomic profiles, and population pharmacokinetic databases to support individualized dosing in vulnerable populations [20,22]. Editorial commentary in the pharmacometrics literature emphasizes that AI is best understood as augmenting, rather than replacing, classical pharmacometric methods, serving to uncover complex covariate patterns while preserving the mechanistic interpretability that regulators and clinicians require [18,22].

AI-based dosing and formulation calculators are also being integrated directly into pharmaceutical decision-making workflows, applying machine learning, deep learning, and natural language processing to predict drug properties, optimize excipients, and support real-time dose adjustment in the context of precision medicine [20]. Nonetheless, the same reviews caution that data quality, model interpretability, and regulatory acceptance remain significant barriers to the routine clinical deployment of AI-based dosing tools [20,21].

5. AI-Integrated 3D Printing for Patient-Specific Dosage Forms

Three-dimensional (3D) printing, or pharmaceutical additive manufacturing, enables the fabrication of dosage forms with patient-specific size, shape, dose, and drug-release profile, offering a direct route to individualized oral and implantable therapeutics [25,27,30]. Because the relationship between print parameters (e.g., infill density, nozzle temperature, print speed) and the resulting mechanical and release properties of the printed dosage form is highly nonlinear, AI has been proposed as a means of navigating this design space more efficiently than traditional trial-and-error process optimization [28,31]. In one study, machine learning models successfully predicted a new set of processing parameters that produced pharmaceutical printlets with zero surface defects across multiple polymer materials, substantially reducing the resources needed for print-process optimization [26].

AI-guided design has also been applied directly to the dosage-form geometry itself. In one representative study, a genetic algorithm coupled with fused deposition modeling was used to design multi-layer capsules containing isoniazid and acetaminophen, achieving precisely tailored fast- and delayed-release profiles for each active pharmaceutical ingredient through structural modification of the capsule architecture rather than changes to the excipient formulation [29,34]. Other groups have used self-organizing maps and multilayer perceptron models to relate the surface-area-to-volume ratio and print

parameters of 3D-printed tablets to their dissolution and drug-release behavior, enabling prediction of theoretical release profiles for complex core–shell and gradient-structured dosage forms [29].

AI is also being applied to quality assurance in pharmaceutical 3D printing. Because acquiring large libraries of real defect images is costly, one study trained seven machine-learning classifiers on 200 photorealistic synthetic images of 3D-printed dosage forms, demonstrating that machine vision can reliably classify dosage-form quality without requiring extensive real-world image datasets [32]. Reviews of the field emphasize that the convergence of AI, 3D printing, and digital health records has particular relevance for pediatric and geriatric populations, for whom flexible, patient-specific dosing (including multidrug polypills) can substantially improve adherence and therapeutic outcomes [27,30].

Table 3. *Representative applications of artificial intelligence in 3D-printed, patient-specific dosage form development.*

Application	AI Method	Outcome / Contribution	Ref.
Print-parameter optimization (FDM)	ML-guided design-of-experiments	Zero-defect printlets across multiple thermoplastic materials by predicting optimal flow rate, speed, and temperature combinations	26
Multi-layer capsule design	Genetic algorithm	Isoniazid/rifampicin and isoniazid/acetaminophen capsules with independently tunable fast- and delayed-release layers	29,34
Release-profile modeling (SOM/MLP)	Self-organizing map + multilayer perceptron	Prediction of diazepam release behavior from surface-area-to-volume ratio and print parameters	29
Machine-vision quality control	Ensemble of 7 machine-learning classifiers trained on synthetic images	Automated classification of 3D-printed dosage form quality without costly real-image datasets	32

6. AI in Closed-Loop and Wearable-Sensor-Integrated Delivery Systems

Closed-loop drug delivery systems combine continuous physiological sensing with algorithm-driven, real-time dose adjustment, most notably in the form of the “artificial pancreas” for automated insulin delivery [39,49]. Modern closed-loop insulin systems integrate a continuous glucose monitor (CGM), a control algorithm, and an insulin pump, eliminating the need for manual glucose monitoring and dose calculation [47,49]. Reinforcement-learning and predictive-control algorithms are used to continuously adjust basal and bolus insulin delivery in response to real-time glucose trends, and clinical evidence indicates that such systems can improve glycemic control relative to conventional open-loop insulin therapy [49,52].

Recent engineering advances have focused on miniaturizing and integrating the sensing and delivery hardware itself. One study reported a bioelectronic artificial pancreas patch that combines a dissolvable microneedle-based glucose sensor with an integrated micropump, achieving stable, long-term glucose sensing and low-power insulin delivery in diabetic rat and pig models without the bulk and cost of conventional commercial closed-loop systems [38]. To address the safety risk posed by erroneous CGM readings, a dual closed-loop system (DuoLoop) has been proposed that combines conventional CGM-controlled insulin delivery with a second, independent glucose-responsive insulin release mechanism, embedding a customized edge-computing algorithm directly within the wearable device; in preliminary in vivo testing this dual-loop design maintained normoglycemia for a significantly greater proportion of time than a single-loop system [42].

Beyond diabetes management, wearable, sensor-integrated transdermal delivery platforms are being explored more broadly, using mechanical, electrical, thermal, acoustic, and glucose-responsive actuation mechanisms to enable stimulus-responsive, on-demand drug release [41,5]. AI-driven modeling of transdermal drug transport and skin kinetics has similarly been proposed as a means of overcoming interpatient variability in percutaneous absorption, a long-standing barrier to precise transdermal dosing [5]. Collectively, these closed-loop and wearable systems represent a shift from static, pre-programmed drug delivery toward dynamic, feedback-controlled therapy in which the AI algorithm functions as the central decision-making component of the delivery system itself [39,42].

7. Generative AI and Digital Twins: An Emerging Frontier

Generative AI models, including generative adversarial networks, variational autoencoders, and, increasingly, diffusion and transformer-based architectures, extend AI's contribution beyond prediction toward de novo design of molecules, carriers, and even synthetic patient data [54,55,69]. Structural biology platforms such as AlphaFold and RoseTTAFold now predict protein structure with near-experimental accuracy, providing a foundation for structure-based design of both small-molecule drugs and the biologic targets relevant to delivery-system engineering [57,62,70]. Building on these structural predictions, generative molecular design frameworks such as PCMol condition transformer-based generative models on AlphaFold-derived

protein structure embeddings to design candidate ligands for specified targets, illustrating how structural and generative AI are converging in modern drug design pipelines [70].

A particularly relevant emerging concept for personalized drug delivery is the digital twin: a dynamic, continuously updated virtual representation of an individual patient's physiology, constructed from multi-omic, imaging, and real-world clinical data [50,52,63]. Generative AI is a key enabling technology for digital twins because it can synthesize realistic, high-dimensional patient data under uncertainty, supporting applications ranging from synthetic control arms in clinical trials to individualized simulation of pharmacokinetic and pharmacodynamic response [63,64]. Reviews of this emerging field describe patient-level digital twins being used to reduce reliance on placebo cohorts, to augment statistical power in trials with rare or heterogeneous populations, and, prospectively, to simulate an individual's expected response to a candidate formulation or dosing regimen before it is administered [63,68]. At the level of pharmaceutical manufacturing, process digital twins constructed from continuous sensor and process analytical technology (PAT) data are being used to adjust mixing, drying, and coating parameters in real time, extending the digital twin concept from the patient to the production of the personalized dosage form itself [6].

Despite this promise, current reviews are careful to note that the clinical translation of generative-AI-enabled digital twins remains limited by challenges in validation, calibration of predictive uncertainty, safety monitoring, and the governance of the synthetic data these models generate [52,64]. Proposed clinical-grade evaluation frameworks emphasize conformal prediction methods for calibrated uncertainty, statistical process control for detecting model drift, and subgroup-based fairness evaluation across race, gender, age, and socioeconomic status, echoing the broader regulatory and ethical concerns discussed in Section 8 [52].

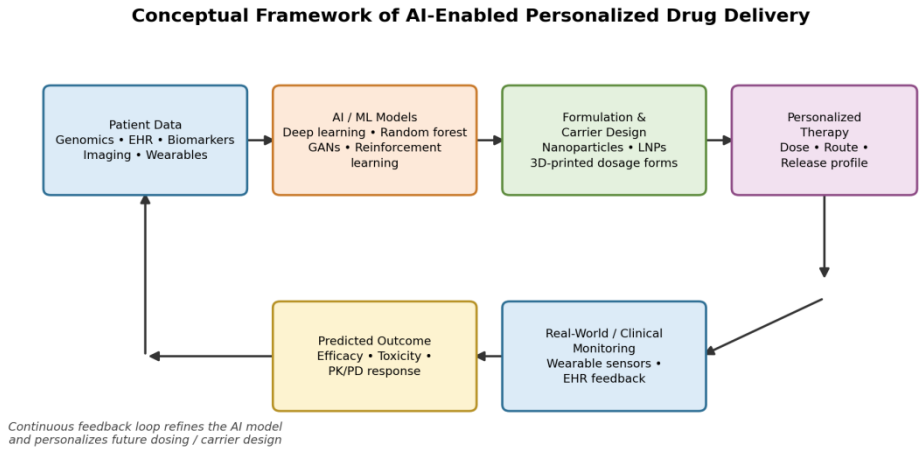


Figure 2. *Conceptual framework illustrating how patient data, AI/ML models, formulation and carrier design, and clinical monitoring are linked through a continuous feedback loop to enable AI-driven personalized drug delivery.*

8. Challenges to Clinical Translation

Despite substantial technical progress, several interrelated challenges continue to limit the routine clinical deployment of AI-driven personalized drug delivery systems. First, high-quality, sufficiently large, and consistently annotated datasets remain scarce in pharmaceutical formulation science; many of the ML models reviewed here were trained on fewer than a thousand experimentally characterized formulations [11,13], raising legitimate concerns about generalizability to structurally or chemically dissimilar candidates [17]. Second, the interpretability of complex deep learning and ensemble models remains a persistent barrier: because these models can involve very large numbers of parameters, it can be difficult to identify which formulation or patient features are driving a given prediction, complicating both scientific validation and regulatory review [17,44].

Third, existing regulatory frameworks were largely designed around static, “locked” products, and are not naturally suited to AI/ML-based software or devices that are intended to continue learning after deployment [56,57,61]. In the United States, the Food and Drug Administration (FDA) has begun to address this gap through its AI/ML-based Software as a Medical Device (SaMD) action plan, predetermined change control plans (PCCPs) that pre-specify the scope of permissible post-deployment model updates, and Good Machine Learning Practice (GMLP) guiding principles [58,61]. In parallel, data privacy frameworks such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States and the General Data Protection Regulation (GDPR) in the European Union govern how patient data may be used to train and validate these models, while institutional review boards and the ethical “Common Rule” govern human-subjects research involved in their development [54,57].

Fourth, algorithmic bias and fairness represent an ongoing concern: models trained predominantly on data from specific populations, healthcare systems, or geographic regions may generalize poorly, or inequitably, to underrepresented groups [44,52]. A recent critical appraisal of FDA-authorized AI-enabled healthcare products highlighted persistent weaknesses in post-market surveillance, transparency about training-data provenance, and enforceable

fairness standards, arguing for a more adaptive, community-engaged regulatory approach [44]. Finally, the translational gap between promising preclinical or retrospective AI studies and prospective clinical validation remains substantial; the great majority of the nanoparticle- and dosing-focused studies reviewed here report in silico or in vitro performance metrics rather than outcomes from controlled clinical trials [10,12,13], underscoring the need for rigorous prospective evaluation before such tools can be safely integrated into routine care.

Table 4. *Principal challenges limiting clinical translation of AI-enabled personalized drug delivery, with representative mitigation strategies.*

Challenge	Description	Potential Mitigation	Ref.
Data scarcity and heterogeneity	Formulation and clinical datasets are often small, siloed across institutions, and generated under inconsistent experimental protocols, limiting model generalizability.	Federated learning across institutions; standardized data-reporting frameworks; synthetic/ augmented data generation.	37,25
Model interpretability (“black box” problem)	Deep learning and ensemble models frequently lack transparent, mechanistically interpretable decision logic, which complicates regulatory and clinical trust.	SHAP/feature-importance analysis; hybrid mechanistic–ML models; explainable-AI (XAI) methods.	17,44
Regulatory uncertainty for adaptive/ continuously learning AI	Conventional medical device and drug approval pathways were designed for static products, not algorithms that evolve after deployment.	FDA predetermined change control plans (PCCPs); Good Machine Learning Practice (GMLP) guiding principles.	58,61
Bias, fairness, and data privacy	Training data that underrepresent certain populations can produce biased predictions; patient data used to train models raise HIPAA/GDPR-related privacy concerns.	Subgroup-based fairness evaluation; privacy-preserving/federated model training; algorithmic impact assessments.	44,54,57
Clinical validation and translational gap	Most AI-driven formulation and dosing studies remain preclinical or retrospective, with limited prospective clinical validation.	Prospective, adequately powered clinical trials; post-market surveillance of deployed AI-enabled products.	44,59

9. Future Perspectives

Several converging trends suggest that the role of AI in personalized drug delivery will continue to expand over the coming decade. First, the integration of multi-omic data (genomic, transcriptomic, proteomic) with AI-driven formulation design is likely to enable increasingly fine-grained matching of carrier systems and dosing regimens to individual disease biology, extending beyond the pharmacokinetic personalization described in Section 4 toward genuinely biology-informed carrier selection [8,50,62]. Second, the maturation of patient-specific and manufacturing-process digital twins, supported by generative AI, is expected to allow candidate formulations and dosing regimens to be evaluated in silico before physical synthesis or administration, potentially shortening development timelines and reducing the number of patients exposed to suboptimal early-phase regimens [51,52,63,64].

Third, the convergence of AI with wearable biosensing and closed-loop delivery hardware, already demonstrated in automated insulin delivery [38,42], is likely to extend to other chronic disease areas in which continuous physiological feedback can inform real-time dose adjustment, such as pain management, anticoagulation, and certain oncologic and cardiovascular therapies [24,41]. Fourth, as generative AI models such as AGILE and LOUNN mature, AI-guided de novo design is expected to move beyond lipid and nanoparticle screening toward the co-design of the carrier and the therapeutic payload as a single, jointly optimized system [33,36,37]. Fifth, continued regulatory evolution, including FDA predetermined change control plans and analogous international frameworks, will be essential to enable continuously learning AI systems to be safely and transparently updated after clinical deployment, rather than requiring full re-approval for every model refinement [58,61].

Realizing this future will require sustained interdisciplinary collaboration among pharmaceutical scientists, data scientists, clinicians, and regulators, together with continued investment in standardized, shareable formulation and clinical datasets that can support model training and external validation [8,17]. If these technical, regulatory, and data-infrastructure challenges are addressed, AI-enabled personalized drug delivery has the potential to shift pharmaceutical care from a population-averaged, one-size-fits-all model toward individualized therapy that is optimized, in near real time, to the specific biology and clinical trajectory of each patient [1,6,50].

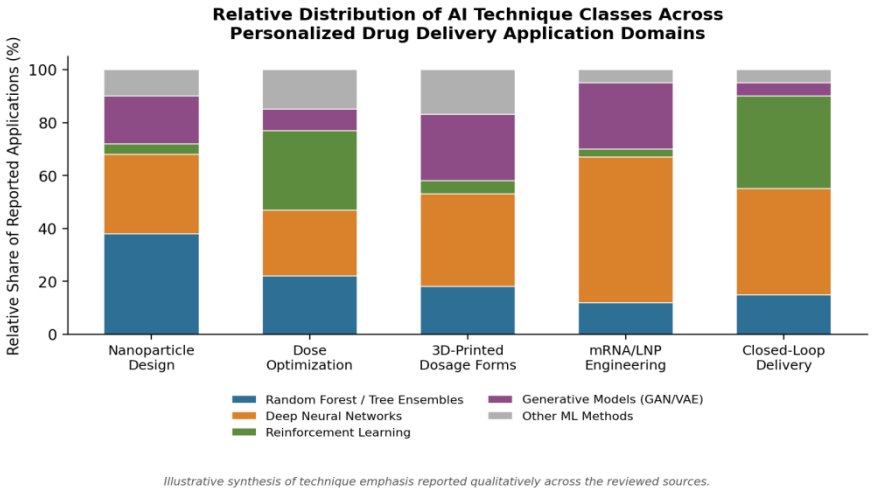


Figure 3. *Illustrative synthesis of the relative emphasis placed on different classes of AI techniques across five major personalized drug delivery application domains, based on qualitative patterns reported across the reviewed literature.*

10. Conclusion

Artificial intelligence is transitioning from a peripheral computational aid to a central methodology in the design of personalized drug delivery systems. Across nanoparticle and lipid nanoparticle engineering, individualized dosing, 3D-printed dosage forms, and closed-loop delivery hardware, machine learning and deep learning models are already demonstrating the ability to predict formulation performance, optimize dosing regimens, and enable real-time, feedback-driven therapy with a precision that would be difficult or impossible to achieve through conventional experimentation alone [1,2,17,38]. At the same time, the field faces substantive and unresolved challenges related to data quality, model interpretability, regulatory adaptation, and equitable, privacy-preserving deployment [44,54,57]. Addressing these challenges through coordinated technical, regulatory, and translational efforts will determine whether AI-enabled personalized drug delivery fulfills its promise of shifting pharmaceutical care toward truly individualized, patient-centered therapy.

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