

Applications of Artificial Intelligence (AI) in the Administration of Medicines and Health Treatments: A Scoping Review

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Abstract

The aim of this study is to identify the applications of artificial intelligence (AI) in the administration of medications and health treatments, with the goal of highlighting its primary uses in therapeutic personalization and describing its contributions to clinical optimization. An exploratory review was conducted using the PRISMA-ScR method, which included searches in high-impact international databases (Scopus and PubMed) and the application of eligibility criteria. The aspects evaluated included the year of publication, the author, the title, the journal and the abstract. This process resulted in the inclusion of a total of 13 articles, which were examined through a thematic analysis, allowing for the identification of emerging categories related to predictive models for the detection of drug interactions, dose adjustment, prevention of medication errors, therapeutic monitoring and decision-making support. There are still gaps in the literature related to data quality and representativeness, healthcare system interoperability, algorithmic governance and the definition of institutional responsibilities. Consequently, the sustainable consolidation of AI in the administration of medicines and health treatments will depend on the convergence of prospective clinical validation, the development of specific ethical and regulatory frameworks, the strengthening of interoperable infrastructures and the preservation of human clinical judgement in hybrid decision-making models.

Keywords: Artificial intelligence, Applications, Drugs, Healthcare treatments, Medicine.

Introduction

Clinical pharmacology works as a bridge between the discovery of molecules in the laboratory and their actual therapeutic application. Its scope is huge, as it's not just about prescribing, but also looking closely at pharmacokinetics (how the drug is absorbed, broken down and passed out of the body) and pharmacodynamics, which figures out how the drug interacts with the target organs (1, 2). These principles are the compass that defines the ideal dosage and frequency for each patient, considering that the biological response is never uniform because genetic, environmental and pathological factors create variability that requires absolute precision (3, 4). In this scenario, medication management becomes an essential issue for people's overall well-being. Medication errors, ranging from inaccurate dosages to undetected allergic interactions, are part of a persistent public health crisis (5, 6). A failure in this process not only leads to physical discomfort

or serious organ damage, but also drastically increases the deterioration of the patient's health. Therefore, medical practice has been reinforced by rigorous verification protocols that ensure that the right person receives the right medication, at the right time and in the right way, while always respecting the patient's right to autonomy and informed refusal of treatment (7, 8). Despite these efforts, the healthcare system remains vulnerable to systemic failures, forcing us to look to technology. In this context, artificial intelligence (AI), which began development in the 1950s and took its first steps in medicine in the 1970s with systems such as Mycin (for the diagnosis of bacterial infections), has had a journey that has not been without obstacles (9, 10). Those early algorithms, although accurate in diagnosing infections, came up against a wall of professional skepticism. Doctors at the time saw the machine as lacking in clinical judgment and empathy, a

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resistance like that faced by evidence-based medicine in its day compared to traditional medicine (11, 12). In the 21st century, AI has gone from being a science fiction promise to becoming a clinical optimization tool. Due to exponential advances in processing power, the technical limitations of the past have been overcome (13, 14). AI now has the potential to free specialists from administrative and repetitive tasks, allowing medical professionals to reclaim their time for direct patient care and reduce the professional burnout that characterizes modern healthcare systems (15, 16).

The most disruptive impact of AI is seen in pharmacological safety and critical moment management, as observed in emergency department discharges (17, 18). At these transition points, where the risk of error is highest, AI acts as an infallible supervisor that instantly analyzes the suitability of prescriptions, blocks questionable interactions and specifically protects vulnerable populations, such as the elderly and pregnant women, by identifying contraindicated medications that could go unnoticed in the chaos of a hospital (19, 20).

In this scenario of increasing therapeutic complexity and digital transformation of the healthcare system, it is necessary to examine in a structured manner how AI is being applied in the administration of medications and the management of healthcare treatments (21, 22). Various researchers (23-28) have provided relevant findings that focus on the evaluation and prediction of data on patient symptoms, analysis of drug profiles and their effects, the importance of machine learning (ML) and deep learning (DL) in pharmacology, drug development, diagnostic accuracy and treatment.

These findings suggest that AI applications in medication administration and treatment are moving toward recording, analyzing and reaching of these, in addition to measuring the effects on patients. This exposes the attributes of AI as a

support in the customization of health treatments and medication administration and shows suggestive aspects in research in this area. By promoting the continuity of this topic, studies encourage AI to reach specialized environments in pharmacology, which leads to the following research question structured under the PICO model: What are the applications of AI in the administration of medications and health treatments? This question guides the analysis toward identifying current uses, knowledge gaps and emerging potentialities of AI in this area of medical practice.

Methodology

A scoping review was performed to identify AI applications in the healthcare sector, specifically in the field of pharmacology. It's considered to expose the different tools and uses of AI in the administration of drugs in health treatments. To this end, the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) protocol (29) was chosen as the theoretical basis, as it provides an organized sequence of steps for discarding and acquiring files, as well as comparing them and synthesizing results. In this regard, this study seeks to answer the following research question: What are the applications of AI in the administration of medications and health treatments?

Eligibility Criteria

In order to ensure relevance, timeliness and methodological consistency, inclusion and exclusion criteria were defined for the selection of studies considered in this review. These criteria made it possible to identify a set of relevant publications based on publication period, language, type of study and thematic approach. Table 1 suggests the selection criteria applied, which guided the process of identifying and purging the set of articles analyzed.

Table 1: Fundamental Factors for Selecting Articles Based on PICO

Component	Inclusion Criteria	Exclusion Criteria
Population	Patients and healthcare professionals involved in the administration and treatment of pharmacology in clinical and hospital surroundings.	Studies focused on experimental models without clinical application (purely computational simulations without clinical data validation).

Intervention	Application of AI-based systems (predictive algorithms, software, clinical decision support systems, ML, among other devices or programs related to pharmacotherapy).	Use of traditional statistical tools without an AI component or that are not directly related to the administration or monitoring of medications.
Comparison	Emphasis on AI-based systems compared to traditional processes.	Studies that do not include explicit or implicit comparison with traditional methods or that do not allow for the evaluation of differences in clinical performance.
Outcomes	Focus on administration, dosing, or adherence to medications, detection of drug interactions, improvement in therapeutic adherence, dose optimization, reduction of adverse events and improvement in clinical decision-making.	Articles that use AI for diagnostic imaging unrelated to drug treatment. Studies that do not present results or indicators related to the administration of drugs and health treatments.
Study design	Documents presenting AI-based applications that specialize in the administration of medications and treatments.	Narrative reviews, editorials, letters to the editor, opinions without empirical support, purely theoretical studies with no practical application in drug administration.
Time frame	Publications with a range of 5 years.	Studies published outside that time frame.
Language	Languages: English and Spanish.	Languages other than English and Spanish.

Search Strategy

For this scoping review, large amounts of information were obtained, mainly from two databases, Scopus and PubMed, in which search filters were prioritized to limit the results to the central theme of the study. Likewise, the multidisciplinary response offered by these platforms was taken into consideration, which guaranteed the acquisition of relevant literature in different areas of medicine, such as pharmacology, pediatrics, cardiology, nursing, oncology, hepatology and geriatrics. In addition, the use of

structured search strategies and predefined selection criteria contributed to strengthening methodological rigor and minimizing possible selection biases.

In terms of search terms, the keywords considered are as follows: "artificial intelligence," "healthcare," "medication," and "treatment." Each search formula was adapted based on the guidelines of the databases used in conjunction with boolean operators (AND, OR). Table 2 shows the databases used, the keywords and the number of records found.

Table 2: Key Terms and Search Platforms Used

Databases	Keywords	Number of Records
Scopus	TITLE-ABS-KEY (AI AND medication AND treatment) AND PUBYEAR > 2015 AND PUBYEAR < 2027 AND (LIMIT-TO (SUBJAREA, "MEDI") OR LIMIT-TO (SUBJAREA, "PHAR") OR LIMIT-TO (SUBJAREA, "NURS") OR LIMIT-TO (SUBJAREA, "HEAL")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (OA, "all"))	381
PubMed	artificial intelligence AND healthcare AND medication AND treatment AND primary care	115
TOTAL		496

Selection of Studies

With regard to the review of these files, the year of publication, author, title, journal and abstract were examined. This process was performed manually using reference lists imported from PubMed and Scopus into EndNote 21 software. Thanks to this reference program, it was possible to identify the absence of duplicate records, an operation carried

out through the automated document review offered by EndNote 21.

Then, using this same tool, relevant terms were specified for the first filter, taking into account the titles and keywords of the files: "artificial intelligence" OR "AI." This screening helped to select 250 files, ensuring that the titles had AI as their central theme or, failing that, as a recurring theme in the research acquired. Subsequently, in the second filter, the following terms were

considered: "medication," "therapy," and "drug delivery." This allowed us to conclude this stage with a total of 67 articles for full reading, with the aim of applying the exclusion criteria based on the content of each one.

Information Processing

A manual review of the 67 articles identified was conducted, applying a qualitative content analysis in accordance with the previously established selection criteria. Priority was given to the depth and relevance of the findings reported in each study. To evaluate the eligibility of the texts, systematic data extraction was performed from the results and discussion sections, based on the criteria defined for the review.

This qualitative evaluation allowed us to identify thematic and content limitations that determined the exclusion of 47 articles. This exclusion is

justified by the null or scarce presence of findings related to the supply of medications based on automated processes, impact on the logistics of scheduling personalized therapies and even on AI-based applications for improving these procedures. In this regard, the process for reaching the total number of selected records ($n = 13$) is presented in the following PRISMA flow diagram, which indicates the screening stages and the number of documents discarded in each stage as shown in Figure 1.

Subsequently, a thematic analysis was performed, highlighting recurring patterns in the selected studies. To this end, development indices were broken down based on categories identified in the findings of the documents. This procedure supported the critical interpretation of the results, facilitating the identification of convergences, divergences and gaps in the analyzed literature.

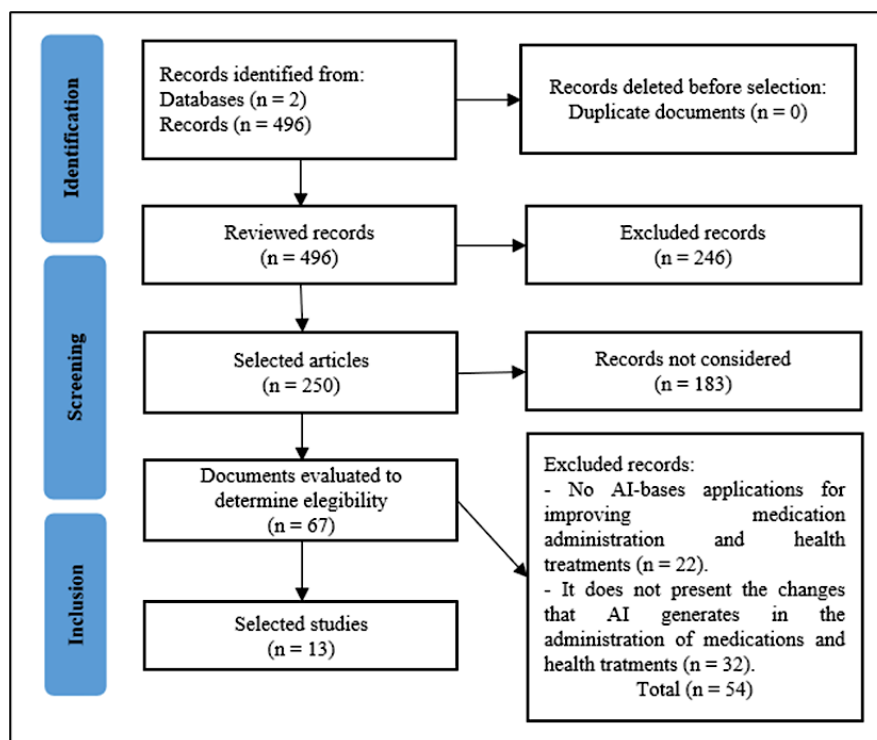


Figure 1: PRISMA Flowchart

Assessment of Methodological Quality

To ensure the methodological quality of the included evidence, an assessment was conducted using two instruments: the Mixed Methods Assessment Tool (MMAT, 2018 version) (30) and the Joanna Briggs Institute (JBI) Checklist (31, 32) for systematic reviews and research syntheses. The MMAT was used to assess the methodological

quality of the included primary studies, taking into account the nature of their designs and research approaches through two initial screening questions and five specific methodological criteria, according to the type of study (qualitative, quantitative experimental, non-randomized quantitative, descriptive quantitative, or mixed methods) as represented in Table 3.

Table 3. Systematic Review Matrix (MMAT Assessment)

Title	Main Conclusion	Type of Study	Journal	MMAT: S1 (Clear Question)	MMAT: S2 (Appropriate data)	MMAT: Category: Design	MMAT: M1	MMAT: M2	MMAT: M3	MMAT: M4	MMAT: M5	References
Predicting treatment retention in medication for opioid use disorder: a machine learning approach using NLP and LLM-derived clinical features	The models developed demonstrated predictive capability based on clinical information and features generated using LLM.	Development/Validation of Predictive Models	Journal of the American Medical Informatics Association	Yes	Yes	Quantitative	Yes	Yes	No	Yes	Yes	(33)
Use of Voice-Based Conversational Artificial Intelligence for Basal Insulin Prescription Management Among Patients with Type 2 Diabetes: A Randomized Clinical Trial	Improvements were observed in insulin titration, adherence and glycemic control compared with standard care.	Randomized clinical trial	JAMA Network Open	Yes	Yes	Quantitative	Yes	No	Yes	Yes	No	(34)
Effectiveness of ChatGPT in clinical pharmacy and the role of artificial intelligence in medication therapy management.	High performance was achieved in resolving pharmacological cases, although there were limitations in recommending specific doses.	Quantitative Evaluation of AI	Journal of the American Pharmacists Association	Yes	Yes	Quantitative	Yes	Yes	Yes	No	Yes	(35)

Developing Clinical Decision Support System using Machine Learning Methods for Type 2 Diabetes Drug Management	El modelo alcanzó elevada precisión en la predicción de medicamentos, mostrando potencial como herramienta de apoyo a decisiones clínicas.	Development of a Predictive Model	Indian Journal of Endocrinology and Metabolism	Yes	Yes	Quantitative	Yes	Yes	Yes	No	Yes	(36)
Impact of a clinical pharmacist-led, artificial intelligence–supported medication adherence program on medication adherence performance, chronic disease control measures and cost savings	Automated identification of adherence gaps made it possible to tailor pharmaceutical interventions to specific patients.	Retrospective quasi-experimental study	Journal of the American Pharmacists Association	Yes	No	Quantitative	Yes	No	No	Yes	No	(37)
Artificial Intelligence and Network Pharmacology Reveal the Medication Rules of Professor Wang Yu-Ying in the Treatment of Climacteric Syndrome	Data mining made it possible to identify prescribing patterns and generate new treatment proposals, which have yet to be experimentally validated.	Quantitative, retrospective, observational	World Journal of Traditional Chinese Medicine	Yes	No	Quantitative	No	Yes	Yes	Yes	No	(38)

Note: For mixed-methods studies, M1–M5 correspond to the five criteria established by the Mixed Methods Appraisal Tool (MMAT), 2018 version. In descriptive quantitative, qualitative and non-randomized quantitative studies, columns M1–M5 represent the five specific criteria defined by the MMAT for each methodological design.

Table 4: JBI Checklist for Systematic Reviews

Title	Main Conclusion	Type of Study	Journal	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	References
Artificial Intelligence (AI) and Drug-Induced and Idiosyncratic Cytopenia: The Role of AI in Prevention, Prediction and Patient Participation	AI makes it possible to predict risks and personalize treatments, but it requires human oversight and further validation.	Narrative Review	Hematology Reports	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	(39)
Nanoparticles and convergence of artificial intelligence for targeted drug delivery for cancer therapy: Current progress and challenges	The combination of AI and nanoparticles offers opportunities to optimize targeted drug delivery, but the available evidence is still limited	Literature Review	Frontiers in Medical Technology	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	(40)
The evolution of antiseizure medication therapy selection in adults: Is artificial intelligence - assisted antiseizure medication selection ready for prime time?	Potential for improving individualized drug selection was identified, although the models require further development.	Critical Review	Journal of Central Nervous System Disease	Yes	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	(41)
Artificial Intelligence-Assisted Clinical Decision-Making: A Perspective on Advancing Personalized Precision Medicine for Elderly Diabetes Patients	There is evidence of potential improvements in personalization and decision-making, which are constrained by issues related to data, transparency and privacy.	Review	Journal of Multidisciplinary Healthcare	Yes	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	(42)
Artificial intelligence and anti-cancer drugs' response	Predictive models show potential utility in anticipating drug resistance and guiding personalized treatments.	Review	Acta Pharmaceutica Sinica B	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	No	(43)
AI-Driven pharmacy practice: Unleashing the revolutionary potential in medication management, pharmacy workflow and patient care	Applications for optimizing pharmaceutical practice are identified, along with ethical, privacy and professional training challenges.	Narrative Review	Pharmacy Practice	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	(44)
Artificial Intelligence in Pharmaceutical Technology and Drug Delivery Design	Opportunities for optimization, cost reduction and efficiency improvements are recognized at various stages of the pharmaceutical industry.	Literature Review	Pharmaceutics	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	No	(45)

Note: Criteria: P1 = Was the review question formulated clearly and explicitly?, P2 = Were the inclusion criteria appropriate for the review question?, P3 = Was the search strategy appropriate?, P4 = Were the sources and resources used to search for studies appropriate?, P5 = Were the criteria used to assess the studies appropriate?, P6 = Was the critical appraisal conducted independently by two or more reviewers?, P7 = Were methods used to minimize errors in data extraction?, P8 = Were the methods used to combine the studies appropriate?, P9 = Was the likelihood of publication bias assessed?, P10 = Were the recommendations on policies and/or practices supported by the presented data? P11 = Were the specific guidelines for further research appropriate.

Meanwhile, the JBI checklist was used to assess the methodological quality of the reviews included in the study, taking into account the criteria established for this type of evidence synthesis as shown in the Table 4. The assessment was conducted independently by the reviewers, following the criteria established in each instrument. The results of both assessments were considered to determine the methodological strength of the evidence and to support the interpretation of the findings.

Results

Characteristics of the Studies

The systematic search identified 13 studies that met the inclusion criteria over a publication period between 2021 and 2026. As summarized in Table 5, the available evidence shows remarkable methodological, thematic and contextual diversity, reflecting the emerging but also evolving state

of the field. The studies were categorized according to their main design, population or scope of application, most relevant findings and their specific contribution to administration of medicines and optimization of therapies.

This characterization reveals that, although research into AI applied to the administration of medicine is distributed across multiple clinical specialties (oncology, diabetes, mental health and preclinical pharmacology), there is an emerging consensus about its transformative potential. However, the diversity in study designs, application contexts and evaluation criteria underscores the need for critical and comparative analysis to discern common patterns, significant contradictions and knowledge gaps that should be addressed in future research. Table 3 provides an overview of this body of evidence and sets the base for the integrative analysis presented in the discussion.

Table 5: Synthesis by Analytical Categories

Methodological Design	Population/Field	Main Findings	Contribution	References
Narrative Review	Hematology	Prediction of cytopenias, pharmacogenomic integration	Predictive Safety	(39)
Literature Review	Oncology and nanomedicine	Personalization using biomarkers, nanorobots	Targeted Optimization	(40)
Critical review	Neurology	ASM (anti-seizure medication) selection, moderate predictive performance	Decision Support	(41)
Review	Geriatric diabetes	AI-CDSS (clinical decision support systems), 50% reduction in errors, +17.9% adherence	Custom Optimization	(42)
Systematic analysis	Oncology	Detection of inappropriate prescriptions, intelligent monitoring	Systemic Security	(43)
Case of study	Traditional medicine	Pharmacology networks, patient stratification	Customization	(38)
Predictive model with ML	Mental health/addictions	NLP (natural language processing) for treatment retention, XGBoost/Random Forest	Optimization and Continuity	(33)
Randomized clinical trial	Type 2 diabetes	Insulin titration: 15 days vs. >56 days, 81.3% control	Dynamic Optimization	(34)
Quantitative evaluation	Clinical pharmacy	ChatGPT in medication management, early detection	Pharmaceutical Support	(35)
Narrative review	Practical pharmacy	100% identification of interactions, dosage limitations	Systematic validation	(44)
CDSS Development of predictive model	Diabetes	CDSS ML for diabetes, high preventive potential	Technical Decision Support	(36)
Literature review	Pharmaceutical technology	AI in formulation design, controlled release	Technological Innovation	(45)
Retrospective quasi-experimental	Pharmacy/adherence	Pharmaceutical program + AI, chronic disease management	Adherence and Monitoring	(37)

Personalization of Therapies and Supply of Medicines

Types of Automated Methods/Models

The studies presented in Table 3 show that AI is shaping up as a comprehensive predictive and adaptive support system in the administration of medications and health treatments. Its application is not limited to task automatization, but also has a direct impact on therapeutic individualization. Through advanced algorithmic models, AI enables the selection of drug treatments tailored to the patient's clinical profile, the optimization of therapeutic combinations and the modification of doses based on dynamic variables, thereby consolidating a precision medicine approach (35, 44).

A consistent trend toward the implementation of automated predictive models aimed at anticipating errors and adverse events was identified. Algorithms such as XGBoost and Random Survival Forest showed superior performance compared to traditional methods when retrospectively analyzing prescription errors, contraindications and deviations from clinical protocols (39). These models enable the construction of dynamic databases that not only record past failures but also generate predictive patterns to prevent their recurrence, thereby strengthening evidence-based clinical decision-making (43).

In the field of therapeutic monitoring, AI plays an important role through continuous monitoring systems and automated reminders that improve treatment adherence (39). The integration of interactive models, including voice-based systems for basal insulin titration in patients with diabetes, not only optimizes glycemic control but also reduces clinical variability and the decision-making burden on healthcare professionals (45). Likewise, the incorporation of language models, such as ChatGPT, into drug management has shown potential in identifying drug interactions and formulating therapeutic recommendations (45). However, the results also warn of limitations related to algorithmic biases and the need for specialized clinical supervision, highlighting that AI currently functions as a support tool and not as a substitute for professional judgment (33).

These findings allow us to understand AI in medication management as an adaptive and a decision support system that intervenes in three key dimensions: therapeutic personalization, risk

prevention and optimization of clinical monitoring. Nevertheless, challenges remain regarding the external validation of models, integration into real clinical environments and the standardization of ethical and regulatory criteria.

Patient Data Collection

AI is based on the integration of large volumes of heterogeneous data, including clinical, pharmacological and demographic information. This massive processing allows to identify high-risk prescriptions and anticipate adverse events with greater accuracy than conventional approaches (43). Despite, the results also emphasize that the effectiveness of these systems depends on structural factors, such as data quality and standardization, the representativeness of the populations included in the training sets and the degree of algorithmic transparency, elements that condition the external validity and clinical applicability of the models.

In this regard, it is noted that the systematic accumulation of longitudinal patient data enables the early detection of adverse reactions and the reduction of medication errors (39). The ML, applied to the analysis of complex databases, allows exploring patterns associated with new pharmacological combinations, expanding the predictive capacity against interactions and unforeseen effects in emerging therapeutic regimens. This prospective dimension transforms AI into a tool that is not only corrective, but also preventive and predictive.

On the other hand, in the field of pharmaceutical care, the integration of AI strengthens professionals' ability to respond to specific patient needs. The incorporation of individual information facilitates interventions that are more tailored to the clinical profile, particularly in complex drug therapies. Likewise, AI-based systems make it possible to identify patterns of response to treatment that would be difficult to detect using traditional methods, reducing clinical uncertainty and promoting more informed decision-making (40).

However, consolidating these advances requires deeper consideration of the quality, standardization and representativeness of the data underpinning predictive models. Dependence on highly digitalized databases and specific populations may limit the external validity and clinical transferability of systems in diverse

contexts. In this regard, it is important to move toward multicenter designs and evaluation frameworks that allow for the assessment of the stability and applicability of these models in real-world, dynamic healthcare scenarios.

Optimizing Therapy Monitoring

The studies reviewed agree that AI has improved treatment monitoring through continuous monitoring systems and dynamic treatment adjustments. One of the most significant applications is observed in the development of smart prosthetics, where ML registers the patient's movement patterns and progressively adjusts the device's functionality, promoting personalized adaptation and improvements in functional performance (38). This evidence reflects the transition towards therapeutic devices capable of learning from the user and adapting their behavior based on longitudinal data.

In the field of remote monitoring, several studies highlight the integration of wearable devices and biometric sensors that capture real-time data on clinical parameters and medication adherence. The collected data is processed using algorithms that enable the detection of therapeutic deviations, the anticipation of risks and the optimization of adjustments to dosages or treatment regimens. This approach not only improves continuity of care, but also transforms follow-up into a dynamic and preventive process.

This approach not only improves continuity of care, but also transforms monitoring into a dynamic and preventive process. However, the results indicate that the accuracy of the responses depends on the level of specificity of the queries made, highlighting the need for professional supervision and structured protocols for their integration into clinical environments. Although the tool showed promise in identifying drug interactions and adverse effects, its effective implementation requires additional validation and control for potential biases.

On the other hand, some traditional AI methods (such as Boost, feedback control systems, Set Covering Machine and logistic regression) have faced limitations in their clinical implementation, mainly due to difficulties in translating the models to clinical environments and integrating them with medication management systems. This gap between algorithmic development and clinical

applicability remains a structural challenge that must be evaluated.

Finally, it is evident that the incorporation of ML models based on pharmacogenetic data and biomarkers enabled more precise and personalized treatment monitoring, thereby reducing the probability of treatment discontinuation due to intolerable side effects (36). These findings reinforce that AI not only optimizes monitoring but also promotes more personalized pharmacotherapy by anticipating individual responses and facilitating early adjustments in drug selection and dosing.

Prediction and Risk Caution of Medications and Therapies

Detection of Pharmacological Interactions

The studies reviewed show that AI has established a central role in managing risks associated with medication administration, particularly through its integration into electronic prescribing systems and clinical dispensing workflows. ML algorithms enable the identification of recurring error patterns, such as incorrect dosages, therapeutic duplication and medication reconciliation errors, resulting in a substantial reduction in preventable errors compared to traditional methods, particularly in patients on multiple medications (42, 44).

From an analytical perspective, ML models have demonstrated the ability to process large volumes of clinical, genomic and pharmacovigilance data, identifying risk factors that may go unnoticed in conventional evaluations (33). In this regard, AI can interrupt the chain of errors early on, particularly during the prescription and medication review phases, by detecting interactions and potential problems before the medication is administered. This approach introduces a preventive component that transforms the error management model from a reactive logic to an anticipatory one (37).

Regarding the prediction of specific risks, the development of models based on XGBoost, Random Survival Forest and logistic regression is effective in predicting discontinuation of buprenorphine-naloxone (BUP-NAL) therapy; This demonstrates superior performance compared to traditional methods (39). In addition, the incorporation of NLP made it possible to extract relevant clinical information from unstructured records, thereby enhancing the models' predictive

capabilities. These findings suggest that AI not only identifies current errors but can also estimate future therapeutic risks in specific contexts.

In the field of pharmacological interaction detection, supervised models based on the molecular and structural characteristics of drugs were developed; this made it possible to classify drug pairs according to their probability of interaction with greater accuracy than approaches based exclusively on clinical rules (35). In a complementary manner, it was demonstrated that deep learning models can integrate structured information (electronic health records, prescriptions, laboratory results) and unstructured data to predict drug-drug interactions before they manifest as clinically relevant adverse events (45). For their part, language model-based tools, such as ChatGPT, demonstrated the ability to identify potential interactions in complex clinical cases, generate alerts related to adverse effects and suggest medication adjustments (such as discontinuing potentially nephrotoxic drugs or adjusting doses) with the goal of reducing immediate risks (36, 36). However, studies caution that, while these tools are effective in detecting current or imminent risks, they lack the inherent ability to predict long-term clinical events without the support of integrated prediction systems and additional longitudinal data.

AI helps mitigate errors resulting from fragmented information and a lack of interoperability among healthcare systems, thereby improving the early detection of risk situations that often remain invisible in conventional approaches. Furthermore, AI is presented as a preventive and predictive system that intervenes at multiple levels of the therapeutic process, such as identifying prescribing errors, detecting interactions, analyzing multimodal data and estimating discontinuation or adverse events (34, 37). However, limitations remain related to clinical integration, system interoperability and long-term predictive capability, suggesting the need for more solid regulatory frameworks and prospective validations.

Discussion

The evidence reviewed confirms that AI is progressively reconfiguring the model of medication administration and has shifted the traditional paradigm (reactive, protocol-driven

and based on static rules) toward a predictive system grounded in multimodal data analysis (23–26). In this context, medication administration is a suitable area for implementing this tool due to the data-intensive, repetitive and longitudinal nature of its processes. Prescribing, dispensing, administering and monitoring treatment generate large volumes of structured and unstructured information that can be integrated to identify patterns, anticipate risks and support individualized decisions (39, 40).

Unlike applications such as diagnostic imaging, where AI focuses on interpreting visual information, medication management involves a chain of successive decisions in which patient characteristics, medical history, prescriptions, drug interactions, dosages, adherence and therapeutic response all come into play (24–28). This characteristic makes pharmacotherapy a particularly favorable setting for systems capable of integrating multimodal and longitudinal information (33, 34, 38).

However, this technological transformation has not been accompanied with the same depth by equivalent developments in clinical validation, algorithmic governance and institutional accountability, revealing a structural asymmetry between technical innovation and regulatory infrastructure (40, 43, 45). From a quality management perspective, these findings allow us to expand the traditional approach—centered on standardization and process control—toward a dynamic conception of quality, in which the predictive capacity of systems must be accompanied by ongoing mechanisms for validation, monitoring and reevaluation (26–28). AI does not replace the principles of quality management; rather, it shifts them toward environments where quality depends on the reliability of data, the stability of models and the institutional capacity to manage their results.

However, although predictive models used for the detection of pharmacological interactions, dose adjustment and prevention of treatment discontinuation superior to traditional methods, the reviewed literature (22–27) prioritizes retrospective metrics over clinically significant indicators, such as reduced morbidity, serious adverse events, or impact on mortality (25, 29). This finding is consistent with studies that demonstrate the potential of predictive and machine learning models to identify risk patterns

and highlights a significant difference compared to research focused specifically on clinical outcomes (26, 27).

This difference can be explained by the predominance of retrospective studies and evaluations of algorithmic performance over prospective designs aimed at measuring clinical outcomes (37, 43, 44). This gap suggests that statistical efficacy does not necessarily translate into a tangible therapeutic benefit, raising the need for prospective, multicenter studies to assess the actual impact on hard clinical outcomes. Therefore, findings supported by quantitative evaluations and validation processes provide relevant evidence regarding the technical potential of these tools; however, the lack of sufficient prospective evidence on clinical outcomes limits the possibility of considering such performance as definitive evidence of therapeutic effectiveness (26,43).

In the field of personalized therapeutic, the integration of clinical, pharmacogenetic and longitudinal data represents an expanded version of precision medicine (24, 27). This finding is consistent with previous studies that have shown that incorporating pharmacogenetic information, biomarkers and clinical characteristics allows for the tailoring of drug selection to patients' specific characteristics. The studies analyzed expand on this perspective by demonstrating that personalization is not limited to the initial selection of treatment but can extend to the monitoring and dynamic adjustment of therapies (41, 43).

Nevertheless, the apparent technical sophistication hides a structural vulnerability: a critical dependence on the quality and representativeness of the data (39, 38) When models are trained on homogeneous populations or highly digitized healthcare systems, there is a risk of reproducing or even amplifying health inequalities in underrepresented contexts. Far from being neutral, AI incorporates the historical asymmetries of the systems that power it (41, 42). Consequently, these findings refine the perspective on precision medicine by introducing a fundamental condition: algorithmic personalization can only be considered clinically sustainable when the data used to build the models adequately represent the populations in which they will be implemented (27, 41).

Furthermore, although the predictive power of these models in treatment selection and optimization is highlighted, the literature reviewed in the research gap analysis shows little discussion of how the models perform in the face of epidemiological changes, therapeutic updates, or dynamic clinical variability (22-26). The stability of algorithms in the face of structural changes in the healthcare context (including model drift and performance degradation) remains an under-explored area (25, 40). This limitation is particularly relevant in the administration of medications, since prescriptions, clinical conditions, treatment guidelines and epidemiological profiles can change continuously (26, 28).

In the detection of medicine interactions, advances in supervised models and machine learning overcome the limitations of systems based exclusively on clinical rules. However, there remains a critical distinction that has not been fully explored between potential pharmacological interaction and actual clinical relevance (34, 39). Maximizing algorithmic sensitivity can lead to over alerting and decision fatigue, which reduces the system's practical effectivity; in this regard, the balance between technical accuracy and clinical applicability represents a central tension within the predictive paradigm (35).

The growing use of intelligent systems in pharmacotherapy raises questions about liability for prediction errors, model auditing and the traceability of automated decisions. The lack of specific regulatory frameworks for AI applied to clinical pharmacology can create gray areas of shared responsibility among clinics, institutions and technology developers. Without clear governance, innovation risks outpacing the healthcare system's regulatory capacity (33, 36, 37).

AI-assisted treatment monitoring also brings about a cognitive transformation in clinical practice. The transition to hybrid models combining human and AI is redefining professional roles, from protocol executors to supervisors of intelligent systems. However, this process carries the risk of technological dependence and a gradual erosion of clinical judgment, unless explicit mechanisms for critical oversight and specialized training are established.

On the other hand, the promise of reducing errors and information fragmentation depends less on

the algorithm itself than on the interoperable architecture of the healthcare ecosystem (39-41). Without effective integration between electronic health records, prescription systems and monitoring platforms, even the most sophisticated models will operate on incomplete data, which could compromise their predictive capabilities and create a false sense of institutional security.

Overall, AI applied to medication administration is not simply a tool for technological optimization, but rather a gradual transformation of the pharmaceutical ecosystem. Therefore, its consolidation will depend on four interdependent pillars: solid clinical validation, specific regulatory governance, systemic interoperability and the preservation of human professional judgment (24-27). In addition to these pillars, there must be the ability to prevent errors throughout the entire medication chain, from prescribing to monitoring, as well as the institutional capacity to ensure transparency, equity, explainability, accountability and information security (23, 33, 43).

Consequently, given the small number of studies included and the heterogeneity of their designs, the findings should be interpreted by distinguishing between trends consistently supported by the available evidence and those applications for which the evidence remains exploratory or preliminary. Future research must move beyond the predominantly retrospective phase and focus on prospective multicenter validation studies, assessments of the impact on hard clinical results, cost-effectiveness analyses and the development of ethical and legal frameworks adapted to AI-assisted pharmacotherapy. Only through this structural convergence will it be possible to prevent technological advancements from outpacing the institutional maturity of the healthcare system.

Conclusion

This scoping review demonstrates that AI is progressively transforming the model of drug administration, shifting from a traditional reactive approach toward predictive systems based on the multimodal analysis of clinical, pharmacogenetic and longitudinal data. The identified applications demonstrate significant progress in therapeutic personalization, early detection of pharmacological interactions, dose optimization and enhanced clinical monitoring. Taken together, the

findings confirm that AI does not limit to automating processes, but structurally reshapes the logic of decision-making in pharmacotherapy. However, this technological expansion is taking place against a context of predominantly retrospective validation and methodological heterogeneity.

Although these models outperform traditional methods in terms of predictive ability, the available evidence regarding their impact on hard clinical results such as reduced morbidity, serious adverse events, or mortality remains limited. In addition, challenges remain regarding the quality and representativeness of data, the interoperability of healthcare systems and effective integration into real-world clinical settings.

In addition, the implementation of AI-based systems raises structural tensions that go beyond the technical level. The lack of specific regulatory frameworks, the need for algorithmic auditing, the definition of institutional responsibilities and the preservation of human clinical judgment are critical factors for its consolidation. Thus, the transition to human-AI hybrid models is redefining professional roles and requires specialized training to prevent technological dependence or the erosion of decision-making autonomy.

Consequently, the consolidation of AI in medicine administration will depend on a convergence of technological innovation, prospective clinical validation, the development of appropriate ethical and legal frameworks and the strengthening of interoperable infrastructures. Overcoming the current gap between algorithmic sophistication and institutional maturity will be crucial to ensuring that AI not only optimizes processes but also makes a sustainable contribution to patient safety and the real improvement of treatment results.

Abbreviations

AI: Artificial Intelligence.

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Author Contributions

All authors contributed equally to this proposed work.

Conflict of Interest

The authors declare no conflicts of interest.

Data Availability

The analyzed data are available on Scopus and PubMed.

Declaration of Artificial Intelligence (AI) Assistance

The authors declare that no AI tools were used. The authors take full responsibility for the content's originality, interpretation and accuracy.

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References

- Cañas M, Buschiazzi HO, Urtasun MA. Therapeutic value and price of the new pharmaceuticals commercialized in Argentina: Are they worth what they cost? *Salud Colect.* 2019;15:e1962. doi:10.18294/sc.2019.1962
- Ryan DK, Maclean RH, Balston A, Scourfield A, Shah AD, Ross J. Artificial intelligence and machine learning for clinical pharmacology. *Br J Clin Pharmacol.* 2024;90(3):629-639. doi:10.1111/bcp.15930
- Cross B, Turner RM, Zhang JE, Pirmohamed M. Being precise with anticoagulation to reduce adverse drug reactions: are we there yet? *Pharmacogenomics J.* 2024;24(7). doi:10.1038/s41397-024-00329-y
- Amaro-Álvarez L, Cordero-Ramos J, Calleja-Hernández MÁ. Exploring the impact of pharmacogenetics on personalized medicine: A systematic review. *Farm Hosp.* 2024;48(6):299-309. doi:10.1016/j.farma.2023.12.004
- Khatun M, Riya AA, Alam MdM, Hossain S, Hira T, Chowdhury IH. Medication error in the provision of healthcare services. *Mod Health Sci.* 2024;7(1):p1. doi:10.30560/mhs.v7n1p1
- Faraj TK. Community Health Impacts of Pesticide Exposure: Pathways, Vulnerable Populations and Public Health Responses. *International Journal of Environmental Research and Public Health.* 2026;23(7):889. doi:10.3390/ijerph23070889
- Nouri A, Lamfon NA, Silsilah G, *et al.* Defining Medication Errors, Prescribing Errors and Adverse Drug Events: A Narrative Review. *Palest Med Pharm J.* 2024;9(3):323-336. doi:10.59049/2790-0231.1204
- Naseralallah L, Stewart D, Price M, Paudyal V. Prevalence, contributing factors and interventions to reduce medication errors in outpatient and ambulatory settings: a systematic review. *Int J Clin Pharm.* 2023;45(6):1359-1377. doi:10.1007/s11096-023-01626-5
- Akinrinmade AO, Adebile TM, Ezuma-Ebong C, *et al.* Artificial Intelligence in Healthcare: Perception and Reality. *Cureus.* 2023;15(9):e45594. doi:10.7759/cureus.45594
- Hadweh P, Niset A, Salvagno M, *et al.* Machine Learning and Artificial Intelligence in Intensive Care Medicine: Critical Recalibrations from Rule-Based Systems to Frontier Models. *J Clin Med.* 2025;14(12):4026. doi:10.3390/jcm14124026
- Guo C, He Y, Shi Z, Wang L. Artificial intelligence in surgical medicine: a brief review. *Ann Med Surg.* 2025;87(4):2180-2186. doi:10.1097/MS9.00000000000003115
- Fang T, Yuan F, Chen Y, *et al.* Emerging role of metagenomic next-generation sequencing in infectious disease diagnostics: Clinical integration and future directions. *Mlife.* 2026;5(2):148-163. doi:10.1002/mlf2.70078
- Younis HA, Eisa TAE, Nasser M, *et al.* A Systematic Review and Meta-Analysis of Artificial Intelligence Tools in Medicine and Healthcare: Applications, Considerations, Limitations, Motivation and Challenges. *Diagnostics.* 2024;14(1):109. doi:10.3390/diagnostics14010109
- Evans MI, Devoe LD, Ryan GF, Britt DW, Macedonia CR. Beyond Incremental: Embracing Transformative Innovation in Women's Health. *Reproductive Medicine.* 2026;7(1):16. doi:10.3390/reprodmed7010016
- Sarantopoulos A, Mastori Kourmpanti C, Yokarasa AL, *et al.* Artificial Intelligence in Infectious Disease Clinical Practice: An Overview of Gaps, Opportunities and Limitations. *Trop Med Infect Dis.* 2024;9(10):228. doi:10.3390/tropicalmed9100228
- Ogut E. Artificial Intelligence in Clinical Medicine: Challenges Across Diagnostic Imaging, Clinical Decision Support, Surgery, Pathology and Drug Discovery. *Clin Pract.* 2025;15(9):169. doi:10.3390/clinpract15090169
- Feng J, Phillips RV, Malenica I, *et al.* Clinical artificial intelligence quality improvement: towards continual monitoring and updating of AI algorithms in healthcare. *Npj Digit Med.* 2022;5(66). doi:10.1038/s41746-022-00611-y
- Da'Costa A, Teke J, Origbo JE, Osonuga A, Egbon E, Olawade DB. AI-driven triage in emergency departments: A review of benefits, challenges and future directions. *Int J Med Inf.* 2025;197:105838. doi:10.1016/j.ijmedinf.2025.105838
- Taylor RA, Sangal RB, Smith ME, *et al.* Leveraging artificial intelligence to reduce diagnostic errors in emergency medicine: Challenges, opportunities and future directions. *Acad Emerg Med.* 2025;32(3):327-339. doi:10.1111/acem.15066
- Dino MJS, Arellano YB, Evangelista AG, *et al.* Utilization of Artificial Intelligence in Reducing the Incidence of Medication Error: A Bibliometric Analysis. *Health Science Reports.* 2025;8(8):e71067. doi:10.1002/hsr2.71067
- Damiani G, Altamura G, Zedda M, *et al.* Potentiality of algorithms and artificial intelligence adoption to improve medication management in primary care: a systematic review. *BMJ Open.* 2023;13(3):e065301. doi:10.1136/bmjopen-2022-065301
- Taherdoost H, Ghofrani A. AI's role in revolutionizing personalized medicine by reshaping pharmacogenomics and drug therapy. *Intell Pharm.*

- 2024;2(5):643-50.
doi:10.1016/j.jipha.2024.08.005
23. González-Pérez Y, Delgado AM, Martínez-Sesmero JM. Approaching artificial intelligence to Hospital Pharmacy. *Farm Hosp.* 2024;48:S35-44.
doi: 10.1016/j.farma.2024.02.007
 24. Samajdar SS, Chatterjee R, Mukherjee S, Dey A, Saboo B, Pal J, Joshi S, Chatterjee N. Artificial Intelligence in Healthcare: Current Trends and Future Directions. *Current Medical Issues.* 2025;23(1):53–60.
doi:10.4103/cmi.cmi_93_24
 25. Wu Y, Wang N, Xiong P, Wang R, Deng J, Ouyang D. Artificial intelligence for drug delivery: Yesterday, today and tomorrow. *Acta Pharm Sin B.* 2026;16(4):2068-2092.
doi:10.1016/j.apsb.2025.09.022
 26. Serrano DR, Luciano FC, Anaya BJ, *et al.* Artificial Intelligence (AI) Applications in Drug Discovery and Drug Delivery: Revolutionizing Personalized Medicine. *Pharmaceutics.* 2024;16(10):1328.
doi:10.3390/pharmaceutics16101328
 27. Ingle S, Yemul M, Lavate A, Desai A. Artificial Intelligence in Drug Delivery System. *Int J Technol.* 2024;14(2):115-124.
doi:10.52711/2231-3915.2024.00017
 28. Hong M, Kang RR, Yang JH, *et al.* Comprehensive symptom prediction in inpatients with acute psychiatric disorders using wearable-based deep learning models: development and validation study. *J Med Internet Res.* 2024;26:e65994.
doi:10.2196/65994
 29. Page MJ, Moher D. Evaluations of the uptake and impact of the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) Statement and extensions: a scoping review. *Syst Rev.* 2017;6(263).
doi:10.1186/s13643-017-0663-8
 30. Hong Q, Pluye P, Fábregues S, *et al.* Mixed Methods Appraisal Tool (MMAT), version 2018: information professionals and researchers. *Education for Information.* 2018;34(10):1-7.
doi:10.3233/EFI-180221
 31. Aromataris E, Fernandez R, Godfrey CM, Holly C, Khalil H, Tungpunkom P. Summarizing systematic reviews: methodological development, conduct and reporting of an Umbrella review approach. *Int J Evid Based Healthc.* 2015;13(3):132-140.
doi:10.1097/XEB.0000000000000055
 32. Barker TH, Hasanoff S, Aromataris E, *et al.* The revised JBI critical appraisal tool for the assessment of risk of bias for analytical cross-sectional studies. *JBI Evid Synth.* 2026;24(3):401-408.
<https://jbi.global/critical-appraisal-tools>
 33. Nateghi F, Lopez I, Tate S, *et al.* Predicting treatment retention in medication for opioid use disorder: a machine learning approach using NLP and LLM-derived clinical features. *J Am Med Inform Assoc.* 2025;32(12):1865-76.
doi:10.1093/jamia/ocaf157
 34. Nayak A, Vakili S, Nayak K, *et al.* Use of Voice-Based Conversational Artificial Intelligence for Basal Insulin Prescription Management Among Patients With Type 2 Diabetes: A Randomized Clinical Trial. *JAMA Netw Open.* 2023;6(12):e2340232.
doi:10.1001/jamanetworkopen.2023.40232
 35. Roosan D, Padua P, Khan R, Khan H, Verzosa C, Wu Y. Effectiveness of ChatGPT in clinical pharmacy and the role of artificial intelligence in medication therapy management. *J Am Pharm Assoc.* 2024;64(2):422-428.e8.
doi:10.1016/j.japh.2023.11.023
 36. Singla R, Aggarwal S, Bindra J, Garg A, Singla A. Developing Clinical Decision Support System using Machine Learning Methods for Type 2 Diabetes Drug Management. *Indian J Endocrinol Metab.* 2022;26(1):44-49.
doi:10.4103/ijem.ijem_435_21
 37. Worrall C, Shirley D, Bullard J, Dao A, Morrisette T. Impact of a clinical pharmacist-led, artificial intelligence-supported medication adherence program on medication adherence performance, chronic disease control measures and cost savings. *J Am Pharm Assoc.* 2025;65(1):102271.
doi:10.1016/j.japh.2024.102271
 38. Hu MY, Yi TX, Liu QR, *et al.* Artificial Intelligence and Network Pharmacology Reveal the Medication Rules of Professor Wang Yu-Ying in the Treatment of Climacteric Syndrome. *World J Tradit Chin Med.* 2024;10(2):180-90.
doi:10.4103/2311-8571.382287
 39. Andrès E, Hajjam EHA, Maloisel F, *et al.* Artificial Intelligence (AI) and Drug-Induced and Idiosyncratic Cytopenia: The Role of AI in Prevention, Prediction and Patient Participation. *Hematol Rep.* 2025;17(3):24.
doi:10.3390/hematolrep17030024
 40. Das KP, Chandra J. Nanoparticles and convergence of artificial intelligence for targeted drug delivery for cancer therapy: Current progress and challenges. *Front Med Technol.* 2023;4:1067144.
doi:10.3389/fmedt.2022.1067144
 41. Gunasekera CL, Sirven JI, Feyissa AM. The evolution of antiseizure medication therapy selection in adults: Is artificial intelligence-assisted antiseizure medication selection ready for prime time? *J Cent Nerv Syst Dis.* 2023;15:1-13.
doi:10.1177/11795735231209209
 42. Hu J, Ren L, Wang T, Yao P. Artificial Intelligence-Assisted Clinical Decision-Making: A Perspective on Advancing Personalized Precision Medicine for Elderly Diabetes Patients. *J Multidiscip Healthc.* 2025;18:4643-51.
doi:10.2147/JMDH.S529190
 43. Long X, Sun K, Lai S, *et al.* Artificial intelligence and anti-cancer drugs' response. *Acta Pharm Sin B.* 2025;15(7):3355-71.
doi:10.1016/j.apsb.2025.05.009
 44. Rammal DS, Alomar M, Palaian S. AI-Driven pharmacy practice: Unleashing the revolutionary potential in medication management, pharmacy workflow and patient care. *Pharm Pract.* 2024;22(2):1-11.
doi:10.18549/PharmPract.2024.2.2958
 45. Vora LK, Gholap AD, Jetha K, Thakur RRS, Solanki HK, Chavda VP. Artificial Intelligence in Pharmaceutical Technology and Drug Delivery Design. *Pharmaceutics.* 2023;15(7):1916.
<https://doi.org/10.3390/pharmaceutics15071916>

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