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Review article

Artificial intelligence in pharmaceutical administration and clinical pharmacy: A comprehensive review of advancements, challenges, and future directions

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ABSTRACT

The integration of artificial intelligence (AI) into healthcare is reshaping medical disciplines, with hospital pharmacy undergoing a significant paradigm shift from a labor-intensive model to an intelligence-driven one. This comprehensive review examines the transformative role of AI in pharmaceutical administration and clinical pharmacy, synthesizing recent advancements, identifying key challenges, and projecting future directions. In pharmacy management, AI optimizes procurement through intelligent platforms, enhances dispensing accuracy and safety via automated systems and robotic technologies, and revolutionizes pharmacovigilance by shifting from spontaneous reporting to proactive, data-driven signal detection using machine learning (ML) and natural language processing (NLP). In clinical practice, AI-powered clinical decision support systems (AI-CDSS) augment clinician judgment by enabling real-time data analysis and improving therapeutic outcomes, while human-AI collaborative pre-prescription review systems significantly enhance medication safety. Furthermore, AI facilitates personalized medicine through the integration of pharmacogenomics and leverages large language models (LLMs) to improve patient engagement and medication adherence. Crucially, this review argues that AI is not a replacement for pharmacists but a catalyst for redefining their professional roles, elevating them from dispensers to clinical decision-makers and multidisciplinary collaborators. Despite its vast potential, the widespread adoption of AI faces significant hurdles, including poor data quality and interoperability, algorithmic "black-box" issues that undermine trust, ethical and privacy concerns, lagging regulatory frameworks, and a lack of long-term economic validation. Looking ahead, the future of intelligent pharmacy will be shaped by the integration of LLMs with knowledge graphs, the rise of explainable AI (XAI), the implementation of federated learning for secure data sharing, and the establishment of end-to-end digital ecosystems. Ultimately, AI is poised to become an indispensable collaborator in pharmacy, fostering a more efficient, intelligent, and patient-centered ecosystem.

1. Introduction

In recent years, breakthroughs in artificial intelligence (AI) technologies such as machine learning (ML), deep learning (DL), natural language processing (NLP), knowledge graphs, and clinical decision support systems (CDSS) have been widely integrated into the healthcare system, reshaping the service mode and management logic of various medical disciplines.[1] Hospital pharmacy, as a key sector for drug clinical

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use and medical quality management, is facing a revolutionary shift from labor-intensive to intelligence-intensive, which is driven by the increasing complexity of clinical medication, the growing demand for medical quality, and the popularization of digital medical construction.[2]

Traditional pharmacy administration relies heavily on manual prescription review, post-hoc data statistics, and empirical decision-making, which are limited by low efficiency, poor consistency, and potential safety risks. Pharmacists spend an excessive amount of time on routine tasks. For instance, one study indicates that pharmacists devote 30%–48% of their working hours to verifying and dispensing medications. When multiplied by the average salary of pharmacists, this time commitment translates into an annual labor cost of USD 38,823 to 62,117 per pharmacist.[3] With the continuous expansion of clinical medication complexity and the continuous improvement of medical quality requirements, the traditional model can no longer fully meet the needs of refined management.

In this context, AI represents a novel technological paradigm for pharmaceutical administration and clinical pharmacy services, with its core value rooted in digitalization, intelligent automation, and enhanced efficiency—enabling real-time surveillance, proactive alerts, automated analytics, and predictive management. This review systematically examines the application value, challenges, and future trends of AI in this field, synthesizing recent evidence and case studies to offer forward-looking perspectives for clinical practice and academic research.

2. AI-enabled pharmaceutical management: from logistics to governance

2.1. Optimizing the pharmaceutical supply chain: intelligent procurement and the SPD model

Pharmaceutical procurement constitutes a critical component of hospital pharmacy management. Rational procurement and scientifically informed preparation can satisfy clinical medication needs while simultaneously reducing drug-related expenditures and alleviating financial burdens on hospitals. Against the backdrop of the zero-markup drug policy and the National Centralized Drug Procurement (NCDP) policy, optimizing the pharmaceutical supply chain has become imperative for hospital pharmacy management. As demonstrated by Wei et al., [4] an intelligent management platform for contracted procurement volume allocation and daily clinical use supervision enables automated task assignment and independent statistical analysis of clinical utilization. This, in turn, improves the operational and regulatory efficiency of centralized drug procurement, ensures the fulfillment of procurement targets, and conserves human resources. Nevertheless, the Supply, Processing, and Distribution (SPD) model—an integrated logistics information technology solution—has yet to be widely adopted in most medical institutions. Its broader application holds significant potential to drive innovation in drug supply within healthcare settings.

2.2. Automated dispensing systems: enhancing efficiency and safety in medication distribution

Conventional manual prescription dispensing is characterized by high repetitive workloads, low efficiency, frequent dispensing errors, and long patient waiting times, which can no longer meet the requirements of modern pharmacy services. Therefore, automated drug dispensing systems have become one of the most in-demand intelligent devices in large hospital pharmacies in recent years. The advantages of such automated systems include ultra-high accuracy, freedom from fatigue, and relatively low costs. For example, a real-world study by Amir et al. [5] demonstrated that a pill recognition model developed using a code-free DL approach performed excellently on the Microsoft Azure Custom Vision platform, achieving 98.7% precision, 95.1% recall, and 98.2% mean average precision (mAP), indicating that AI-based pill recognition systems are feasible and cost-effective. A health technology assessment conducted across six European countries indicates that automated drugs dispensing systems may encounter initial challenges, attributable to potential resistance from healthcare professionals and substantial investment requirements. Ultimately, however, healthcare professionals acknowledged a range of benefits associated with automated dispensing systems, with economic analyses demonstrating cost savings ranging from 17.9% to 26.6%.[6] Chen et al. [7] also explored automated recognition of traditional Chinese medicine (TCM) decoction pieces using an association rule mining technology to improve efficiency in TCM dispensing based on the frequent pattern growth algorithm. Practice has shown that this approach reduces drug selection time, eases the physical burden on pharmacists, shortens patient waiting time, and improves overall patient satisfaction. Furthermore, the application of automated infusion dispensing robots in pharmacy intravenous admixture services (PIVAS) has greatly reduced occupational exposure among medical staff.[8] The Department of Pharmacy, Kobe City Medical Center General Hospital, Hyogo, Japan, introduced a sterile preparation robot for cancer chemotherapy which has been used in combination. By 2023, a total of 30,266 preparations were completed, of which 12,276 were performed by the robot, significantly improving operational efficiency while ensuring safety.[9] The aforementioned case studies, which exemplify the automation of pharmacy operations to enhance both accuracy and efficiency, hold significant implications for regions contending with population aging or workforce shortages.

2.3. AI in pharmacovigilance: from spontaneous reporting to proactive signal detection

The rapid advancement of AI has garnered significant attention for its application in pharmacovigilance, establishing it as a prominent area within pharmaceutical sciences. Traditional ADR monitoring methods suffer from inherent limitations, most notably substantial underreporting, which compromises patient safety. Integrating AI techniques—particularly ML and NLP—into pharmacovigilance systems offers a viable solution to these challenges. As demonstrated by Dsouza et al., [10] incorporating ML and NLP into ADR prediction systems enhances efficiency and accuracy by reducing reliance on manual data processing. A substantial body of literature further confirms that AI technologies yield favorable performance in ADR prediction across specific diseases or patient populations. Notably, research indicates that certain antidepressant-containing polypharmacy regimens may trigger complex safety signals in specific subgroups of breast cancer survivors.[11] This underscores the necessity of personalized risk assessment and vigilant medication safety strategies for these unique patient populations, highlighting critical considerations for future big data applications in healthcare.

2.4. Digital intelligence-driven collaboration of "Three-Medical" coordination: A framework for integrated decision-making

Promoting the high-quality development and governance of "Three-Medical" (medical care, medical insurance, and pharmaceuticals) coordination is an important practice for China to advance the modernization of its national governance system and capacity. This concept applies not only to national policy orientation but also to the scientific management of medical institutions. For medical institutions, the development of a multi-criteria decision-making model and AI-based evaluation tool that comprehensively integrates effectiveness, safety, economy, adaptability, and equity will undoubtedly provide a scientific basis for optimizing healthcare, medical insurance, and pharmaceutical policies at both institutional and regional levels. This tool is required to integrate diverse real-world data sources, including electronic medical records, medical insurance reimbursement data, adverse drug reaction surveillance data, drug consumption data, and patient health management platform data. By employing data mining techniques, ML

algorithms, and health economic models, it enables a comprehensive analysis of multiple indicators, such as clinical efficacy, health outcomes, adverse reactions, and cost-effectiveness. A case in point is Lvliang, Shanxi Province. By integrating data and building models to timely analyze and feedback problems, it has improved medical quality and ensured the rational use of medical insurance funds.[12]

3. AI in clinical pharmacy: transforming patient care

3.1. AI-powered clinical decision support systems (AI-CDSS): Augmenting clinical judgment

The AI-based Clinical Decision Support System (AI-CDSS) is an advanced system built on AI technologies. It employs cutting-edge algorithms such as ML and data mining to interpret and analyze large volumes of medical data. The goal of AI-CDSS is to provide technical support for clinicians and assist them in making accurate and effective decisions throughout the entire diagnostic process, thereby improving the quality and efficiency of medical services. One of the core advantages of AI-CDSS lies in its intelligence and user-friendliness. It is designed from the outset to serve as an "intelligent assistant" for physicians, rather than a new burden that requires substantial time and energy to learn. In recent years, a growing number of studies have begun to explore the impact of AI-CDSS adoption on rational clinical medication use. For instance, a study conducted by Lin[13] demonstrated that the AI-CDSS group exhibited significantly greater advantages in antibiotic prescription, decision-making efficiency, and the appropriateness of antibiotic selection at all time points. During the critical early stage of treatment, effective antibiotic selection and reliance on AI-CDSS contribute to improving patient prognosis. The mortality rate in the AI-CDSS group was also lower than that in the control group. Meanwhile, numerous studies have focused on clinicians' willingness to use AI-CDSS. A study by Zhao[14] indicated that performance expectancy, social influence, and personal innovativeness have a positive impact on physicians' willingness to adopt AI-CDSS, while technology anxiety exerts a negative impact. In the design and construction of AI-CDSS in the future, these factors should be taken into consideration, rather than merely referring to technical standards. The prediction and timely alerting of drug-drug interactions (DDIs) also represent a critical component of AI-powered clinical decision support systems (AI-CDSS). To assist clinicians in optimizing therapeutic decisions, various AI models have been developed to predict potential DDIs with increasing accuracy and clinical relevance.[15] A Swiss research team conducted an in silico and *in vitro* study on the mechanism of drug-drug interaction between fludarabine and busulfan.[16] The results indicate that fludarabine is unlikely to alter the pharmacokinetics of busulfan via the glutathione conjugation pathway. The study also highlights the importance of experimentally validating in silico observations in drug research, a finding that offers valuable insights for the broader research community.

3.2. Pre-prescription review systems: A Human-AI collaborative approach to medication safety

In China, conducting pre-prescription medication reviews prior to billing is a critical responsibility and service performed by hospital pharmacists. Major hospitals are actively exploring a human-computer collaborative pre-prescription review model, wherein an automated rational drug use system conducts preliminary screening, followed by manual verification by pharmacists. A study conducted by Yue[17] analyzed the operational model of a pre-prescription review intelligent decision-making system in a county-level hospital and evaluated its intervention effectiveness in outpatient and emergency services. This retrospective study examined data from October 2022 to August 2023, focusing on the types and severity of issues triggered by outpatient and emergency prescriptions, as well as the rationality of prescriptions within the system. Compared to the pre-intervention period (October 2022), the number of problematic prescriptions—related to indications, dosages, special populations, drug compatibility, administration routes, and contraindications—showed a downward trend. Extending this system to medical alliances to establish a regional prescription review model would further promote the high-quality development of pharmaceutical services. It is anticipated that the widespread adoption of AI-driven prescription review systems will fundamentally reshape both the content and model of hospital pharmaceutical services. Pharmacists should therefore proactively adapt to this impending transformation.

3.3. Advancing personalized medicine: the convergence of pharmacogenomics and AI

Personalized medicine involves customizing treatment plans, disease prevention measures, and health maintenance strategies based on individual characteristics, with pharmacogenomics serving as a key tool to improve treatment outcomes and prevent adverse reactions. Advances in genomics have transformed pharmacogenetics, which traditionally focused on single gene-drug pairings, into pharmacogenomics that encompasses all “omics” fields (such as proteomics, transcriptomics, metabolomics, and metagenomics).[18] Meanwhile, the rapid development of AI technology has provided a solution to address the extremely complex and massive volume of data generated in this field. Pharmacogenomic testing is increasingly shifting toward the use of panels of “pharmacogenes”, which simultaneously test for most genetic variants known to influence responses to commonly prescribed drugs with established clinical utility. For instance, at the Mayo Clinic, an alert is automatically triggered when a prescription is issued for any of 17 established drug–gene pairs.[19] While this represents an important initial step, the ultimate goal is to obtain pharmacogenomic data for individual patients in advance and integrate it into electronic health records (EHRs), thereby enabling seamless incorporation of pharmacogenomic insights into routine clinical workflows. Another significant advancement is the transformation of personalized medication management through AI technology. By integrating a patient's diagnostic data, examination results, and medication outcomes across various institutions and time points, AI enables a more precise approach to current diagnosis and treatment, paving the way for truly continuous pharmaceutical care. Once these data challenges are resolved and digital twin technology reaches full maturity, dynamic virtual patient models will become feasible. Such models could predict how benefit-risk profiles evolve under varying degrees of drug exposure, thereby enabling truly personalized medicine. For example, an Italian research team developed a multiscale medical digital twin integrating physiologically based pharmacokinetic modeling with an eco-evolutionary pharmacodynamic module. Calibrated using data from 1634 neonates, this model successfully optimized the full course of antibiotic therapy in silico.[20] Although limited to a specific disease and patient population, this case offers a compelling glimpse into future trends.

3.4. Enhancing patient engagement and medication adherence: leveraging large language models and AI analytics

Large Language Models (LLMs) have brought new transformations to patient medication education and adherence management. By understanding patients' age, educational level, and disease status, LLMs can generate personalized and easy-to-understand medication guidance, including medication time, dosage, precautions, and possible adverse reactions, which addresses the problem of poor patient understanding caused by standardized medication instructions. For instance, a large-scale study by Charles Worrall et al. [21] confirmed that, following the implementation of a pharmacist-led improvement program integrated with AI analytics, medication adherence improved across all three disease state indicators among the enrolled patients. Moreover, adherent patients showed a reduction in total monthly healthcare expenditures

per member compared to non-adherent patients. Another important practical application of AI in patient medication management is the risk assessment of polypharmacy safety in older adults. Research by Kyle Bringhurst et al. [22] demonstrates the potential of AI in managing polypharmacy, particularly in enhancing medication safety, improving adherence, and predicting risk factors associated with medication-related errors in elderly patients.

4. AI technologies and their deployment in hospital pharmacy practice

The preceding sections have detailed specific application cases across various branches of medication management and pharmaceutical care. From the perspective of technological evolution, hospital pharmacy is currently undergoing a paradigm shift: transitioning from rule-based systems (Expert Systems) to data-driven approaches (Machine Learning/Deep Learning), and now advancing toward cognitive intelligence (Large Language Models). While Large Language Models (LLMs) undoubtedly represent one of the most prominent concepts in AI today—as illustrated in Fig. 1, which outlines the concepts and relationships of common AI technologies—clinical practice does not necessitate the indiscriminate adoption of the latest trends. Instead, the focus should be on identifying specific practical needs and selecting appropriate, cost-effective AI solutions.

To be specific, expert systems remain a cost-effective choice for scenarios with explicit rules and scarce data, such as regulatory compliance checks; machine learning excels in prediction tasks backed by extensive labeled datasets, such as drug concentration forecasting; deep learning is indispensable for processing unstructured data, including images and complex texts; LLMs offer disruptive efficiency gains for complex natural language interactions and knowledge generation. Table 1 summarizes the concepts, algorithmic examples, strengths, limitations, and applicable healthcare scenarios for these key technologies. In practical application, these technologies are not mutually exclusive but are moving toward convergence. For instance, a comprehensive smart pharmacy service covering the entire "pre-diagnosis, intra-diagnosis, and post-diagnosis" chain could be constructed by integrating these tools: utilizing LLMs for patient consultation, invoking Expert System rule bases for safety quality control, and employing Deep Learning models for individualized risk assessment.

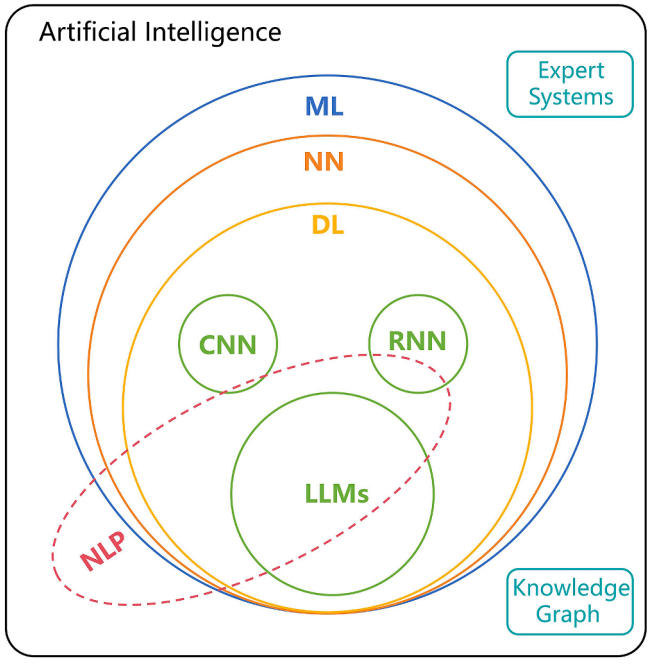


Fig. 1. The most common concepts in the field of artificial intelligence and their relationships.
ML: Machine Learning, NN: Neural Networks, DL: Deep Learning, LLMs: Large Language Models, CNN: Convolutional Neural Network, RNN: Recurrent Neural Network, NLP: Natural Language Processing.

5. Redefining the role of hospital pharmacists in the AI Era: from dispensers to clinical decision-makers and beyond

Based on the preceding discussion, it is clear that the advancement of AI has profoundly transformed the traditional roles and responsibilities of pharmacists. Consequently, it is imperative to delineate the relationship and positioning between AI, pharmaceutical care, and pharmacy management practices. The integration of AI does not replace pharmacists, but rather redefines their professional value. By automating repetitive and data-intensive tasks including routine prescription review, drug inventory management, and ADR screening, AI enables pharmacists to prioritize higher-level clinical responsibilities. This role reconstruction unfolds across four key dimensions: first, pharmacists are evolving from manual operators into clinical decision-makers, using AI tools to analyze complex patient data and contribute to individualized therapy, particularly in critical or multimorbid cases.[43] Second, their role is expanding from in-hospital dispensers to full-cycle medication managers, enabled by AI-powered follow-up systems and telepharmacy that support continuous patient monitoring and education beyond hospital settings. Third, they are transitioning from experience-based practitioners to data-driven performance improvers, leveraging AI to analyze real-world prescribing patterns, identify risks, and drive quality improvement.[44] Fourth, pharmacists are becoming multidisciplinary professionals who integrate pharmacy with big data and AI, requiring new competencies to collaborate with engineers and optimize intelligent systems.

However, a global shortage of such hybrid talent currently remains a key barrier to deeper AI–pharmacy integration. Therefore, in the future, both academic education and clinical training should prioritize the development of pharmacists' AI literacy and competencies.[45] Cultivating pharmacists with hybrid competencies in both pharmaceutical sciences and AI requires a multi-pronged strategy encompassing: (1) develop a digital and AI-driven competency framework for pharmacists[46]; (2) vertical integration of AI content into pharmacy curricula from entry-level through advanced training[47]; (3) vigorously cultivate faculty with an AI background; (4) experiential and simulation-based learning opportunities[48]; (5) interprofessional collaboration with data science and engineering disciplines[49]; (6) embedding of AI ethics and data privacy instruction throughout training; (7) creation of credentialing and continuing professional development pathways for the existing workforce[50]; and (8) targeted efforts to address regional disparities in training infrastructure.

At this stage, it is important for pharmacists to embrace AI as an invaluable tool in their daily practice, rather than succumbing to excessive anxiety over the potential disruption posed by emerging technologies. After all, for hospital pharmacy, the ultimate value of AI is not to become an "omnipotent brain," but rather, by virtue of its efficiency as a tool, to free pharmacists from tedious, repetitive tasks—giving them more time to delve into clinical practice and optimize medication regimens, ultimately providing patients with higher-quality, more efficient pharmaceutical care (Fig. 2).

6. Navigating challenges and constraints in clinical application

6.1. Data quality and interoperability

Data serves as the foundation for AI applications, and its quality and interoperability directly influence the performance of AI models. Currently, medical data used in AI-driven pharmaceutical applications face several challenges, including multi-source heterogeneity,

Table 1
A comparison of AI technologies in hospital pharmacy: Descriptions, algorithms, advantages, disadvantages, and applications.

Technology Branch	Brief Description	Algorithm Examples	Advantages	Disadvantages	Main Problems Solved	Applications
Expert Systems[23]	A symbol-based AI branch that explicitly encodes human expert knowledge (IF-THEN rules) for logical reasoning, representing typical knowledge representation and inference technology.	Rule-based inference engines (e.g., Prolog), MYCIN,[24] DENDRAL.[25]	**High interpretability**: transparent reasoning paths and traceable decisions **Low data dependency**: no large training datasets needed, suitable for rule-defined, knowledge-complete domains.	**Knowledge acquisition bottleneck**: rules require manual coding, costly and incomplete **Poor flexibility**: cannot handle ambiguous, unknown, or unstructured problems **Difficult maintenance**: rule conflicts arise with scale	Automates standardized, solves the "from-zero-to-basic" rule-checking problem.	Early antibiotic prescription auditing systems Basic drug interaction screening[26] Rationality checks for well-defined regulatory standards.
Machine Learning[27]	An AI subfield that autonomously learns patterns from data without explicit programming, derives its performance from data quality and quantity while fundamentally relying on generalization capability.	**Supervised**: Linear Regression Support Vector Machine Decision Trees Random Forest **Unsupervised:** K-means clustering **Reinforcement:** Q-learning	**Data-driven**: discovers hidden patterns from historical data **Diverse algorithms**: works well on structured data, even with small datasets **Moderate interpretability** (compared to deep learning).	**Relies on feature engineering**: manual feature extraction, time-consuming and domain-dependent **Limited capability:** difficulty processing high-dimensional unstructured data like images and text	Transforms pharmacy decision-making from experience-based to data-driven through machine learning.	Adverse drug reaction prediction[28] Initial dose optimization for narrow-therapeutic-window drugs (e.g., vancomycin)[29] Drug demand forecasting and inventory management[30]
Neural Networks[31]	Biologically-inspired computational models with layered architecture (input, hidden, output layers) that use backpropagation for weight optimization—the foundation of deep learning.	Multi-Layer Perceptron (MLP) Backpropagation algorithm	**Strong nonlinear fitting**: can theoretically approximate any complex function **Automatic feature extraction**: learns feature representations from raw data	**Requires large data**: prone to overfitting **Poor interpretability**: "black box" nature **High computational demands**	Enables automatic feature learning—eliminating manual feature engineering—making it uniquely suited for complex pharmacy data (images, speech, text) where traditional machine learning struggles	Direct use is limited, but forms the core of models processing medical images (CNN) and sequential data (RNN) in pharmacy.
Deep Learning[32]	Represents the evolution of neural networks through deep architectures—multiple hidden layers that enable automatic hierarchical feature extraction and end-to-end learning.	Convolutional Neural Network, CNN (image analysis) Recurrent Neural Network, RNN/ Long Short-Term Memory, LSTM (sequential data) Transformer	**Automatic feature extraction**: eliminates manual feature engineering **High accuracy**: excels on unstructured data (images, audio, complex text)	**"Black box" problem**: poor interpretability, a major obstacle in high-stakes medical domains **Resource-intensive**: requires massive data and compute **Sensitive hyperparameters**: tedious tuning	Discovers deep correlations in massive, high-dimensional, unstructured data, solving complex pattern recognition problems (e.g., imaging, omics)	Mining genomic/proteomic data for biomarkers to guide precision medicine[33] Processing complex temporal physiological data.
Large Language Models[34]	Representing a paradigm shift in deep learning, large language models leverage ultra-deep Transformer architectures with self-supervised pre-training on massive unlabeled text, evolving from task-specific models to universal foundation models with emergent reasoning capabilities.	GPT series DeepSeek Bidirectional Encoder Representations from Transformers, BERT The core architecture of the aforementioned large language models is based on the Transformer model, which employs the self-attention mechanism to enable global dependency modeling of input sequences and context-aware feature extraction.	**Strong generality and transferability**: adapts to diverse tasks via few-shot prompting **Revolutionary interaction**: enables human-AI collaboration through natural language **Knowledge integration**: compresses vast world knowledge	**Enormous compute consumption**: extremely high training and deployment costs **"AI hallucinations"**: may generate plausible but incorrect information **Stale knowledge**: lags behind real-time updates	Upgrades pharmacy services from rule-driven to cognitive intelligence via powerful language understanding and generation Dramatically improves efficiency, addresses workforce shortages and knowledge application bottlenecks	Intelligent pharmacy chatbot (24/7 AI pharmacist)[35] Automated prescription review and evaluation[36] Pharmacovigilance signal detection and report generation[37]

(*continued on next page*)

Table 1 (*continued*)

Technology Branch	Brief Description	Algorithm Examples	Advantages	Disadvantages	Main Problems Solved	Applications
Natural Language Processing[38]	An interdisciplinary field of AI and linguistics, aiming to enable computers to understand, interpret, and generate human language. Key technology for intelligent human-computer interaction.	Named Entity Recognition (drug names, dosages) Relation Extraction Text Classification Sentiment Analysis NLP models based on BERT/LLMs	**Unlocks unstructured text**: extracts key information from free text such as medical records, literature, and prescriptions **Automated processing**: efficiently handles massive documentation	**Language complexity**: challenges with ambiguity, metaphors, domain jargon **Context-dependent**: performance limited by context length and clarity	Transforms massive unstructured pharmacy text data into structured, computable knowledge, breaking information silos and providing the data foundation for higher-level intelligent applications (e.g., clinical decision support systems)	Extracting patient medication and allergy histories from electronic health records[39] Building drug knowledge graphs[40] Intelligent analysis of ADR reports[41] Handling free-text patient medication inquiries[42]

inconsistent standards, incomplete data, and low data quality. For instance, the formats of EHRs, laboratory information systems, and pharmacy management systems vary across hospitals, and the presence of missing values and data errors compromises the effectiveness of AI model training. Moreover, the lack of data-sharing mechanisms between hospitals and departments has led to the emergence of "data silos", restricting AI models from accessing sufficient sample data for training and optimization.[51] In the context of AI-based pharmacovigilance, for example, the inability to share ADR data across multiple centers limits the generalization capability of the models.[52] Furthermore, inconsistencies in data standards hinder the comparison and integration of findings across different studies, ultimately impeding the broader adoption and application of AI technologies. Another representative failure of AI in healthcare is IBM Watson for Oncology. The system was trained primarily on a limited number of virtual cases and the personal preferences of a few experts, rather than on large-scale real-world patient data and evidence-based clinical guidelines.[53] Consequently, it frequently generated unsafe and inaccurate treatment recommendations. This failure resulted in substantial losses for IBM. Despite investing billions of dollars in the project, IBM was ultimately forced to sell it, and partnerships with multiple hospitals were terminated. The collapse also undermined public confidence in medical AI. Building on this failure, experts now exercise extreme caution regarding the data used to train large models. However, due to the current lack of standardized guidelines and legal regulations, data quality remains a critical concern that requires ongoing attention.

6.2. *Algorithmic interpretability and trustworthiness*

The "black-box" nature of certain complex AI models, such as DL systems, limits their acceptance in clinical settings and poses challenges for clinical decision-making and accountability. Clinicians and pharmacists are often unable to fully comprehend the reasoning or basis behind AI-generated recommendations, leading to reluctance in relying on such systems—particularly in complex clinical scenarios. Evidence from a randomized controlled trial indicates that pharmacists' trust in AI significantly diminishes after observing model errors, thereby hindering the effective implementation of AI-based tools.[54] Another critical example is the case of Oracle Cerner's Electronic Health Record system, where safety issues directly resulted in patient deaths.[55] This system serves as the core infrastructure for the U.S. Department of Veterans Affairs (VA). The system exhibited numerous vulnerabilities and software defects across key workflows, including prescription ordering, medication dispensing, medication recording, and the transmission of allergy information. Specifically, critical errors caused over 11,000 medical orders to be "lost". Furthermore, medication and allergy data for as many as 250,000 veterans were potentially compromised during transmission between systems. Moreover, the accuracy and reliability of AI models are highly dependent on the quality of data and algorithmic design. Models trained on biased or unrepresentative datasets may produce skewed recommendations, potentially compromising medication safety. For example, if the underlying data used to train an AI-assisted decision--making system exhibit significant disparities in terms of race, age, gender, or geographic region, the system's applicability to other populations may be considerably limited and its recommendations potentially inaccurate.[56] Another independent study revealed that the model might suffer from significant bias when applied across different hospitals and populations, with performance falling far short of clinical standards.[57] Underscoring the need for independent and rigorous validation, the study found that the model identified only 7% of sepsis patients who did not receive timely antibiotic treatment, while missing 67% of actual cases and generating a high volume of false alerts. Enhancing the interpretability and trustworthiness of AI models is therefore a critical prerequisite for their successful integration into clinical practice.

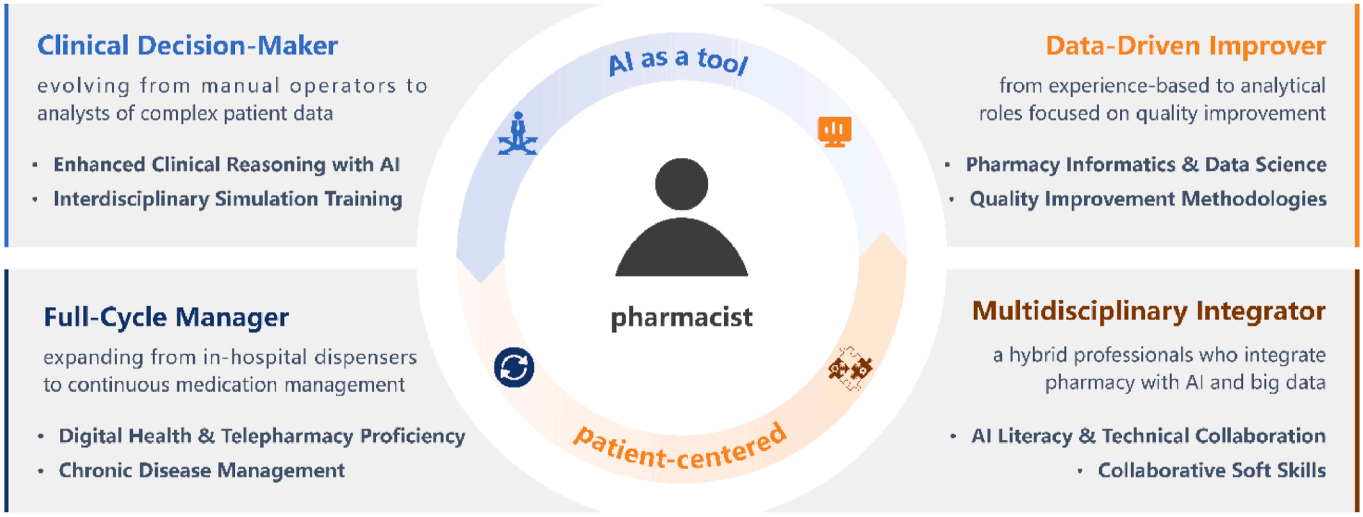


Fig. 2. Professional roles and competencies of pharmacists in the AI Era.

6.3. *Ethical, privacy and security*

Algorithmic bias presents a critical ethical concern. When training data incorporates biases related to gender, race, or geography, AI models may generate skewed recommendations, potentially undermining the fairness of healthcare delivery. For instance, if a model is trained predominantly on data from male patients, its recommendations may not be generalizable to female patients, resulting in inaccurate medication dosage suggestions.[58] Furthermore, the attribution of decision-making responsibility poses an ethical dilemma: in cases where adverse events occur as a result of AI-generated recommendations, it remains a complex challenge to determine whether liability rests with the AI developer, the healthcare institution, or the attending clinician or pharmacist.[59] In addition, the deployment of AI in clinical pharmacy and pharmaceutical administration entails the processing of substantial volumes of sensitive patient data, including EHRs, genetic information, and medication histories. This necessitates robust data protection measures and adherence to stringent ethical standards to prevent information leakage and misuse.[60] The concentration of this data makes it a prime target for breaches, requiring robust technical safeguards to prevent information leakage and misuse.

6.4. *Lagging standards and regulations*

Based on the above analysis, it is evident that globally, the healthcare sector is confronted with a notable deficiency in standardized frameworks governing the validation, updating, regulation, and liability attribution of AI. The absence of unified criteria for performance evaluation, clinical validation, and quality control of AI systems poses significant challenges to ensuring the safety and efficacy of AI-enabled applications.[61] Accordingly, the urgent enhancement and refinement of such standards are imperative. Moreover, the rapid evolution of AI technologies often outstrips the pace of regulatory adaptation, resulting in outdated oversight mechanisms. The current approval and supervision processes for AI systems tend to be rigid and protracted, thereby hindering the timely deployment and scalability of AI innovations.[62] For instance, AI models typically undergo frequent updates and iteration cycles; however, existing regulatory frameworks are ill-equipped to accommodate such dynamic changes, potentially exposing the healthcare system to unforeseen risks.[63] Hence, the establishment of a flexible, scientifically robust, and harmonized regulatory infrastructure is essential to safeguarding the sustainable and responsible integration of AI into pharmaceutical and healthcare practice.

As AI accelerates its penetration into the healthcare sector, establishing a regulatory framework that both fosters technological innovation and ensures safety and reliability has become a global consensus. Currently, China, the United States, the European Union, and Japan have each developed preliminary legal frameworks and policy orientations with distinct focuses (Table 2). Their core differences primarily manifest in regulatory approaches, the balance between innovation and safety, and philosophies regarding data governance. However, the legal practices in these jurisdictions remain incomplete, necessitating further enhancement of the comprehensiveness and full-process coverage of AI governance. An ideal regulatory system for AI in healthcare requires not only a high-level strategic blueprint but also agile and pragmatic rule evolution.

6.5. *Long-term verification of economic benefits and cost recovery*

Although Budget Impact Analysis (BIA) provides a valuable decision-making framework for evaluating specific pharmaceutical service models,[73] there remains a lack of multi-center, long-term empirical studies to assess the cost-effectiveness impact of AI on pharmaceutical services. This evidence gap is particularly prominent in primary care hospitals, where resource allocation decisions are often most sensitive to both cost constraints and efficiency improvements. Given the substantial capital investment required for the deployment and operation of such automated technologies, the absence of robust real-world evidence limits the capacity of healthcare administrators and policymakers to make evidence-based judgments regarding the long-term value, operational sustainability, and potential clinical benefits of these devices.[74] Addressing this research gap through well-designed, multi-institutional empirical studies will not only consolidate the economic evidence base for pharmaceutical automation but also facilitate the more equitable and evidence-informed integration of automated equipment into diverse healthcare delivery settings.

7. Future directions: Forging an intelligent and collaborative pharmacy ecosystem

With the continuous advancement of AI and the deep integration of digital technologies in healthcare, the development of clinical pharmacy and pharmaceutical administration over the next five years is expected to follow five key trends:

First, the combination of LLMs and knowledge graphs will become the standard configuration for intelligent pharmacy systems. This

Table 2
Comparison of AI healthcare regulations across four countries and regions.

Dimension	China	United States	European Union	Japan
Regulatory Approach	Government-led national strategy, with a core focus on industrial planning.	FDA-led prudential innovation, with a core focus on product market approval.	Systematic risk-based regulation, with a core focus on strict compliance.	Innovation-friendly strategic guidance, with a core focus on flexible legislation.
Innovation & Safety	Fosters innovation via clear strategic plans and phased targets, while imposing strict data security requirements.	Fosters innovation via streamlined approvals and dedicated funding, while strengthening oversight of algorithmic bias.[64]	Fosters innovation via a buffer of postponed regulatory applicability, while maintaining stringent overall requirements.[65]	Fosters innovation via non-binding guidelines and relaxed data policies, while addressing ethical concerns.[66]
Data Governance	Emphasizes data security and privacy, with safety and control as a prerequisite for application development.	Emphasizes privacy and security of training data (e.g., HIPAA[67]).	Emphasizes GDPR compliance, while providing a special channel for bias correction.[68]	Emphasizes easing access to training data via planned legal revisions.[69]
Liability Definition	Is still developing specific liability rules, though regulations emphasize full-chain supervision.	Is experiencing a contest between federal and state legislative systems.[70]	Has explicitly defined damages liability by incorporating AI software into the Product Liability Directive.[71]	Is exploring a preliminary framework for allocating AI-related civil liability.[72]

integration enables the fusion of general and specialized intelligence, allowing systems to address patient inquiries, generate personalized medication guidance, and assist pharmacists in complex tasks such as clinical consultations, prescription review, and individualized regimen design.[75] For instance, coupling LLMs with Clinical Pharmacogenetics Implementation Consortium (CPIC) guidelines facilitates intelligent interpretation of pharmacogenomic data and provides actionable clinical insights.

Second, explainable AI (XAI) will become a prerequisite for clinical implementation. To address the "black box" nature of traditional algorithms, XAI enhances transparency by clarifying the rationale behind AI-driven recommendations.[76] This fosters trust among clinicians and pharmacists and supports accountability. For example, XAI-based clinical decision support systems can explicitly justify drug–drug interaction alerts and dosage suggestions, thereby promoting more informed clinical decisions.[77]

Third, federated learning will enable multicenter modeling while ensuring data security. By allowing data to remain within institutional boundaries, federated learning breaks down data silos and facilitates collaborative model training across hospitals without compromising patient privacy.[78] This approach can be used to develop robust pharmacovigilance models that integrate ADR data from multiple institutions, thereby improving signal detection sensitivity.

Fourth, end-to-end digital management will span pharmacy, clinical care, nursing, medical records, and insurance.[79] Intelligent pharmacy platforms integrated with hospital information systems, laboratory information systems, and imaging archives will enable seamless digital workflows—from prescription ordering and review to dispensing, medication monitoring, and follow-up. Such integration enhances both efficiency and quality.

Fifth, the advancement of On-device AI bridges the "last mile" of patient medication. The core value of On-device AI in hospital pharmacy lies in deploying AI capabilities directly on local devices.[80] This approach safeguards medical data privacy while enabling millisecond-level real-time response and offline availability, thereby covering the entire process of patient medication. Its application scenarios span the full spectrum from outpatient to inpatient care, and from pharmacy dispensing to bedside administration.

Sixth, the competency framework for clinical pharmacist training will be restructured, with a focus on data literacy and AI proficiency.[81] Academic institutions and healthcare organizations will increasingly emphasize interdisciplinary education, incorporating coursework in AI, big data, and pharmacogenomics to cultivate digitally adept pharmacy professionals. Additionally, enhanced collaboration between pharmaceutical sciences and AI research will drive innovation and support the development of next-generation intelligent pharmacy applications.

8. Conclusion

The integration of AI into hospital pharmacy is driving a paradigm shift from isolated automation to comprehensive intelligentization. Despite ongoing challenges related to model interpretability, regulatory adaptation, and workforce development, continued technological advancement and optimized human–machine collaboration are positioning AI as a cornerstone of high-quality pharmaceutical services. By enabling more continuous, intelligent, and efficient pharmacy operations, AI is set to enhance both clinical pharmacy service and pharmaceutical administration. Within this evolving landscape, AI tools are expected to function not as competitors, but as assistants, collaborators, and force multipliers for pharmacists.

CRediT authorship contribution statement

Xi Chen: Writing – original draft, Visualization, Conceptualization. **Pengfei Jin:** Methodology, Data curation, Conceptualization. **Haiyan Mai:** Visualization, Investigation. **Shuhong Liang:** Supervision, Data curation. **Yaodong Ping:** Validation, Software. **Chen Wang:** Writing – review & editing. **Yingbo Zhao:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

This review is based on published data and sources, all of which are

cited appropriately in the manuscript and listed in the reference list.

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