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THE IMPACT OF ARTIFICIAL INTELLIGENCE (AI) ON DRUG DELIVERY SYSTEMS

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Abstract

Artificial Intelligence (AI) is transforming drug delivery systems from empirical trial-and-error formulation to predictive, data-driven design. This narrative review provides a comprehensive overview of the integration of AI in drug delivery systems. We examine the impact of AI on the design, formulation, and evaluation of drug delivery systems, and the applications of these systems in targeted and controlled-release drug delivery, implantable and wearable devices, and robotics-assisted administration. We review the role of AI in pharmacokinetic evaluation and its importance in personalised medicine. Furthermore, we critically analyse the current challenges and limitations that hinder the use of AI in the design and formulation of drug delivery systems. AI/Machine

learning tools and platforms such as XGBoost, Random Forest, and Artificial Neural Networks have revolutionised drug delivery carriers through formulation optimisation, drug-excipient compatibility prediction, modelling of drug-release profiles, and selection of formulation materials and nanocarriers. The ability of AI tools to predict critical quality attributes, including particle size, zeta potential, tablet disintegration time, dissolution rate and release profiles, encapsulation efficiency and pharmacokinetic parameters, facilitates drug carrier design. However, the clinical usefulness of AI is limited by a lack of standardised datasets, technical and computational issues, regulatory hurdles, scalability challenges, GMP translation challenges, cost, and ethical concerns. Future perspectives focus on the development of closed-loop drug delivery systems and the integration of AI with other technologies, including digital twins, design of experiments, 3D printing, nanotechnology and biotechnology. Hence, there should be collaboration among formulation scientists, regulatory specialists, and clinicians to develop explainable, trustworthy AI that is environmentally sustainable and economically feasible.

1. Introduction

Drug delivery systems, like other technologies, have continued to evolve over the years, with the aid of researchers. This evolution reflects a better understanding of disease pathogenesis, advances in pharmaceutical sciences and technology, materials science and technology, molecular pharmacology, and the need for personalized medicines [1]. Conventional drug delivery systems developed substantially during the 19th and 20th centuries with the invention of compressed tablets in 1840's [2], gelatin capsules in the 1830's, the hypodermic injection in the 1850s, etc. [3,4]. Before this period, traditional medicine practices (e.g., herbal medicines and crude preparations) were used to manage diseases [5]. Conventional drug delivery systems gained extensive popularity due to many advantages. These include high manufacturing efficiency, especially at large scale; Another advantage of conventional drug delivery systems is the high patients' convenience, as these formulations are easy to take by patients, they are also affordable and have a long shelf-life [6]. Suffice it to say that conventional drug delivery systems also suffer several drawbacks such as limited bioavailability, fluctuations in blood plasma levels, inability to provide sustained release of the active pharmaceutical ingredient, and poor targeting of specific tissues lead to systemic side effects. For instance, the conventional delivery of doxorubicin results in unspecified distribution which may cause cardiotoxicity, nausea, vomiting, and alopecia [7]; also, insulin cannot be effectively administered as an oral tablet because it is degraded in the gastrointestinal tract [8]. The need to surmount these challenges and ultimately improve patient care has led to the invention of novel drug delivery systems. Novel drug delivery systems comprise sophisticated technology merged into these conventional drug delivery systems to ensure that the right dose of the drug reaches the targeted site in an efficient manner [9]. Novel drug delivery systems have broad categories of classification. These include the controlled drug delivery systems, targeted drug delivery systems, nanotechnology-based drug delivery systems (e.g., liposomes, nanomicelles, dendrimers, nanogels etc.), hydrogels-based systems, transdermal systems, stimuli responsive (SMART) systems, biomimetic drug delivery systems and gene and mRNA delivery systems. Even though these novel systems are meant to mitigate the limitations of the conventional systems, they are not without their challenges. A major challenge with the novel drug delivery systems is the poor clinical translation, often called the 'bench to bedside gap', an example is with the BIND-014 (prostate-specific membrane antigen (PSMA) – targeted nanoparticle which contained docetaxel). Although preclinical and early clinical trials were successful [10], it did not become the major clinical breakthrough as expected. Mukherjee et al. (2022) reported that its failure was as a result of its delivery platform not meeting the response rate required to continue enrolling patients in its clinical studies [11]. Another critical challenge with the novel systems is the limited targeting efficiency. Even though these systems are target-enhanced, they still face tough biological barriers like the blood-brain barrier and mucosal barriers. They may also be cleared by macrophages before reaching the targeted sites [12]. Other challenges include long term safety concerns, (Li et al. (2021) showed that repeated use of stealth-coated nanoparticles may cause

immune responses, leading to faster clearance, greater accumulation in the liver, and liver toxicity. This shows that long-circulating nanocarriers may have safety concerns, especially when used repeatedly [13]), high manufacturing costs, limited personalization (as some patients different in genetics, metabolism and disease progression) and stability issues as some may be susceptible to biological and chemical degradation [12]. Thus, these challenges have led to a paradigm shift in drug delivery technologies, paving the way for the emergence of artificial intelligence -assisted drug delivery systems. Artificial intelligence (AI) may be defined as a branch of computer science that enables machines to perform tasks that normally would require human intelligence. These include recognizing patterns, learning from data, making predictions, solving problems and making decisions [14]. Several artificial intelligence techniques have been explored in drug delivery systems, these include artificial neural networks, deep learning models, machine learning models, regression and decision tree models, support vector machines, Bayesian optimization, Reinforcement learning, Digital twins, and AI integrated with nanotechnology, biosensors and smart devices [15]. In addition to mitigating the challenges associated with novel drug delivery systems, the integration of AI into drug delivery systems is also as a result of advancements in computational techniques, machine learning algorithms and data analytics. Furthermore, AI-driven drug delivery can be combined with other cutting-edge technologies, such as Clustered Regularly Interspace Short Palindromic Repeats (CRISPR) for gene editing, blockchain for data management, and Internet of things (IoT) for real-time patient monitoring, to create better and more advanced drug delivery systems in the future [16,17]. Several AI-assisted drug delivery platforms have successfully progressed from in silico design to preclinical validation, while some are moving toward clinical translation. For instance, the AI-Guided Ionizable Lipid Engineering (AGILE) platform of Xu et al. (2024) combined deep learning with combinatorial chemistry to hasten the discovery of ionizable lipids for mRNA delivery. This study used neural network models to perform in silico screening of libraries of hundreds of thousands of lipids, and further synthesised the best performing candidates for testing. Lipid nanoparticles identified by AI were able to efficiently and cell-specifically deliver mRNA in vitro and in vivo, paving the way for rapid development of next-generation delivery technologies [18]. In addition, Wang et al. (2024) showed how artificial intelligence can be used for the rational design of ionizable lipids for mRNA delivery, with models able to predict and optimise structures with suitable delivery properties without laboratory experimentation [19]. These studies demonstrate how artificial intelligence can shorten the development timeline of delivery systems from computer-assisted design to screening and testing, therefore aiding the translation of this technological field. Here, we reveal how AI can be employed in multiple areas in drug-delivery research from formulation optimisation and excipient-drug compatibility to drug-release prediction, nanocarrier design, targeted and smart delivery, pharmacokinetics, and personalised therapy. We also describe the challenges for successful translation of these AI-enabled technologies to the field of medicine, including data collection and preparation, model building and validation, interpretability, ethics and privacy issues, regulation, and costs of implementation. Furthermore, new horizons such as AI-enabled nanotherapy, gene delivery, robotics and automation, and personalised delivery systems are

discussed. By linking these developments to translational challenges, we hope to give a wider perspective of the current and future use of AI in drug-delivery research.

1.1 Scope and Focus of the Review

This review focuses on the application of artificial intelligence (AI) in the design, formulation, evaluation and optimization of drug-delivery systems. This review also focuses on the use of machine learning, deep learning, artificial neural networks, Bayesian optimization, and other artificial intelligence-based methods in formulations optimization, compatibility of drugs with excipients, predicting drug release, and designing nanocarriers. Moreover, this paper highlights the use of AI in targeted drug delivery, controlled release drug delivery systems, wearable and implantable drug-delivery devices, robotic drug administration, and pharmacokinetics/ADME modeling. The use of AI in personalized medicine, patient-data analysis, design of personalized dosages, predicting patients' response to treatment, and incorporating genomic and biomarker information is also considered in this review. The emerging areas in AI-assisted drug delivery that are being explored currently include closed-loop drug delivery systems, digital twins, the convergence of AI and nanotechnology/biotechnology, and the use of AI for advanced manufacturing of drug delivery systems. Besides these applications, some of the challenges that might hinder the development and implementation of AI-assisted drug delivery technologies are also highlighted in this review.

1.2 Literature Search Strategy

A narrative literature search was conducted using PubMed and Google Search to identify publications addressing the application of artificial intelligence (AI) in drug-delivery research. The search covered literature available up to October 2026 and used combinations of keywords related to artificial intelligence, machine learning, deep learning, drug delivery, pharmaceutical formulation, drug–excipient compatibility, drug release, nanocarriers, targeted drug delivery, pharmacokinetics, personalised medicine, wearable and implantable drug-delivery systems, closed-loop drug delivery, digital twins, robotics, and pharmaceutical automation. Additional relevant studies were identified by screening the reference lists of key publications. Studies were included when they applied AI, machine learning, deep learning, or related computational approaches directly to drug-delivery design or development, including formulation optimisation, drug–excipient compatibility, drug-release prediction, nanocarrier development, pharmacokinetic or ADME modelling, personalised dosing, wearable or implantable delivery systems, robotics-assisted drug administration, and emerging adaptive delivery technologies. Priority was given to studies reporting quantitative model performance, experimental validation, independent or external validation, or clinically relevant outcomes. Relevant review articles were included to provide background and identify additional primary studies, while regulatory documents were considered where they provided information on model validation, implementation, quality, or regulatory considerations. Publications addressing AI in general healthcare or drug discovery without a substantive connection to drug delivery were excluded. The selected literature was subsequently organised according to the major themes of the review, including AI applications in

drug-delivery design and formulation, AI-enabled delivery systems, pharmacokinetic and personalised medicine applications, challenges and limitations, and emerging future directions.

2.0 The impact of AI on the design and formulation of drug delivery systems

The impact of AI on the design and formulation of drug delivery systems is substantial as it integrates optimization of formulations, design of targeted drug delivery systems, design of personalized medicines, predictive modelling, smart and responsive drug delivery and manufacturing and quality control. Prior to the utilization of AI, the formulation of drug delivery systems depended on pharmaceutics principles, experimental trials and errors, statistical design of experiments (DoE), empirical models and the experience of the formulator. This process took years. Impressively, the emergence of AI has reduced the experimental hurdles through the utilization of machine learning which helps to identify complex linear relationships and reduce the number of experiments. Bayesian optimization, active learning and reinforcement learning also helps to optimize formulation characteristics. Digital twins has also been utilized to process data to support continuous manufacturing, process adjustment and personalize drug dosing. Thus AI represents a shift from traditional trial and error sequence to iterative, data driven and increasingly autonomous design [15]. AI integrates diverse data with machine-learning approaches to support a range of drug-delivery applications, from formulation optimisation and drug–excipient compatibility to drug-release prediction and nanocarrier design, as illustrated in Figure 1. These applications are discussed in the following sections.

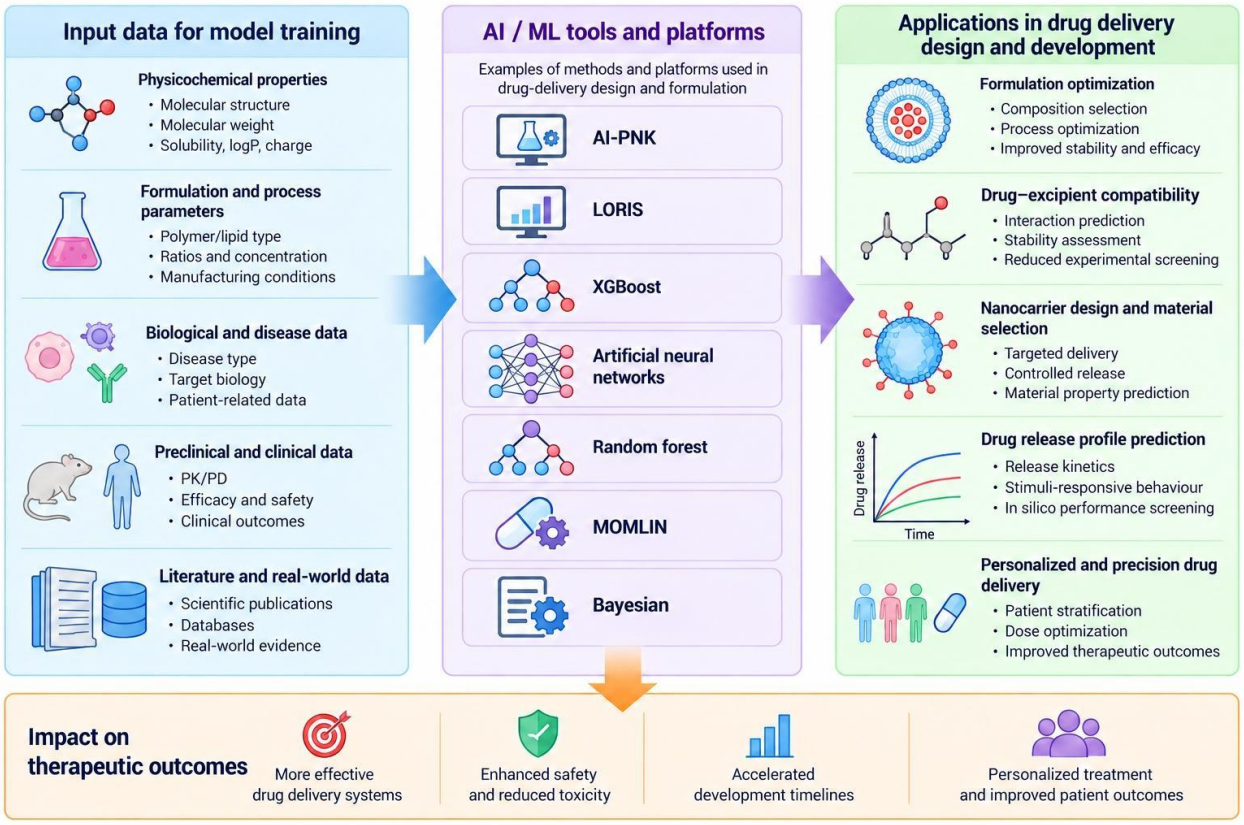


Figure 1. AI-driven framework for drug-delivery design and development. Image was created with the assistance of bioRender.

2.1 Role of Machine Learning in Formulation Optimization

Ros et al. (2026) defined machine learning as computational techniques that allow systems to learn patterns from data and use the acquired knowledge to make predictions or decisions without being explicitly programmed to perform a particular task [20]. Algorithms are often utilized by machine learning models that could estimate outcomes for untested formulations. This permits researchers to explore various designs for formulations more effectively. Machine learning can be categorized into three major learning paradigms, these are supervised learning, unsupervised learning and reinforcement learning. Each paradigm encompasses a major range of algorithms suited to different types of pharmaceutical formulations. While supervised learning utilizes models trained on labelled data, unsupervised learning utilizes models or patterns in unlabeled data. Reinforcement learning utilizes trial and error interactions to make decisions through positive feedback received from previous behaviors. Machine learning helps in predicting behaviors like particle size, encapsulation efficiency, dissolution rate, drug loading, stability from formulation variables [21]. Zulbeari et al. (2025) demonstrated that machine learning can support pharmaceutical suspension by learning relationships between formulation variables and physical stability. Using 72 datasets, the researchers developed an explainable ML model that predicted

suspension with approximately 91% accuracy and identified stabilizer concentration and milling bead size as important determinants of formulation performance. However, the limited dataset, restricted range of APIs and formulation variables and need for experimental and mechanistic validation highlights important barriers to the generalizability of ML- based formulation design [22]. Similarly, Seegobin et al. (2024) demonstrated the application of machine learning to the optimization of polymeric nanoparticle formulations by combining Design of Experiments (DOE) with machine learning for the development of PLGA nanoparticles prepared by nanoprecipitation. The study generated experimental datasets using different DOE approaches, including an extremes design (n = 48), central composite design (n = 60), and full-factorial design (n = 144), while a 165-point training dataset comprising the DOE data and 21 additional randomized formulations was used for machine-learning analysis. Several supervised machine-learning algorithms were evaluated for the prediction of nanoparticle particle size and zeta potential. The machine learning model, Extreme Gradient Boosting, also called XGBoost showed the best predictive performance for particle size, with machine learning generally providing lower prediction errors and higher coefficients of determination than DOE. The ML models also identified important formulation parameters influencing particle size, demonstrating their ability to extract relationships from formulation data beyond conventional statistical modelling. However, both DOE and ML showed relatively poor predictive performance for zeta potential, indicating that the effectiveness of machine learning may vary according to the specific critical quality attribute being modelled [23]. These findings demonstrate that integrating DOE-generated experimental data with machine learning can support more efficient nanoparticle formulation optimization, particularly when experimental datasets are limited, although experimental validation remains necessary. Machine Learning models such as Support Vector Machines (SVMs), Random Forest (RF) classifiers, and Artificial Neural Networks (ANNs) are popular algorithms used to identify nonlinear relationships between chemical structures and drug behavior across different dosage forms. For example, machine-learning algorithms such as deep learning have produced promising results in predicting solubility and other drug-characterization parameters in various solvent systems. Thus, they can help separate drug candidates more effectively for further development from a library of drug compounds. The ANN model has been used in the development of controlled-release formulations. The model learns specialized and sophisticated abilities from the input data using Chem software and the output data. The best *in vitro* dissolution-time profiles are predicted to identify the best tablet formulations based on two ideal *in vitro* dissolution-time profiles and two desirable in vivo release profiles [21].

Machine learning can further reduce the experimental burden associated with formulation optimization through active learning and Bayesian optimization. Recently, Cheong et al. (2026) reported the development of an automated machine-learning algorithm to identify optimal alginate hydrogel formulations for controlling drug delivery. In this work, a set of 120 alginate formulations loaded with bovine serum albumin was prepared as a seed library and modeled via Gaussian process regression to estimate the cumulative amount of drug released. Then, a sequential optimization process, including Bayesian optimization and active learning, was carried out to

choose the next formulations for evaluation from the predicted release data and their uncertainties using the model. With this process, near zero-order drug release was obtained after only two optimizations. Machine learning could thus be used to identify optimal formulations experimentally from a wide range of possibilities by determining the experiments to be conducted, not performing all possible experiments. Near zero-order sustained drug delivery was also obtained using the optimized formulation for chondroitinase ABC single enzyme nanoparticle without further optimization [24]. Collectively, the studies mentioned above show that machine-learning methods could significantly outperform traditional DOE approaches for prediction of critical formulation attributes provided that there are nonlinear relationships between the variables in the data. However, their performance heavily depends on the quality and quantity of data and the particular attribute that is predicted. Therefore, even with advances in the area of predictive modelling, the validation of models through experiments is still needed. In general, the information currently available does not show that AI methods are superior to the existing formulation development techniques across the board. The success of AI seems to depend on the number and the complexity of variables and the particular critical quality attribute that should be predicted. DoE can be useful for experimentation and data analysis even for small sets of data, while ML methods could be more flexible if nonlinear relationships are expected and large multidimensional datasets are available.

2.2 AI for Predicting Drug-Excipient Compatibility

Traditional drug–excipient compatibility assessment relies on experimental techniques such as differential scanning calorimetry (DSC), Fourier-transform infrared spectroscopy (FTIR), X-ray diffraction (XRD), and stability studies, which can be time-consuming and resource-intensive. AI-based approaches provide a complementary strategy by learning relationships between drug and excipient characteristics and previously reported compatibility outcomes. For example, Patel et al.(2023) developed DE-INTERACT, an artificial neural network-based tool trained using more than 3,500 drug–excipient instances, which achieved a validation accuracy of 91.61% and successfully identified experimentally confirmed drug–excipient incompatibilities [25]. Beyond compatibility screening, machine learning can also learn relationships between formulation composition and product performance. Using 1,983 tablet formulations, Momeni and Tabesh evaluated several machine-learning approaches for predicting tablet disintegration time and hardness from formulation and physicochemical attributes, with a deep neural network achieving particularly high predictive performance for tablet hardness [26]. Similarly, ML has been utilized for predicting drug-release profiles from the tablet formulations, which were developed using 377 formulations with 20 APIs and 80 excipients [27]. These results indicate that AI could take formulation development to the next level by helping predict not only compatibility but also critical quality attributes and drug-release profile. Apart from compatibility prediction and performance prediction, machine learning has also been applied in excipient selection. Vidal-Henriquez et al. (2025) developed the Excipient Prediction Software (ExPreSo), a supervised machine-learning approach which could assist in excipient pre-selection for protein and peptide

biopharmaceuticals. The model was built based on the data of 335 regulatory-approved biopharmaceutical products and protein-specific properties and drug-product properties. ExPreSo showed a good predictive ability regarding nine commonly used excipients and could help reduce the experimental efforts during the early stage excipient selection [28]. However, the performance of predictive AI models largely depends on the availability of large datasets with a diversity of APIs and excipient combinations. The majority of available AI models are trained on relatively small-sized datasets, thus potentially limiting their generalization abilities in other types of drugs and formulations [21]. Furthermore, acceptance by regulatory agencies, interpretability, and the requirement for experimental verification of prediction results are still major obstacles [21]. Therefore, currently AI is considered an auxiliary technology in predicting drug compatibility rather than a replacement for traditional tests. Regardless of these challenges, further advancements in machine learning and data science are likely to improve prediction performance in the future.

2.3. Data-driven Modelling of Drug Release Profiles

Traditionally, mathematical models such as Zero order model, First order model, Higuchi model and Korsmeyer-Peppas model were utilized to fit the results of dissolution studies. This is often called the mechanistic approach. Data driven modelling of drug release profiles utilizes machine learning and statistical findings to predict how medicines dissolve from delivery systems without requiring exhaustive trial and error experiments. It often requires input parameters like polymer types and manufacturing or process parameters. Algorithms like random Forest(RF), XGboost and Artificial Neural Networks (ANN) aid to identify complex patterns. They, thus predict full time dependent dissolution curves or estimate kinetic parameters for standard release models like Weibul and Korsmeyer-Peppas models [29]. Data-driven approaches are increasingly being explored as a way of predicting drug-release behaviour from formulation characteristics. Sousa et al. (2025) compared artificial neural networks (ANN) with functional data analysis combined with design of experiments (FDA-DOEs) to predict the dissolution profiles of polyethylene oxide-based extended-release matrix tablets. Using data from 91 formulations, both approaches were able to generate predicted release profiles that closely matched the experimental results. The study also showed that the concentration and molecular weight of the polymer influenced the pattern and extent of drug release, demonstrating how data-driven models can help link formulation variables with release behaviour [30]. However, the usefulness of these models is still influenced by the amount and diversity of data available for model development. In addition, the study focused on a particular extended-release formulation and in vitro dissolution conditions, so it remains unclear how well the models would perform with other drug-delivery systems or whether they could predict in vivo drug release and pharmacokinetic behaviour. Expanding these models using larger and more diverse datasets, together with manufacturing and physiological variables, could therefore improve their reliability and broader application in drug-delivery development. Similarly, Protopapa et al. (2025) investigated the ability of machine-learning models to predict drug-release profiles from tablet formulation composition. Using 377 directly compressed tablet

formulations and dissolution data collected over 480 min, the researchers evaluated six machine-learning techniques and found that random forest and extreme gradient boosting provided the strongest predictive performance. A second modelling strategy predicted parameters of the Weibull and modified first-order release models, which were subsequently used to reconstruct the dissolution profiles. The findings demonstrate that machine learning can be used not only to predict the overall drug-release profile but also to extract information related to release kinetics from formulation data. However, the moderate predictive performance observed in cross-validation also highlights the need for larger and more diverse datasets and further development of kinetic-informed models before such approaches can be broadly applied to formulation development [27]. Together, these studies show that data-driven models can help predict drug-release behaviour from formulation data, potentially reducing trial-and-error in formulation development, although larger and more diverse datasets are still needed to improve their reliability and wider application.

2.4 AI in Nanocarrier Design and Material Selection

Nanocarriers like liposomes, nanoparticles, polyplexes, dendrimers, nano self-emulsifying systems, and transferosomes are used in the preparation of nanomedicines to target drugs to specific parts of the body and enhance their concentration at the site of action. This method is important for targeting drugs to cancer cells or sites of infection and for delivering drugs with challenging physicochemical properties across physiological barriers like the blood–brain barrier, stratum corneum, or intestinal epithelium [31]. Designing successful nanomedicine therapeutics is intricately complex, and ensuring the proper characterization of nanoparticle size, shape, surface modifications, and material is essential, since these features determine key factors such as circulation time, cellular uptake, and, finally, its site in the biological system. Numerous potential nanomaterials in preclinical tests unexpectedly indicate toxicity, inadequate biodistribution or insufficient therapeutic benefit in clinical trials. It is essential to establish a more effective and reasonable procedure for the design and development of nanomaterials. Combining multidimensional data sets, including chemical synthesis, physicochemical characterization, pharmacokinetics and various biological responses [32], increases the probability of success. To solve these challenges, AI algorithms are a valuable tool in predicting the properties, effectiveness and stability of nanoparticles for design and optimization purposes. Thus, scientists are able to create nanoparticles in a certain way for effective application, including drug choice, dose determination and the choice of stimuli-responsive materials. There are several scientific works that prove the potential of data-driven approaches in improving the design and material selection of nanocarriers. So, Zhang et al. (2025) designed a platform called TuNa-AI, which is a hybrid machine-learning system that combines automated formulation with AI for simultaneous optimization of nanoparticle composition and drug–excipient ratio. Based on the dataset of 1,275 formulations with various drugs, excipients, and molar ratios, the system was able to increase the success rate of nanoparticle formation by 42.9%. AI-guided approach was also successfully used in the optimization of venetoclax nanoparticles and in reducing excipient usage by 75% in a

trametinib formulation without compromising in vitro effectiveness and in vivo pharmacokinetic performance. These results show how AI technologies can go beyond predictive analysis to optimize the composition of nanocarriers, although additional validation is required. [33]. In another study, Ortiz-Perez et al. (2024) utilized DoE along with iterative machine learning in the design of PLGA-PEG nanoparticles. Using an initial dataset of approximately 29 formulations, the model selected subsequent formulations for experimental testing and was subsequently used to screen a virtual library of 100,000 candidates, demonstrating how AI can reduce the number of formulations that need to be experimentally explored [34]. More recently, Hanafy et al. (2025) applied a combined DoE and machine-learning strategy to 180 lipid nanoparticle (LNP) formulations to identify compositions associated with cell-specific delivery. These selected formulations were then confirmed in vivo to have preferred spleen targeting with changed tissue tropism [35]. All these studies exemplify the process of shifting from a traditional experiment design to a more predictive and iterative nanocarrier design using AI, but the lack of independent dataset usage and low number of in vivo validations conducted present significant challenges for the generalization of such models.

3.0 AI-enabled drug delivery systems and applications

AI algorithms and machine learning are applied to large datasets to effectively predict the behavior of drugs. By simulating the formation and delivery of drugs, several such scenarios can be thoroughly analyzed to optimize drug delivery and reduce the need for trial-and-error models [36]. In drug targeting, AI analyses complex biological and formulation datasets to identify the optimal carrier systems, targeting ligands and administration strategies. AI models can predict how vehicles interact with biological delivery barriers, and blood-brain barriers. AI enhances controlled release systems by predicting drug-release kinetics using formulation variables and material characteristics. Machine -learning algorithms can model complex relationships between polymers, drug properties and environmental conditions to predict release profiles before testing [37].

In smart drug delivery systems, AI can analyze sensor data and determine the optimal timing and dosage of drug release, enabling adaptive and personalized treatment strategies. In implantable and wearable drug delivery devices, AI algorithms monitor biomarkers such as heart rate, blood pressure, blood glucose concentration, oxygen saturation and, physical activity and determine where the adjustments in drug administration are required. Implantable delivery devices can also use AI-driven feedback loops to provide precise dosing based on changing physiological conditions. Thus, AI facilitates more individualised treatment while reducing the risks associated with underdosing or overdosing. Robotics and AI are transforming drug administration by improving precision, reducing human error, and enabling automation of complex medical procedures. AI algorithms can guide robotic systems during drug preparation, compounding, dispersing and, administration. The integration of AI and robotics is especially valuable in precision medicine, where treatment decisions must be tailored to individual patient characteristics [21]. These applications will be discussed in subsections below with case studies.

3.1 AI in Targeted Drug Delivery

A significant development in the pharmaceutical field is targeted drug delivery, which focuses on delivering therapeutic agents to specific tissues and cells while reducing exposure to the rest of the patient's body. Traditional methods of drug delivery were nearly epidemic in their biodistribution, reflecting the widespread distribution of the drug throughout the patient's body. Very little of the drug reaches the targeted site of action, and the rest can become toxic to other body cells. Artificial intelligence (AI)-based targeted drug delivery is one of the best-known ways to help drugs reach their intended sites of action. A variety of new strategies, including the use of software techniques, have recently been developed. The combination also improved precision and made the entire design process efficient and optimized through data collected at different delivery stages [38].

The integration of machine learning (ML) and deep learning (DL) models with nanotechnology and carrier design is at the core of AI-driven targeted delivery. Nanocarriers, such as liposomes, polymeric nanoparticles, dendrimers, and inorganic nanoparticles, are employed to encapsulate therapeutic agents and deliver them to specific tissues through passive or active targeting. These carriers can be modified in terms of properties such as size, shape, surface charge, and ligand density, which determine their biodistribution, cellular uptake, and therapeutic efficiency [39]. Machine learning models are deployed to predict the best ligand–receptor interactions, carrier surface characteristics, and particle-associated properties to provide effective tumour targeting.

Chou et al. (2023) developed an AI-assisted PBPK model for nanoparticle tumour delivery in mice, achieving R^2 values of 0.83, 0.56 and 0.82 for tumour delivery at 24 h, 168 h and maximum delivery, respectively; the model also showed good agreement with experimentally measured tumour pharmacokinetic profiles, with 133 of 288 datasets achieving $R^2 \geq 0.70$ [40]. Mi et al. (2024) subsequently evaluated several machine-learning models for predicting nanoparticle distribution to tumours and major organs, with the deep neural network giving test-set R^2 values of 0.41 for tumour, 0.42 for heart, 0.79 for liver, 0.45 for spleen, 0.87 for lung and 0.83 for kidney; the model was further used to screen 7,000 virtual nanoparticle formulations, identifying 377 candidates predicted to achieve tumour delivery of 3–4% of the injected dose [41]. In brain-targeted delivery, Yousfan et al. (2024) analysed 403 data points and found that linear mixed-effects models provided strong predictive performance, while factors including administration route, nanoparticle properties, drug characteristics and release behaviour were associated with brain delivery; importantly, predictions were subsequently tested using two newly prepared nanoparticle formulations administered intranasally and intravenously, providing experimental support for the model [42]. Together, these findings provide experimental evidence that AI can move targeted nanomedicine from simply characterizing nanoparticles toward predicting tumour and brain delivery and prioritizing formulations for experimental testing.

3.2 AI for Controlled Release Mechanisms

Traditional approaches towards obtaining controlled and smart release systems require the use of polymer matrices, coatings, or stimuli-responsive materials, but the optimization process requires numerous repetitions of experiments and empirical formulas, which is time- and resource-

consuming. Here, AI models provide a data-driven approach to overcoming the problem in question, because they are able to predict release profiles and adjust formulation parameters in order to obtain desired release kinetics. Moreover, AI models are able to identify patterns from in vitro dissolution, in vivo physicochemical properties, and environmental conditions in order to develop smart and controlled-release systems without performing extensive analysis [29]. Machine learning models have also been successfully used in improving the process of development of controlled-release systems by analyzing complex correlations between formulation factors and drug release behavior. Deng et al. (2023) obtained machine-learning models based on data from 286 microsphere formulations with small-molecule drugs and tested 14 algorithms. The consensus model provided a good prediction of in vitro drug release at 37 °C and 45 °C with R^2 of 0.880 and 0.958, respectively, while experimental microsphere formulations confirmed the accuracy of the model [43]. More recently, Song et al. (2026) have designed a two-stage machine learning-based model with a dataset of 321 release profiles for 89 drugs encapsulated in PLGA microspheres. The XGBoost model performed the best, with a mean absolute error of 0.126 and a Pearson correlation coefficient of 0.831. It is worth mentioning that the model could predict successfully using an external dataset for olaparib- and semaglutide-loaded microspheres with mean absolute errors of 0.096 and 0.068, respectively [44]. These findings show that AI can help predict drug-release behaviour from formulation characteristics and may reduce the experimental effort required during controlled-release formulation development. However, most available models remain focused on in vitro release, and their ability to predict in vivo release and pharmacokinetic behaviour across different drugs, polymers and dosage forms remains to be established. Larger and more diverse datasets, together with broader prospective and in vivo validation, will therefore be important for improving the reliability and wider application of AI-driven controlled-release modelling.

3.3 Use of AI in Implantable and Wearable Delivery Devices

Smart systems have multimodal sensors that track physiological and biochemical parameters, such as heart activity, glucose and biomarkers, in real time. With these capabilities, these systems can enable the early detection of diseases, the management of chronic diseases and precision therapeutics, transitioning the healthcare system from being largely reactive to a real-time system with active prevention of chronic diseases. By addressing significant challenges such as the increased prevalence of chronic diseases, an ageing population and limited access to healthcare, AI systems make wearables more effective. These wearable devices can detect irregular heartbeats, help prevent heart attacks, monitor diabetes and control blood sugar levels to avoid complications [45]. Artificial intelligence is increasingly being incorporated into wearable drug-delivery technologies, but the maturity of these systems varies considerably. An early example is the study by Bagde et al.(2023) who combined quality-by-design with a semi-supervised machine-learning approach to optimize the morphology and print fidelity of dissolving microneedles for sustained ibuprofen delivery. The optimized patches were first evaluated through in-vitro skin-permeation

experiments, where approximately 2 mg/cm² of ibuprofen was continuously permeated over 72 h. Importantly, the study progressed beyond in-vitro testing to pharmacokinetic evaluation in rats, where the optimized microneedle patch produced an $AUC_{0–48}$h of 62,812.02 ± 11,128.39 ng·h/mL, a Cmax of 3,717.43 ± 782.25 ng/mL and a Tmax of 2.66 ± 1.12 h [46].Thus, this work represents a preclinical in-vivo proof of concept in which AI was used primarily for device/formulation optimization rather than autonomous control of drug administration. A more advanced wearable platform was reported by Yang et al. (2025) who developed a microneedle-based continuous biomarker/drug monitoring (MCBM) system capable of simultaneously measuring glucose and metformin in interstitial fluid. The sensing components were characterized in vitro before the complete system was evaluated in vivo in diabetic rats. The wearable device transmitted glucose and metformin measurements to a smartphone application, where conversion algorithms processed the electrochemical signals and decision-making algorithms performed pharmacokinetic/pharmacodynamic analysis to provide medication recommendations. The authors therefore demonstrated in-vivo proof of concept for continuous therapeutic-drug monitoring and pharmacologically informed dose adjustment, rather than direct autonomous drug administration [47]. This distinction is important: the system demonstrates the sensing and computational components required for future closed-loop drug delivery, but the reported study did not establish a machine-learning system that autonomously administered metformin.

The integration of machine learning with wearable biosensing has progressed further in a 2026 study by Sun et al. (2026) who developed a skin-interfaced microneedle patch capable of continuously measuring six metabolic biomarkers; glucose, uric acid, cholesterol, sodium, potassium and pH from dermal interstitial fluid. The platform was validated in vivo in animal models and incorporated a machine-learning pipeline for automatic feature extraction and health-state assessment. The model achieved a classification accuracy of 0.996 for distinguishing normal from diet-induced metabolic dysfunction and an R^2 of 0.977 for estimating the degree of metabolic disturbance [48]. However, this system is primarily a machine-learning-enabled wearable sensing platform, not a drug-delivery device, and therefore represents an intermediate stage in the development of intelligent therapeutic systems: AI interprets continuously acquired biological information, but the study does not demonstrate autonomous drug administration. The transition toward actual closed-loop drug delivery is illustrated by Zhao et al., (2026) who developed a dual-microneedle system integrating continuous glucose monitoring with feedback-controlled insulin delivery. The glucose sensor demonstrated a linear range of 1–34 mM and stable performance for seven days, while an electroosmotic pump provided voltage-tunable insulin delivery. In in-vivo experiments, the system produced a 55% reduction in blood glucose and achieved 88% Clarke Error Grid Zone A accuracy [49]. Nevertheless, this system should not be classified as a fully AI-controlled drug-delivery device because its feedback mechanism was based on glucose sensing and controlled electroosmotic insulin release rather than a demonstrated machine-learning decision-making algorithm. It is better regarded as an in-vivo closed-loop proof-of-concept that provides an engineering foundation for future AI-controlled wearable drug-delivery systems. Taken together, these studies demonstrate a gradual progression from AI-assisted formulation and

device optimization → in-vitro characterization → in-vivo animal validation → intelligent wearable sensing → closed-loop drug delivery. However, the field has not yet reached widespread clinical implementation of fully autonomous AI-controlled drug-delivery devices. The most compelling evidence is the pre-clinical animal studies at present. However, further validation in humans with regards to continuous monitoring of physiological parameters, analysis through AI and autonomous adjustment of the drug delivery system is lacking. This highlights a major research gap in the area, and for future research to address this gap, further validation through long term stability of sensors, accuracy of AI analysis, safety of autonomous decision making for dosing and finally human clinical trials must be done.

3.4 Robotics and AI in Drug Administration Systems

Robotics and artificial intelligence (AI) technologies are progressively revolutionizing drug delivery systems as a way of achieving greater precision, automation, and personalization in medication administration. While the former makes predictions and assists with decisions, the latter helps with the physical processes of drug preparation and delivery. Robotics is used in the health care sector for accurate drug preparation, compounding, and dispensing, which ensures that there is little room for human error in the process. Modern robotic drug delivery systems help to deliver drugs using intelligent infusion systems, injectors, and even implantable delivery systems with great precision. When combined with AI, such drug delivery systems will analyze patient-specific physiological information and use the same to determine the appropriate amount of drug delivery. Microrobotics and catheter-guided robot-assisted systems are among the emerging drug delivery systems that help in targeting specific tissues for drug delivery and ensure that healthy tissues do not get exposed to any drug. Closed-loop robotic drug delivery systems will also make use of the AI and robotics technology for patient monitoring, dosage calculation, and delivery without much human intervention [50]. It is also important to distinguish AI-based decision-making from conventional control engineering. Some automated drug-delivery systems use predefined rules, proportional–integral–derivative (PID) control, or model-predictive control (MPC) rather than machine-learning algorithms. Therefore, the presence of automated feedback or dose adjustment does not by itself establish that a system is AI-driven. In this review, systems are considered AI-enabled when machine-learning or related AI methods contribute explicitly to prediction, optimisation, decision-making, or adaptation, whereas systems based solely on conventional feedback-control strategies are considered automated or closed-loop technologies rather than AI systems. Despite challenges relating to regulatory approval, clinical validation, cybersecurity, and implementation costs, the integration of robotics and AI is expected to play an increasingly important role in the development of next-generation intelligent drug-administration systems. Clinical evidence shows that robotics has progressed from automated medication dispensing to robots performing tasks traditionally undertaken by healthcare professionals. In hospital pharmacy, implementation of the ROWA Vmax robotic dispensing system reduced dispensing errors from 1.31% to 0.63% of prescriptions and reduced daily staff time spent on stock management by 59.3%, demonstrating the potential of robotics to improve medication safety and

reduce repetitive workload [51]. More recently, the Florence humanoid robotic nurse assistant was evaluated in an actual hospital ward involving 67 patients. Florence autonomously navigated to patients, identified them using facial recognition, measured vital signs, and delivered pre-loaded medications. Although patients generally reported positive interactions and nurses recognized its potential for routine tasks, concerns remained regarding navigation, patient identification and medication safety [52]. These examples demonstrate a progression from robotic medication handling toward robots performing patient-facing medication-administration tasks; however, current systems remain largely automation-based rather than fully AI-autonomous, with human professionals still responsible for prescribing, clinical judgement and medication selection.

4.0 The impact of AI on the pharmacokinetics and evaluation of drug delivery systems

AI in pharmacokinetics is revolutionary in view of the rapid and accurate prediction on drug kinetics [53]. Algorithms have contributed to the expansion of knowledge about diseases through identification of dysregulated molecular mechanisms, novel drug targets, and in silico efficacy of drugs [54].

4.1 AI in ADME Modeling

Tanihata & Iwata (2026) stated that absorption, distribution, metabolism, and excretion (ADME) is crucial for drug discovery and development, dose optimization, and safety evaluation, pharmacokinetic (PK) interactions are a product of those processes. It was pointed out by Tanihata and Iwata that due to advances in AI and ML ADME predictions have become much more accurate, especially for small molecules [55]. All rational decisions made about drugs are based on pharmacokinetics, which is a quantitative science of drug absorption, distribution, metabolism, and excretion in the body, whether it is the selection of an initial dose in the first clinical trials or dose increment or reduction for a specific patient in complex patient populations [54].

Prediction in Absorption: The process of absorption occurs due to a number of interrelated factors including solubility in aqueous media, membrane permeability, intestinal motility, and active transport [56]. Current machine learning models are capable of predicting the Caco-2 cell line permeability, P-glycoprotein efflux ratios, and human intestinal absorption with the precision comparable to that of experimental interrelated factors measurements [57]. Nevertheless, the study conducted by Bennett-Lenane et al. (2022) revealed that there still remains an important drawback in current absorption models because of the underestimation of the absorption influence of the formulations [58]. In other words, existing models of artificial intelligence are designed only for the prediction of the intrinsic absorption properties of molecules depending on their chemical structure without consideration of the effect of co-excipients, particle size, polymorphism, and surface properties resulted from the synthesis and manufacturing process.

Prediction of Distribution: Volume of distribution (Vd) and plasma protein binding (PPB) are important parameters of PK that control the extent of drug permeation through the tissue and the

amount of pharmacologically active and free compound. Identifying the most accurate predictive models of these ADME properties, while also ensuring mechanistic interpretability is essential for improving the reliability and understanding of PK predictions. This explainable artificial intelligence (XAI) technique is a direct answer to the "black box" problem of deep learning models in PK and limits their regulatory approval, as it allows the verification of the physiological reasoning behind the models' predictions. One of the main limitations of drug distribution modeling that has yet to be resolved is the lack of quality data regarding the distribution of drugs at tissue-specific level in humans [59]. Majority of AI models are based on in vitro experiments regarding plasma protein binding and lipophilicity in estimating volume of distribution (Vd). They have limited access to measurements regarding drug partitioning at a tissue level, which could enable the prediction of more accurately how drug accumulates in organs such as the brain, liver and adipose tissue [60].

Predictions of Metabolism and Excretion: According to Hosey et al.(2014), renal clearance and biliary excretion are two major methods of drug elimination from the body, and correct prediction of these methods is required to make dosing adjustments in renal and hepatic insufficiencies [61]. At present, AI models can predict renal clearance corrected for glomerular filtration rate and biliary excretion based on structural descriptors, where GNN approaches demonstrate better predictive ability than classical QSAR methods [62]. A practical gap in this domain is the near-complete absence of AI models validated specifically for the pediatric, geriatric, and renally compromised patient populations in whom standard pharmacokinetic assumptions are most likely to fail [63].

4.2 Predictive Pharmacokinetic Simulations Using AI

A revolutionary integrative paradigm was introduced by Chou and Lin in 2023. Based on ML, it uses publicly available pharmacokinetic databases, typically available at no cost, to predict the input parameters required by PBPK models for novel compounds. ML models provide a quicker and improved way to predict the required PBPK input parameters, eliminating the need for a great deal of experimental parameter estimation, a process that was once very time-consuming and a significant bottleneck [60]. A fundamental challenge in PBPK model development is the acquisition of the large number of physiological and chemical-specific ADME parameters required to populate model equations, a process that has historically required extensive experimental investment. However, despite all these developments, many gaps still exist in AI-integrated PBPK models [64]. As an illustration, the PBPK databases, which are used to feed training ML algorithms, are mostly dominated by small molecule drug therapeutics and physiologic parameters of healthy adults, lacking relevant information on biologics, nanoformulations, pediatrics, and dysfunctional organs. This results in a system-wide bias in model development with respect to potential extrapolation errors that exactly occur in areas where accurate dosing is required [65].

4.3 AI for Bioavailability and Stability Studies

The quality of pharmaceuticals is described by their stability. Stability data play an essential role in the product lifecycle management of pharmaceuticals. The term ‘stability’ does not refer to a physicochemical attribute but to the ‘assurance of quality’ of pharmaceuticals according to their label claims. Early in formulation development, the selection of excipients, packaging materials, and advisable manufacturing procedures is determined by data from screening and stability studies of the formulation [66]. AI and other predictive modelling approaches are helping to make pharmaceutical stability testing more predictive and data-driven, while reducing reliance on lengthy time-based assessments. They can also support regulatory submissions, determine suitable storage conditions, and help predict the retest period and shelf life of pharmaceutical products [67]. AI, automation, and digital technologies are likely to make pharmaceutical stability testing more efficient by improving data analysis, prediction, and real-time monitoring [68].

5.0 Relevance of AI in personalized medicine

Personalized medicine, which is also referred to as precision medicine, is the approach to healthcare that customizes the prevention, diagnosis, and treatment of diseases based on the specific individual’s genetic composition, physiology, lifestyle, and environment. One of the roles of artificial intelligence in precision medicine is allowing decisions and treatments in healthcare to be customized to an individual patient’s characteristics rather than using a uniform standard approach. The personalized medicine understands that the patient will have different reactions to the same medication due to genetic differences, physiology, lifestyle, disease, and environmental factors. Artificial intelligence allows the processing and analysis of large and complex datasets from sources like genomic sequencing, electronic health records, medical images, and wearable devices to establish a pattern that is not identifiable by traditional statistical techniques [69]. In pharmaceutical sciences, artificial intelligence allows the prediction of patients' responses to medicines, the optimization of dosing regimens, and the development of personalized drug delivery systems. Moreover, through personalized medicine, AI aids in patient stratification for the identification of sub-populations of patients that are most likely to respond positively to certain therapies. This will mainly be useful for the treatment of conditions that are difficult to treat, such as cancer, cardiovascular diseases, and rare genetic diseases, since there is variation in treatment outcomes from individual to individual. Through the aid of AI, personalized medicine has great potential in improving clinical results and making treatments more efficient and cost-effective. However, various hurdles related to data quality, privacy, algorithm transparency, and regulatory acceptance need to be sorted out before personalized medicine driven by AI realizes its potential fully [69]. In relation to drug delivery, personalized medicine is not limited to choosing what treatment should be given to an individual. The information about the patient can also be used to formulate, dose, administer, and monitor a medicine. Information related to pharmacokinetics can

be used to select dose and dosing interval, while disease severity or physiological status can determine the route and delivery device chosen. Thus, the key contribution of AI to personalized drug delivery is its ability to connect patient-level information with delivery-related decisions, rather than simply predicting treatment response.

5.1 Artificial Intelligence-Based Patient Data Analysis

AI-based analysis of patient data is defined as the application of machine-learning algorithms and deep learning technology in combination with advanced computing capabilities to process, interpret, and derive insights from massive and complicated data sets that belong to the healthcare sector. The analyzed data can be electronic health records, genomic data, laboratory test results, medical imaging data, wearable device data, and patient-reported data. By applying artificial intelligence to the data, one obtains the opportunity to quickly analyze huge amounts of data, which cannot be processed through traditional statistical analysis. In the drug development and healthcare sector, AI-based patient data analysis helps to identify disease patterns, predict patient treatment outcomes, and assess risks for individual patients. Machine-learning algorithms can process data related to patient characteristics, genetic information, and physiology to predict patient response to certain treatments, and thus help healthcare providers choose an effective treatment approach for patients [70]. AI also helps to identify previously unknown relationships between biomarkers and disease development, helping to make diagnoses and manage the disease. This aspect is especially important in the case of cancer, cardiovascular disease, and neurological disorders because of the differences in treatment response of patients. The AI Drug Mix and Dose Advisor (AIDA), for instance, used electronic medical records from 107,854 type 2 diabetes patients to predict glycaemic outcome and make recommendations regarding drug combinations and dosage. The accuracy of the algorithm was tested using internal, external, and temporal validation datasets. Its efficacy was found to be higher than that of conventional therapy by about 0.40 – 0.68 percentage points in HbA1c reduction [71]. Although this AI application holds a lot of promise, there are still some issues in AI patient data analysis associated with data quality, data privacy, transparency of algorithms, and regulatory acceptance of AI. Besides, the accuracy of predictions made by AI depends on the presence of huge datasets. As such, at the moment, AI is considered to be a tool supporting decision-making but not an alternative to human expertise. However, developments in data science and machine learning are expected to facilitate the application of AI in patient data analysis.

5.2 Precision Dosage Design with AI Technology

Precision dose design is the process of calculating a dose suitable for an individual patient taking into account individual features of patients. AI is useful in achieving this objective by processing large amounts of data about patient demographics, genetic features, medical history, pharmacokinetics and pharmacodynamics of a particular drug to make predictions about how a drug would work in an individual body. Machine learning tools will be used to recognize

parameters that affect drug effectivity and toxicity, thereby optimizing dosing strategies to minimize negative drug reactions [21]. Moreover, AI could help to create a strategy of adaptive dosing using the clinical data of a particular patient and information about how he reacts to a dose. This contributes to the general idea of precision medicine as drug dosing goes beyond the generalization among populations. A good example of such a technology is CURATE.AI that uses individualized dose response data to calculate appropriate drug doses. One example of application of this tool is ibrutinib dosing in an 80-year-old patient with Waldenström macroglobulinemia during two years. The system progressively updated the patient's dose–response profile and recalibrated dose recommendations following systemic changes, demonstrating the potential of AI to support adaptive, patient-specific dose optimisation rather than relying solely on fixed dosing strategies (Figure 2) [72].

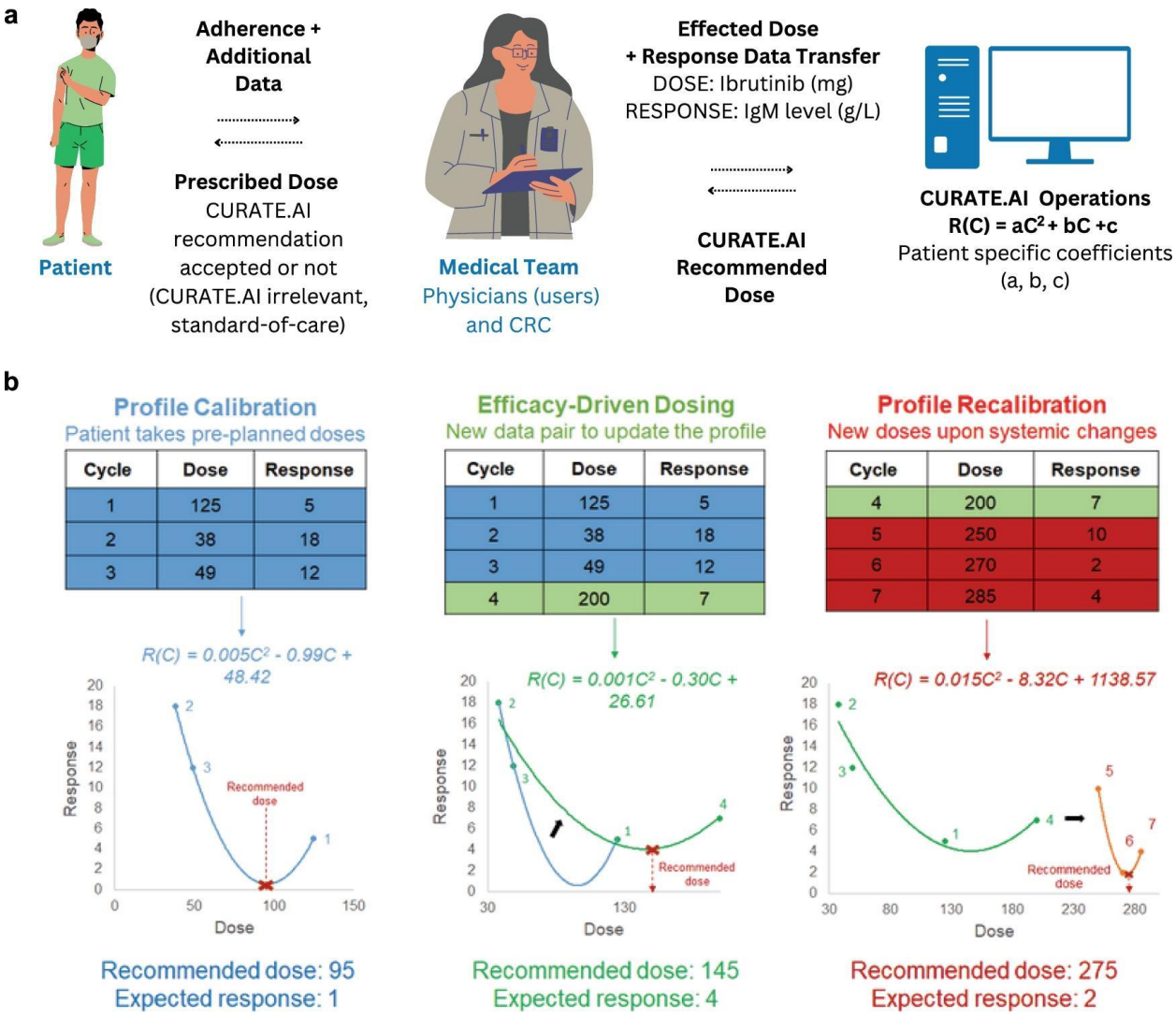


Figure 2. CURATE.AI workflow for personalised and adaptive drug dosing. (a) Interaction between the patient, medical team and CURATE.AI system, showing the transfer of dose and response data and generation of patient-specific dose recommendations. (b) Sequential stages of patient-profile calibration, efficacy-driven dosing and profile recalibration following systemic changes. Adapted from Blasiak et al.(2024) [72].

5.3 Predictive Algorithms for Patient's Response

Predictive algorithms refer to artificial intelligence (AI) and machine-learning models using patient-related information for predicting the reaction of a patient to certain drugs. The algorithms use patient data, which include genetics, past medical history, laboratory tests, physiological factors, and personal attributes for developing predictive patterns of therapeutic results. Predictive algorithms help the healthcare providers in making rational decisions about treatment based on predictions about the effectiveness of the drug therapy, its toxicity level, and potential adverse reactions. The pharmaceutical and clinical application of predictive algorithms includes assistance in finding the appropriate treatment options, establishing proper dosages, and identifying patients who will benefit from specific medications. Predictive algorithms can be especially useful in treating cancer, cardiovascular disease, and other illnesses characterized by variable drug reaction patterns among different patients. Thus, the algorithms can be used for increasing treatment effectiveness and minimizing the number of adverse reactions. In 2024, Chang et al. introduced LORIS (Logistic Regression-Based Immunotherapy-Response Score), a machine-learning model for predicting the responses of patients to immune checkpoint inhibitors. The researchers used data from 2,881 patients treated with immunotherapy and 18 types of solid cancers. They used six characteristics in their study, namely age, type of cancer, and tumor mutation load, among others, to predict the patient's reaction and survival rate to LORIS. This shows the possibility of using AI to choose personalized treatment by knowing which patient can benefit from the treatment [73].

5.4 Integration of AI with Genomic and Biomarker Data

The use of AI in conjunction with genomics and biomarkers is the use of AI techniques to analyze genetic data and biomarkers for the purposes of enhancing the diagnosis, prognosis, treatment, and outcomes of diseases. Genomic data are information from the genes of a particular person and the various genetic differences. Biomarkers, on the other hand, are measurable characteristics such as

proteins, enzymes, or changes in gene expression that give clues to any pathological or physiological processes. The use of AI makes it possible to process large datasets of genetic information and biomarkers and establish patterns that may be difficult to identify using conventional methodologies. Genomics and biomarkers combined with AI will enhance precision medicine through patient stratification, biomarker discovery, disease risk prediction, and treatment response prediction. Through machine learning and deep learning techniques, AI will make it possible to determine patients who will respond to certain treatments, hence enabling the personalization of treatment. AI will also help in the identification of new biomarkers and genetic differences of significance to treatment [74].

MOMLIN (multi-modal and -omics machine learning integration) framework was proposed by Rashid and Selvarajoo (2024) for integrating clinical information, mutations, gene expression, tumor microenvironment data, and pathway data into a machine learning-based framework to detect markers associated with drug response. Using patient data from 147 patients with breast cancer, MOMLIN discriminated between responders and non-responders and found several multimodal biomarkers associated with drug response. For instance, MOMLIN detected a multimodal marker consisting of mutations in genes HMCN1 and COL5A1, expression of genes FBXO2 and CSF3R, and $CD8^+$ T cell features among responders. The results obtained had an average AUC of 0.989 and illustrate how AI techniques can combine various types of biological data to find complex biomarkers that could not be discovered separately [75]. In summary, AI has been explored in personalised and precision medicine, with benefits in analysing large datasets, including genomic and biomarker data, using tools such as AIDA and MOMLIN, which help establish disease patterns and outcomes, enhance patient stratification, and support personalised medicine. Moreover, CURATE.AI, LORIS and other similar AI tools have facilitated the prediction of patients' responses and the design of precision dosage forms. Hence, AI tools have aided in personalised and precision medicine through patient data analysis, patient stratification and dose optimisation, resulting in cost-effective medicines, improved therapeutic outcomes, and lower toxicity. However, barriers such as cost, the need for large databases and ethical issues need to be addressed for greater clinical usefulness of AI in personalised medicines. A key summary of the applications of AI is seen in Table 1 below.

Table 1. Summary of AI applications in drug-delivery systems and supporting evidence

Area of drug delivery	AI/model type	Data source and size	Main application/outcome	Performance achieved	Level of evidence	Main limitation	Ref.
Formulation optimisation	Explainable ML; supervised ML; XGBoost	Pharmaceutical suspension dataset: 72 datasets	Prediction of suspension performance and identification of important formulation variables	~91% prediction accuracy; stabilizer concentration and milling bead size identified as important variables	In silico/model development	Small dataset; limited API and formulation-variable range; experimental/mechanistic validation required	[22]
Polymeric nanoparticle formulation optimisation	XGBoost and other supervised ML models combined with DoE	PLGA nanoparticle datasets: 48 extremes, 60 central composite, 144 full-factorial; 165-point training dataset	Prediction of particle size and zeta potential	XGBoost showed strongest prediction for particle size; prediction of zeta potential was relatively poor	In vitro/exploratory formulation studies	Performance varied with critical quality attribute; limited independent validation	[23]
Active-learning formulation optimisation	Gaussian process regression, Bayesian optimisation and active learning	120 BSA-loaded alginate hydrogel formulations	Iterative optimisation of controlled drug release	Near-zero-order release achieved after two optimisation iterations	In vitro	Limited to the formulation system studied; broader validation required	[24]
Drug–excipient compatibility	Artificial neural network (DE-INTERACT)	More than 3,500 drug–excipient instances	Prediction of drug–excipient incompatibility	91.61% validation accuracy; experimentally confirmed incompatibilities identified	In silico with experimental confirmation	Generalisability depends on diversity and quality of drug–excipient data; experimental confirmation remains necessary	[25]

Area of drug delivery	AI/model type	Data source and size	Main application/outcome	Performance achieved	Level of evidence	Main limitation	Ref.
Drug-product performance prediction	Machine learning/deep neural network	1,983 tablet formulations	Prediction of tablet disintegration time and hardness	Deep neural network showed particularly high predictive performance for tablet hardness; numerical metric not reported in the review	In silico/formulation data	Exact performance metric and external validation are not reported in the review	[26]
Drug-release profile prediction	ANN; functional data analysis + DoE	91 polyethylene-oxide extended-release matrix tablet formulations	Prediction of dissolution/release profiles	Both approaches generated release profiles that closely matched experimental profiles	In vitro	Model developed under specific formulation and dissolution conditions; uncertain generalisation to other delivery systems and in vivo release	[30]
Drug-release and kinetic-parameter prediction	Six ML approaches, including Random Forest and XGBoost	377 directly compressed tablet formulations; 20 APIs and 80 excipients; dissolution over 480 min	Prediction of complete drug-release profiles and kinetic parameters	Random Forest and XGBoost provided the strongest predictive performance; review reports moderate cross-validation performance	In vitro	Dataset diversity and generalisability remain limited; further kinetic-informed and external validation required	[27]

Area of drug delivery	AI/model type	Data source and size	Main application/outcome	Performance achieved	Level of evidence	Main limitation	Ref.
Nanocarrier design/material selection	Iterative ML combined with DoE	PLGA-PEG nanoparticles; approximately 29 initial formulations; virtual library of 100,000 candidates	Selection and optimisation of nanoparticle formulations	ML guided subsequent experimental formulation selection and virtual screening	In vitro/ex vivo formulation development	Small initial experimental dataset and limited independent external validation	[34]
Lipid nanoparticle design for targeted delivery	DoE + machine learning	180 LNP formulations	Identification of formulations associated with cell-specific delivery/tissue tropism	Selected formulations demonstrated preferential spleen expression and altered tissue tropism	In vitro + in vivo	Relatively limited dataset and independent external validation	[35]
Tumour-targeted nanoparticle delivery	ML-assisted physiologically based pharmacokinetic (PBPK) modelling	288 nanoparticle tumour PK datasets	Prediction of nanoparticle tumour delivery in mice	$R^2 = 0.83$ at 24 h, 0.56 at 168 h and 0.82 for maximum delivery; 133/288 datasets achieved $R^2 \geq 0.70$	In silico + in vivo mouse data	Predictive performance varied across datasets; human translation remains uncertain	[40]

Area of drug delivery	AI/model type	Data source and size	Main application/outcome	Performance achieved	Level of evidence	Main limitation	Ref.
Nanoparticle tissue/tumour distribution	Deep neural network and other ML models	534 tumour-delivery + 1,972 organ-distribution datasets; 7,000 virtual formulations screened	Prediction of tumour and organ distribution and prioritisation of candidate formulations	Test-set R^2: tumour 0.41, heart 0.42, liver 0.79, spleen 0.45, lung 0.87, kidney 0.83; 377 virtual candidates predicted to achieve 3–4% injected dose to tumour	In silico + mouse-derived data	No prospective experimental validation of all 377 predicted candidates; performance varied substantially by organ	[41]
Brain-targeted nanoparticle delivery	Linear mixed-effects models and other statistical/ML models	403 observations from 237 publications	Prediction of nanoparticle brain delivery and identification of factors associated with delivery	Strong predictive performance reported; predictions subsequently tested using two newly prepared nanoparticle formulations	In silico + in vivo	Heterogeneous literature-derived dataset and small experimental validation set	[42]
Controlled drug release	ML consensus model; 14 algorithms	286 microsphere formulations	Prediction of drug release from microspheres	Consensus model R^2 = 0.880 at 37°C and 0.958 at 45°C	In vitro + experimental validation	Primarily in vitro; broader applicability to different drugs, polymers and physiological conditions remains uncertain	[43]

Area of drug delivery	AI/model type	Data source and size	Main application/outcome	Performance achieved	Level of evidence	Main limitation	Ref.
Controlled release from PLGA microspheres	Two-stage XGBoost model	321 release profiles from 89 drugs	Early and full drug-release prediction	MAE = 0.126; Pearson r = 0.831; external MAE = 0.096 for olaparib and 0.068 for semaglutide	In vitro + external validation	In vivo release and PK prediction remain insufficiently established	[44]
AI-optimised wearable/microneedle drug delivery	Semi-supervised ML + quality-by-design	Experimental formulation/device data; specific dataset size not stated	Optimisation of 3D-printed dissolving microneedles for sustained ibuprofen delivery	~2 mg/cm² over 72 h in vitro; rat $AUC_{0–48h}$ = 62,812.02 ± 11,128.39 ng·h/mL	In vitro + in vivo rat	AI was used mainly for formulation/device optimisation, not autonomous drug administration	[46]
Wearable therapeutic monitoring	Signal-processing/decision algorithms with PK/PD analysis	Glucose and metformin measurements from diabetic rats	Continuous monitoring of glucose and metformin and pharmacologically informed dose adjustment	In vivo proof of concept; numerical predictive metric not reported in the review	In vitro + in vivo	Did not demonstrate autonomous AI-controlled drug administration	[47]
ML-enabled wearable biosensing	Machine-learning classification/regression pipeline	Six metabolic biomarkers measured using microneedle platform	Health-state classification and estimation of metabolic dysfunction	Classification accuracy = 0.996; R^2 = 0.977	In vivo animal study	Primarily a sensing system rather than a drug-delivery system; no autonomous drug administration demonstrated	[48]

Area of drug delivery	AI/model type	Data source and size	Main application/outcome	Performance achieved	Level of evidence	Main limitation	Ref.
Closed-loop insulin delivery	Glucose-feedback control; not demonstrated ML control	Diabetic animal model	Continuous glucose monitoring with feedback-controlled insulin delivery	55% reduction in blood glucose; 88% Clarke Error Grid Zone A	In vivo	Feedback control was not based on a demonstrated ML decision-making algorithm; clinical validation lacking	[49]
Robotic medication dispensing	Robotic automation; AI not demonstrated as the primary controller	Hospital pharmacy implementation	Automated medication dispensing and stock management	Dispensing errors reduced from 1.31% to 0.63%; stock-management time reduced by 59.3%	Clinical/hospital implementation	Primarily automation rather than fully AI-autonomous decision-making	[51]
Robotic patient-facing medication administration	Humanoid robotic system with navigation, facial recognition and vital-sign monitoring	67 hospital patients	Patient navigation, identification, vital-sign measurement and delivery of pre-loaded medications	Clinical ward feasibility demonstrated; quantitative AI prediction metric not reported	Clinical/hospital implementation	Concerns regarding navigation, patient identification and medication safety; human professionals remain responsible for clinical decisions	[52]

Area of drug delivery	AI/model type	Data source and size	Main application/outcome	Performance achieved	Level of evidence	Main limitation	Ref.
AI-based patient-data analysis/precision treatment	Machine learning applied to EHR data	107,854 patients with type 2 diabetes	Prediction of glycaemic outcomes and recommendation of drug combinations/dose adjustments	Estimated HbA1c improvement of 0.40–0.68 percentage points compared with standard care; internal, external and temporal validation	Retrospective/clinical data analysis	Model-based estimate rather than prospective randomised clinical evidence	[71]
Precision dosing	CURATE.AI; patient-specific dose–response modelling	Individual patient dose–response and treatment-response data	Individualised ibrutinib dose optimisation	Dosing dynamically guided over 2 years in an 80-year-old patient with Waldenström macroglobulinemia	Clinical case study	Single-patient case study; broader clinical validation required	[72]
Prediction of treatment response	Logistic regression-based ML (LORIS)	2,881 immunotherapy-treated patients across 18 solid tumour types	Prediction of immunotherapy response and survival	Model used six clinical/biological features; numerical performance metric not reported in the review	Clinical retrospective data	Further clinical validation required	[73]

Area of drug delivery	AI/model type	Data source and size	Main application/outcome	Performance achieved	Level of evidence	Main limitation	Ref.
Integration of genomic/biomarker data	Multimodal machine-learning framework (MOMLIN)	147 breast cancer patients; clinical, mutation, gene-expression, tumour-microenvironment and pathway data	Identification of multimodal biomarkers associated with treatment response	Average AUC = 0.989	Clinical/retrospective patient data	Small patient cohort and need for independent clinical validation	[75]

6.0 Challenges and Limitations of AI in Drug Delivery Systems

Despite all these opportunities, there are multiple obstacles that impede the use of AI in drug delivery systems. AI models need a large amount of high-quality and diverse data; therefore, insufficient, inadequate, or biased datasets can affect the accuracy of predictions and reliability of the models. There is also a problem with the ethics and privacy of the collected patient data, especially in combination with wearable and connected healthcare devices. Besides, AI systems demand advanced computing capacity, complex algorithms, and skilled specialists, which affects the availability of such technologies. Moreover, there is no clear regulation on the validation and approval of such AI systems, which also limits their usage in the healthcare sector. Finally, it is worth mentioning the high cost of developing, implementing, and maintaining AI models that can be another limitation for both research and practical use of AI in drug delivery. Despite the mentioned barriers to using AI in this sphere, there is much potential in optimizing the processes related to drug delivery with AI. The major challenges that impede the development of drug delivery systems using AI technologies are presented in Figure 3.

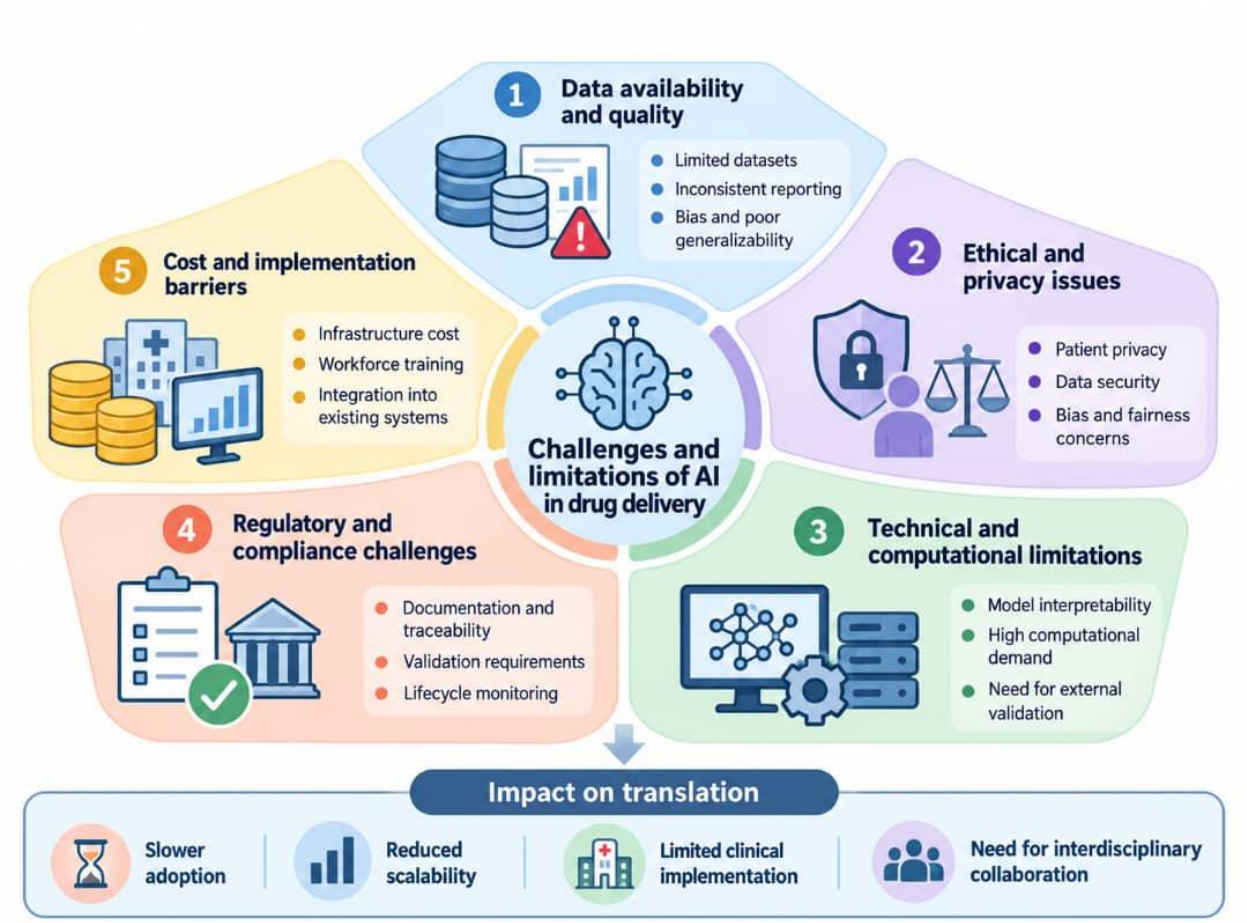


Figure 3. Major challenges and limitations affecting the translation of AI-driven drug-delivery systems. Image was created with the assistance of bioRender.

6.1 Data Quality and Availability Issue

The quality, completeness, and accessibility of data remain major challenges to the reliable application of AI in drug-delivery research. Pharmaceutical datasets are often relatively small, heterogeneous and fragmented, while differences in formulation composition, experimental conditions and reporting practices can make datasets difficult to combine. A recent analysis of liposomal drug-release data found that important formulation characteristics and experimental conditions were frequently missing, limiting the amount of usable information available for AI modelling [76]. In addition, technology, data governance, privacy, and infrastructure constraints have been recognized as crucial barriers to the adoption of AI in the health care industry. However, in addition to that, the danger of algorithmic bias in the case when the used datasets are not representative of the populations to which AI tools are applied was pointed out by Ahmed et al (2023) [77]. Regarding the field of drug delivery, Seegobin et al. (2024) showed that, even though the machine learning approaches can predict several PLGA nanoparticles' properties quite well, the accuracy varies depending on the property [23]. Hence, standardized reporting, curated and

accessible datasets, data harmonization, and external validation through novel experimental datasets are crucial.

6.2 Ethical and Privacy Concerns

The other major concern related to the use of AI technology in drug delivery and personalized medicine is the ethical and privacy issues that may arise, given the nature of information that may be used to build AI models in this case. First of all, besides the risk of hacking personal health information, there might be a problem with AI itself leaking sensitive data. For instance, it was shown that genetic data can be exposed by a machine-learning model created for personalized warfarin dosing [78]. Moreover, according to a 2025 scoping review of 38 articles, privacy and security violations, lack of informed consent process, and data leakage were among the main barriers for the reuse of health-related data for AI applications [79]. The above-mentioned problems are especially relevant to AI personalized therapy, as it might utilize health and genomic data in order to develop treatment strategies or dose adjustments.

6.3 Technical and Computational Limitations

Though promising, there are some technical and computational challenges that come with the use of AI for drug delivery applications. The primary problem associated with AI involves the poor interpretability of complex machine-learning models when predictions are hard to interpret in terms of formulation and biological variables. For instance, Song et al. (2026) built an interpretable two-stage XGBoost model based on 321 drug-release profiles of 89 drugs encapsulated into PLGA microspheres. Though the model provided an MAE of 0.126 and the Pearson correlation coefficient of 0.831, the contribution of various variables such as molecular weights of the drug and polymer, and polymer concentration to drug release was revealed using the SHAP approach. The model was further validated using olaparib and semaglutide external data sets with MAE of 0.096 and 0.068, correspondingly. It proves that the importance of interpretability and external validation when using AI for formulation optimization. Furthermore, the model performance can significantly differ depending on the formulation property [44]. In particular, the study performed by Seegobin et al. (2024) suggested the application of design of experiments together with machine learning in order to optimize PLGA nanoparticles. Although XGBoost was successful in predicting particle sizes, both the machine learning algorithms and design of experiment models had relatively high errors when predicting zeta potential, demonstrating that while a predictive model can perform satisfactorily on one formulation parameter, it might not necessarily work well for other formulation characteristics [23]. Likewise, Chou et al. (2023) applied machine learning together with the physiology-based pharmacokinetics (PBPK) model to predict the delivery of nanoparticles in tumours of mice, and they obtained an R^2 of 0.83, 0.56, and 0.82 at 24 h, 168 h, and maximum delivery, respectively, with only 133 of the 288 datasets having an $R^2 \geq 0.70$; this indicates the challenge involved in predicting such complex biological behavior in a dataset [40]. Thus, AI models should be cross-validated and subjected to experiments and, when possible, combined with PBPK models and human expertise prior to being deployed in making drug-

delivery decisions. One of the major issues of machine learning models is overfitting and data leakage, especially with drug-delivery datasets having relatively fewer observations compared to the model parameters or with formulations from the same experiment being part of the training and testing datasets. The potential for such techniques exists to lead to seemingly excellent predictive performance that is not necessarily sustainable when the model is used with actual independent formulations, batches, laboratories, or patients. The applicability domain of a model thus needs to be considered: one needs to take care while making predictions if the chemical structure of the new compound(s), the composition of the formulation(s), process conditions, or the biological properties of the new patients lie outside the range covered by the training set. Model development thus requires proper partitioning of the data, nested or cross-validation where necessary, external independent data sets, uncertainty assessment, and prospective experimentation. Reproducibility in other laboratories and manufacturing batches is also crucial since variations in the raw material sources, instruments, process conditions, and analytical techniques may affect the performance of the formulation.

6.4 Regulatory and Compliance Challenges

The rapid development of AI in pharmaceutical research and drug delivery presents regulatory challenges because existing regulatory frameworks were not originally designed for continuously evolving, data-driven technologies. Nevertheless, regulatory authorities are increasingly developing specific approaches for the responsible use of AI. In 2024, the European Medicines Agency (EMA) adopted a reflection paper addressing the use of AI and machine learning throughout the medicinal-product development, from drug discovery to post-authorisation activities, with emphasis on appropriate validation, data quality, human oversight and risk management [80]. The US Food and Drug Administration (FDA) subsequently issued draft guidance in January 2025 proposing a risk-based framework for assessing the credibility of AI models according to their specific context of use when AI-generated information is submitted to support decisions concerning the safety, effectiveness or quality of drugs and biological products [81].These considerations are particularly relevant to AI-assisted drug-delivery systems, where AI may influence formulation design, manufacturing, quality control or patient-specific dosing. The FDA and EMA have also jointly established ten guiding principles for good AI practice in drug development, covering evidence generation and monitoring across research, clinical development, manufacturing and safety monitoring [82]. Therefore, future implementation of AI in drug delivery will require documented model development and validation, appropriate human oversight, traceability, lifecycle monitoring and robust quality-control procedures to demonstrate that AI-assisted processes consistently meet established standards for pharmaceutical quality, safety and efficacy. These considerations should also be aligned with established pharmaceutical quality and development principles. International Council for Harmonisation (ICH) Q8–Q10 provide an important framework for pharmaceutical development, quality-risk management and pharmaceutical quality systems, while credibility assessment of computational models emphasises demonstrating that a model is fit for its intended context of use. For AI-enabled drug-delivery

systems, validation should therefore address not only predictive performance during development but also the consequences of model updates, changes in input data, software modifications and changes in manufacturing processes. Where adaptive algorithms are incorporated into GMP-regulated processes, appropriate change-control procedures, version control, performance monitoring and predefined criteria for revalidation will be necessary to ensure that model evolution does not compromise product quality or patient safety.

6.5 Implementation Barriers and Cost of AI

In addition to technical barriers and regulatory constraints, the deployment of AI in drug delivery research and practice may also be constrained by resource-related requirements, including financial, infrastructural and workforce needs. The deployment of AI technology may entail investments in computing capacity, software and secure data, AI model validation, maintenance, and specialized technical expertise. In a systematic review of 59 papers on infrastructure, interoperability, training for the workforce, financial resources and maintenance have been identified as some of the most important factors impeding successful implementation, and it has been noted that implementation may entail significant restructuring of the existing information technology system [77]. Such barriers may be especially salient in pharmaceutical production, where AI applications need to be integrated with existing machines and quality control procedures and cannot be implemented as stand-alone technologies. Furthermore, AI algorithms need to be updated periodically in light of new data, which creates continuous demands for validation and maintenance. This has been found recently in the context of healthcare as well [83]. Hence, for the success of AI-based drug delivery, apart from making investments in the required computational facilities, training of the workforce, interoperability with the current pharmaceutical system, maintenance of the technology, and proper cost-benefit analysis would be essential.

7.0 Future Perspectives

7.1 Emerging Directions in AI-Enabled Drug Delivery

Future research into AI-enhanced drug delivery systems may extend beyond prediction and optimization and go into personalization and integration of the technology into digital systems. An example of such a direction for research involves the integration of AI with 3D printing to design personalized dosages through patient needs matching with formulations and production. Current research demonstrates how AI-enabled 3D printing may enable the formulation optimization, release, and on-demand production of personalized drugs [84]. In general, AI may become the means to facilitate the integration of formulation design, pharmacokinetics prediction and digital manufacturing [85].

7.2 Toward Autonomous and Closed-Loop Drug Delivery

A key future research area includes closed-loop drug delivery systems which involve continuous physiological monitoring, computation and decision making, and automated drug delivery based on physiological conditions rather than on pre-programmed dosing regimens. Paci et al. (2025)

have highlighted the emerging combination of biosensors with wearable/implantable delivery devices, and algorithms based on artificial intelligence as a potential route towards such adaptive and personalized therapies. Nonetheless, the clinical adoption of such systems requires further advancements in terms of biosensor stability, integration, safety, regulatory approval, and clinical evidence [86]. The digital twin concept involves creating a computational representation of a patient, formulations, or even a manufacturing process, and updating it based on new data in order to allow predictive analysis and personalized decision making. In recent years, pharmaceutical science has been advancing ideas for the use of digital twins in applications from drug discovery and manufacturing to personalized medicine. However, there are still several major issues related to data integration, reliability of models, regulation, and privacy [87,88].

7.3 AI–Nanotechnology–Biotechnology Convergence

The emergence of interactions between AI and nanotechnology/biotechnology is likely to lead to the development of ever more advanced drug delivery systems. Within the domain of nanomedicine, machine learning is able to help with navigating through the vast design space of nanocarrier compositions, including predicting the properties related to their delivery efficiency and tissue distribution patterns. For instance, a transformer-based neural network introduced in 2025 was designed specifically to tackle the complexity of the composition of lipid nanoparticles and provide computational predictions regarding their properties and performance [89]. In connection with biotechnology, there are emerging applications of machine learning for the engineering of artificial cells and receptors or genetically programmed circuits, which can serve as living drug delivery platforms [90]. The same applies to the AI-assisted analysis and engineering of extracellular vesicles that allows for optimizing targeting, cargo loading, and delivery [91]. It appears that the future will see the integration of AI with biological and nanotechnological systems rather than its usage as a standalone computational technique.

7.4 Priorities for Future Research

7.4.1 Development of Standardized and FAIR-Compliant Datasets

Future studies must focus on creating curated and standard datasets which could help build an AI model in drug delivery. FAIR (Findable, Accessible, Interoperable and Reusable) data principles must be implemented in future drug-delivery AI studies to make sure that formulation, nanocarrier and pharmacokinetics datasets are easily reusable and integrated. This is especially the case with nanomedicines because their formulation and in vitro release data can be found scattered across multiple articles and laboratories and are often reported in different parameter sets. The recent study on nanomedicine formulations and release data made ready for AI showed the importance of databases and reporting guidelines in improving data accessibility and harmonization [76].

7.4.2 Development of Multimodal and Multiscale AI

In the future, it is important that AI tools be used more and more to incorporate information gathered on different scales in drug delivery, from molecules and formulations to

pharmacokinetics, biodistribution, imaging, omics, and clinical results. It seems that these multistep approaches will give a more complete picture of the complexity of the interactions involved in drug delivery than the use of models based on separate datasets. The creation of digital twins and AI-based multiphysics models is one such approach [92].

7.4.3 Prioritisation of Explainable and Trustworthy AI

As AI becomes increasingly involved in formulation design, dose optimisation and patient-specific drug delivery, explainability and trustworthy model development will become increasingly important. Future research should therefore combine predictive performance with interpretable modelling, uncertainty estimation, appropriate external validation and transparent reporting. Regulatory initiatives already emphasise clear context of use, data governance, multidisciplinary expertise, risk-based performance assessment and lifecycle management as important elements of responsible AI development [82]. These principles should be incorporated into AI-driven drug-delivery research from model development through clinical and manufacturing implementation.

7.4.4 Strengthening Interdisciplinary Collaboration and Knowledge Transfer

The development of clinically useful AI-driven drug-delivery systems will require collaboration among pharmaceutical scientists, computational scientists, engineers, pharmacologists, clinicians, data scientists, regulatory specialists and ethicists. AI models developed in isolation may have limited translational value if they cannot be integrated with experimental workflows, manufacturing systems or clinical practice. Implementation studies in healthcare have identified information-technology infrastructure, access to knowledge, organisational factors and workflow integration as important determinants of successful AI adoption [93]. Future research should therefore encourage multidisciplinary collaborations, shared model repositories, benchmarking datasets and reproducible computational workflows.

7.4.5 International Harmonization of Regulatory Frameworks

As AI-enabled drug-delivery technologies become increasingly integrated into pharmaceutical development and manufacturing, greater international harmonisation of regulatory expectations will be important. The FDA and EMA issued ten guiding principles on good AI practices for drug development in 2026, covering issues such as human-centered design, risk-based approach, data governance, model development, performance testing and management [82]. In future regulatory research, it would be beneficial to elaborate upon these principles to develop internationally consistent approaches to the validation, documentation, change control, and monitoring of AI-powered pharmaceutical devices.

7.4.6 Sustainability, Cost and Equitable Access

When looking into the future development of AI-based drug-delivery mechanisms, one should take not only into account their technological performance, but also the question of their sustainability, economic viability and availability. On the one hand, there may be certain limitations connected with the computational power required, expertise needed, and the cost of maintaining the system. On the other hand, digital health solutions can improve accessibility and decrease costs associated with treatment; yet they may increase inequality in access to technology [94]. Future research should therefore incorporate life-cycle and cost-effectiveness assessments, energy-efficient computational approaches, scalable manufacturing strategies and equity considerations into the development of AI-enabled drug-delivery technologies. Designing affordable, interoperable and context-appropriate systems will be particularly important for ensuring that advances in AI-driven drug delivery are not restricted to highly resourced healthcare settings.

Conclusion

Artificial intelligence is increasingly becoming an important component of drug-delivery research, extending its application from formulation optimisation and nanocarrier design to drug-release modelling, targeted delivery, pharmacokinetic evaluation, personalised dosing, and wearable, implantable and adaptive delivery systems. The studies reviewed demonstrate that AI can identify complex relationships within formulation and biological datasets and help prioritise promising formulations and delivery strategies, thereby reducing experimental burden. Nonetheless, it is currently apparent that the use of AI must be seen as a complementary strategy rather than as a substitute for experimental research and clinical practice. The accuracy and reliability of AI-based methods for drug delivery are still determined by the quality of data, proper validation, interpretability, and experimental/clinical evaluation. New approaches in which AI is combined with nanotechnology, biotechnology, advanced manufacturing, biosensors, digital twins, and closed-loop systems may provide new chances for personalization and adaptation of drug delivery, yet they have different states of clinical implementation. In essence, the value of using AI in drug delivery must be assessed in terms of safety, efficiency, repeatability, affordability, and clinical significance beyond mere predictive accuracy and computational efficiency.

List of Abbreviations

ADME…Absorption, Distribution, Metabolism and Excretion

AGILE…AI-Guided Ionizable Lipid Engineering

AI…Artificial Intelligence

AIDA…AI Drug Mix and Dose Advisor

ANN….Artificial Neural Network

API….Active Pharmaceutical Ingredient

AUC…Area Under the Curve

BSA…Bovine Serum Albumin

Cmax…Maximum Plasma Concentration

CRISPR…Clustered Regularly Interspaced Short Palindromic Repeats

DL…Deep Learning

DoE…Design of Experiments

DSC…Differential Scanning Calorimetry

EHR…Electronic Health Record

EMA…European Medicines Agency

FAIR…Findable, Accessible, Interoperable and Reusable

FDA…Food and Drug Administration

FDA-DOEs… Functional Data Analysis Combined with Design of Experiments

FTIR…. Fourier-Transform Infrared Spectroscopy

GMP…Good Manufacturing Practice

GNN…Graph Neural Network

HbA1c…Glycated Haemoglobin

ICH… International Council for Harmonisation

IoT…. Internet of Things

LNP…Lipid Nanoparticle

LORIS…Logistic Regression-based Immunotherapy-Response Score

MAE…Mean Absolute Error

ML…Machine Learning

MOMLIN… Mmulti-modal and -omics Machine Learning Integration

mRNA…Messenger RNA

PBPK…Physiologically Based Pharmacokinetic

PD…Pharmacodynamic

PEG…Polyethylene Glycol

P-gp ... P-glycoprotein

PK … Pharmacokinetic

PLGA…Poly(lactic-co-glycolic acid)

PLGA-PEG…Poly(lactic-co-glycolic acid)–Polyethylene Glycol

PPB…Plasma Protein Binding

PSMA: Prostate-Specific Membrane Antigen

QSAR…Quantitative Structure–Activity Relationship

RF…Random Forest

SHAP…Shapley Additive Explanations

SVM…Support Vector Machine

Tmax…Time to reach Maximum Plasma Concentration

Vd…Volume of Distribution

XAI…Explainable Artificial Intelligence

XGBoost…Extreme Gradient Boosting

XRD…X-ray Diffraction

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