Smart Pharmaceutical Formulation and Drug Delivery Using AI

Prikshit Thakur[1], Dr. Shivalika [2], Akriti Vyas [3], Priyanshi [4], Ritika [5]

[1]Student, Abhilashi College of Pharmacy, Ner chowk, Himachal Pradesh, 175008, India

[2]Associate Professor, Abhilashi College of Pharmacy, Ner chowk, Himachal Pradesh, 175008 India

[3]Assistant Professor, Abhilashi College of Pharmacy, Ner chowk, Himachal Pradesh, 175008 India

[4]Student, Abhilashi College of Pharmacy, Ner chowk, Himachal Pradesh, 175008, India

[5]Student, Abhilashi College of Pharmacy, Ner chowk, Himachal Pradesh, 175008, India

DOI: https://doi.org/10.51584/IJRIAS.2026.11050136

Received: 08 May 2026; Accepted: 13 May 2026; Published: 06 June 2026

ABSTRACT

Artificial intelligence and machine learning are transforming pharmaceutical formulation and drug delivery by shifting traditional trial-and-error approaches towards data-driven, predictive methodologies. This study examines the potential of AI to enhance drug development efficiency, optimise formulation design, and address significant pharmaceutical challenges such as elevated development costs, inadequate drug solubility, and intricate formulation variables. Artificial intelligence techniques, including support vector machines, deep learning models, and artificial neural networks, facilitate the rapid analysis of large datasets to predict critical quality attributes such as stability, bioavailability, and drug release profiles. AI integration in pre-formulation studies diminishes experimental workload and accelerates decision-making by facilitating accurate predictions of physicochemical properties. AI-assisted compatibility analysis and excipient selection also make formulations work better and last longer. Self-emulsifying drug delivery systems, nanomedicine, and controlled-release formulations are advanced uses that show how AI can make treatments work better. AI also cuts down on the time and money needed for traditional methods of drug discovery, target identification, and virtual screening by a large amount. AI-driven methods are more efficient, repeatable, and scalable than human-generated formulations, but issues with data quality, regulatory acceptance, and model interpretability still exist. AI also helps with managing the lifecycle, predicting stability, and optimising drug delivery systems. This makes products better and lowers the number of failures. The combination of AI with digital prototyping and Design of Experiments helps intelligent manufacturing and formulation innovation even more. Despite these drawbacks, hybrid approaches that combine human knowledge with AI capabilities hold the key to the future of pharmaceutical sciences. All things considered, AI-driven formulation techniques have enormous potential to transform pharmaceutical research by increasing precision, shortening development times, and improving patient outcomes.

Keywords: Artificial Intelligence, Drug delivery system, Designs of Experiment, Machine learning.

INTRODUCTION

The combination of machine learning and artificial intelligence techniques has recently been a major catalyst in the revolution of pharmaceutical formulation design. This fusion of cutting- edge computational techniques with conventional pharmaceutical sciences presents previously unheard-of chances to spur innovation and optimise procedures throughout the drug development spectrum. Machine learning is a subfield of artificial intelligence that focuses on learning strategies that are appropriate for machines. These strategies enable machines to learn valuable information from external input data, just like humans do, and to enhance their processing capabilities based on newly learned data. Machine learning is often recognised as the most effective method for predicting illnesses such as heart disease and asthma. Artificial Intelligence improves the design of preclinical and clinical

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

studies, forecasts toxicity, and expedites regulatory decision-making in drug development. The nature of the particular ceramic being processed as well as the requirements for density, surface finish, size, and geometrical complexity of the part all play a role in choosing the best Additive manufacturing process for a given application. AI's potential for the pharmaceutical sector. In recent years, neural networks have become a feasible alternative. Neural networks are mathematical structures that can "learn" correlations in data without user input. AI employs methods for gathering the massive volumes of data produced by those clinical trials, thereby lowering the number of data workers needed for the same. Artificial intelligence is the term used to describe the simulation of human intelligence in machines that have been trained to think, learn, and solve problems in ways that are similar to human cognitive processes. AI has many uses in a variety of sectors, such as healthcare, banking, entertainment, and transportation. It can be applied to simple automation tasks as well as more complicated procedures like predictive analytics, data analysis, and decision-making. By increasing productivity, accuracy, and the capacity to manage massive amounts of data, AI technologies like computer vision, machine learning, and natural language processing have completely transformed these sectors. Artificial intelligence is a field of computer science that focuses solely on solving problems and building machines that can perform tasks that would otherwise require human operators and intelligence. Artificial intelligence, 3D printing, robots, and nanotechnology are examples of digital health-care innovations that have enormous potential to influence the future of healthcare by lowering human error, enhancing therapeutic results, and enabling long-term data monitoring. In many scientific fields, AI has become a game-changing in silico tool, and its potential to improve pharmaceutical 3D printing technology is becoming more widely acknowledged. A key component of drug development is the creation of pharmaceutical formulations that are stable, safe, and effective. Formulation scientists have traditionally used empirical techniques and trial-and-error experimentation to optimise drug-excipient combinations, process parameters, and dosage forms. These conventional methods often take a lot of time and money, and they might not always yield the most dependable or efficient outcomes. Artificial intelligence in nanomedicine, including liposomes, solid lipid nanocarriers, niosomes, and self-micro emulsifying drug delivery systems, has recently been adopted by pharmaceutical research and development. The use of nanomedicines to address problems with toxicity, poor aqueous drug solubility, and lack of site-targeting following drug administration has grown. Techniques like self-emulsifying drug delivery systems are becoming more and more acknowledged as practical methods, techniques like SEDDS are becoming more and more acknowledged as practical methods. Through self-emulsification, SEDDS improve the bioavailability of poorly soluble medications, facilitating better absorption and distribution of active ingredients in the gastrointestinal tract, through self-emulsification. SEDDS improve the bioavailability of poorly soluble medications, facilitating better absorption and distribution of active ingredients in the gastrointestinal tract. Institutions are increasingly using AI-based solutions that aim to improve society's well-being because it can also be used to solve public policy issues. Modern computers' ability to process information and AI tools have made it possible for them to be used in a variety of institutional tasks, addressing both internal and external issues. In the past, finding appropriate formulations that guarantee both medication efficacy and patient safety frequently required a great deal of laboratory experimentation and trial and error. Complex biological, chemical, and clinical data can be analysed by AI algorithms at previously unheard-of speeds, revealing patterns that human researchers might miss. These milestones underscore a shift from speculative promise to practical utility, highlighting the capacity of AI to accelerate development timelines, reduce costs, and improve the likelihood of clinical success.

Current Pharmaceutical Challenges:

The pharmaceutical industry is dealing with previously unheard-of difficulties in the areas of manufacturing, regulatory approval, drug discovery, formulation development, and lifecycle management. The cost, time, and complexity of creating pharmaceutical products that are safe, effective, and stable keep rising despite tremendous advancements in science and technology. AI has emerged as a crucial enabling technology to address many of these challenges in a methodical, predictive, and economical way, as the analysis of the chosen literature makes abundantly evident.

High Cost and Time Consumption in Drug Development:

The lengthy and expensive drug development process is one of the pharmaceutical industry's biggest problems. Trial-and-error experimentation is a major component of traditional formulation development, necessitating

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

extensive laboratory testing, animal studies, and clinical trials. Every formulation modification, particularly in later phases, may necessitate regulatory resubmissions and bioequivalence studies, which would raise costs and postpone market entry.

Poor Drug Solubility and Bioavailability:

Poor aqueous solubility is a common feature of recently discovered drug molecules, and it has a direct impact on bioavailability and therapeutic efficacy. The target site frequently does not receive adequate drug concentrations from conventional dosage forms. Solid dispersions, lipid-based drug delivery systems, and nano-formulations have all gained popularity as a result of this difficulty.

Complexity of Pharmaceutical Formulations:

These days, pharmaceutical products are more than just basic concoctions of excipients and active ingredients. Particle size, spatial distribution, and excipient interactions are examples of qualitative, quantitative, and structural characteristics that determine formulation performance instead.

Data Limitations and Poor Data Quality:

A significant issue has been brought to light by the growing application of AI and machine learning in pharmaceutical development: the availability and quality of data. The quality of the datasets used to train AI models determines their dependability. Numerous pharmaceutical databases contain data produced using various protocols or standards and are unstructured, lacking, or inconsistent.

Regulatory and Validation Challenges:

For pharmaceutical products, regulatory bodies demand transparency, reproducibility, and a solid scientific basis. Although in silico modelling and AI-driven formulation design can greatly speed up development, regulatory validation of AI-based tools is still a significant obstacle.

Role of Artificial Intelligence in Addressing These Challenges:

The reviewed literature continuously shows how AI transforms pharmaceutical development by moving away from empirical experimentation and towards data-driven, predictive decision-making.

AI in Formulation Design and Optimization:

AI tools like deep learning models, random forests, support vector machines and artificial neural networks have demonstrated a remarkable capacity to model intricate relationships between formulation variables and product quality attributes. These models are highly accurate in predicting the mechanical characteristics of dosage forms, drug release profiles, dissolution behaviour, and disintegration time.

AI-Based Excipient Selection and Compatibility Prediction:

Once thought to be inert, excipients are essential for stability, bioavailability, and manufacturing. AI models make it possible to quickly screen excipient libraries and predict degradation risks, polymorphic transitions, and drug–excipient compatibility.

AI in Stability Prediction and Lifecycle Management:

Stability prediction is among the most significant uses of AI. To forecast beyond-use dates and shelf life, AI driven platforms like Smart Formulation systems integrate molecular descriptors, formulation composition, packaging type, and environmental factors. This method provides a workable substitute for long-term stability studies, especially for generic and compounded goods. AI supports post-approval modifications, reformulation tactics, and product optimisation in lifecycle management. This is particularly helpful in the development of generic drugs, where it is crucial to quickly adjust to changes in regulations and raw material variability.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

AI and Quality by Design Integration:

AI makes multivariate risk assessment and design space exploration possible, which significantly enhances QbD principles. AI models facilitate the proactive identification of critical material attributes and critical process parameters by learning from experimental and historical data.

Limitations and Regulatory Considerations:

Notwithstanding its benefits, adopting AI is fraught with issues pertaining to regulatory acceptance, model interpretability, and data quality. Since many AI models operate as "black boxes", it can be challenging to justify predictions in regulatory filings.

AI Tool Application in Dosage Form Designs:

Because it has a direct impact on drug stability, bioavailability, therapeutic efficacy, and patient compliance, dosage form design is a crucial phase in pharmaceutical development. Traditional formulation development is a time-consuming, costly, and resource-intensive process that primarily relies on empirical methods and repeated laboratory trials. Traditional methods frequently fail to effectively optimise formulation variables due to the growing complexity of drug molecules and delivery systems. A potent tool for overcoming these obstacles is artificial intelligence, which includes machine learning, deep learning and data-driven modelling approaches. AI makes it possible to predict critical quality attributes, find hidden patterns, and analyse large and complex datasets quickly. Consequently, pre-formulation studies, excipient selection, dosage form optimisation, quality prediction, and advanced drug delivery systems are all using AI more and more.

Role of AI in Pre-Formulation Studies:

Understanding the physicochemical characteristics of API, such as their solubility, stability, polymorphism, and compatibility with excipients, is the goal of pre-formulation studies. Drug solubility, hygroscopicity, and degradation tendencies can be accurately predicted by machine learning algorithms, various tools and models occurring in ML like random forest models, support vector machines and artificial neural networks. These forecasts expedite decision-making in the early stages of formulation development and greatly minimise the need for extensive laboratory screening.

AI-Based Excipient Selection and Optimization:

To find the best formulations, AI models can examine multivariate datasets that include excipient type, concentration, and physicochemical characteristics. Research has demonstrated that when it comes to forecasting tablet characteristics like hardness and disintegration time, AI-based models perform better than traditional statistical techniques. AI also makes it easier to find new polymeric excipients for targeted and controlled-release drug delivery systems, which promotes formulation innovation. Dotmatics Platform are AI based tools that are enabled the formulation optimization.

AI in Quality Prediction and Stability Studies:

Another significant use of AI in dosage form design is quality prediction. By offering scientifically supported predictions, these predictive tools support regulatory submissions and help shorten the time and expense of long-term stability studies during early development stages.

Role of AI in Drug Discovery and Development:

The high expense, protracted timelines, and high attrition rates typically associated with pharmaceutical research have been addressed by artificial intelligence, which has emerged as a game-changing technology in drug discovery and development. From target identification to post-marketing surveillance, artificial intelligence improves efficiency at several stages of the drug development pipeline by combining machine learning, deep learning, neural networks, and data-driven modelling.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

Target Identification and Validation:

AI is essential for locating new biological targets linked to illnesses. Large-scale omics datasets, such as transcriptomics, proteomics, and genomics, can be analysed by machine learning algorithms to find genes and protein interactions linked to disease. Researchers can validate targets more quickly than with traditional experimental methods thanks to sophisticated computational models that predict protein structure, function, and drug–target interactions. Pattern recognition in intricate biological networks is made easier by AI driven bioinformatics tools, which also drastically cut down on the time needed to generate hypotheses and validate targets.

Hit Identification and Virtual Screening:

AI speeds up hit identification in early drug discovery by using quantitative structure activity relationship modelling and virtual screening. Conventional approaches to high-throughput screening are expensive and time-consuming. AI based virtual screening finds possible hits with good pharmacological qualities and high binding affinities by analysing millions of chemical compounds in silico using predictive algorithms. The prediction of biological activity, toxicity, and pharmacokinetic characteristics is improved by machine learning techniques like support vector machines, artificial neural networks, and deep learning models. These models improve the accuracy of active compound predictions by learning from past chemical and biological data. AI powered QSAR models optimise compound selection prior to laboratory synthesis by correlating molecular descriptors with biological activity.

Drug Repurposing:

AI has greatly improved methods for repurposing drugs. Artificial intelligence algorithms find novel therapeutic applications for approved medications by examining current clinical and molecular data. In order to find hidden connections between medications and illnesses, machine learning models search through clinical trial databases, biomedical literature, and empirical data. Because the safety profiles of current medications are known, this method cuts down on development time and expense.

Comparing AI-generated to human-generated formulations:

Traditional formulation development procedures have changed as a result of the incorporation of artificial intelligence into pharmaceutics. Pharmaceutical formulations have traditionally been created using expert intuition, trial-and-error testing, and empirical knowledge. But new research shows that AI, especially machine learning and generative models, can create, optimise, and even produce new formulations. There are significant variations in creativity, efficiency, reproducibility, scalability, and data dependency between formulations produced by AI and those created by humans.

Traditional Human-Generated Formulations:

Iterative experimentation, previous literature, and domain expertise are all major components of human-generated formulations. Researchers manually optimise formulation parameters like critical material attributes, critical process parameters, and critical quality attributes in drug delivery systems and nanomedicine. For instance, a number of interrelated factors, such as particle size, cholesterol content, drug hydrophobicity, release media composition, pH, and temperature, affect how drugs release in liposomal systems.

AI-Generated Formulations:

AI-generated formulations predict or create new compositions by using machine learning algorithms that have been trained on massive datasets. By evaluating intricate relationships between APIs and excipients and forecasting stability, bioavailability, and efficacy, artificial intelligence improves formulation design.

Challenges and Future Perspectives:

Future advancements will probably use hybrid strategies that combine human expertise with AI-driven

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

prediction. To fully utilise AI's potential, open-access, carefully curated databases for formulation and nanomedicine data must be established.

Key Differences Between AI-Generated and Human-Generated:

The key difference between AI generated and Human Generated are about the Creativity, innovation, speed, efficiency, data dependency, reproducibility and standardization. Main key difference between AI and Human generated formulation are about those formulations that are occurs according to new innovation, reproducibility, Creativity etc.

Optimization of Drug Delivery Systems using AI and ML:

The optimisation of drug delivery systems has changed dramatically as a result of the incorporation of artificial intelligence and machine learning into pharmaceutical sciences. Drug delivery development has historically mainly relied on empirical trial-and-error techniques, which were expensive, time-consuming, and frequently ineffective. However, a methodical, data-driven approach that improves formulation accuracy, stability, bioavailability, and overall therapeutic effectiveness has been introduced by AI-driven predictive modelling and data analytics. While machine learning, a subset of artificial intelligence, allows systems to learn from data and enhance performance without explicit programming, artificial intelligence refers to computer systems that can mimic human intelligence. These technologies examine vast and intricate datasets in pharmaceutics to find trends and connections between excipients, formulation parameters, and drug characteristics. This ability has been especially helpful in improving drug delivery methods like transdermal systems, liposomes, nanoparticles, and controlled-release tablets. Formulation design is one of the main uses of AI in drug delivery optimisation. Multiple formulation parameters, such as polymer concentration, particle size, pH, solubility, and excipient compatibility, can be evaluated concurrently by ML algorithms. AI models are able to forecast the ideal compositions that guarantee increased stability, efficacy, and bioavailability by recognising nonlinear relationships between these variables. This lessens the effort required for experiments and increases the likelihood of creating reliable formulations. Predicting drug stability is another important area where AI plays a big role. Safety, therapeutic efficacy, and shelf life are all directly impacted by stability. Degradation pathways under varied environmental conditions, including temperature, humidity, and light exposure, are simulated by AI models. ML algorithms can precisely forecast possible degradation products and stability problems in the early stages of development by examining physicochemical and environmental data. This predictive ability guarantees improved product quality and reduces expensive reformulations. AI tools are used in preclinical development to mimic biological processes and forecast how drugs will behave in the body. Predictive modelling like this lessens reliance on animal testing and recurring lab experiments. AI-powered simulations help save time and money by optimising dosage forms prior to clinical trials. Additionally, ML-based analytics increase the chance of clinical success by assisting in the early identification of possible toxicity or instability issues. Different AI & Machine Learning tools for optimization of drug delivery are ANN, SVM & random forest models.

AI in Pre formulation Research:

Pharmaceutical development is based on pre-formulation research, which focuses on characterising active pharmaceutical ingredients prior to formulation into an appropriate dosage form. Solubility, pKa, partition coefficient, polymorphism, stability, hygroscopicity, particle size, and drug–excipient compatibility Are among the physicochemical characteristics that are studied. Pre-formulation has historically relied on costly and time-consuming trial-and-error methods and extensive laboratory experimentation. Predictive modelling, data-driven decision-making, and expedited screening have all been made possible by the combination of artificial intelligence and machine learning, which has drastically changed this stage. By forecasting drug characteristics and refining formulation parameters prior to experimental validation, artificial intelligence aids in the early stages of pharmaceutical development. In order to produce accurate predictions and reduce experimental failures, AI models examine sizable datasets that include environmental factors, excipient characteristics, degradation data, and molecular descriptors.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

AI in Physicochemical Property Prediction:

Poor aqueous solubility is a significant pre-formulation challenge, particularly for drugs classified as class II and IV by the Biopharmaceutics Classification System. Regression models, support vector machines, and artificial neural networks are examples of machine learning algorithms that can forecast solubility using physicochemical descriptors and molecular structure.

Solid-State Characterization and Polymorphism:

Drug stability, dissolution rate, and bioavailability are all greatly impacted by polymorphism. Formulation failure may result from unexpected polymorphic transitions during development. AI-based models forecast potential solid-state transformations and polymorphic stability by analysing thermal and crystallographic data. Predictive modelling supports Quality by Design principles by assisting in the early identification of stable crystal forms, according to the review on AI in generic formulation development.

Drug–Excipient Compatibility Studies:

Pre-formulation compatibility studies are crucial to prevent degradation, instability, or decreased therapeutic efficacy. Stress studies conducted under accelerated conditions are a component of traditional compatibility testing. However, by examining chemical structures and past compatibility data, AI models are able to forecast how APIs and excipients will interact.

Stability and Degradation Prediction:

An additional crucial element of pre-formulation is stability assessment. Artificial intelligence algorithms examine the kinetics of degradation in various environmental settings, including exposure to light, humidity, and temperature. Using accelerated stability data, predictive models can model long-term stability behaviours.

A.I. in the Controlled-Release Tablet Formulation:

Traditional formulation methods frequently involve trial-and-error testing, which can be time-consuming and resource-intensive. Artificial intelligence techniques such as machine learning, artificial neural networks, genetic algorithms, and fuzzy logic models were developed to circumvent these limitations.

Designing Controlled-Release Tablets with Artificial Neural Networks:

Based on formulation and process features, ANN models are used to predict the drug release profile in controlled release tablet formulation. In one study, controlled-release dose forms were developed using ANN models and pharmacokinetic simulations.

Combining AI and Pharmacokinetic Modelling:

Pharmacokinetic modelling is crucial to the design of controlled release tablets because the therapeutic efficacy of a dose form depends on how the drug is absorbed, transported, metabolized, and eliminated in the body. Using ANN models, researchers can simulate different formulation compositions and determine which combinations produce dissolution profiles that match intended pharmacokinetic goals.

Advantages of AI-Powered Controlled-Release Formulation:

Using artificial intelligence to create controlled release tablets has a number of important advantages for pharmaceutical research and manufacturing. First, by improving prediction accuracy for drug release behaviour, AI systems enable more reliable design of sustained-release dosage forms. AI contributes to improved product quality and industrial efficiency. By predicting optimal formulation parameters and process conditions, AI solutions help reduce product performance variability and ensure consistent production results. These advantages are making AI a more valuable tool in the development of pharmaceutical products.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

Processing and Formulation Variable Optimization:

One of AI's primary advantages in the creation of pharmaceutical formulations is its ability to continuously evaluate a number of formulation and processing factors. Controlled release tablets often contain complex combinations of active pharmaceutical ingredients, polymers, binders, fillers, and lubricants. Each component influences the stability and rate of release of the finished product. AI techniques that can evaluate include genetic algorithms and neural networks the relative importance of these elements and select the optimal combinations.

Use of AI Tools For Better Product Development:

Utilizing AI Tools to Improve Product Development:

AI has become a key technical improvement in many fields, including pharmaceuticals, manufacturing, and digital technology. It makes it much easier to make products. By using AI solutions, businesses can look at huge amounts of data, improve the efficiency of their designs, and cut the time and cost of developing new products. Machine learning, neural networks, genetic algorithms, and computer vision are all examples of artificial intelligence technologies that are important for making new products today because they help people make better decisions and be more creative.

Product Development and Artificial Intelligence's Role:

In the past, people used their own experiences, experiments, and trial-and-error methods to develop new products. But these methods can take a lot of time and money. AI systems help get around these limits by looking at complicated datasets and finding patterns that people might miss. For example, artificial neural networks can predict events and find connections in huge datasets without having to use pre-made mathematical models. This feature lets engineers and researchers quickly pick the best product configuration by comparing different design options.

Data-driven development and intelligent manufacturing:

In modern manufacturing settings, sensors and monitoring systems create a lot of data. AI techniques are essential for the analysis of this vast quantity of organized and unstructured data. Machine learning algorithms can be used to optimize production processes in real time, find patterns, and predict how systems will behave. For example, computer vision systems can watch over machines in factories and find problems like small cracks, machines that move in strange ways, or mistakes in production.

Cost-Reduction and Digital Prototyping:

Another big benefit of AI tools is that they can help with digital prototyping. AI lets businesses test product ideas in a virtual environment before making real prototypes. During the early stages of development, developers can identify design issues by simulating the product's performance in various configurations.

AI for Predicting Clinical Outcomes in Dermatology:

AI for Dermatology Clinical Outcome Prediction:

These tools look at complex clinical, imaging, and biological datasets to figure out how well a patient will respond to therapy, how their illness will progress, and how happy they will be with their care. AI-driven predictive technologies can help dermatologists make better treatment plans, cut down on trial-and-error methods, and give each patient the care they need, since the way a disease shows up and how a person responds to treatment can be very different. Recent studies show that AI is being used more and more to guess how well treatments will work for a number of skin problems, including psoriasis, skin cancer, and viral skin infections. Initial data indicates encouraging predictive accuracy and clinical applicability, notwithstanding the relatively limited research in this domain compared to diagnostic AI applications.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

Predicting Treatment Response and Disease Outcomes:

One of the most important uses of AI in dermatology is to predict how well treatments will work. Machine learning models can look at things like a patient's demographics, clinical parameters, disease severity scores, and treatment history to find patterns that can help them figure out whether a treatment will work or not.

Predicting Response in Viral Skin Diseases:

Traditional wart treatment methods often involve trying different treatments, such as cryotherapy or immunotherapy, until one works. Developed a fuzzy logic-based predictive model to tackle this issue, utilizing data from 180 patients undergoing wart therapy. The model got an AUC of 0.902 because it was able to predict treatment outcomes with 80% accuracy for cryotherapy and 98% accuracy for immunotherapy. These models are very helpful in clinical practice because they give doctors clear rules for making decisions that are easy to understand.

Future Perspectives:

AI in dermatology is moving toward making integrated prediction platforms that use clinical data, imaging analysis, and patient-reported outcomes. These tools could help dermatologists make the best choice, guess how the condition will get worse, and give better advice to patients.

AI Driven Microbiome and Prebiotics Modulation:

AI- Prebiotics Modulation with Prebiotics Modulation:

Machine learning and artificial intelligence have recently become powerful tools for research in dermatology and cosmetics, especially when it comes to changing the skin microbiome. The skin microbiome, which is made up of many different types of microorganisms that live on human skin, is important for keeping the immune system in balance, keeping the skin barrier strong, and keeping the skin healthy in general. Dysbiosis, or an imbalance of microbes, is linked to acne, rosacea, dermatitis, and other inflammatory skin diseases. AI-driven methods are being used more and more to look at microbiome datasets, predict how microbes will interact with each other, and make targeted prebiotic formulations that improve skin health and restore microbial balance.

The Skin Microbiome's Function in Dermatological Health:

The skin microbiome is made up of a wide range of bacteria, fungi, and other microorganisms that live in specific areas on the skin's surface. These bacteria help protect the skin by controlling immune responses and keeping harmful organisms from settling on the epidermal barrier. Changes in the microbial composition, on the other hand, could make these protective roles less effective.

AI-Powered Methods for Microbiome Studies:

AI technology has made it much easier to look at huge microbiome datasets. Machine learning algorithms can find patterns in microbial communities and predict how certain substances will change the microbiome's makeup. Traditional experimental techniques for investigating microbial interactions are time-consuming and inadequate for analysing complex data. AI, on the other hand, makes it possible to do high-throughput analysis and predictive modelling, which makes it easier to find new chemicals that change the microbiome.

Outcomes and Benefits of AI-Driven Microbiome Modulation:

AI-driven microbiome manipulation has a lot of benefits for skin care and beauty products. These include making products work better, finding ingredients faster, and being able to make skincare products that are unique to each person's microbiome profile.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

AI Applications in Preservatives Development:

AI Uses in the Development of Preservatives:

Preservatives are important parts of cosmetic products because they keep them from getting contaminated by bacteria and make sure, they stay stable while they are being stored and used. However, there is a big need for safer alternatives because more people are learning about the health risks of some preservatives, like parabens, formaldehyde-releasing agents, and isothiazolin4ones. AI-driven predictive models are now being used to speed up the making of preservatives by looking at huge databases of chemicals and toxins. This helps scientists find new antimicrobial compounds and better judge their safety.

Preservatives' Function in Cosmetic Formulations:

Preservatives are necessary to keep cosmetics safe from bacteria and extend their shelf life. Preservatives protect against contamination by bacteria, fungi, and yeast. This is important because cosmetics often have water and organic materials that help microbes grow. Without good preservation methods, cosmetic products can go bad quickly, which is bad for users' health. Traditionally, preservatives have been found through trial-and-error and experimental screening. To assess the antibacterial activity, stability, and toxicity of these procedures, substantial laboratory testing is necessary. These methods are costly, time-consuming, and often necessitate animal testing to evaluate safety. The use of AI technologies makes it possible to predict preservation qualities in silico before they are confirmed in experiments, which is a better option. One of the most important things about a preservative is that it kills bacteria. AI systems can use information about microbial inhibition to figure out the minimum inhibitory concentration needed to stop microbial growth. Researchers can determine the effectiveness of preservation chemicals without engaging in extensive microbiological studies by computationally predicting Minimum Inhibitory Concentration values. Also, machine learning can help formulators find combinations of preservatives that work well together, so they can use lower amounts of each compound and still get good antibacterial protection. This method makes the formulation safer while also lowering the risk of irritation or allergic reactions.

AI applications in surfactants designs:

Applications of AI in Surfactant Design:

Surfactants are an important part of many personal care and cosmetic products, like shampoos, cleansers, creams, and emulsions. Because their molecules are amphiphilic, they can make foam, stabilize emulsions, dissolve hydrophobic substances, and lower surface tension. Surfactants are very important for determining the texture, sensory qualities, and cleaning power of cosmetic compositions because they play these important roles. But traditional methods for developing surfactants rely heavily on time-consuming and resource-intensive empirical experiments and trial-and-error methods. The use of AI technologies has greatly improved this process by making it easier to do virtual screening, predictive modelling and find new surfactant molecules.

Surfactants' Function in Cosmetic Formulations:

Surfactants are molecules that have both hydrophilic and hydrophobic parts. They are needed for processes like emulsification, detergency, wetting, and foaming because they can work with both water and oils. Surfactants are used in cosmetics to clean hair and skin, spread active ingredients, and make the product more appealing to the senses.

Using Generative AI to Create New Surfactant Compounds:

Generative machine learning algorithms can explore chemical spaces and suggest molecular structures with useful properties. Two well-known methods in this field are variational autoencoders and generative adversarial networks. These generative models learn patterns from large databases of current surfactants and then use that knowledge to make new chemical structures that meet certain requirements. The AI model quickly finds new surfactants by making candidate molecules that meet these needs.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

AI-Powered Cleaning Formulation Optimization:

One important use of AI in making surfactants is to make cleaning formulations work better. Surfactant systems often have complicated mixes of different parts that don't interact in a straight line. These interactions can have a big effect on the final qualities of cosmetic products, like how well they clean, how they feel on the skin, and how thick the foam is.

AI in Cosmetic Formulation:

AI in the Formulation of Cosmetics:

Artificial intelligence and machine learning are changing the field of cosmetic science for the better by making it easier to make safer, more efficient, and highly personalized products. Cosmetic formulation has always depended on empirical experimentation and repeated trial-and-error testing to find the right combinations of ingredients. But thanks to advances in AI technologies, scientists can now more accurately and effectively predict formulation results by looking at huge amounts of chemical, biological, and sensory data. These breakthroughs are changing how cosmetics are researched and developed by making safety evaluations better, speeding up the discovery of new components, and making products work better.

AI's Place in the Development of Cosmetic Products:

To make cosmetics, you have to carefully choose and mix chemicals like surfactants, polymers, perfumes, preservatives, antioxidants, and prebiotics. Each part has an effect on performance, texture, stability, and safety. Before testing in a lab, researchers can use AI-based predictive modelling methods to guess how these chemicals will work and how they will interact with each other. This feature makes formulations more accurate and cuts the time and cost of product development by a huge amount.

AI in the Design and Optimization of Ingredients:

One of the best things about AI for making cosmetics is that it can help with the design and optimization of individual chemicals. AI models can predict important surfactant properties, such as essential micelle concentration, hydrophilic–lipophilic balance, toxicity, and biodegradability. Quantitative structure–activity relationship models use machine learning to look at molecular structures and guess how well they will work.

Customized Cosmetic Development:

AI is also used in the cosmetics industry to make personalized skincare products. More and more, people want products that are made just for their skin type, lifestyle, and the environment they live in. AI systems look at data like pictures of your skin, genetic information, microbiome profiles, and lifestyle factors to suggest personalized cosmetic formulations.

Artificial intelligence and its applications:

Applications of Artificial Intelligence:

Artificial intelligence is a game-changing tool in modern science, especially in medical and pharmaceutical research. It lets machines act like people by letting them think, learn, and make decisions. Artificial intelligence, along with its subfields machine learning and deep learning, are necessary for analysing complicated datasets and finding hidden patterns that are hard to find with traditional methods.

AI's Use in Drug Discovery:

One of the most important things AI can do is help make new drugs. AI has changed the way drugs are discovered in the early stages by making it easier to find leads, identify targets, and improve processes. AI can save time and money by finding potential drug targets and simulating how molecules and targets interact by looking at

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

biological datasets. AI-based methods like Quantitative Structure–Activity Relationship modelling link chemical structures and biological activity. These models significantly decrease the number of candidates required for in vivo research by facilitating the prediction of a compound's toxicity and efficacy before experimental evaluation.

Drug Repurposing and De Novo Design:

AI methods have made a big difference in de novo drug design, which is the process of making new compounds with the biological properties you want. To make new chemical structures, advanced neural network topologies like Variational Autoencoders, Recurrent Neural Networks, and Adversarial Autoencoders are used. AI also helps repurpose drugs by finding new ways to use already-approved ones to treat different conditions. AI models can cut down on the time and money needed for traditional drug development by using genetic, phenotypic, and chemical data to find new uses for drugs.

AI in the Development of Formulations:

Traditional formulation development is often tedious and dependent on trial-and-error techniques. Artificial intelligence is a better alternative because it can predict how active pharmaceutical ingredients and excipients will interact with each other. AI-based models can help improve formulation factors like stability, solubility, and drug release profiles.

DoE Software Integration with AL/ML:

The integration of Design of Experiments with Artificial Intelligence and Machine Learning has markedly advanced pharmaceutical research, particularly in formulation development and process optimization. DoE has been used in the past to carefully look at how different formulation variables and responses are related to each other.

Evolution from Conventional DoE to AI-Driven Systems:

DoE is a statistical method that helps find important process parameters and improve formulations by looking at the correlations between factors and responses. Even though traditional DoE methods work well, they have trouble with high-dimensional datasets and nonlinear variable connections. AI and ML get around these problems by looking at complicated datasets without needing to make any assumptions about how the data is spread out.

Integration of DoE Software with AI/ML Platforms:

Modern DoE software platforms like Minitab, JMP and Citrine Informatics now have AI/ML features. These tools let researchers make predictive models, run experiments, and improve formulations with little effort. The integration lets are the experiments of design automated, more data analysis advancement, Real time prediction and optimization and also time less and less money spend on the experiments.

Virtual Experimentation and Predictive Design Space:

AI integration makes it possible to create predictive design spaces, where the properties of formulations or processes can be guessed before real experiments are done. Supervised machine learning models are often used to predict things like solubility, permeability, stability.

Pharmaceutical Formulation Applications:

There are many ways that AI and DoE can be used together in the pharmaceutical sciences, including the making drugs work better, prediction of drug loading in carriers, Predictive modelling and optimization, study stabilization and the advanced drug delivery systems.

Some AI powered predictive formulation tools for early formulation designing:

Pharmaceutical development has been profoundly changed by the incorporation of Artificial Intelligence and Machine Learning into early-stage formulation design. Conventional formulation techniques mostly rely on trial-and-error experimentation, which is labour-intensive, resource-intensive, and frequently ineffective.

AI's Function in Early Formulation Design:

The examination of intricate interactions between formulation components, physicochemical qualities, and processing factors is made possible by AI-based predictive modelling. Usually, datasets with data on medication composition, excipient properties, molecular descriptors, and formulation conditions are used to train these technologies. AI models can forecast important characteristics including solubility, dissolution rate, stability, permeability and ADMET behaviour by using supervised learning approaches.

Formulation AI Platform

One of the most prominent AI-powered tools for early formulation design is Formulation AI, a web-based platform designed for in silico formulation development. This platform hosts multiple servers capable of predicting and designing various dosage forms, including the nanocrystals, liposomes, solid dispersions and the self-emulsifying drug delivery systems.

AI Tools for Nanocarrier Selection and Drug Loading:

Predictive tools driven by AI are also essential for choosing appropriate nanocarriers and optimizing medication loading. These models enable researchers to choose the best carrier and formulation approach by predicting how a novel medicinal molecule would behave in a particular delivery system. This method decreases trial-and-error experimentation and increases formulation efficiency.

Combining Molecular Docking and Simulations:

AI-powered prediction tools are being used more and more with molecular docking and molecular dynamics simulations.

AI for Dermatology Clinical Outcome Prediction:

In dermatology, artificial intelligence has demonstrated great promise for improving diagnostic accuracy, facilitating customized treatment regimens, and predicting clinical outcomes. Recent research indicates that by analysing large datasets gathered from dermatological images, patient records, and genomic data, machine learning, deep learning, and predictive modelling techniques can estimate disease development, treatment response, and potential side effects.

The Role of AI in Clinical Outcome Prediction:

Artificial intelligence has emerged as a revolutionary tool in dermatology that enhances patient care and enables more accurate clinical outcome prediction. AI systems use advanced computational techniques like machine learning, deep learning, and predictive analytics to process vast volumes of dermatological data.

Precise Forecasting and Diagnosis Through Images:

The most significant applications of AI in dermatology are the analysis of skin images for diagnosis and outcome prediction. Dermatology is a visually oriented profession, so making clinical decisions often depends on accurately interpreting skin lesions. A kind of deep learning technique called convolutional neural networks can examine dermoscopic and clinical images to find subtle morphological characteristics associated with a range of skin conditions.

Customized Methods for Dermatological Treatment:

Another noteworthy finding from the examined studies is the ability of AI systems to support customized dermatological care. Personalized medicine aims to modify treatment regimens according to each patient's distinct characteristics. AI models integrate data from multiple sources, including genetic information, environmental exposure, lifestyle traits, and medical history, to predict distinct treatment responses.

Safety and Tolerability Estimation:

Another significant application of AI is forecasting the safety and tolerability of dermatological and cosmetic procedures. Computational models can replicate biological reactions to chemicals and identify potential risks before clinical testing.

A.I in Formulation of Immediate-release tablets:

AI's Place in the Development of Immediate-Release Tablets:

Artificial intelligence has become an increasingly important tool in pharmaceutical formulation development, especially in the design and optimization of solid dosage forms such as immediate-release tablets. Immediate-release tablets active pharmaceutical ingredient is rapidly released after consumption, promoting quick drug absorption and therapeutic action.

Artificial Neural Networks for Immediate-Release Tablets:

One of the most popular AI techniques for developing pharmaceutical formulations is the use of artificial neural networks. ANNs are composed of connected nodes that process data and are made to mimic the composition and function of the human brain, and they learn from experimental datasets. These models are able to find hidden correlations between different formulation factors and predict product attributes with high accuracy.

Optimization Using Genetic Algorithms and Hybrid AI Models:

In addition to neural networks, genetic algorithms are often used for optimization in pharmaceutical formulation development. Genetic algorithms are computational techniques influenced by biological evolution. They use strategies like crossover, mutation, and selection to find the best solutions to difficult problems. Immediate-release tablets have improved formulation factors through the use of neural networks and genetic algorithms. For example, experimental data from pill formulations were analysed using a hybrid ANN genetic algorithm model. This combined approach determined the optimal combinations that produced the desired tablet qualities by evaluating the importance of different formulation ingredients and processing factors.

Ontology-Based Expert Systems for Immediate-Release Tablets:

Another AI-based technique used in the creation of immediate-release tablets is ontology-based expert systems. By storing structured knowledge about pharmaceutical ingredients, manufacturing processes, and formulation techniques, these systems enable automated decision-making during formulation creation. One such system is the Ontology-based Expert System for Pharmaceutical Immediate-Release Tablet Production, which was developed to assist pharmacists in creating generic immediate-release tablets in a lab setting.

A.I in Product Development:

Overview of Artificial Intelligence in Product Development:

Pharmaceutical development often involves numerous steps, including drug discovery, formulation development, manufacturing process optimization, and quality control. AI technologies are now powerful tools that can analyse complex datasets and find relationships between product attributes and formulation factors. Before conducting experimental testing, researchers can predict product performance and simulate formulation

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

behaviour using fuzzy logic techniques, genetic algorithms, artificial neural networks, and machine learning algorithms. By using these tools, researchers can improve formulation design decision-making and streamline product development procedures.

AI Uses in the Development of Cosmetic and Dermo cosmetic Products:

Machine learning algorithms are increasingly being used to predict product performance and analyse how cosmetic chemicals interact. Texture, stability, rheological behaviour, and shelf life are important formulation characteristics that may anticipated by these models. AI-driven predictive modelling reduces the need for traditional trial-and-error experimentation, allowing researchers to develop safer and more effective cosmetic formulas.

Hybrid AI Models for Optimal Formulation:

Several pharmaceutical applications use hybrid AI models, which combine multiple approaches, to improve prediction accuracy. For example, neural networks can be combined with fuzzy logic systems or evolutionary algorithms to create more powerful optimization models. Fuzzy logic is one computer technique that can handle ambiguity and erroneous data. In the pharmaceutical product development industry, fuzzy logic systems help researchers analyse complex data and make decisions about formulation optimization. Neural networks and fuzzy logic combine to give complex formulation systems greater flexibility and improved prediction capabilities,

Developing Drug Delivery Systems using AI Applications:

Artificial intelligence has also played a major role in advanced medication delivery methods. These systems aim to improve the therapeutic efficacy of drugs by controlling the rate and location of drug release in the body. AI models can simulate complex drug delivery procedures and predict formulation behaviour under a variety of conditions.

A.I. in the Development of Hard Gelatin Capsule Shell Formation:

Overview of the Formulation of Hard Gelatin Capsules:

A powerful tool for improving formulation development processes is artificial intelligence. Artificial neural networks, expert systems, fuzzy logic models, and hybrid computational systems are examples of AI techniques that evaluate complex formulation datasets and predict drug performance. These predictive algorithms allow pharmaceutical experts to create ideal capsule formulations faster and with fewer experimental trials. AI systems have the ability to process large experimental datasets and identify relationships between formulation factors and product attributes. This characteristic makes AI very useful for developing formulations for hard gelatin capsules, where a variety of factors influence the capsule's performance and drug release.

Artificial Neural Networks in the Development of Capsule Shell Formulation: Artificial neural networks are one of the most widely used AI techniques in pharmaceutical formulation research. Artificial neural networks are computational models that use experimental data to find patterns, drawing inspiration from biological neural networks. ANN models have been used to convert experimental data into information that formulation scientists can use to create formulations for hard gelatin capsules. The models can assess the results of previous experiments and generate suggestions for the development of new formulations. This eliminates the need for extensive laboratory testing and allows researchers to predict the characteristics of possible capsule formulations.

Expert Systems for Hard Gelatin Capsule Formulation:

Expert systems are another essential AI method used in the development of pharmaceutical formulations. These systems mimic the decision-making skills of human experts by evaluating complex problems using stored data and logical principles.One well-known example of an expert system used in the creation of capsule formulations is the Capsugel expert system, which was developed as a centralized platform for producing powder formulations

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

in hard gelatin capsules. By merging formulation knowledge with experimental data, this technology generates recommended capsule formulations.

AI in the Selection and Optimization of Excipients:

AI plays an important role in the selection and optimization process of the excipients. And AI also helps to transforms excipient selection from a trial-and-error process into the data driven prediction model.

Overview of Optimizing Excipients using AI:

Excipients are crucial components of pharmaceutical formulations that have an impact on medication stability, bioavailability, manufacturability, and patient acceptance. Empirical data and laborious, occasionally fruitless trial-and-error testing have always been the foundation for excipient selection. AI technologies, which facilitate data-driven decision-making and predictive modelling, have significantly improved this process.

AI's Role in Excipient Selection:

AI is crucial for choosing the right excipients based on the physicochemical properties of APIs. Machine learning algorithms are used to analyse large datasets containing information on excipient properties, compatibility, and performance outcomes. Possible incompatibilities between APIs and excipients could be predicted by these models, which is essential to avoid formulation instability or reduced efficacy. By evaluating variables like solubility, hygroscopicity, and chemical reactivity, AI technologies assist in selecting excipients that increase drug efficacy and stability. AI-based systems can also recommend excipients based on desired formulation properties such as targeted distribution, controlled release, or instant release. Consequently, there is less need for manual screening and more formulation efficiency.

Increasing the Concentration of Excipient:

In addition to selection, AI is highly effective at optimizing excipient concentrations. ANNs and genetic algorithms can be used to model these nonlinear interactions and predict the optimal excipient concentrations to produce the desired product properties, such as stability, hardness, friability, and dissolution rate. For example, studies have shown that ANN models outperform conventional regression methods when predicting tablet properties based on various excipient concentrations. By allowing formulators to achieve optimal performance with few experimental attempts, this feature saves time and money.

Optimizing Formulation Design with Multiple Objectives:

One of AI's key advantages in excipient optimization is its ability to optimize multiple objectives. Pharmaceutical formulations must meet multiple requirements simultaneously, such as mechanical strength, fast disintegration, and controlled drug release.

CONCLUSION

In conclusion, using artificial intelligence in drug formulation and delivery is a big step forward from the old trial-and-error methods to a more effective, data-driven system. The paper talks about how AI technologies like neural networks, machine learning, and deep learning have made many parts of drug development much better, from pre-formulation studies to making the final product better. AI lets you quickly look at complicated datasets, which lets you accurately guess important quality traits like stability, solubility, bioavailability, and drug release profiles. AI has also helped the pharmaceutical industry solve big problems like high development costs, long timelines, and complicated formulations. You don't have to do as many experiments in the lab because it can pick the best excipients, guess how drugs and excipients will interact, and simulate stability conditions. This not only speeds up development, but it also makes formulations easier to reproduce and more reliable. When you compare AI-generated and human-generated formulations, you can see that AI is better at speed, scalability, and accuracy. However, it also shows that human expertise is still very important. Data quality, regulatory acceptance, and model interpretability are still very important things to think about before it can be used widely, even though it has a lot of potential. But AI isn't just for drugs. It can also be used to make cosmetics, change the microbiome, and predict clinical outcomes, showing how useful and broad it is. The future of drug development will likely rely on a combination of human expertise and AI-generated insights. AI is going to change the field of pharmaceutical sciences by making things run more smoothly, cutting costs, and making it possible to make safer, more effective, and more personalised treatments. This will make healthcare better all over the world.

REFERENCES

1. Abd-algaleel, Shaymaa A., Hend M. Abdel-Bar, Abdelkader A. Metwally, and Rania M. Hathout. "Evolution of the Computational Pharmaceutics Approaches in the Modeling and Prediction of Drug Payload in Lipid and Polymeric Nanocarriers." Pharmaceuticals 14, no. 7 (2021): 645. https://doi.org/10.3390/ph14070645.
2. Abdellatif, Ahmed A. H., Hamdoon A. Mohammed, Riaz A. Khan, et al. "Nano-Scale Delivery: A Comprehensive Review of Nano-Structured Devices, Preparative Techniques, Site-Specificity Designs, Biomedical Applications, Commercial Products, and References to Safety, Cellular Uptake, and Organ Toxicity." Nanotechnology Reviews 10, no. 1 (2021): 1493–559. https://doi.org/10.1515/ntrev-2021-0096.
3. Achary, Patnala Ganga Raju. "Applications of Quantitative Structure-Activity Relationships (QSAR) Based Virtual Screening in Drug Design: A Review." Mini-Reviews in Medicinal Chemistry 20, no. 14 (2020): 1375–88. https://doi.org/10.2174/1389557520666200429102334.
4. Agatonovic-Kustrin, S., and R. Beresford. "Basic Concepts of Artificial Neural Network (ANN) Modeling and Its Application in Pharmaceutical Research." Journal of Pharmaceutical and Biomedical Analysis 22, no. 5 (2000): 717–27. https://doi.org/10.1016/S0731-7085(99)00272-1.
5. Agrwal, Akansha, Rohit Kumar, Swati Maheshwari, et al. "Mathematical and Artificial Intelligence Techniques in Modern Drug Discovery: A Review." Drug Development Research 87, no. 1 (2026): e70212. https://doi.org/10.1002/ddr.70212.
6. Ahirwar, Kailash, and Rahul Shukla. "Preformulation Studies: A Versatile Tool in Formulation Design." In Drug Formulation Design, edited by Rahul Shukla, Aleksey Kuznetsov, and Akbar Ali. IntechOpen, 2023. https://doi.org/10.5772/intechopen.110346.
7. Ahirwar, Kailash, and Rahul Shukla. "Preformulation Studies: A Versatile Tool in Formulation Design." In Drug Formulation Design, edited by Rahul Shukla, Aleksey Kuznetsov, and Akbar Ali. IntechOpen, 2023. https://doi.org/10.5772/intechopen.110346.
8. Ahirwar, Kailash, and Rahul Shukla. "Preformulation Studies: A Versatile Tool in Formulation Design." In Drug Formulation Design, edited by Rahul Shukla, Aleksey Kuznetsov, and Akbar Ali. IntechOpen, 2023. https://doi.org/10.5772/intechopen.110346.
9. Alharbi, Sultan K. "Advancing Identification of Transformation Products and Predicting Their Environmental Fate: The Current State of Machine Learning and Artificial Intelligence in Antibiotic Photolysis." Applied Sciences 16, no. 1 (2025): 267. https://doi.org/10.3390/app16010267.
10. Ali, Kazi Asraf, Sk Mohin, Puja Mondal, Susmita Goswami, Soumya Ghosh, and Sabyasachi Choudhuri. "Influence of Artificial Intelligence in Modern Pharmaceutical Formulation and Drug Development." Future Journal of Pharmaceutical Sciences 10, no. 1 (2024): 53. https://doi.org/10.1186/s43094-024-00625-1.
11. Ali, Kazi Asraf, Sk Mohin, Puja Mondal, Susmita Goswami, Soumya Ghosh, and Sabyasachi Choudhuri. "Influence of Artificial Intelligence in Modern Pharmaceutical Formulation and Drug Development." Future Journal of Pharmaceutical Sciences 10, no. 1 (2024): 53. https://doi.org/10.1186/s43094-024-00625-1.
12. Allen, Loyd V. "Dosage Form Design and Development." Clinical Therapeutics 30, no. 11 (2008): 2102–11. https://doi.org/10.1016/j.clinthera.2008.11.015.
13. Álvarez-Machancoses, Óscar, and Juan Luis Fernández-Martínez. "Using Artificial Intelligence Methods to Speed up Drug Discovery." Expert Opinion on Drug Discovery 14, no. 8 (2019): 769–77. https://doi.org/10.1080/17460441.2019.1621284.
14. Alves, Thais F. R., Margreet Morsink, Fernando Batain, et al. "Applications of Natural, Semi-Synthetic,

and Synthetic Polymers in Cosmetic Formulations." Cosmetics 7, no. 4 (2020): 75. https://doi.org/10.3390/cosmetics7040075.
15. Amer, Yousef, Chidiebere Jeffrey Ogochukwu, and Ashraf Zaghwan. "AI-Driven Circular Manufacturing Framework for Predictive Material Flow Optimisation." Intelligent Systems with Applications 30 (May 2026): 200651. https://doi.org/10.1016/j.iswa.2026.200651.
16. Anklam, Elke, Martin Iain Bahl, Robert Ball, et al. "Emerging Technologies and Their Impact on Regulatory Science." Experimental Biology and Medicine 247, no. 1 (2022): 1–75. https://doi.org/10.1177/15353702211052280.
17. Asif, Sohaib, Yi Wenhui, Saif- ur-Rehman, et al. "Advancements and Prospects of Machine Learning in Medical Diagnostics: Unveiling the Future of Diagnostic Precision." Archives of Computational Methods in Engineering 32, no. 2 (2025): 853–83. https://doi.org/10.1007/s11831-024-10148-w.
18. Aumklad, Porawan, Phuvamin Suriyaamporn, Suwanee Panomsuk, Boonnada Pamornpathomkul, and Praneet Opanasopit. "Artificial Intelligence-Aided Rational Design and Prediction Model for Progesterone-Loaded Self-Microemulsifying Drug Delivery System Formulations." Science, Engineering and Health Studies, July 18, 2024, 24050002. https://doi.org/10.69598/sehs.18.24050002.
19. Badini, Silvia, Stefano Regondi, and Raffaele Pugliese. "Unleashing the Power of Artificial Intelligence in Materials Design." Materials 16, no. 17 (2023): 5927. https://doi.org/10.3390/ma16175927.
20. Barton, John H., and Ezekiel J. Emanuel. "The Patents-Based Pharmaceutical Development Process: Rationale, Problems, and Potential Reforms." JAMA 294, no. 16 (2005): 2075. https://doi.org/10.1001/jama.294.16.2075.
21. Baveye, Philippe C., Wilfred Otten, Alexandra Kravchenko, et al. "Emergent Properties of Microbial Activity in Heterogeneous Soil Microenvironments: Different Research Approaches Are Slowly Converging, Yet Major Challenges Remain." Frontiers in Microbiology 9 (August 2018): 1929. https://doi.org/10.3389/fmicb.2018.01929.
22. Benbya, Hind, Thomas H. Davenport, and Stella Pachidi. "Artificial Intelligence in Organizations: Current State and Future Opportunities." SSRN Electronic Journal, ahead of print, 2020. https://doi.org/10.2139/ssrn.3741983.
23. Bhalani, Dixit V., Bhingaradiya Nutan, Avinash Kumar, and Arvind K. Singh Chandel. "Bioavailability Enhancement Techniques for Poorly Aqueous Soluble Drugs and Therapeutics." Biomedicines 10, no. 9 (2022): 2055. https://doi.org/10.3390/biomedicines10092055.
24. Bhatia, Nitish, Mohd Masih Uzzaman Khan, and Saahil Arora. "The Role of Artificial Intelligence in Revolutionizing Pharmacological Research." Current Pharmacology Reports 10, no. 6 (2024): 323–29. https://doi.org/10.1007/s40495-024-00367-x.
25. Bouslimani, Amina, Ricardo Da Silva, Tomasz Kosciolek, et al. "The Impact of Skin Care Products on Skin Chemistry and Microbiome Dynamics." BMC Biology 17, no. 1 (2019): 47. https://doi.org/10.1186/s12915-019-0660-6.
26. Bulusu, Krishna C., Rajarshi Guha, Daniel J. Mason, et al. "Modelling of Compound Combination Effects and Applications to Efficacy and Toxicity: State-of-the-Art, Challenges and Perspectives." Drug Discovery Today 21, no. 2 (2016): 225–38. https://doi.org/10.1016/j.drudis.2015.09.003.
27. Chahuan, Abhishek, Abhishek Verma, Devank Shekho, Ritika Mishra, and Ankit Awasthi. "Revolutionizing the World of Pharmaceuticals: Unleashing theGame-Changing Power of 3D Printing." Current Drug Targets 25, no. 8 (2024): 513–16. https://doi.org/10.2174/0113894501304163240429081741.
28. Chaudhary, Shivang, Prakash Muthudoss, Thiagarajan Madheswaran, Amrit Paudel, and Vinod Gaikwad. "Artificial Intelligence (AI) in Drug Product Designing, Development, and Manufacturing." In A Handbook of Artificial Intelligence in Drug Delivery. Elsevier, 2023. https://doi.org/10.1016/B978-0-323-89925-3.00015-0.
29. Chauhan, Shikha Baghel, Indu Singh, Ananya Dwivedi, and Asmitaa Dimri. "AI-Enhanced Personalized Skincare: Implications for Skin Microbiome Diversity and Pharmacogenomics Precision in Dermatology." Current Pharmacogenomics and Personalized Medicine 22 (August 2025): e18756921368686. https://doi.org/10.2174/0118756921368686250621143748.
30. Chen, Shuangdi, Zhaofeng Li, Bimal Chitrakar, et al. "Minimum Inhibitory Concentration (MIC) of Essential Oils Against Microorganisms: Methods, Function, Accuracy Factors and Application." Food

Reviews International 40, no. 10 (2024): 3445–70. https://doi.org/10.1080/87559129.2024.2357612.

31. Chen, Xing, Chenggang Clarence Yan, Xiaotian Zhang, et al. "Drug–Target Interaction Prediction: Databases, Web Servers and Computational Models." Briefings in Bioinformatics 17, no. 4 (2016): 696–712. https://doi.org/10.1093/bib/bbv066.
32. Chen, Yixin, Troy W. McCall, Anand R. Baichwal, and Marvin C. Meyer. "The Application of an Artificial Neural Network and Pharmacokinetic Simulations in the Design of Controlled-Release Dosage Forms." Journal of Controlled Release 59, no. 1 (1999): 33–41. https://doi.org/10.1016/S0168-3659(98)00171-0.
33. Chopra, Hitesh, Annu, Dong K. Shin, et al. "Revolutionizing Clinical Trials: The Role of AI in Accelerating Medical Breakthroughs." International Journal of Surgery 109, no. 12 (2023): 4211–20. https://doi.org/10.1097/JS9.0000000000000705.
34. Chou, Wei-Chun, and Zhoumeng Lin. "Machine Learning and Artificial Intelligence in Physiologically Based Pharmacokinetic Modeling." Toxicological Sciences 191, no. 1 (2023): 1–14. https://doi.org/10.1093/toxsci/kfac101.
35. Cook, D. F., C. T. Ragsdale, and R. L. Major. "Combining a Neural Network with a Genetic Algorithm for Process Parameter Optimization." Engineering Applications of Artificial Intelligence 13, no. 4 (2000): 391–96. https://doi.org/10.1016/S0952-1976(00)00021-X.
36. Dangeti, Appalaraju, Deekshi Gladiola Bynagari, and Krishnaveni Vydani. "Revolutionizing Drug Formulation: Harnessing Artificial Intelligence and Machine Learning for Enhanced Stability, Formulation Optimization, and Accelerated Development." International Journal of Pharmaceutical Sciences and Medicine 8, no. 8 (2023): 18–29. https://doi.org/10.47760/ijpsm.2023.v08i08.003.
37. Dangeti, Appalaraju, Deekshi Gladiola Bynagari, and Krishnaveni Vydani. "Revolutionizing Drug Formulation: Harnessing Artificial Intelligence and Machine Learning for Enhanced Stability, Formulation Optimization, and Accelerated Development." International Journal of Pharmaceutical Sciences and Medicine 8, no. 8 (2023): 18–29. https://doi.org/10.47760/ijpsm.2023.v08i08.003.
38. Darji, Mittal A., Rahul M. Lalge, Sushrut P. Marathe, et al. "Excipient Stability in Oral Solid Dosage Forms: A Review." AAPS PharmSciTech 19, no. 1 (2018): 12–26. https://doi.org/10.1208/s12249-017-0864-4.
39. Dayan, Nava, ed. Handbook of Formulating Dermal Applications: A Definitive Practical Guide. 1st ed. Wiley, 2016. https://doi.org/10.1002/9781119364221.
40. Desai, Jagruti, Prince Dhameliya, and Swayamprakash Patel. "Optimizing Critical Quality Attributes of Fast Disintegrating Tablets Using Artificial Neural Networks: A Scientific Benchmark Study." Drug Development and Industrial Pharmacy 50, no. 12 (2024): 995–1007. https://doi.org/10.1080/03639045.2024.2434640.
41. Desai, Jagruti, Prince Dhameliya, and Swayamprakash Patel. "Optimizing Critical Quality Attributes of Fast Disintegrating Tablets Using Artificial Neural Networks: A Scientific Benchmark Study." Drug Development and Industrial Pharmacy 50, no. 12 (2024): 995–1007. https://doi.org/10.1080/03639045.2024.2434640.
42. Dey, Hrithik, Nisha Arya, Harshita Mathur, Neel Chatterjee, and Ruchi Jadon. "Exploring the Role of Artificial Intelligence and Machine Learning in Pharmaceutical Formulation Design." International Journal of Newgen Research in Pharmacy & Healthcare, June 30, 2024, 30–41. https://doi.org/10.61554/ijnrph.v2i1.2024.67.
43. Dey, Hrithik, Nisha Arya, Harshita Mathur, Neel Chatterjee, and Ruchi Jadon. "Exploring the Role of Artificial Intelligence and Machine Learning in Pharmaceutical Formulation Design." International Journal of Newgen Research in Pharmacy & Healthcare, June 30, 2024, 30–41. https://doi.org/10.61554/ijnrph.v2i1.2024.67.
44. Dey, Hrithik, Nisha Arya, Harshita Mathur, Neel Chatterjee, and Ruchi Jadon. "Exploring the Role of Artificial Intelligence and Machine Learning in Pharmaceutical Formulation Design." International Journal of Newgen Research in Pharmacy & Healthcare, June 30, 2024, 30–41. https://doi.org/10.61554/ijnrph.v2i1.2024.67.
45. Di Guardo, Antonio, Federica Trovato, Carmen Cantisani, et al. "Artificial Intelligence in Cosmetic Formulation: Predictive Modeling for Safety, Tolerability, and Regulatory Perspectives." Cosmetics 12, no. 4 (2025): 157. https://doi.org/10.3390/cosmetics12040157.

46. Di Guardo, Antonio, Federica Trovato, Carmen Cantisani, et al. "Artificial Intelligence in Cosmetic Formulation: Predictive Modeling for Safety, Tolerability, and Regulatory Perspectives." Cosmetics 12, no. 4 (2025): 157. https://doi.org/10.3390/cosmetics12040157.
47. DiFeo, Thomas J. "Safety and Efficacy: The Role of Chemistry, Manufacturing, and Controls in Pharmaceutical Drug Development." Drug Development and Industrial Pharmacy 30, no. 3 (2004): 247–57. https://doi.org/10.1081/DDC-120030428.
48. Duarte, Joana Galvão, Maria Galvão Duarte, Ana Paula Piedade, and Filipa Mascarenhas-Melo. "Rethinking Pharmaceutical Industry with Quality by Design: Application in Research, Development, Manufacturing, and Quality Assurance." The AAPS Journal 27, no. 4 (2025): 96. https://doi.org/10.1208/s12248-025-01079-w.
49. Dumitriu Buzia, Olimpia, Ana Maria Păduraru, Claudia Simona Stefan, et al. "Strategies for Improving Transdermal Administration: New Approaches to Controlled Drug Release." Pharmaceutics 15, no. 4 (2023): 1183. https://doi.org/10.3390/pharmaceutics15041183.
50. Gaikwad, Vinod L., Neela M. Bhatia, Sujit A. Desai, and Manish S. Bhatia. "Quantitative Structure Property Relationship Modeling of Excipient Properties for Prediction of Formulation Characteristics." Carbohydrate Polymers 151 (October 2016): 593–99. https://doi.org/10.1016/j.carbpol.2016.05.114.
51. Gaikwad, Vinod L., Neela M. Bhatia, Sujit A. Desai, and Manish S. Bhatia. "Quantitative Structure Property Relationship Modeling of Excipient Properties for Prediction of Formulation Characteristics." Carbohydrate Polymers 151 (October 2016): 593–99. https://doi.org/10.1016/j.carbpol.2016.05.114.
52. Gannot, G., Ma Cutting, Dj Fischer, and Lj Hsu. "Reproducibility and Transparency in Biomedical Sciences." Oral Diseases 23, no. 7 (2017): 813–16. https://doi.org/10.1111/odi.12588.
53. Garud, Kunal Sandip, Simon Jayaraj, and Moo-Yeon Lee. "A Review on Modeling of Solar Photovoltaic Systems Using Artificial Neural Networks, Fuzzy Logic, Genetic Algorithm and Hybrid Models." International Journal of Energy Research 45, no. 1 (2021): 6–35. https://doi.org/10.1002/er.5608.
54. Ghalayini, Alaa M., and James S. Noble. "The Changing Basis of Performance Measurement." International Journal of Operations & Production Management 16, no. 8 (1996): 63–80. https://doi.org/10.1108/01443579610125787.
55. Ghosh, Moumita, and A. Thirugnanam. "Introduction to Artificial Intelligence." In Artificial Intelligence for Information Management: A Healthcare Perspective, vol. 88, edited by K. G. Srinivasa, Siddesh G. M., and S. R. Mani Sekhar. Studies in Big Data. Springer Singapore, 2021. https://doi.org/10.1007/978-981-16-0415-7_2.
56. Goel, Akash, Amit Kumar Goel, and Adesh Kumar. "The Role of Artificial Neural Network and Machine Learning in Utilizing Spatial Information." Spatial Information Research 31, no. 3 (2023): 275–85. https://doi.org/10.1007/s41324-022-00494-x.
57. Gong, Youdi, Guangzhen Liu, Yunzhi Xue, Rui Li, and Lingzhong Meng. "A Survey on Dataset Quality in Machine Learning." Information and Software Technology 162 (October 2023): 107268. https://doi.org/10.1016/j.infsof.2023.107268.
58. Grice, Elizabeth A., and Julia A. Segre. "The Skin Microbiome." Nature Reviews Microbiology 9, no. 4 (2011): 244–53. https://doi.org/10.1038/nrmicro2537.
59. Grigoryan, Artur, Stefan Helfrich, Valentin Lequeux, et al. "Smart Formulation: AI-Driven Web Platform for Optimization and Stability Prediction of Compounded Pharmaceuticals Using KNIME." Pharmaceuticals 18, no. 8 (2025): 1240. https://doi.org/10.3390/ph18081240.
60. Gupta, Dhruv, Anuj A. Biswas, Rohan Chand Sahu, Sanchit Arora, Dinesh Kumar, and Ashish K. Agrawal. "Advancing Pharmaceutical Intelligence via Computationally Prognosticating the In-Vitro Parameters of Fast Disintegration Tablets Using Machine Learning Models." European Journal of Pharmaceutics and Biopharmaceutics 204 (November 2024): 114508. https://doi.org/10.1016/j.ejpb.2024.114508.
61. Gupta, Rohan, Devesh Srivastava, Mehar Sahu, Swati Tiwari, Rashmi K. Ambasta, and Pravir Kumar. "Artificial Intelligence to Deep Learning: Machine Intelligence Approach for Drug Discovery." Molecular Diversity 25, no. 3 (2021): 1315–60. https://doi.org/10.1007/s11030-021-10217-3.
62. Gupta, Rohan, Devesh Srivastava, Mehar Sahu, Swati Tiwari, Rashmi K. Ambasta, and Pravir Kumar. "Artificial Intelligence to Deep Learning: Machine Intelligence Approach for Drug Discovery." Molecular Diversity 25, no. 3 (2021): 1315–60. https://doi.org/10.1007/s11030-021-10217-3.

63. Gupta, Shweta, Rajesh Kesarla, and Abdelwahab Omri. "Formulation Strategies to Improve the Bioavailability of Poorly Absorbed Drugs with Special Emphasis on Self-Emulsifying Systems." ISRN Pharmaceutics 2013 (December 2013): 1–16. https://doi.org/10.1155/2013/848043.
64. Gupta, Shweta, Rajesh Kesarla, and Abdelwahab Omri. "Formulation Strategies to Improve the Bioavailability of Poorly Absorbed Drugs with Special Emphasis on Self-Emulsifying Systems." ISRN Pharmaceutics 2013 (December 2013): 1–16. https://doi.org/10.1155/2013/848043.
65. Hagendorff, Thilo, and Katharina Wezel. "15 Challenges for AI: Or What AI (Currently) Can't Do." AI & SOCIETY 35, no. 2 (2020): 355–65. https://doi.org/10.1007/s00146-019-00886-y.
66. Halla, Noureddine, Isabel P. Fernandes, Sandrina A. Heleno, et al. "Cosmetics Preservation: A Review on Present Strategies." Molecules 23, no. 7 (2018): 1571. https://doi.org/10.3390/molecules23071571.
67. Hassan Ali. "Artificial Intelligence in Multi-Omics Data Integration: Advancing Precision Medicine, Biomarker Discovery and Genomic-Driven Disease Interventions." International Journal of Science and Research Archive 8, no. 1 (2023): 1012–30. https://doi.org/10.30574/ijsra.2023.8.1.0189.
68. Hassan, Raouf, and Mohammad Reza Kazemi. "Data-Driven Frameworks to Robustly Predict Solubility Parameter of Diverse Polymers." Scientific Reports 15, no. 1 (2025): 31157. https://doi.org/10.1038/s41598-025-12758-1.
69. Hassija, Vikas, Vinay Chamola, Atmesh Mahapatra, et al. "Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence." Cognitive Computation 16, no. 1 (2024): 45–74. https://doi.org/10.1007/s12559-023-10179-8.
70. Haykal, Diala. "Emerging and Pioneering AI Technologies in Aesthetic Dermatology: Sketching a Path Toward Personalized, Predictive, and Proactive Care." Cosmetics 11, no. 6 (2024): 206. https://doi.org/10.3390/cosmetics11060206.
71. Haykal, Diala. "Emerging and Pioneering AI Technologies in Aesthetic Dermatology: Sketching a Path Toward Personalized, Predictive, and Proactive Care." Cosmetics 11, no. 6 (2024): 206. https://doi.org/10.3390/cosmetics11060206.
72. Hoffmann, Rudolf, and Christoph Reich. "A Systematic Literature Review on Artificial Intelligence and Explainable Artificial Intelligence for Visual Quality Assurance in Manufacturing." Electronics 12, no. 22 (2023): 4572. https://doi.org/10.3390/electronics12224572.
73. Husnain, Ali, Saad Rasool, Ayesha Saeed, Ahmad Yousaf Gill, and Hafiz Khawar Hussain. "AI'S Healing Touch: Examining Machine Learning's Transformative Effects On Healthcare." Journal of World Science 2, no. 10 (2023): 1681–95. https://doi.org/10.58344/jws.v2i10.448.
74. Jamialahmadi, Hamid, Ghazaleh Khalili-Tanha, Elham Nazari, and Mostafa Rezaei-Tavirani. "Artificial Intelligence and Bioinformatics: A Journey from Traditional Techniques to Smart Approaches." Gastroenterology and Hepatology from Bed to Bench (IR) 17, no. 3 (2024). https://doi.org/10.22037/ghfbb.v17i3.2977.
75. Jiang, Junhuang, Xiangyu Ma, Defang Ouyang, and Robert O. Williams. "Emerging Artificial Intelligence (AI) Technologies Used in the Development of Solid Dosage Forms." Pharmaceutics 14, no. 11 (2022): 2257. https://doi.org/10.3390/pharmaceutics14112257.
76. Johnstone, Iain M., and D. Michael Titterington. "Statistical Challenges of High-Dimensional Data." Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 367, no. 1906 (2009): 4237–53. https://doi.org/10.1098/rsta.2009.0159.
77. Kakkar, Ashok, Giovanni Traverso, Omid C. Farokhzad, Ralph Weissleder, and Robert Langer. "Evolution of Macromolecular Complexity in Drug Delivery Systems." Nature Reviews Chemistry 1, no. 8 (2017): 0063. https://doi.org/10.1038/s41570-017-0063.
78. Kalasz, Huba, and Istvan Antal. "Drug Excipients." Current Medicinal Chemistry 13, no. 21 (2006): 2535–63. https://doi.org/10.2174/092986706778201648.
79. Khater, Tarek, Sara Awni Alkhatib, Aamna AlShehhi, et al. "Generative Artificial Intelligence Based Models Optimization towards Molecule Design Enhancement." Journal of Cheminformatics 17, no. 1 (2025): 116. https://doi.org/10.1186/s13321-025-01059-4.
80. Khozeimeh, Fahime, Roohallah Alizadehsani, Mohamad Roshanzamir, Abbas Khosravi, Pouran Layegh, and Saeid Nahavandi. "An Expert System for Selecting Wart Treatment Method." Computers in Biology and Medicine 81 (February 2017): 167–75. https://doi.org/10.1016/j.compbiomed.2017.01.001.
81. Kinter, Lewis B., and Joseph J. DeGeorge. "Scientific Knowledge and Technology, Animal

Experimentation, and Pharmaceutical Development." ILAR Journal 57, no. 2 (2016): 101–8. https://doi.org/10.1093/ilar/ilw027.

82. Kulkarni, Mangesh, Disha Joshi, and Swayamprakash Patel. "Harnessing the Power of DE-Interact (Drug-Excipient Interaction): An Artificial Intelligence (AI)-Based Predictive Tool for Drug-Excipient Interaction in Formulation Development." Journal of Pharmaceutical Innovation 21, no. 1 (2026): 23. https://doi.org/10.1007/s12247-025-10236-9.
83. Kumar, Ashutosh, Ghanshyam Das Gupta, and Sarjana Raikwar. "Artificial Intelligence Technologies Used for the Assessment of PharmaceuticalExcipients." Current Pharmaceutical Design 30, no. 6 (2024): 407–9. https://doi.org/10.2174/0113816128285827240119095013.
84. Kumar Dutta, Ashim. "Introductory Chapter: Surfactants in Household and Personal Care Formulations - An Overview." In Surfactants and Detergents, edited by Ashim Kumar Dutta. IntechOpen, 2019. https://doi.org/10.5772/intechopen.89245.
85. Kumar Dutta, Ashim. "Introductory Chapter: Surfactants in Household and Personal Care Formulations - An Overview." In Surfactants and Detergents, edited by Ashim Kumar Dutta. IntechOpen, 2019. https://doi.org/10.5772/intechopen.89245.
86. Kumar, Sethu Arun, Thirumoorthy Durai Ananda Kumar, Narasimha M. Beeraka, et al. "Machine Learning and Deep Learning in Data-Driven Decision Making of Drug Discovery and Challenges in High-Quality Data Acquisition in the Pharmaceutical Industry." Future Medicinal Chemistry 14, no. 4 (2022): 245–70. https://doi.org/10.4155/fmc-2021-0243.
87. Leader, Ralph. "The Pharmaceutical Drug Development Lifecycle: A Comprehensive Examination of the Scientific, Regulatory, and Commercial Processes Governing the Discovery, Development, Approval, and Post-Marketing Surveillance of Therapeutic Agents in Modern Life Sciences." Preprint, SSRN, 2025. https://doi.org/10.2139/ssrn.5948134.
88. L'Heureux, Alexandra, Katarina Grolinger, Hany F. Elyamany, and Miriam A. M. Capretz. "Machine Learning With Big Data: Challenges and Approaches." IEEE Access 5 (2017): 7776–97. https://doi.org/10.1109/ACCESS.2017.2696365.
89. Li, Zhouxiao, Konstantin Christoph Koban, Thilo Ludwig Schenck, Riccardo Enzo Giunta, Qingfeng Li, and Yangbai Sun. "Artificial Intelligence in Dermatology Image Analysis: Current Developments and Future Trends." Journal of Clinical Medicine 11, no. 22 (2022): 6826. https://doi.org/10.3390/jcm11226826.
90. Luengo, Gustavo S., Odile Aubrun, and Frederic Restagno. "Foams in Cosmetics: New Trends in Detergency, Friction, Coatings." Current Opinion in Colloid & Interface Science 77 (June 2025): 101906. https://doi.org/10.1016/j.cocis.2025.101906.
91. Mandava, Sampath. "Accelerating Innovation: Artificial Intelligence for Scientific and Pharmaceutical Breakthroughs." Preprint, SSRN, 2025. https://doi.org/10.2139/ssrn.5749982.
92. Mansour, Heidi M., MinJi Sohn, Abeer Al-Ghananeem, and Patrick P. DeLuca. "Materials for Pharmaceutical Dosage Forms: Molecular Pharmaceutics and Controlled Release Drug Delivery Aspects." International Journal of Molecular Sciences 11, no. 9 (2010): 3298–322. https://doi.org/10.3390/ijms11093298.
93. Mansour, Heidi M., MinJi Sohn, Abeer Al-Ghananeem, and Patrick P. DeLuca. "Materials for Pharmaceutical Dosage Forms: Molecular Pharmaceutics and Controlled Release Drug Delivery Aspects." International Journal of Molecular Sciences 11, no. 9 (2010): 3298–322. https://doi.org/10.3390/ijms11093298.
94. Marquez, Ronald, Maria S. Ortiz, Nelson Barrios, et al. "Surfactants Produced from Carbohydrate Derivatives: Part 2. A Review on the Value Chain, Synthesis, and the Potential Role of Artificial Intelligence within the Biorefinery Concept." Journal of Surfactants and Detergents 28, no. 1 (2025): 25–76. https://doi.org/10.1002/jsde.12766.
95. Master of Science in Management Information Systems, College of Business, Lamar University, USA, Sanjai Vudugula, Sanath Kumar Chebrolu, et al. "integrating artificial intelligence in strategic business decision-making: a systematic review of predictive models." International Journal of Scientific Interdisciplinary Research 04, no. 01 (2023): 01–26. https://doi.org/10.63125/s5skge53.
96. Mathew, Daniel Enemona, Deborah Uzoamaka Ebem, Anayo Chukwu Ikegwu, Pamela Eberechukwu Ukeoma, and Ngozi Fidelia Dibiaezue. "Recent Emerging Techniques in Explainable Artificial

Intelligence to Enhance the Interpretable and Understanding of AI Models for Human." Neural Processing Letters 57, no. 1 (2025): 16. https://doi.org/10.1007/s11063-025-11732-2.
97. Mazumdar, Hirak, Kamil Reza Khondakar, Suparna Das, Animesh Halder, and Ajeet Kaushik. "Artificial Intelligence for Personalized Nanomedicine; from Material Selection to Patient Outcomes." Expert Opinion on Drug Delivery 22, no. 1 (2025): 85–108. https://doi.org/10.1080/17425247.2024.2440618.
98. Mirakhori, Fahimeh, and Sarfaraz K. Niazi. "Harnessing the AI/ML in Drug and Biological Products Discovery and Development: The Regulatory Perspective." Pharmaceuticals 18, no. 1 (2025): 47. https://doi.org/10.3390/ph18010047.
99. Moon, M. Jae. "Searching for Inclusive Artificial Intelligence for Social Good: Participatory Governance and Policy Recommendations for Making AI More Inclusive and Benign for Society." Public Administration Review 83, no. 6 (2023): 1496–505. https://doi.org/10.1111/puar.13648.
100. Nagpure, Nishita, Harshal Raut, Shubham Kamble, and Tirupati Rasala. "Redefining Preclinical Research Paradigms: AI-Driven Drug Discovery as a Transformative Approach to Accelerate Innovation, Improve Predictive Accuracy, and Reduce Reliance on Animal Testing." Journal of Drug Delivery and Therapeutics 15, no. 10 (2025): 115–28. https://doi.org/10.22270/jddt.v15i10.7394.
101. Naharros-Molinero, Almudena, María Ángela Caballo-González, Francisco Javier De La Mata, and Sandra García-Gallego. "Chewable Soft Gelatin Capsules: Design and Formulation Strategies for a Patient-Preferred Dosage Alternative." Macromolecular Materials and Engineering 311, no. 2 (2026): e00323. https://doi.org/10.1002/mame.202500323.
102. Obaidullah, Ahmad J., and Wael A. Mahdi. "Machine Learning-Based Analysis on Pharmaceutical Compounds Interaction with Polymer to Estimate Drug Solubility in Formulations." Scientific Reports 15, no. 1 (2025): 23683. https://doi.org/10.1038/s41598-025-05535-7.
103. Obaidullah, Ahmad J., and Wael A. Mahdi. "Machine Learning-Based Analysis on Pharmaceutical Compounds Interaction with Polymer to Estimate Drug Solubility in Formulations." Scientific Reports 15, no. 1 (2025): 23683. https://doi.org/10.1038/s41598-025-05535-7.
104. Ogunjobi, Taiwo Temitope, Precious Nkeiruka Ohaeri, Olamide Tayo Akintola, et al. "Bioinformatics Applications in Chronic Diseases: A Comprehensive Review of Genomic, Transcriptomics, Proteomic, Metabolomics, and Machine Learning Approaches." Medinformatics, ahead of print, February 6, 2024. https://doi.org/10.47852/bonviewMEDIN42022335.
105. Panda, Pratikeswar, and Rajaram Mohapatra. "Revolutionizing Patient Safety: Machine Learning and AI for the Early Detection of Adverse Drug Reactions and Drug-Induced Toxicity." Current Artificial Intelligence 02 (December 2024): e29503752308394. https://doi.org/10.2174/0129503752308394241013165241.
106. Pande, Shantanu. "Liposomes for Drug Delivery: Review of Vesicular Composition, Factors Affecting Drug Release and Drug Loading in Liposomes." Artificial Cells, Nanomedicine, and Biotechnology 51, no. 1 (2023): 428–40. https://doi.org/10.1080/21691401.2023.2247036.
107. Panwar, Rohan, Anuradha Mishra, Abhisar Sahu, Syed Naved Quadri, M. Z. Abdin, and Saman Fatima. "Implementing QbD for Nano-Pharmaceuticals and Complex Formulations to Achieve Predictable and High-Quality Outcomes." AAPS PharmSciTech 27, no. 1 (2026): 71. https://doi.org/10.1208/s12249-025-03308-z.
108. Parvatikar, Prachi P., Sudha Patil, Kedar Khaparkhuntikar, et al. "Artificial Intelligence: Machine Learning Approach for Screening Large Database and Drug Discovery." Antiviral Research 220 (December 2023): 105740. https://doi.org/10.1016/j.antiviral.2023.105740.
109. Pathan, Irfan, Arif Raza, Adarsh Sahu, et al. "Revolutionizing Pharmacology: AI-Powered Approaches in Molecular Modeling and ADMET Prediction." Medicine in Drug Discovery 28 (December 2025): 100223. https://doi.org/10.1016/j.medidd.2025.100223.
110. Patil, Sharvari, Sandeep Kumar, Dasari Mallikarjuna Rao, and Kishore Rewatkar. "Current Regulatory Framework and Challenges for the Approval of ComplexGenerics in the US and the EU." Current Indian Science 02 (January 2024): e2210299X269535. https://doi.org/10.2174/012210299X269535231203164108.
111. Qi, Chongchong, and Xiaolin Tang. "Slope Stability Prediction Using Integrated Metaheuristic and Machine Learning Approaches: A Comparative Study." Computers & Industrial Engineering 118 (April 2018): 112–22. https://doi.org/10.1016/j.cie.2018.02.028.

112. Ranjbar, Shahla, Abbasali Emamjomeh, Fatemeh Sharifi, et al. “Lipid-Based Delivery Systems for Flavonoids and Flavonolignans: Liposomes, Nanoemulsions, and Solid Lipid Nanoparticles.” Pharmaceutics 15, no. 7 (2023): 1944. https://doi.org/10.3390/pharmaceutics15071944.
113. Rauch, Erwin, and Dominik T. Matt. “Artificial Intelligence in Design: A Look into the Future of Axiomatic Design.” In Design Engineering and Science, edited by Nam Pyo Suh, Miguel Cavique, and Joseph Timothy Foley. Springer International Publishing, 2021. https://doi.org/10.1007/978-3-030-49232-8_21.
114. Ritschel, W. A. “Biopharmaceutic and Pharmacokinetic Aspects in the Design of Controlled Release Peroral Drug Delivery Systems.” Drug Development and Industrial Pharmacy 15, nos. 6–7 (1989): 1073–103. https://doi.org/10.3109/03639048909043666.
115. Rubin, A. Erik, Srinivas Tummala, Douglas A. Both, Chenchi Wang, and Edward J. Delaney. “Emerging Technologies Supporting Chemical Process R&D and Their Increasing Impact on Productivity in the Pharmaceutical Industry.” Chemical Reviews 106, no. 7 (2006): 2794–810. https://doi.org/10.1021/cr040674i.
116. Sabu, Kevin Philip, and Rony Rajan Paul. “Picotechnology: Advancing Precision in Bioimaging and Disease Diagnosis.” In A Journey from Nanotechnology to Picotechnology, vol. 47, edited by Shrikaant Kulkarni. Lecture Notes in Nanoscale Science and Technology. Springer Nature Switzerland, 2026. https://doi.org/10.1007/978-3-032-07228-3_13.
117. Salawi, Ahmad. “Self-Emulsifying Drug Delivery Systems: A Novel Approach to Deliver Drugs.” Drug Delivery 29, no. 1 (2022): 1811–23. https://doi.org/10.1080/10717544.2022.2083724.
118. Sartaj, Ali, Anjali Rajora, Juveria Usmani, Sweeti Bana, Annu, and Javed Ali. “AI-Driven Drug Formulation Development: Transforming the Future of Pharmaceutical Drug Development from Discovery to Regulatory Aspects.” Journal of Pharmaceutical Innovation 21, no. 1 (2026): 54. https://doi.org/10.1007/s12247-025-10244-9.
119. Schierle, Felicitas, Jon Lindström Bolmgren, Mette Deleuran, Oliver Welter, and Vanessa Gebauer. “Precision Dermatology 2050: AI -driven Personalized Monitoring and Individualized Treatment.” Journal of the European Academy of Dermatology and Venereology 40, no. 3 (2026): 431–39. https://doi.org/10.1111/jdv.70248.
120. Schiff, Gordon D., David Klass, Josh Peterson, Gaurav Shah, and David W. Bates. “Linking Laboratory and Pharmacy: Opportunities for Reducing Errors and Improving Care.” Archives of Internal Medicine 163, no. 8 (2003): 893. https://doi.org/10.1001/archinte.163.8.893.
121. Seiler, Christian. “CHAPTER 8. Oral Controlled Release Technology and Development Strategy.” In Drug Discovery, edited by Geoffrey D. Tovey. Royal Society of Chemistry, 2018. https://doi.org/10.1039/9781782620402-00173.
122. Singh, Inderbir, Jaswinder Kaur, Sukhanpreet Kaur, Bibhuti Ranjan Barik, and Rakesh Pahwa. “Artificial Neural Networks and Neuro-Fuzzy Models: Applications in Pharmaceutical Product Development.” Brazilian Archives of Biology and Technology 66 (2023): e23210769. https://doi.org/10.1590/1678-4324-2023210769.
123. Sobolieva, Hanna, and Anastasia Ivanova. “the personalisation revolution: how artificial intelligence is transforming the cosmetics industry, making consumers the source of innovation.” Three Seas Economic Journal 6, no. 1 (2025): 69–75. https://doi.org/10.30525/2661-5150/2025-1-11.
124. Spathis, Dimitris, and Panayiotis Vlamos. “Diagnosing Asthma and Chronic Obstructive Pulmonary Disease with Machine Learning.” Health Informatics Journal 25, no. 3 (2019): 811–27. https://doi.org/10.1177/1460458217723169.
125. Srivastava, Madhumita, Shiv Nandan, Aliza Zaidi, et al. “Artificial Intelligence Driven Applications in Analytical Chemistry, Drug Discovery, and Food Science: Advancements, Outlook, and Challenges.” ChemistrySelect 10, no. 16 (2025): e202404446. https://doi.org/10.1002/slct.202404446.
126. Tanoli, Ziaurrehman, Markus Vähä-Koskela, and Tero Aittokallio. “Artificial Intelligence, Machine Learning, and Drug Repurposing in Cancer.” Expert Opinion on Drug Discovery 16, no. 9 (2021): 977–89. https://doi.org/10.1080/17460441.2021.1883585.
127. Teshome, Ejigayehu, Sirawdink Fikreyesus Forsido, H. P. Vasantha Rupasinghe, and Ebisa Olika Keyata. “Potentials of Natural Preservatives to Enhance Food Safety and Shelf Life: A Review.” The Scientific World Journal 2022 (September 2022): 1–11. https://doi.org/10.1155/2022/9901018.

128. Thacharodi, Aswin, Prabhakar Singh, Ramu Meenatchi, et al. "Revolutionizing Healthcare and Medicine: The Impact of Modern Technologies for a Healthier Future—A Comprehensive Review." Health Care Science 3, no. 5 (2024): 329–49. https://doi.org/10.1002/hcs2.115.
129. Tiwari, Prafulla C., Rishi Pal, Manju J. Chaudhary, and Rajendra Nath. "Artificial Intelligence Revolutionizing Drug Development: Exploring Opportunities and Challenges." Drug Development Research 84, no. 8 (2023): 1652–63. https://doi.org/10.1002/ddr.22115.
130. Travitzky, Nahum, Alexander Bonet, Benjamin Dermeik, et al. "Additive Manufacturing of Ceramic-Based Materials." Advanced Engineering Materials 16, no. 6 (2014): 729–54. https://doi.org/10.1002/adem.201400097.
131. Vamathevan, Jessica, Dominic Clark, Paul Czodrowski, et al. "Applications of Machine Learning in Drug Discovery and Development." Nature Reviews Drug Discovery 18, no. 6 (2019): 463–77. https://doi.org/10.1038/s41573-019-0024-5.
132. Velásco-Mejía, A., V. Vallejo-Becerra, A. U. Chávez-Ramírez, J. Torres-González, Y. Reyes-Vidal, and F. Castañeda-Zaldivar. "Modeling and Optimization of a Pharmaceutical Crystallization Process by Using Neural Networks and Genetic Algorithms." Powder Technology 292 (May 2016): 122–28. https://doi.org/10.1016/j.powtec.2016.01.028.
133. Vora, Lalitkumar K., Amol D. Gholap, Keshava Jetha, Raghu Raj Singh Thakur, Hetvi K. Solanki, and Vivek P. Chavda. "Artificial Intelligence in Pharmaceutical Technology and Drug Delivery Design." Pharmaceutics 15, no. 7 (2023): 1916. https://doi.org/10.3390/pharmaceutics15071916.
134. Vora, Lalitkumar K., Amol D. Gholap, Keshava Jetha, Raghu Raj Singh Thakur, Hetvi K. Solanki, and Vivek P. Chavda. "Artificial Intelligence in Pharmaceutical Technology and Drug Delivery Design." Pharmaceutics 15, no. 7 (2023): 1916. https://doi.org/10.3390/pharmaceutics15071916.
135. Vora, Lalitkumar K., Amol D. Gholap, Keshava Jetha, Raghu Raj Singh Thakur, Hetvi K. Solanki, and Vivek P. Chavda. "Artificial Intelligence in Pharmaceutical Technology and Drug Delivery Design." Pharmaceutics 15, no. 7 (2023): 1916. https://doi.org/10.3390/pharmaceutics15071916.
136. Wang, Jia-Chang, Hitesh Dommati, and Sheng-Jen Hsieh. "Review of Additive Manufacturing Methods for High-Performance Ceramic Materials." The International Journal of Advanced Manufacturing Technology 103, nos. 5–8 (2019): 2627–47. https://doi.org/10.1007/s00170-019-03669-3.
137. Wang, Jun, Hota GangaRao, Ruifeng Liang, and Weiqing Liu. "Durability and Prediction Models of Fiber-Reinforced Polymer Composites under Various Environmental Conditions: A Critical Review." Journal of Reinforced Plastics and Composites 35, no. 3 (2016): 179–211. https://doi.org/10.1177/0731684415610920.
138. Wang, Q., and C. R. Chatwin. "Key Issues and Developments in Modelling and Simulation-Based Methodologies for Manufacturing Systems Analysis, Design and Performance Evaluation." The International Journal of Advanced Manufacturing Technology 25, nos. 11–12 (2005): 1254–65. https://doi.org/10.1007/s00170-003-1957-7.
139. Weichert, Dorina, Patrick Link, Anke Stoll, Stefan Rüping, Steffen Ihlenfeldt, and Stefan Wrobel. "A Review of Machine Learning for the Optimization of Production Processes." The International Journal of Advanced Manufacturing Technology 104, nos. 5–8 (2019): 1889–902. https://doi.org/10.1007/s00170-019-03988-5.
140. Wilson, Wendy I., Yun Peng, and Larry L. Augsburger. "Generalization of a Prototype Intelligent Hybrid System for Hard Gelatin Capsule Formulation Development." AAPS PharmSciTech 6, no. 3 (2005): E449–57. https://doi.org/10.1208/pt060356.
141. Wong, Carmen K., Samuel S. Ho, Bandana Saini, David E. Hibbs, and Romano A. Fois. "Standardisation of the FAERS Database: A Systematic Approach to Manually Recoding Drug Name Variants." Pharmacoepidemiology and Drug Safety 24, no. 7 (2015): 731–37. https://doi.org/10.1002/pds.3805.
142. Xin, Hai, Akashdeep Singh Virk, Sabitoj Singh Virk, Foluso Akin-Ige, and Samiul Amin. "Applications of Artificial Intelligence and Machine Learning on Critical Materials Used in Cosmetics and Personal Care Formulation Design." Current Opinion in Colloid & Interface Science 73 (October 2024): 101847. https://doi.org/10.1016/j.cocis.2024.101847.
143. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. "Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development." Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue V May 2026

https://doi.org/10.55218/JASR.2025160702.
144. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
145. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
146. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
147. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
148. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
149. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
150. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
151. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
152. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
153. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
154. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
155. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.
156. Yadav, Amrendra Pratap, Gurdeep Singh, Mukesh Kumar Singh, and Anurag Chaudhary. “Artificial Intelligence in Optimizing Formulations and Excipients: Revolutionizing Pharmaceutical Product Development.” Journal of Advanced Scientific Research 16, no. 07 (2025): 9–18. https://doi.org/10.55218/JASR.2025160702.

157. Yunusov, Timur. "Artificial Intelligence for Surfactant Science and Applications: A Review." Preprint, March 16, 2026. https://doi.org/10.26434/chemrxiv.15000942/v1.
158. Zhang, Linda L. "Product Configuration: A Review of the State-of-the-Art and Future Research." International Journal of Production Research 52, no. 21 (2014): 6381–98. https://doi.org/10.1080/00207543.2014.942012.
159. Zhang, Yu, Yongrui Xiao, Dimitrios Tsaoulidis, and Tao Chen. "An Early Decision-Making Algorithm for Accelerating Topical Drug Formulation Optimisation." Computers & Chemical Engineering 201 (October 2025): 109224. https://doi.org/10.1016/j.compchemeng.2025.109224.
160. Zimmer, Markus. "Forced Degradation and Long-Term Stability Testing for Oral Drug Products: A Practical Approach." In Methods for Stability Testing of Pharmaceuticals, edited by Sanjay Bajaj and Saranjit Singh. Methods in Pharmacology and Toxicology. Springer New York, 2018. https://doi.org/10.1007/978-1-4939-7686-7_4.
161. Zocca, Andrea, Paolo Colombo, Cynthia M. Gomes, and Jens Günster. "Additive Manufacturing of Ceramics: Issues, Potentialities, and Opportunities." Journal of the American Ceramic Society 98, no. 7 (2015): 1983–2001. https://doi.org/10.1111/jace.13700.
162. Zong, Zhijuan, and Yu Guan. "AI-Driven Intelligent Data Analytics and Predictive Analysis in Industry 4.0: Transforming Knowledge, Innovation, and Efficiency." Journal of the Knowledge Economy 16, no. 1 (2024): 864–903. https://doi.org/10.1007/s13132-024-02001-z.
163. Bourquin, Jacques, Heinz Schmidli, Peter Van Hoogevest, and Hans Leuenberger. "Comparison of Artificial Neural Networks (ANN) with Classical Modelling Techniques Using Different Experimental Designs and Data from a Galenical Study on a Solid Dosage Form." European Journal of Pharmaceutical Sciences 6, no. 4 (1998): 287–300. https://doi.org/10.1016/S0928-0987(97)10025-2.
164. Chauhan, Shikha Baghel, Indu Singh, Manya Singh, and Chirag Jain. "AI-Powered Excipient Innovation: Transforming Drug Design, ADMETProfiling, and Formulation Developmen." Current Topics in Medicinal Chemistry 26 (March 2026). https://doi.org/10.2174/0115680266431788260223072453.
165. Damian, Festo, Mohammad Harati, Jeff Schwartzenhauer, Owen Van Cauwenberghe, and Shawn D. Wettig. "Challenges of Dissolution Methods Development for Soft Gelatin Capsules." Pharmaceutics 13, no. 2 (2021): 214. https://doi.org/10.3390/pharmaceutics13020214.
166. Desai, Jagruti, Prince Dhameliya, and Swayamprakash Patel. "Optimizing Critical Quality Attributes of Fast Disintegrating Tablets Using Artificial Neural Networks: A Scientific Benchmark Study." Drug Development and Industrial Pharmacy 50, no. 12 (2024): 995–1007. https://doi.org/10.1080/03639045.2024.2434640.
167. Ferreira, Tiago, Artur Cavaco-Paulo, and Tarsila G. Castro. "Artificial Intelligence, Molecular Dynamics, and Beyond: Computational Insights In Cosmetics Research and Formulation Design." ChemPlusChem 90, no. 10 (2025): e202500340. https://doi.org/10.1002/cplu.202500340.
168. Manyikana, Martina, Yahya E. Choonara, Lomas K. Tomar, et al. "A Review of Formulation Techniques That Impact the Disintegration and Mechanical Properties of Oradispersible Drug Delivery Technologies." Pharmaceutical Development and Technology 21, no. 3 (2016): 354–66. https://doi.org/10.3109/10837450.2014.996897.
169. Panakanti, Ravikiran, and Ajit S. Narang. "Impact of Excipient Interactions on Drug Bioavailability from Solid Dosage Forms." Pharmaceutical Research 29, no. 10 (2012): 2639–59. https://doi.org/10.1007/s11095-012-0767-8.
170. Rakotonirina, Adèle, Tatiana Galperine, and Eric Allémann. "Fecal Microbiota Transplantation: A Review on Current Formulations in Clostridioides Difficile Infection and Future Outlooks." Expert Opinion on Biological Therapy 22, no. 7 (2022): 929–44. https://doi.org/10.1080/14712598.2022.2095901.
171. Singh, Inderbir, Jaswinder Kaur, Sukhanpreet Kaur, Bibhuti Ranjan Barik, and Rakesh Pahwa. "Artificial Neural Networks and Neuro-Fuzzy Models: Applications in Pharmaceutical Product Development." Brazilian Archives of Biology and Technology 66 (2023): e23210769. https://doi.org/10.1590/1678-4324-2023210769.