Metaheuristic Optimization Review

♦ ISSN: 3066-280X Vol: 07, No. 02, 2026 ♦ PP. 13–27

♦ Article DOI: https://doi.org/10.54216/MOR.070202

REVIEW ARTICLE

Drug Classification in Clinical Pharmacy: Principles, Applications, and Implications for Patient-Centered Care

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Received: June 28, 2026 Revised: July 30, 2026 Accepted: September 07, 2026 ⋆ Corresponding author

ABSTRACT

Drug classification in clinical pharmacy is increasingly important for organizing medication knowledge, supporting therapeutic decisions, and improving patient-centered pharmaceutical care. As healthcare data become more complex, traditional rule-based classification approaches may be insufficient for interpreting heterogeneous drug-related information, including medication histories, molecular descriptors, clinical indicators, adverse-event records, prescription patterns, and patient-specific risk factors. This review examines how artificial intelligence, machine learning, deep learning, feature selection, optimization, and decision-support systems contribute to drug classification in clinical pharmacy. The review discusses the role of intelligent models in medication safety assessment, drug–drug interaction monitoring, personalized therapy, pharmacy-service planning, and operational medication management. It also highlights major challenges related to data quality, interpretability, generalizability, workflow integration, and ethical implementation. Overall, intelligent drug classification can strengthen clinical pharmacy practice when computational models are transparent, clinically meaningful, and aligned with professional pharmaceutical judgment.

Keywords: Artificial intelligence ▪ Drug classification ▪ Clinical pharmacy ▪ Machine learning ▪ Medication safety

1. INTRODUCTION

Drug classification in clinical pharmacy has become an increasingly important research direction because modern pharmaceutical care depends on the ability to organize, interpret, and use drug-related information in a clinically meaningful manner. In clinical settings, pharmacists and healthcare professionals are required to evaluate therapeutic indications, patient characteristics, drug safety profiles, pharmacokinetic behavior, adverse-event risks, possible drug–drug interactions, and treatment suitability under conditions of growing data complexity. Traditional classification approaches, which often rely on fixed taxonomies, manual interpretation, or rule-based grouping, can be useful for standard documentation but may be limited when applied to heterogeneous clinical data. As healthcare systems move toward more personalized, evidence-based, and digitally supported decision-making, artificial intelligence-based classification offers a stronger analytical foundation for identifying hidden relationships among drug properties, patient profiles, and therapeutic outcomes [1]. Figure 1 presents an illustrative graphical summary of the methodological categories commonly discussed in drug classification research within clinical pharmacy. The figure organizes the reviewed methodological directions into major categories, including deep learning approaches, machine learning approaches, hybrid or integrated models, optimization techniques, feature selection methods, fuzzy and uncertainty-based methods, data-centric approaches, Internet of Things and sensor-based approaches, operational or logistics models, and clinical decision-support systems. This graphical representation helps clarify the methodological orientation of the review by separating dominant computational

families from emerging or more specialized research directions; the chart should be interpreted as a conceptual visualization unless its counts are replaced with values obtained from a formal bibliometric analysis.

The illustrative distribution shown in Figure 1 indicates that deep learning approaches can be positioned as a leading methodological direction because advanced neural architectures are increasingly used for complex healthcare classification tasks. Machine learning approaches also occupy a major position because they remain widely applicable to structured clinical, pharmaceutical, and patient-related datasets. Hybrid and integrated models appear as an important methodological category because they combine multiple computational strategies to improve classification robustness, model adaptability, and predictive reliability. Optimization techniques and feature selection methods are also strongly relevant to drug classification because they help refine model structure, reduce unnecessary input variables, and improve the balance between predictive performance and interpretability.

The lower-positioned categories in Figure 1 should not be interpreted as less important; rather, they represent more specialized or emerging directions within clinical pharmacy analytics. Fuzzy and uncertainty-based methods are useful when classification boundaries are not sharply defined, which is common in clinical decision-making. Data-centric approaches emphasize the importance of dataset quality, preprocessing, and bias reduction before model training. Internet of Things and sensor-based approaches support continuous patient or pharmacy-system monitoring, while operational and logistics models connect drug classification with medication availability, inventory behavior, and service-management requirements. Clinical decision-support systems represent the final practical layer, where computational classification outputs are translated into tools that can assist pharmacists and healthcare professionals in medication review, risk evaluation, and patient-centered therapeutic planning.

The need for intelligent drug classification is reinforced by the increasing diversity of data generated across clinical pharmacy, drug development, and patient-care workflows. Drug-related datasets may include demographic variables, medication histories, molecular descriptors, clinical measurements, treatment-response indicators, adverse-event records, prescription patterns, and pharmacy-service utilization data. These data sources are rarely uniform, and they often contain high-dimensional, incomplete, imbalanced, or noisy features that complicate conventional analysis. Machine learning methods can support the transformation of such data into predictive and classificatory knowledge by learning from complex patterns rather than depending only on predefined assumptions. This capability is particularly relevant in pharmacy-related decision-support systems, where classification outputs may assist in drug-use assessment, therapeutic monitoring, and medication-safety evaluation [2].

A central challenge in drug classification is the selection of informative features from large and sparse datasets. Pharmaceutical and biomedical datasets frequently contain many candidate variables, yet only a limited subset may contribute meaningfully to classification performance. Including irrelevant or redundant features can increase computational cost, reduce model interpretability, and weaken generalization when the model is applied to new clinical cases. Feature selection is therefore essential because it can improve classification efficiency while helping researchers and clinicians identify the most influential variables associated with drug behavior, safety, and therapeutic relevance. In this context, optimization-based feature selection has become valuable for handling high-dimensional biomedical data, especially when the objective is to improve predictive accuracy while reducing unnecessary input complexity [3].

Drug classification also has direct implications for personalized medicine, where treatment decisions increasingly depend on matching drug characteristics with patient-specific biological and clinical conditions. In this setting, classification models can support the identification of drug sensitivity patterns, potential therapeutic response groups, and clinically relevant associations between drugs and disease-related data. Such models may help improve treatment stratification by recognizing relationships that are difficult to detect through manual assessment alone. This is particularly important when patients differ in genetic background, disease subtype, previous medication exposure, comorbidities, and response profiles. Therefore, intelligent classification can contribute to more individualized pharmaceutical care by supporting the interpretation of complex drug-response information in a systematic and data-driven manner [4].

Metaheuristic optimization has attracted attention in healthcare classification because many clinical prediction and drug-related classification problems involve search spaces that are large, nonlinear, and difficult to solve using simple deterministic procedures. In these problems, the classification task is not limited to training a predictive model; it may also require selecting features, tuning hyperparameters, balancing conflicting objectives, and improving model robustness. Metaheuristic algorithms can support these requirements by exploring candidate solutions and identifying improved configurations for classification models. Their value becomes particularly visible when applied to medical datasets that contain overlapping class boundaries, imbalanced observations, and complex associations among clinical variables. Accordingly, metaheuristic-assisted classification can strengthen the design of computational pharmacy models by improving both predictive performance and model configuration [5].

Advanced feature selection and classification strategies are especially important in medical and pharmacy-related datasets because the consequences of misclassification may affect clinical interpretation, medication planning, and decision-support reliability. Unlike general classification problems, clinical pharmacy applications require attention not only to accuracy but also to stability, transparency, and the practical relevance of selected variables. A model that performs well numerically may still be difficult to justify if it depends on features that lack clinical meaning or if its classification behavior cannot be interpreted by healthcare professionals. Therefore, feature selection should be understood as both a computational and clinical requirement, since it can reduce dimensionality while improving the clarity of the relationships used by the model to distinguish between drug-related categories or patient-response groups [6].

The clinical usefulness of drug classification is also connected to the broader development of diagnostic and predic-

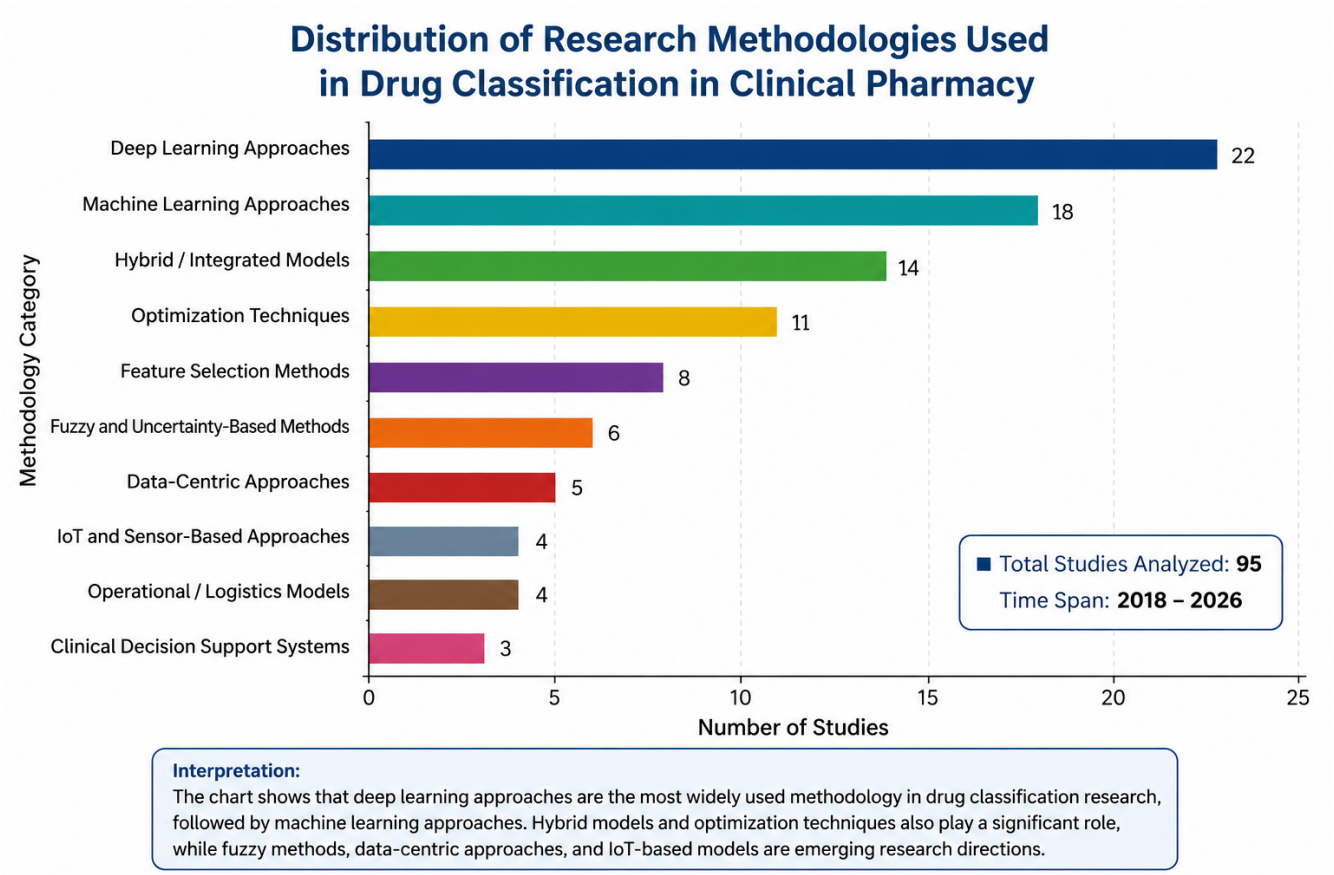

Figure 1. Illustrative graphical distribution of methodological categories relevant to drug classification in clinical pharmacy. The chart organizes major methodological directions, including deep learning, machine learning, hybrid models, optimization, feature selection, fuzzy reasoning, data-centric methods, sensor-based systems, operational models, and clinical decision-support approaches.

tive healthcare systems. Many medication-related decisions occur within a larger clinical environment where disease diagnosis, prognosis, comorbidity assessment, and treatment selection are interdependent. Classification models developed for healthcare prediction can therefore provide methodological insights for pharmacy applications, particularly in relation to data preprocessing, model evaluation, feature reduction, and optimization. When classification frameworks are designed carefully, they can support safer and more consistent decision-making by reducing dependence on subjective interpretation and by providing structured evidence from patient data. This connection highlights the importance of adapting robust healthcare classification methods to drug-centered tasks in clinical pharmacy [7].

Drug classification in clinical pharmacy should not be limited to therapeutic categories alone, because pharmacy practice also involves understanding patient access, service utilization, and the social factors that influence medication-related care. Machine-learning analyses of healthcare needs and access barriers provide a methodological basis for examining service inequalities. Extending these approaches to pharmacy services could help identify groups with limited access or unmet needs, although pharmacy-specific data and validation would be required. This perspective is important because the effectiveness of drug classification depends not only on computational modeling of drug properties but also on the clinical and service contexts in which medications are prescribed, dispensed, monitored, and evaluated [8].

The digital transformation of pharmacy systems has also expanded the role of intelligent classification beyond direct clinical decision-making into operational and inventory-related functions. Smart pharmacies increasingly rely on connected systems, automated monitoring, and predictive models to manage stock availability, reduce medication shortages, optimize dispensing workflows, and support timely access to essential drugs. In such environments, classification models may help organize drug inventories, identify demand patterns, prioritize high-risk medications, and support automated decision-making for pharmacy management. This operational dimension is relevant to clinical pharmacy because poor stock management, delayed availability, or inefficient distribution can affect treatment continuity and patient safety. Therefore, intelligent classification can support both the clinical and logistical dimensions of modern pharmacy practice [9].

Artificial intelligence-based drug classification must ultimately be positioned within a broader pharmaceutical decision-support ecosystem that includes healthcare supply chains, clinical workflows, patient-centered care, and responsible data governance. The successful use of classification models depends on the quality of input data, the suitability of selected features, the transparency of model behavior, the validity of evaluation metrics, and the ability of healthcare professionals to interpret and apply model outputs. Although intelligent classification can improve drug-related analysis, its implementation must avoid overdependence on black-box predictions and should be guided by clinical relevance, ethical safeguards, and practical usability. Therefore, this re-

view examines drug classification in clinical pharmacy as a multidimensional research area that connects artificial intelligence, machine learning, feature selection, optimization, pharmacy-service management, and personalized therapeutic decision-making [10].

2. LITERATURE REVIEW

The literature on intelligent drug classification and clinical pharmacy analytics reflects a gradual movement from isolated predictive modeling toward broader computational frameworks capable of supporting medication-related decision-making across molecular, clinical, operational, and service-oriented dimensions. Earlier data-driven healthcare studies mainly focused on whether machine learning models could classify disease states or predict clinical outcomes with acceptable accuracy; however, more recent pharmacy-related research has extended this objective toward understanding how drug information, patient characteristics, biochemical descriptors, medication-use behavior, and healthcare-system variables can be structured into useful classification tasks. This development is important because drug classification in clinical pharmacy is not a single computational activity. It may involve grouping drugs according to therapeutic role, predicting drug response, identifying potential safety risks, recognizing interaction patterns, distinguishing pharmacological profiles, or supporting medication-management decisions. Therefore, the reviewed literature should be interpreted as a connected body of work in which classification models, optimization techniques, biomedical feature engineering, and pharmaceutical decision-support systems contribute to the broader goal of improving clinical interpretation and pharmacy practice.

A major direction in the literature concerns the use of computational intelligence for drug–drug interaction prediction. This area is highly relevant to clinical pharmacy because interaction risks represent one of the most critical factors affecting medication safety, especially among patients receiving multiple therapies. Conventional interaction screening can identify known interaction pairs, but it may be less effective when the objective is to infer previously unobserved interaction patterns from complex drug-related data. Graph-based computational frameworks address this limitation by learning relationships among drugs, with skip connections, additional neural layers, and training refinements used to evaluate different interaction-prediction architectures. Such frameworks are useful because drug–drug interaction prediction requires the classification of relationships rather than the classification of isolated drug entities. In this setting, the model must evaluate how two or more drugs may behave when considered together, which increases the complexity of the classification problem. The literature therefore suggests that interaction-oriented classification can strengthen clinical pharmacy decision support by helping pharmacists assess potential medication risks before they result in adverse therapeutic consequences [11].

Another important stream of research focuses on quantitative structure–activity relationship modeling and cheminformatics-based classification. This direction is valuable because it connects drug classification with molecular descriptors, chemical properties, and computational representations of pharmacological activity. In clinical pharmacy, such models can support the interpretation of how structural characteristics may relate to therapeutic effect, toxicity, or drug behavior. Feature selection is particularly important in this context because molecular datasets often contain a large number of descriptors, many of which may be redundant, weakly informative, or statistically unstable. When irrelevant descriptors are included, classification models may become unnecessarily complex and less interpretable. By contrast, descriptor selection can improve the clarity of the model by retaining variables that contribute more directly to the classification of drug-like compounds or pharmacological categories. The literature indicates that combining cheminformatics representations with supervised learning provides a useful pathway for transforming molecular information into structured classification outputs that can support early-stage pharmaceutical assessment and computational drug evaluation [12].

A further body of literature examines general medical diagnosis classification as a methodological foundation for pharmacy-related classification problems. Although diagnostic classification and drug classification are not identical, they share several computational concerns, including data imbalance, feature relevance, algorithm selection, validation reliability, and the need to compare model behavior across different statistical indicators. Medical diagnosis studies are useful for clinical pharmacy research because medication decisions often depend on diagnostic context, disease subtype, comorbidity patterns, and patient-specific risk profiles. A drug classification model that ignores these clinical dimensions may produce outputs that are technically accurate but clinically incomplete. Therefore, diagnostic machine learning literature contributes indirectly to drug classification by demonstrating how classification pipelines can be evaluated under controlled conditions, how different algorithms respond to structured biomedical data, and how statistical measures can be used to compare predictive reliability. This methodological evidence is important for developing pharmacy-oriented models that are not only computationally effective but also suitable for integration into clinical decision-support environments [13].

The literature also includes studies that investigate feature selection and neural classification performance as independent methodological problems. This direction is relevant because many clinical pharmacy datasets contain heterogeneous variables such as medication attributes, patient demographics, laboratory indicators, adverse-event information, prescription records, and clinical history. A classifier trained on all available variables may appear comprehensive, but excessive dimensionality can reduce transparency and increase the possibility that the model learns weak or misleading associations. Feature-selection-based classification studies, therefore, provide a methodological basis for designing more compact, stable, and interpretable models. In particular, neural classifiers can benefit from carefully selected inputs because the architecture can focus on informative signals rather than distributing learning capacity across noisy variables. This is important for clinical pharmacy because interpretability and reliability are often as important as numerical performance. A model used to support medication-related decisions should provide a defensible relationship between the selected fea-

tures and the classification output, especially when the result may influence therapeutic evaluation or patient monitoring [14].

Deep learning-based disease monitoring literature provides another relevant perspective because it demonstrates how intelligent systems can manage continuous, large-scale, and multimodal healthcare data. While this research direction is not limited to drug classification, it is useful for clinical pharmacy because medication management increasingly occurs within digitally connected healthcare environments. Patient monitoring data, wearable signals, hospital records, pharmacy databases, and disease-progression indicators can all affect how medications are classified, prioritized, or evaluated in practice. Deep learning models are particularly useful when the data contain complex nonlinear relationships or when disease-related patterns must be detected from large volumes of information. For drug classification, this suggests that future systems may move beyond static drug labels and instead classify medications according to dynamic patient context, monitored disease status, and predicted care requirements. Such a direction can make classification more clinically responsive, because the same medication may have different relevance depending on the patient's condition, treatment stage, and monitoring evidence available at the time of decision-making [15].

Across these studies, the literature shows that intelligent drug classification in clinical pharmacy is shaped by several distinct but complementary research directions. Interaction prediction contributes to medication-safety assessment by classifying relational risks between drugs. Cheminformatics modeling contributes to molecular-level interpretation by linking chemical descriptors with pharmacological classification. Medical diagnosis classification provides methodological lessons for validating healthcare models under clinically meaningful evaluation conditions. Feature-selection research supports dimensionality reduction and interpretability in complex pharmacy datasets. Deep learning-based monitoring extends the discussion toward dynamic healthcare environments where drug classification may depend on real-time patient and disease information. These directions do not represent repeated versions of the same problem; rather, each one addresses a different layer of the clinical pharmacy classification ecosystem. Together, they indicate that the future of drug classification will likely depend on the integration of molecular data, clinical evidence, safety signals, patient monitoring, and optimized machine learning pipelines within transparent and clinically usable decision-support systems.

Despite the progress demonstrated in the reviewed literature, several methodological gaps remain evident. Many studies emphasize predictive performance, but fewer provide sufficient discussion of how classification outputs can be interpreted by pharmacists or translated into medication-related decisions. This gap is important because clinical pharmacy requires models that can be trusted, explained, and aligned with professional judgment. In addition, several classification pipelines are evaluated on specific datasets, which may limit generalization when applied to different patient groups, drug categories, clinical settings, or pharmacy-service environments. Another concern is that optimization and feature selection are often treated as technical improvements rather than as mechanisms for improving clinical clarity. For drug classification, the selected features should not only improve accuracy but should also make sense within pharmacological, therapeutic, or patient-care reasoning. Therefore, future research should give greater attention to clinical interpretability, external validation, workflow integration, and the practical relationship between model outputs and pharmacy decision-making.

Overall, the literature demonstrates that artificial intelligence-based drug classification is moving toward a more comprehensive and clinically connected research direction. The reviewed works collectively show that classification in this field can benefit from hybrid learning frameworks, molecular descriptor analysis, diagnostic machine learning principles, feature-selection strategies, and deep healthcare monitoring models. However, the value of these techniques depends on how effectively they are adapted to the specific requirements of clinical pharmacy. A useful drug classification system should not function only as a numerical classifier; it should support medication safety, therapeutic interpretation, patient-centered decision-making, and operational reliability. For this reason, the present review positions drug classification in clinical pharmacy as a multidimensional topic that requires both computational rigor and clinical relevance. This perspective allows the review to examine not only how models are developed, but also how they may contribute to safer, clearer, and more evidence-based pharmaceutical care. Table 1 summarizes representative artificial intelligence, machine learning, optimization, and healthcare decision-support methodologies that can inform drug classification research in clinical pharmacy by showing how different data types, modeling strategies, and operational objectives contribute to classification-oriented pharmaceutical intelligence.

The methodological studies summarized in Table 1 collectively demonstrate that drug classification in clinical pharmacy should be understood as a broad computational problem that extends beyond the direct assignment of drugs into fixed therapeutic groups. The selected references represent a diverse methodological landscape in which artificial intelligence, machine learning, deep learning, metaheuristic optimization, mathematical programming, fuzzy reasoning, inventory modeling, and connected healthcare systems contribute different analytical roles. This diversity is important because clinical pharmacy classification does not depend on a single data structure or a single modeling objective. Instead, it may require the interpretation of patient-centered information, drug-related descriptors, clinical service patterns, diagnostic indicators, pharmaceutical supply variables, and operational constraints. For this reason, the methodology matrix was designed to show how different computational approaches can support classification-oriented pharmaceutical intelligence from complementary perspectives without reducing the topic to one narrow predictive task.

The first methodological direction represented in the table concerns personalized health optimization. This direction is relevant to drug classification because pharmaceutical decisions are increasingly influenced by patient-specific health conditions, wellness indicators, treatment goals, and individualized care requirements. Evolutionary and nature-inspired optimization methods provide a useful computational basis

Table 1. Representative computational methodologies relevant to drug classification in clinical pharmacy

Study focus	Data type	Methodological approach	Main objective
Personalized health optimization [16]	Patient-centered health indicators	Evolutionary computing and nature-inspired optimization	Supports individualized health-oriented decision-making by showing how adaptive search strategies can be used to optimize complex wellness and care-related variables.
Clinical trial personalization [17]	Patient covariates and treatment allocation data	D-optimal design with sequential allocation	Improves treatment-effect estimation by accounting for patient covariates and allocating participants efficiently between experimental and control arms.
Emergency healthcare routing [18]	Injury locations, severity, and ambulance demand	K-means++ clustering and time-variant SPEA2	Optimizes dynamic ambulance routes by balancing travel distance and patient ride time while accounting for injury severity and changing demand.
Pharmaceutical supplier ranking [19]	Supplier criteria and order-allocation data	Machine learning, multi-criteria ranking, and mixed-integer programming	Uses learned supplier weights to support supplier selection and order allocation while balancing supply-chain cost and reliability.
Secure attribute selection [20]	Industrial Internet of Things attributes	Hybrid firefly-based attribute selection and split-point mechanism	Demonstrates how optimized attribute selection can reduce irrelevant inputs and improve the security of connected intelligent systems used in data-intensive environments.
Clinical decision support [21]	Liquid-based cytology image data	Deep learning-based decision-support system	Supports automated clinical identification by extracting diagnostic patterns from medical images and assisting healthcare professionals in classification-oriented decisions.
Sensor-based disease prognosis [22]	Electrocardiogram sensor data	Hybrid deep learning architecture with resource allocation	Enables continuous disease detection and prognosis by combining connected sensing with optimized computational processing for healthcare monitoring.
Multi-modal disease classification [23]	Breathing audio and chest-wall video data	Deep learning with audio–visual feature fusion	Improves disease classification by combining complementary data representations, which is relevant to drug classification tasks requiring heterogeneous clinical inputs.
Genetic-data diagnosis [24]	Breast cancer gene-expression data	Seagull optimization for feature selection with random forests	Selects informative gene subsets for breast cancer classification, supporting a more compact representation of diagnostic patterns.
Queueing-inventory healthcare modeling [25]	Patient-flow and medical-waste data	Data-driven queueing-inventory system	Links healthcare service demand with inventory behavior, supporting operational planning in settings where patient care and material availability are interdependent.
Fuzzy medical differentiation [26]	Chinese medicine syndrome data	Evolutionary fuzzy learning	Handles uncertainty in medical classification by combining fuzzy reasoning with evolutionary learning for syndrome differentiation and clinical pattern recognition.
Pharmaceutical cold-chain logistics [27]	Cold-chain inventory and routing data	Inventory-routing optimization	Improves pharmaceutical distribution by jointly considering inventory movement, logistics efficiency, economic cost, and environmental impact in medicine supply systems.
Adaptive production control [28]	Kanban system and simulation data	Particle swarm optimization-based adaptive system design	Provides an optimization-based perspective for adaptive operational control, which can inform pharmacy inventory and dispensing-flow management under changing demand.
Patient quality-of-life prediction [29]	Patient-reported healthcare data	Prototype machine learning prediction model	Supports patient-centered clinical interpretation by predicting quality-of-life measures that may influence medication review, care planning, and pharmacy-service evaluation.

for this type of problem because they are designed to search complex solution spaces where many variables interact simultaneously. In clinical pharmacy, such approaches can inform models that do not simply classify drugs according to general labels, but instead evaluate how medication-related decisions may vary according to patient profiles. This methodological perspective supports the movement from generalized classification toward more personalized classification, where the suitability, priority, or risk of a drug category can be interpreted in relation to individual health characteristics.

The second direction focuses on clinical trial personalization through D-optimal experimental design and sequential treatment allocation. This reference is methodologically important because clinical trials provide structured evidence for treatment response, safety, and therapeutic effectiveness, all of which are central to drug classification in clinical pharmacy. Covariate-aware trial design can help determine how patients are allocated between treatment groups and how treatment effects are estimated for personalized medicine; the optimal allocation need not be balanced. Although this approach is

not a drug classifier in the narrow sense, it contributes to the methodological foundation of classification by improving the structure of the evidence used to distinguish treatment responses. In pharmacy-related research, this is valuable because drug categories and treatment recommendations should ideally be supported by carefully optimized evidence rather than by uncontrolled or poorly balanced clinical observations.

The third methodological group addresses emergency healthcare routing and service-delivery optimization. Its relevance to clinical pharmacy lies in the fact that drug classification is not only a computational issue related to drug properties, but also a practical issue connected to how medicines and healthcare services reach patients under constrained conditions. Multi-objective routing models can balance travel distance and patient ride time while accounting for injury severity and changing ambulance demand. This is important for pharmaceutical care because medication availability and timely delivery can directly affect treatment continuity, particularly during emergencies, disasters, and public-health crises. Therefore, this methodology contributes an operational dimension to the review by showing how optimization models can support the classification and prioritization of healthcare needs in contexts where access and urgency are central considerations.

The pharmaceutical supplier-ranking methodology adds a supply-chain decision-support perspective to the methodological framework. Clinical pharmacy depends on the continuous availability of safe, reliable, and appropriate medications, and this availability is strongly influenced by supplier selection, procurement quality, distribution reliability, and industrial decision-making. Machine learning can estimate supplier-criterion weights, which can then be combined with multi-criteria ranking and mixed-integer order allocation to balance supply-chain reliability and cost. This is relevant to drug classification because medication categories are not only defined by therapeutic use, but also by their management requirements, supply sensitivity, quality assurance demands, and availability risks. By including supplier-ranking methodology, the table connects computational classification with the broader pharmaceutical ecosystem in which drugs are selected, sourced, stocked, and delivered.

The secure attribute-selection methodology provides a technical perspective on how irrelevant or excessive variables can be reduced in connected intelligent systems. Although this reference is drawn from an industrial Internet of Things context, its methodological value for clinical pharmacy lies in the optimized selection of attributes from complex data environments. Drug classification models often depend on datasets that include many variables, not all of which are useful for prediction or interpretation. Attribute selection can improve model efficiency by reducing unnecessary inputs, while also improving clarity by retaining the variables that contribute most strongly to the classification task. In pharmacy-related applications, this is particularly important because excessive feature complexity may limit clinical interpretability and make it difficult for pharmacists or healthcare professionals to understand why a model assigns a drug, patient, or treatment pattern to a specific class.

The deep learning-based decision-support methodology demonstrates how image-centered clinical classification can support automated healthcare interpretation. While the specific application area is diagnostic image analysis, the methodological structure is relevant to drug classification because it shows how deep feature extraction, feature reduction, and optimized classification can be integrated into a single decision-support pipeline. Clinical pharmacy can benefit from this type of methodology when drug classification is linked to diagnostic evidence, disease stage, or patient monitoring outputs. For example, if a medication category is selected according to disease severity or clinical phenotype, then automated diagnostic classification may become part of the broader drug-decision pathway. This reference therefore contributes to the table by showing how classification systems can combine deep representations with optimized learning to support healthcare decisions that may later influence pharmaceutical care.

The sensor-based disease-prognosis methodology introduces the role of continuous monitoring data in healthcare classification. In modern clinical pharmacy, medication-related decisions are increasingly influenced by real-time or near-real-time patient information, including physiological signals, disease progression indicators, and remote monitoring data. The use of sensor data with hybrid deep learning and resource allocation demonstrates how healthcare systems can classify or predict patient conditions under connected monitoring environments. This is relevant to drug classification because the same drug may have different clinical relevance depending on a patient's current physiological status, risk level, or disease trajectory. Therefore, this methodology supports a dynamic understanding of classification in which drug-related decisions can be informed by continuously updated patient data rather than static records alone.

The multi-modal disease classification methodology contributes another distinct perspective by emphasizing the integration of heterogeneous data representations. Clinical pharmacy data are often multi-modal because they may include structured clinical variables, medication histories, laboratory results, imaging outputs, genetic information, patient-reported outcomes, and service-use records. A classification model based on only one data source may fail to capture the full clinical context needed for reliable pharmaceutical interpretation. Multi-modal frameworks address this limitation by combining complementary representations that can strengthen model performance and contextual understanding. This methodological principle is directly useful for drug classification because drug categories, therapeutic suitability, and patient response patterns may depend on multiple forms of evidence rather than one isolated variable group.

The genetic-data diagnosis methodology highlights the importance of biologically informed classification. Genetic information can reveal patient-level differences that influence disease susceptibility, treatment response, and medication sensitivity. In clinical pharmacy, this is closely related to pharmacogenomics and personalized therapy, where classification may involve identifying which patients are more likely to benefit from a drug, experience toxicity, or require dose adjustment. A combination of seagull-optimization feature selection and random forest classification illustrates how informative gene-expression subsets can support breast cancer classification. For drug classification, this methodological direction is significant because it moves the discussion toward

patient-specific biological evidence, allowing classification systems to become more precise and clinically meaningful.

The queueing-inventory healthcare methodology provides a service-system perspective that is different from direct patient or drug prediction. Healthcare delivery depends on the interaction between patient flow, resource availability, medical materials, and operational timing. In pharmacy practice, similar relationships exist between prescription demand, stock availability, dispensing workload, waste control, and service continuity. A data-driven queueing-inventory framework is therefore relevant because it shows how healthcare systems can be modeled as dynamic operational environments rather than isolated clinical datasets. This perspective supports drug classification by linking medication categories to operational behavior, such as demand intensity, storage requirements, usage frequency, and waste sensitivity. It also helps clarify that intelligent pharmacy systems must consider both clinical meaning and logistical feasibility.

The fuzzy medical differentiation methodology contributes an uncertainty-handling perspective. Clinical and pharmaceutical data are often ambiguous because symptoms, treatment responses, medication risks, and patient conditions may not always fit sharply defined categories. Fuzzy learning is useful in this context because it allows classification boundaries to be represented more flexibly. This is particularly important when drug classification depends on partially overlapping therapeutic roles, uncertain clinical indicators, or patient presentations that do not belong clearly to one category. By combining evolutionary learning with fuzzy reasoning, this methodological direction shows how intelligent systems can support classification under uncertainty while preserving a degree of interpretability. In clinical pharmacy, this is valuable because pharmacists often work with incomplete, evolving, or probabilistic evidence when evaluating medication-related decisions.

The pharmaceutical cold-chain logistics methodology introduces a specialized operational requirement that is directly connected to drug management. Some medications require strict temperature control, careful routing, and environmentally sensitive storage conditions. Inventory-routing optimization for cold-chain logistics is therefore relevant to drug classification because certain drug categories may be distinguished not only by therapeutic purpose but also by handling requirements, storage constraints, distribution sensitivity, and environmental impact. This perspective expands the meaning of classification by showing that pharmaceutical intelligence must account for how drugs behave within supply systems. For clinical pharmacy, this is especially important because classification that ignores logistical conditions may fail to support safe and reliable medication access.

The adaptive production-control methodology provides an optimization-based view of how operational systems can respond to changing demand. Although adaptive Kanban systems are often discussed in production environments, the methodological principle can inform pharmacy workflow and inventory management. Pharmacies must frequently respond to fluctuations in medication demand, prescription volume, dispensing pressure, and stock movement. Particle swarm optimization-based adaptive control demonstrates how system parameters can be tuned to improve responsiveness and reduce inefficiency. This methodological perspective is relevant to drug classification because medications can be grouped or prioritized according to demand behavior, replenishment needs, shortage risk, or service impact. It therefore contributes a process-optimization layer to the overall methodology matrix.

The patient quality-of-life prediction methodology adds a patient-centered evaluation dimension. Clinical pharmacy should not evaluate medication-related decisions only through technical or operational criteria; it should also consider how treatment and care affect patient well-being. Machine learning models that predict quality-of-life measures provide an example of how patient-reported outcomes can be incorporated into healthcare analytics. This perspective is important for drug classification because medications may be classified not only by pharmacological action but also by their relationship to patient experience, symptom burden, treatment satisfaction, and long-term care outcomes. Including this reference helps ensure that the methodology matrix does not treat drug classification as a purely technical problem, but rather as part of a broader patient-centered care framework.

Overall, the methodology references in Table 1 show that drug classification in clinical pharmacy requires a multidimensional methodological foundation. Some studies contribute optimization principles, others contribute machine learning pipelines, while others provide evidence from healthcare operations, diagnostic modeling, sensor-based monitoring, biological data analysis, fuzzy reasoning, or pharmaceutical logistics. This combination is useful because drug classification is influenced by molecular characteristics, clinical conditions, patient-specific evidence, healthcare access, supply-chain reliability, and service-delivery constraints. The value of the methodology matrix is therefore not limited to listing previous studies; it organizes them according to the distinct methodological roles they can play in building more reliable, interpretable, and clinically relevant drug classification systems. By connecting computational intelligence with pharmaceutical practice, the reviewed methodologies provide a foundation for developing classification frameworks that can support safer medication management, improved decision support, and more adaptive clinical pharmacy services.

2.1 Clinical Foundations of Drug Classification

Drug classification in clinical pharmacy is not limited to arranging medications under broad therapeutic labels; rather, it represents a structured clinical process through which drug information is organized according to pharmacological action, therapeutic purpose, safety profile, patient suitability, administration route, monitoring requirements, and expected clinical role. This classification process is essential because pharmacists rely on drug categories to interpret medication appropriateness, compare therapeutic alternatives, identify potential risks, and support evidence-based recommendations. In practice, the same medication may be viewed through several classification lenses depending on the clinical question being addressed. A drug may belong to one category when considered according to its mechanism of action, another category when evaluated according to its indication, and a different practical group when assessed according to monitoring burden, adverse-effect potential, or interaction

sensitivity. This multidimensional nature makes drug classification a complex task that requires more than static grouping. Figure 2 presents a comprehensive conceptual illustration of drug classification in clinical pharmacy. The figure shows that drug classification is not restricted to a single therapeutic label, but rather represents a multidimensional clinical process that connects therapeutic purpose, pharmacological mechanism, chemical structure, route of administration, safety profile, and patient-centered factors. This structure is important in clinical pharmacy because pharmacists do not evaluate medications only according to their general category; instead, they interpret each medication according to its clinical indication, mechanism of action, formulation, possible risks, monitoring requirements, and suitability for individual patient conditions. Therefore, the classification framework shown in Figure 2 supports rational drug selection, improves medication review, strengthens patient-specific therapy planning, and assists healthcare professionals in organizing drug-related information in a clinically meaningful manner.

The central component of Figure 2 represents drug classification as the main organizing concept in clinical pharmacy, while the surrounding categories explain the major criteria used to interpret medication use in practice. Therapeutic classification groups drugs according to their clinical indication, such as antibiotics, antihypertensives, antidiabetics, and analgesics. Pharmacological classification focuses on the mechanism of action, allowing healthcare professionals to understand how a drug produces its therapeutic effect. Chemical classification organizes drugs according to structural similarity, which can be useful when comparing related compounds or anticipating class-related properties. Route-based classification highlights how administration method influences onset, absorption, patient adherence, and clinical suitability. Safety and risk classification emphasizes contraindications, adverse effects, drug–drug interactions, and monitoring requirements, which are essential for preventing medication-related harm. Finally, patient-centered factors show that drug classification must be interpreted according to age, comorbidities, renal or hepatic impairment, pregnancy status, and dose-adjustment needs. Together, these dimensions demonstrate that clinical pharmacy classification is a practical decision-support process that connects drug knowledge with individualized patient care.

In clinical pharmacy, accurate classification supports safer and more consistent decision-making because it helps organize large volumes of medication-related knowledge into interpretable structures. When drug classes are clearly defined, pharmacists can more effectively recognize therapeutic duplication, evaluate substitution possibilities, identify contraindicated combinations, and determine whether a treatment aligns with patient-specific needs. This role becomes particularly important in patients with chronic diseases, polypharmacy, renal or hepatic impairment, advanced age, pregnancy-related considerations, or complex treatment histories. In these cases, drug classification can guide medication review by allowing clinicians to understand not only what a drug is, but also how it behaves within the patient's broader therapeutic plan. Therefore, classification functions as a bridge between pharmacological knowledge and practical clinical judgment.

A clinically meaningful classification framework should also account for the difference between general drug identity and contextual drug use. General identity refers to the stable properties of a drug, such as its therapeutic class or pharmacodynamic target. Contextual use refers to how the same drug is applied in a specific patient, condition, dose, route, or care setting. This distinction is important because pharmacy decisions often depend on contextual interpretation rather than general classification alone. For example, two drugs may appear similar within a broad category, yet differ substantially in monitoring needs, adverse-event risk, interaction profile, or suitability for specific patient groups. As a result, advanced drug classification should support both standardized organization and flexible clinical interpretation.

2.2 Data Organization for Pharmacy-Oriented Classification

The development of drug classification models depends heavily on the quality and organization of the data used to represent medications, patients, and clinical contexts. Pharmacy-related data may originate from prescription records, electronic health systems, laboratory results, adverse-event reports, drug formularies, molecular descriptors, treatment outcomes, dispensing logs, and patient-monitoring platforms. These sources often differ in structure, completeness, terminology, and clinical meaning, which makes data organization a critical stage before any classification approach can be applied. Poorly structured data can lead to misleading classification outputs, even when advanced computational methods are used. Therefore, pharmacy-oriented classification requires careful preparation of input variables so that the model reflects clinically meaningful relationships rather than accidental patterns.

A major challenge in this stage is the transformation of raw pharmacy data into usable classification features. Drug names, dosage forms, strengths, frequencies, therapeutic indications, contraindications, adverse events, and patient characteristics must be standardized to reduce ambiguity. Medication records may include brand names, generic names, abbreviations, spelling variations, and incomplete documentation, all of which can affect classification consistency. Similarly, patient-related variables may contain missing values, measurement differences, or time-dependent changes that influence how a drug should be interpreted. For this reason, data organization should not be treated as a purely technical preprocessing step. It is a clinical knowledge-structuring process that determines whether the classification model can represent the real meaning of medication use in practice.

Effective pharmacy data organization should also preserve the relationship between drug information and patient context. A classification system that only uses drug-level variables may be useful for general grouping, but it may be insufficient for clinical decision support when patient-specific interpretation is required. Conversely, a model that includes patient variables without clear medication descriptors may fail to capture the pharmacological basis of classification. A balanced framework should therefore connect drug attributes with patient characteristics, clinical conditions, monitoring indicators, and treatment outcomes. This integration allows classification outputs to become more relevant to clinical pharmacy because they reflect both the medication itself and the environment in which it is used. As a result, organized

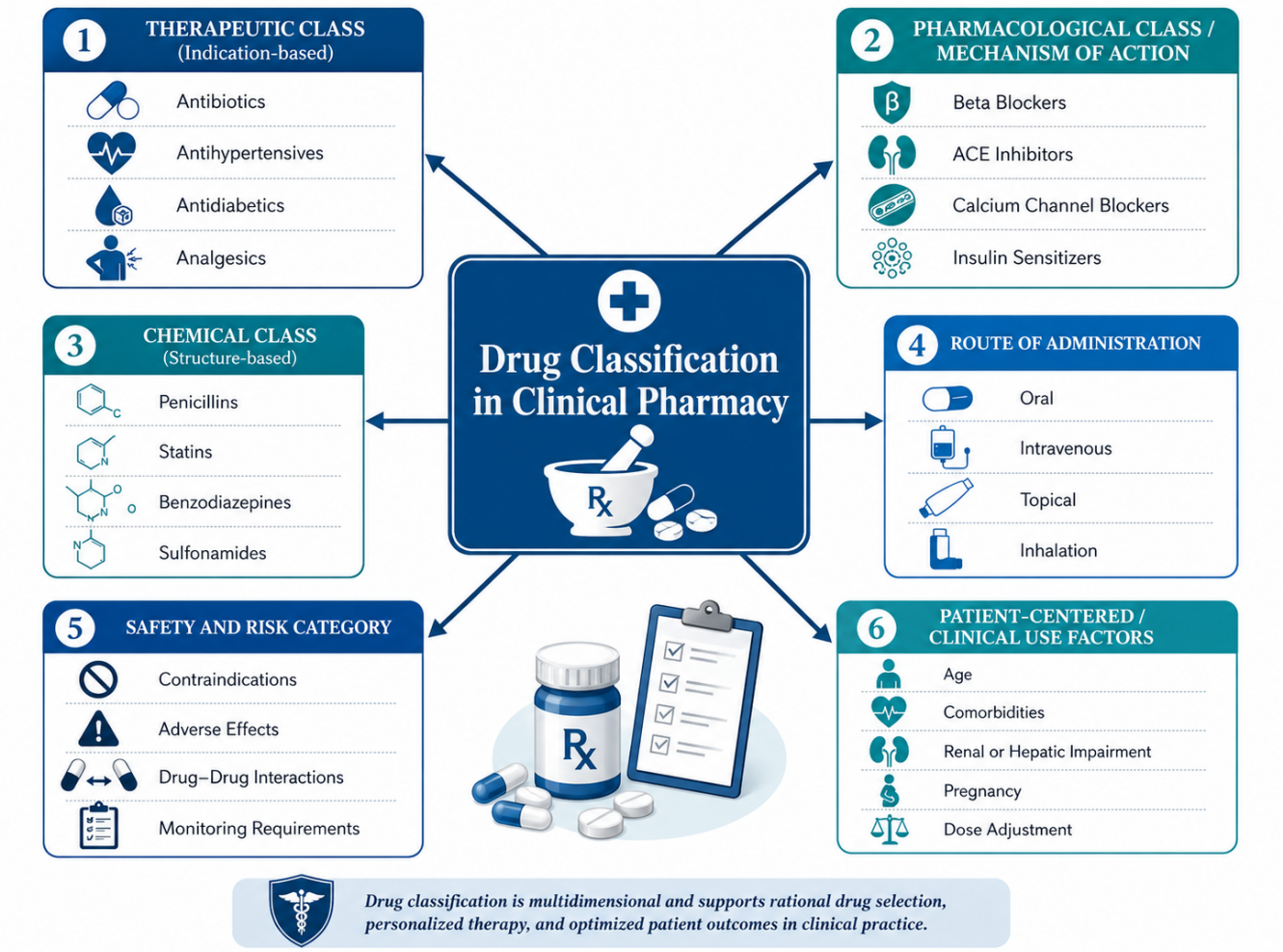

Figure 2. Conceptual framework of drug classification in clinical pharmacy. The figure illustrates the major dimensions used to classify medications, including therapeutic class, pharmacological mechanism of action, chemical class, route of administration, safety and risk category, and patient-centered clinical-use factors.

data become the foundation for reliable, interpretable, and clinically applicable classification.

2.3 Translation of Classification Outputs into Clinical Pharmacy Practice

The practical value of drug classification depends on whether classification outputs can be translated into useful pharmacy decisions. A model may generate technically accurate categories, but its clinical usefulness remains limited if pharmacists cannot interpret the output, connect it to patient care, or apply it within medication-management workflows. In clinical pharmacy, classification results should support actions such as medication review, therapeutic comparison, risk identification, dosage evaluation, monitoring prioritization, formulary management, and patient counseling. Therefore, the success of a classification framework should not be judged only by computational performance; it should also be evaluated according to its ability to assist professional reasoning and improve the clarity of medication-related decisions.

For classification outputs to be useful in practice, they must be presented in a way that aligns with clinical workflow. Pharmacists require information that is concise, interpretable, and connected to the reason for classification. If a system classifies a medication as high risk, interaction-sensitive, monitoring-intensive, or therapeutically suitable, it should provide enough supporting information to explain why that classification is relevant. This is especially important in patient-facing and multidisciplinary settings, where pharmacists may need to communicate recommendations to physicians, nurses, caregivers, or patients. A classification output that cannot be explained may create uncertainty, reduce trust, and limit adoption. Therefore, interpretability should be considered a practical requirement rather than an optional feature.

Drug classification systems should also be designed to complement clinical expertise rather than replace it. Pharmacy practice involves judgment, patient communication, ethical responsibility, and case-specific reasoning that cannot be fully captured by automated classification alone. Intelligent classification can strengthen this process by organizing evidence, highlighting relevant risks, and reducing cognitive burden, but final interpretation should remain connected to professional assessment. This human-centered role is particularly important when medication decisions involve vulnerable patients, uncertain evidence, conflicting guidelines, or individualized therapeutic goals. In this sense, drug classification becomes most valuable when it functions as a decision-support layer that improves the pharmacist's ability to evaluate medication use safely, efficiently, and transparently.

3. DISCUSSION

The reviewed body of work indicates that drug classification in clinical pharmacy should be interpreted as a knowledge-organization and decision-support problem rather than as a narrow computational task that assigns medications to predefined labels. In practical pharmacy environments, classification gains value when it helps structure the relationship between drug properties, patient characteristics, therapeutic goals, safety requirements, and service constraints. This means that an effective classification framework should not only identify the category to which a drug belongs, but should also clarify why that category is clinically relevant, how it may affect medication review, and how it can support safer decision-making. Such an interpretation is especially important because clinical pharmacy operates at the intersection of pharmacological evidence, patient-centered care, and healthcare-system limitations. Therefore, the significance of drug classification lies in its ability to convert fragmented pharmaceutical and clinical information into a form that can be understood, evaluated, and applied by healthcare professionals. Figure 3 presents a structured workflow for artificial intelligence-assisted medication safety and drug–drug interaction monitoring in clinical pharmacy. The figure explains how clinical pharmacy can benefit from a connected and intelligent monitoring framework that begins with patient-related and medication-related clinical inputs, proceeds through an artificial intelligence analysis engine, and finally generates clinically actionable outputs that support safer pharmaceutical care. This type of framework is important because medication safety in clinical pharmacy depends on the pharmacist's ability to integrate multiple sources of patient information, identify possible therapy-related risks, and intervene before medication-related harm occurs. Accordingly, the workflow shown in Figure 3 illustrates a practical model through which artificial intelligence can support the early recognition of interaction risks, contraindications, dose-adjustment needs, adverse-event probability, and monitoring priorities.

The left side of Figure 3 represents the clinical input layer, which forms the foundation of the entire medication-safety workflow. This layer includes patient demographics, current medications, allergy history, laboratory results, comorbidities, and renal or hepatic function. These variables are essential because medication safety cannot be evaluated in isolation from patient context. A drug that is appropriate for one patient may become unsafe for another because of age, organ impairment, allergic predisposition, concurrent therapy, or disease-related complexity. Therefore, the figure emphasizes that safe medication assessment begins with the collection of comprehensive and clinically meaningful input data. In clinical pharmacy practice, this input layer reflects the routine information that pharmacists review during medication reconciliation, treatment validation, and pharmacotherapy assessment.

The middle section of Figure 3 illustrates the artificial intelligence analysis engine, which functions as the core computational component of the workflow. This analytical layer is divided into several interrelated tasks, including data integration, risk scoring, interaction screening, dose assessment, and anomaly detection. Data integration is important because medication safety evaluation often requires combining heterogeneous clinical information from different sources into a unified analytical structure. Risk scoring helps estimate the overall likelihood of medication-related harm by synthesizing relevant patient and treatment variables. Interaction screening focuses on identifying potential drug–drug or drug–disease interactions that may not be immediately obvious during manual review. Dose assessment evaluates whether the prescribed dosage is appropriate in light of patient-specific characteristics, while anomaly detection supports the identification of unusual or high-risk patterns that may require additional attention. Together, these analytical stages demonstrate that artificial intelligence can support clinical pharmacy not only by automating detection tasks, but also by organizing complex medication-safety evidence into a coherent decision-support process.

The right side of Figure 3 presents the clinical output layer, which translates computational analysis into actionable pharmacy recommendations. These outputs include drug–drug interaction alerts, contraindication warnings, dose-adjustment recommendations, adverse-event risk identification, monitoring priorities, and pharmacist intervention. This part of the figure is particularly important because it shows that the final purpose of intelligent medication-safety systems is not merely to classify risk, but to support practical clinical action. Interaction alerts can prompt pharmacists to review combinations that may cause harm, contraindication signals can identify situations in which a drug should be avoided, and dose-adjustment recommendations can improve the safety of prescribing in vulnerable patients. Adverse-event risk outputs can help prioritize surveillance, while monitoring recommendations can guide follow-up assessments. The inclusion of pharmacist intervention as a final output reinforces the fact that artificial intelligence serves as a support tool rather than a replacement for professional judgment.

The lower part of Figure 3 summarizes the broader clinical impact of the workflow by linking the analysis process with safer prescribing, reduced medication errors, personalized therapy, and better patient outcomes. This section highlights the practical value of integrating artificial intelligence into medication-safety monitoring. Safer prescribing results from the early identification of clinically relevant risks before the medication reaches the patient in an unsafe form. Reduced medication errors emerge when automated screening complements manual review and helps identify omissions, inappropriate combinations, or dosage inconsistencies. Personalized therapy is strengthened because medication decisions are adjusted according to individual patient factors rather than relying only on generalized treatment assumptions. Better patient outcomes represent the broader consequence of these improvements, as safer and more individualized pharmacotherapy can reduce preventable harm and improve treatment quality.

Overall, Figure 3 presents medication safety in clinical pharmacy as a layered and intelligent process in which patient information, medication data, and computational analytics are connected within a single decision-support workflow. The figure clarifies that artificial intelligence can enhance medication review by structuring risk assessment, improving the consistency of screening procedures, and supporting targeted pharmacist intervention. At the same time, it preserves the

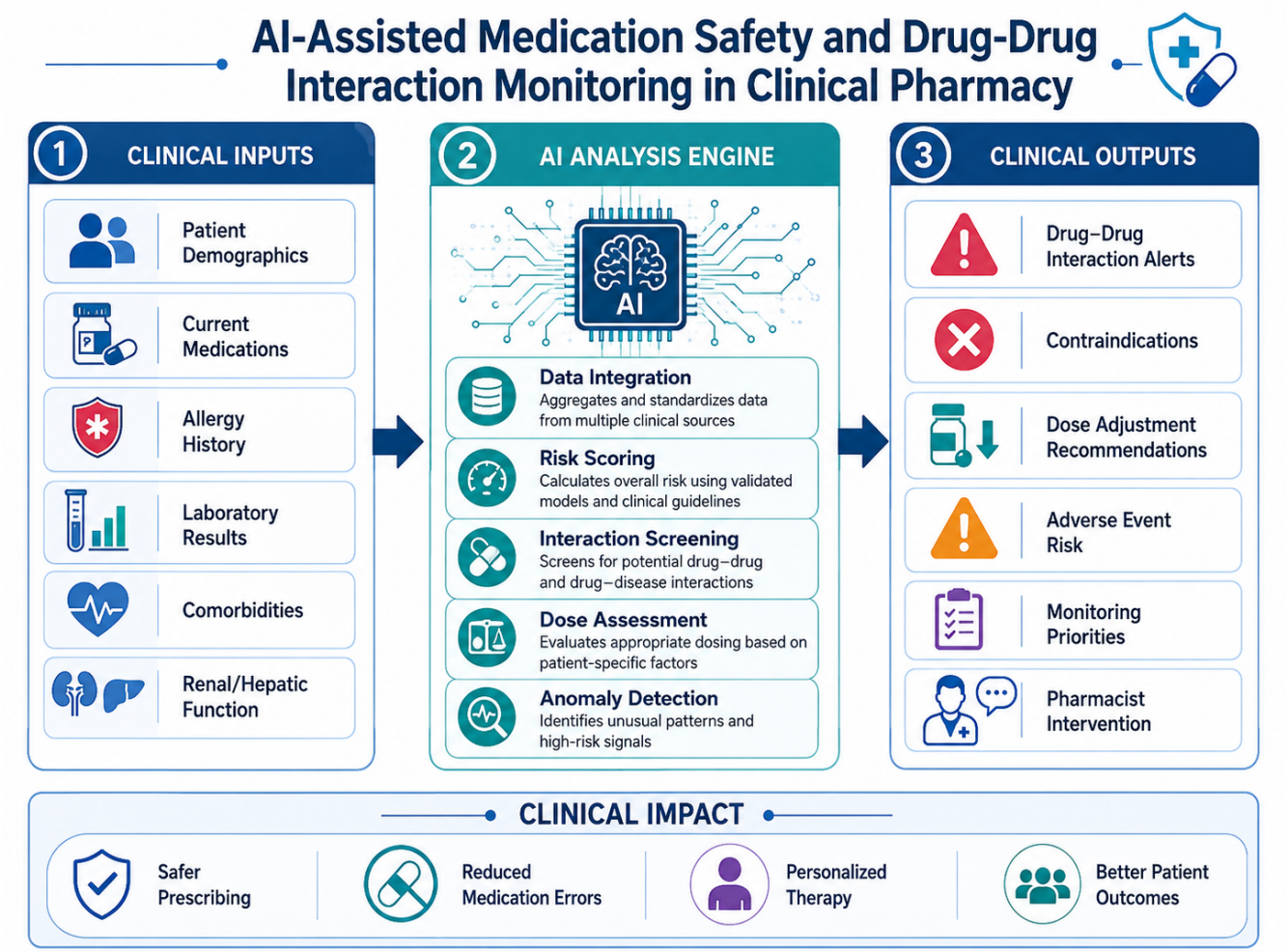

Figure 3. Artificial intelligence-assisted medication safety and drug–drug interaction monitoring workflow in clinical pharmacy. The figure shows how clinical inputs are processed through an artificial intelligence analysis engine to generate clinical outputs such as interaction alerts, contraindication detection, dose-adjustment recommendations, adverse-event risk assessment, monitoring priorities, and pharmacist intervention, ultimately improving medication safety and patient outcomes.

central role of the pharmacist by positioning the clinician as the final interpreter of alerts, recommendations, and safety signals. In this way, the workflow demonstrates how artificial intelligence-assisted medication-safety monitoring can strengthen pharmaceutical care through a balanced combination of data-driven analysis and clinical expertise.

The methodology matrix presented in Table 1 shows that drug classification is supported by several methodological directions, each contributing a different analytical function. Optimization-based methods contribute adaptive search and configuration capabilities, while machine learning models provide predictive and classification mechanisms for structured healthcare data. Deep learning approaches extend this capacity when complex patterns must be extracted from high-dimensional or multimodal information. Fuzzy learning introduces flexibility when clinical boundaries are uncertain, and operational models connect pharmaceutical classification with inventory, logistics, access, and service-delivery decisions. The importance of this methodological diversity is that no single computational approach is sufficient for representing the full complexity of clinical pharmacy. Instead, classification systems become more meaningful when they are designed as integrated frameworks that can handle clinical evidence, patient variability, drug-related characteristics, and pharmacy-service requirements together.

A major implication emerging from this review is that the clinical usefulness of drug classification depends strongly on how well the model output can be interpreted within pharmacy workflows. In many artificial intelligence applications, classification performance is commonly assessed using numerical indicators, but clinical pharmacy requires an additional layer of interpretability. A classification result should be explainable in terms of medication risk, therapeutic relevance, patient suitability, monitoring need, or operational priority. Without this interpretive layer, even a highly accurate model may remain difficult to adopt because pharmacists and clinicians need to understand the reasoning behind the classification before using it in medication-related decisions. This requirement is particularly important in cases involving polypharmacy, chronic disease management, high-alert medications, renal or hepatic impairment, and patients with complex treatment histories. In these situations, drug classification must support professional judgment rather than replace it.

The discussion also highlights the importance of data meaning in pharmacy-oriented classification. Clinical pharmacy data are not simply numerical inputs; they represent medication histories, patient conditions, care processes, therapeutic

decisions, and safety observations. If these data are poorly structured, incomplete, inconsistently coded, or disconnected from clinical context, the resulting classification may become unreliable even when advanced algorithms are applied. For this reason, data preparation in drug classification should be treated as a clinical modeling stage rather than a routine preprocessing step. Variables must be selected and organized in a way that preserves their pharmaceutical meaning. Drug names, dosage forms, routes of administration, contraindications, interaction indicators, laboratory findings, and patient-specific characteristics should be harmonized so that the model can reflect meaningful relationships rather than superficial statistical associations.

Another important consideration is that drug classification systems should be evaluated according to their ability to generalize across different pharmacy settings. A model trained on a specific dataset may perform well within that environment but may not maintain the same reliability when applied to another hospital, population, formulary, prescribing culture, or medication-management system. This issue is critical because clinical pharmacy practice varies across institutions and healthcare systems. Differences in documentation standards, available medications, patient demographics, disease prevalence, and prescribing protocols can influence classification performance. Therefore, future classification frameworks should be tested under conditions that reflect practical variability. External validation, multicenter data, temporal testing, and sensitivity analysis can help determine whether the model is robust enough for real-world pharmacy use.

The role of feature selection deserves particular attention because it connects computational efficiency with clinical clarity. In drug classification, a large number of variables may be available, but not all variables contribute meaningful information. Including excessive or irrelevant features can increase model complexity and reduce transparency. More importantly, it can make the classification output harder to interpret by healthcare professionals. A carefully designed feature-selection strategy can help identify the variables that carry the strongest clinical or pharmaceutical relevance. This can improve the model not only by reducing unnecessary dimensionality, but also by making the classification process more understandable. In clinical pharmacy, this is essential because selected features should be defensible from both computational and professional perspectives.

The reviewed methodologies also suggest that drug classification can benefit from being connected to patient-centered outcomes. A medication category may be clinically meaningful only when it is interpreted in relation to patient response, quality of life, treatment burden, adherence, adverse-event risk, and monitoring requirements. This perspective expands classification beyond the drug itself and places it within the broader patient-care pathway. For example, a medication may belong to the same therapeutic class as another drug but differ in its suitability for a specific patient because of tolerability, comorbidity profile, administration complexity, or expected benefit. A patient-centered classification framework can therefore support more individualized pharmaceutical care by linking drug categories with the real conditions under which medications are used.

Operational pharmacy considerations further broaden the meaning of classification. In clinical practice, medications are not only prescribed and evaluated; they are also procured, stored, dispensed, monitored, and replenished. Some drugs require cold-chain handling, others demand strict monitoring, and some may be associated with shortage risks or high operational sensitivity. Classification systems that ignore these practical dimensions may provide incomplete support for pharmacy management. By incorporating operational variables, intelligent classification can help distinguish drugs according to handling requirements, supply vulnerability, service demand, and resource implications. This is important because medication safety depends not only on correct therapeutic selection, but also on the reliable availability and proper management of pharmaceutical products.

The integration of drug classification with decision-support systems must also consider the human role in clinical pharmacy. Artificial intelligence can organize evidence, detect patterns, and reduce cognitive burden, but medication-related decisions require professional accountability. Pharmacists must interpret classification outputs in light of patient history, clinical judgment, ethical considerations, and interdisciplinary communication. Therefore, the most appropriate role of intelligent classification is assistive rather than autonomous. The model should provide structured information that strengthens the pharmacist's ability to evaluate medication use, but the final decision should remain connected to clinical expertise. This human-centered approach can improve trust and reduce the risk of overreliance on automated predictions.

From a research perspective, the field would benefit from classification frameworks that are more transparent, clinically grounded, and implementation-aware. Future models should be designed with attention to data provenance, variable meaning, workflow compatibility, validation diversity, and interpretability. In addition, the connection between model development and pharmacy practice should be strengthened by involving clinical experts during problem formulation, feature definition, evaluation design, and output interpretation. This collaboration can help ensure that classification systems address real medication-management needs rather than abstract computational objectives. As drug classification becomes increasingly influenced by artificial intelligence, its success will depend on the ability to balance predictive capability with clinical usability, safety awareness, and professional relevance.

4. CONCLUSION

This review examined drug classification in clinical pharmacy as a multidimensional area that connects artificial intelligence, machine learning, deep learning, feature selection, optimization, healthcare analytics, and pharmaceutical decision support. The discussion shows that drug classification should not be viewed as a simple labeling process. Instead, it should be understood as a structured approach for organizing medication-related knowledge and supporting clinical interpretation. A useful classification framework must be able to connect drug characteristics with patient conditions, therapeutic objectives, safety considerations, and pharmacy-service requirements.

The reviewed literature and methodology matrix indicate

that different computational approaches contribute distinct strengths to pharmacy-oriented classification. Some methods improve prediction, others support dimensionality reduction, while additional approaches address uncertainty, personalization, monitoring, logistics, and healthcare-service management. This diversity confirms that drug classification cannot rely on a single technical pathway. It requires an integrated framework capable of reflecting the complexity of real clinical pharmacy practice. Such a framework should be accurate, interpretable, adaptable, and aligned with the professional responsibilities of pharmacists.

A central conclusion of this review is that the value of intelligent drug classification depends on clinical usability. Models must provide outputs that pharmacists can understand and apply within medication review, risk assessment, treatment planning and patient counseling workflows. Classification systems that produce accurate but unexplained outputs may have limited practical value. Therefore, future research should prioritize transparent model behavior, clinically meaningful feature selection, careful data organization, and validation across diverse healthcare settings. These elements are necessary for moving drug classification from experimental modeling toward reliable clinical implementation.

Overall, artificial intelligence-based drug classification has strong potential to improve pharmaceutical care by supporting safer medication management, clearer therapeutic interpretation, and more evidence-based decision-making. However, this potential can only be realized when computational development is guided by clinical relevance, ethical responsibility, and practical workflow integration. The future of drug classification in clinical pharmacy should therefore focus on building decision-support systems that strengthen professional judgment, improve medication safety, and support patient-centered care without replacing the essential role of pharmacists in clinical decision-making.

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