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Research Article

Artificial Intelligence in Pharmacy Practice: Applications, Benefits, Challenges, And Future Perspectives

Avinash Bajpai^{1*}, Sachin Sharma²

^{1 2}Assistant Professor, I.T.S College of Pharmacy, Muradnagar, Ghaziabad, Uttar Pradesh, India

Corresponding Author: * Avinash Bajpai

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Abstract

Artificial intelligence (AI) is rapidly reshaping pharmacy practice, extending across drug discovery, clinical decision support, medication dispensing, pharmacovigilance, precision dosing, and patient engagement. This narrative review synthesizes current peer-reviewed literature to describe the principal applications, benefits, challenges, and future directions of AI within pharmacy practice. A structured search of PubMed, ScienceDirect, and Google Scholar identified relevant reviews, primary studies, and commentaries published primarily between 2010 and 2026. AI technologies—including machine learning, deep learning, natural language processing, and, more recently, generative AI and large language models—have been applied to accelerate target identification and molecule design, to power clinical decision support systems that flag drug–drug interactions and potentially inappropriate prescriptions, to automate dispensing through robotics, to detect adverse drug reactions from structured and unstructured data sources, to individualize dosing through pharmacogenomic and pharmacokinetic modelling, and to support medication adherence through chatbots, smart devices, and predictive analytics. Reported benefits include reductions in dispensing and prescribing errors, shorter turnaround times, cost savings, and improved patient adherence and satisfaction. However, adoption is constrained by concerns surrounding data privacy, algorithmic bias, poor interoperability, a scarcity of prospective clinical validation, unresolved questions of legal liability, and workforce readiness. Looking forward, the literature points toward explainable and auditable AI, tighter integration of multi-omic and real-world data, clearer regulatory pathways, and a redefined pharmacist role in which pharmacists supervise, validate, and contextualize AI-generated recommendations rather than being displaced by them. Realizing the full potential of AI in pharmacy will require coordinated investment in data infrastructure, prospective clinical validation, ethical governance, and pharmacy curricula that build AI literacy among current and future practitioners.

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1. INTRODUCTION

Artificial intelligence (AI) was formally conceived in the mid-twentieth century, beginning with Alan Turing's seminal question of whether machines could think (Turing, 1950) and later formalized by McCarthy (1997) as "the science and engineering of making intelligent machines, especially intelligent computer programs." In the decades since, AI has evolved from a theoretical discipline into a suite of practical technologies—machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision, and, most recently, generative AI built on large language models (LLMs)—that are embedded in everyday life. Healthcare has been among the sectors most transformed by this evolution. AI now informs diagnostic imaging, risk prediction, surgical robotics, and drug development, and its trajectory in medicine has been described as one of the most consequential technological shifts of the current era (Davenport & Kalakota, 2019; Kaul et al., 2020; Secinaro et al., 2021).

Pharmacy practice sits at the intersection of clinical decision-making, medication logistics, and direct patient care, making it a natural domain for AI-enabled innovation. Pharmacists are responsible for medication reconciliation, therapeutic monitoring, dispensing accuracy, patient counselling, and interprofessional collaboration, all of which generate and depend upon large volumes of structured and unstructured data (Garcia-Cardenas et al., 2020). As prescription volumes, medication regimen complexity, and administrative burden have grown, so too has interest in technologies capable of augmenting pharmacists' cognitive and operational capacity. AI-enabled tools can rapidly analyze electronic health records (EHRs), laboratory results, and medication histories to flag drug–drug interactions, identify patients at risk of adverse drug events (ADEs), and support real-time, patient-specific recommendations (Chalasanani et al., 2023).

The scope of AI applications in pharmacy is broad. Upstream, AI accelerates the identification of druggable targets and candidate molecules, compressing timelines that traditionally required a decade or more (Ferreira & Carneiro, 2025). Midstream, AI-driven clinical decision support systems (CDSS) assist pharmacists and prescribers in avoiding prescribing errors and potentially inappropriate medications (Sutton et al., 2020). Downstream, robotic dispensing systems, smart packaging, and adherence-monitoring devices extend the reach of pharmaceutical care into community and home settings (Takase et al., 2022; Alahmari et al., 2022). More recently, conversational AI and LLM-based tools have begun to mediate direct patient interactions, from answering over-the-counter medication queries to supporting medication counselling at scale (Al-Safadi et al., 2026; Pap & Oniga, 2024).

Despite this promise, the translation of AI research into routine pharmacy workflows remains uneven. Scoping and systematic reviews consistently report that current implementations are weighted toward workflow and productivity gains—such as identifying prescriptions requiring pharmacist intervention or streamlining mass-screening services—rather than direct improvements in patient health outcomes, and that most

supporting evidence derives from retrospective, single-institution studies with limited external validity (Ranchon et al., 2023; Simpson & Qasim, 2025). Ethical, legal, and workforce questions—spanning data privacy, algorithmic bias, accountability for AI-assisted errors, and the redefinition of the pharmacist's professional role—remain incompletely resolved (Hou et al., 2026).

1.1 OBJECTIVES OF THE REVIEW

This narrative review aims to (1) summarize the principal technological building blocks of AI relevant to pharmacy; (2) map the current landscape of AI applications across drug discovery, clinical decision support, pharmacovigilance, precision dosing, dispensing automation, medication adherence, and supply chain management; (3) synthesize the reported benefits of these applications for medication safety, efficiency, and patient outcomes; (4) critically examine the ethical, technical, regulatory, and workforce challenges that constrain adoption; and (5) outline emerging directions and research priorities that will shape the next generation of AI-enabled pharmacy practice.

1.2 METHODOLOGY

This review adopts a narrative synthesis approach appropriate for a broad, rapidly evolving, and interdisciplinary topic. Literature was identified through structured searches of PubMed, ScienceDirect, and Google Scholar using combinations of the terms "artificial intelligence," "machine learning," "deep learning," "natural language processing," "large language models," "pharmacy practice," "clinical pharmacy," "pharmacovigilance," "medication safety," and "pharmacogenomics." Priority was given to peer-reviewed systematic and scoping reviews, original research with clearly reported outcomes, and authoritative commentaries published between 2010 and 2026, supplemented by seminal foundational works. Reference lists of identified reviews were hand-searched to locate additional primary studies. As a narrative rather than systematic review, this work does not follow a formal PRISMA protocol; its purpose is to provide a comprehensive, critically appraised synthesis rather than an exhaustive or fully reproducible search.

2. Overview of Artificial Intelligence: Core Concepts and Technologies

A working understanding of AI's core technological subfields is necessary to appreciate its varied applications in pharmacy. Artificial intelligence is an umbrella term for computational systems that perform tasks normally associated with human intelligence, such as pattern recognition, prediction, language understanding, and decision-making (Bohr & Memarzadeh, 2020). Machine learning, a subset of AI, refers to algorithms that improve their performance on a task through exposure to data rather than through explicit rule-based programming. Common ML approaches used in pharmacy research include supervised learning methods such as logistic regression, random forests, gradient-boosted trees, and support vector

machines, which are trained on labelled datasets to predict outcomes such as adverse drug events or medication non-adherence.

Deep learning, a further subset of ML, employs multi-layered artificial neural networks capable of learning hierarchical representations directly from raw data, including chemical structures, medical images, and free text. Deep neural networks underlie many of the most impactful recent advances in drug discovery, including graph neural networks used to model molecular structures and predict drug–target interactions (Ferreira & Carneiro, 2025). Natural language processing enables computers to interpret and generate human language, and is the technology underlying tools that extract adverse drug reaction (ADR) mentions from clinical notes, patient forums, and social media (Oyebode & Orji, 2023; Dandala et al., 2019; Yang et al., 2019).

Generative AI represents the most recent wave of innovation, encompassing models capable of producing new content—text, images, or molecular structures—rather than merely classifying or predicting from existing data. Large language models, trained on vast corpora of text, can engage in open-ended conversation, summarize literature, and answer medication-related questions with a fluency that has enabled their rapid uptake in patient-facing and administrative pharmacy applications (Al-Safadi et al., 2026; Pap & Oniga, 2024). Clinical decision support systems integrate these underlying technologies into structured tools that match individual patient data against a computerized knowledge base to generate patient-specific alerts or recommendations, historically through rule-based logic and increasingly through ML-based risk scoring (Sutton et al., 2020).

The maturation of these technologies has been accompanied by growing healthcare-specific infrastructure—electronic health records, standardized drug interaction databases such as DrugBank and SIDER, and adverse-event repositories such as the U.S. Food and Drug Administration Adverse Event Reporting System (FAERS)—that supply the large, labelled datasets on which supervised ML models depend (Chalasani et al., 2023). It is the convergence of algorithmic advances with this expanding data infrastructure that has made pharmacy-specific AI applications increasingly feasible over the past decade.

3. Applications of Artificial Intelligence in Pharmacy Practice

AI applications span the entire medication-use continuum, from the discovery of new chemical entities to the moment a patient takes a dose at home. This section reviews the major application domains identified in the literature, organized from upstream pharmaceutical research through to downstream patient-facing services.

3.1 Drug Discovery and Development

Traditional drug discovery is characterized by high cost, lengthy timelines, and high attrition rates, with a single approved medicine historically requiring ten to fifteen years

and billions of dollars to bring to market. AI/ML methodologies—including deep learning, graph neural networks, and transformer-based architectures—are now applied across the discovery pipeline, from target identification through lead discovery, hit-to-lead optimization, and preclinical safety assessment (Ferreira & Carneiro, 2025). Quantitative structure–activity relationship (QSAR) modelling, molecular docking simulations, and de novo molecular generation using generative models allow researchers to screen and design candidate compounds computationally before committing to costly wet-laboratory synthesis, substantially narrowing the search space and shortening early-stage discovery timelines. While pharmacists are not typically the primary users of these upstream tools, an understanding of AI-driven drug discovery is increasingly relevant to pharmacy education, formulary evaluation, and the interpretation of newly approved therapies whose development relied heavily on computational methods.

3.2 Clinical Decision Support Systems

Clinical decision support systems represent one of the most mature and widely deployed applications of AI in pharmacy practice. A CDSS is designed to improve healthcare delivery by matching individual patient characteristics against a computerized knowledge base and presenting patient-specific assessments or recommendations to the clinician (Sutton et al., 2020). Traditional, rule-based CDSS relied on pharmacists to customize and validate static alert thresholds; AI-enabled CDSS instead apply ML algorithms to continuously analyze EHR data, flagging potentially inappropriate medication orders, dosing errors, contraindications, and clinically significant interactions with greater sensitivity and fewer false positives than static rule sets (Chalasani et al., 2023). A hybrid decision-support tool combining machine learning with rule-based alerts, for example, has been reported to identify high-risk medication orders with an area under the receiver operating characteristic curve (AUROC) of 0.81 while reducing false alerts relative to conventional systems, illustrating the potential of hybrid human–AI architectures to improve both sensitivity and pharmacist trust in system output. Across hospital and community settings, AI-enabled CDSS have been used to prioritize high-risk patients, predict adverse drug events before they occur, and support pre-prescription review, positioning pharmacists as active supervisors of algorithmic output rather than passive recipients of static alerts.

3.3 Adverse Drug Reaction Detection and Pharmacovigilance

Adverse drug reactions remain a leading cause of morbidity, hospitalization, and healthcare expenditure, and AI has been extensively applied to their prediction, detection, and surveillance. Predictive approaches combine chemical, structural, and taxonomic drug properties with known ADR data to forecast reactions before widespread clinical exposure. Early decision-tree models achieved predictive accuracies of 78.9–90.2% for allergic, renal, central nervous system, and hepatic reactions using structure–activity relationships

(Hammann et al., 2010), while network-based approaches have combined structural and pharmacological features to predict previously unknown ADRs, achieving an AUROC of 0.87 in prospective evaluation (Cami et al., 2011). Knowledge-graph methods linking drugs, protein targets, indications, and adverse reactions have achieved comparable discriminative performance while also generating biologically interpretable hypotheses about mechanisms of toxicity (Bean et al., 2017), and random-walk and inductive logic programming approaches have been used to predict adverse reaction profiles directly from drug–target–reaction networks (Rahmani et al., 2016; Bresso et al., 2013).

A parallel and increasingly important strand of pharmacovigilance research applies NLP to unstructured text—clinical notes, discharge summaries, and, notably, patient-generated content on social media and health forums—to detect ADR signals that may not yet appear in formal spontaneous reporting systems. Systems such as MADEX have been developed to jointly extract medication mentions, dosing information, and adverse event relations from clinical narratives using named entity recognition and relation-extraction models, achieving F1 scores exceeding 0.82 on benchmark datasets (Yang et al., 2019; Dandala et al., 2019; Chapman et al., 2019). Because patients often report side effects on social platforms well before they appear in the peer-reviewed literature or regulatory databases, NLP-based mining of platforms such as patient health forums has been used to detect novel cutaneous and other ADRs months in advance of formal clinical reporting, offering a complementary, real-time surveillance channel alongside traditional pharmacovigilance infrastructure (Oyebode & Orji, 2023). In neonatal and paediatric populations, where traditional ADR reporting is sparse, machine-learning-derived risk scores that combine severity and probability estimates have been developed specifically to support pharmacist-led surveillance in high-risk units (Yalçın et al., 2022).

3.4 Drug–Drug Interaction Screening

Predicting clinically significant drug–drug interactions (DDIs) require integrating multiple drug characteristics against curated interaction databases such as DrugBank, SIDER, TWOSIDES, and proprietary clinical references. Computational DDI prediction methods fall broadly into similarity-based, network-based, and machine-learning approaches, the latter increasingly outperforming rule-based screening for detecting subtle or previously undocumented interactions, including drug-induced QTc-interval prolongation. Recent comparative evaluations of commercial AI-based interaction-screening platforms against conventional drug interaction databases, using real-world patient data, have highlighted meaningful variability in sensitivity and specificity across tools, underscoring that AI-based DDI screening should complement rather than fully replace pharmacist clinical judgment (Domíán et al., 2025). Emerging work has also begun to assess the capability of general-purpose large language models to perform DDI analysis, with systematic mapping reviews finding promising

but inconsistent performance relative to purpose-built pharmacological databases, reinforcing the continued need for pharmacist oversight when AI tools are used for interaction checking (Mondal et al., 2025).

3.5 Precision Dosing and Pharmacogenomics

Interindividual variability in drug response—driven by genetics, renal and hepatic function, comorbidities, and concomitant medications—has long complicated dosing decisions for narrow-therapeutic-index drugs such as vancomycin, digoxin, and warfarin. AI-assisted dosing tools integrate pharmacokinetic and pharmacodynamic models with patient-specific covariates to generate individualized dosing recommendations, extending traditional therapeutic drug monitoring toward model-informed precision dosing. Reinforcement-learning approaches have shown particular promise in oncology, where dynamic dosing platforms adjust chemotherapy regimens based on a patient's own longitudinal response data rather than population averages, and machine-learning models for high-risk drugs such as vancomycin have been reported to outperform traditional population pharmacokinetic approaches in achieving target trough concentrations.

Pharmacogenomics—the study of how genetic variation influences drug response—has been transformed by AI's capacity to navigate complex, high-dimensional genomic data. Machine learning and deep learning algorithms are used to identify genetic markers associated with drug efficacy and toxicity, to predict optimal drug selection and dosage from genotype, and to integrate multi-omic data (genomic, transcriptomic, proteomic, and metabolomic) to build more comprehensive models of individual drug response than genotype alone permits (Taherdoost & Ghofrani, 2024; Judijanto, 2026). For pharmacists, AI-enabled pharmacogenomic decision support offers a pathway toward routine, clinically actionable use of genotype data—for example, in guiding warfarin, clopidogrel, or codeine dosing—that has historically been limited by the complexity of manual interpretation.

3.6 Robotic Dispensing and Pharmacy Automation

Medication dispensing errors—including wrong-drug, wrong-dose, and wrong-strength errors—have historically accounted for a substantial share of preventable medication harm, driven in part by rising prescription volumes and constrained staff time per prescription. Robotic dispensing systems, which combine barcode verification, machine vision, and automated storage-and-retrieval mechanisms, have been deployed across hospital and community pharmacy settings to address this problem. A prospective evaluation of an automated dispensing robot operating alongside pharmacy support staff reported that the total incidence of prevented dispensing errors fell from 0.204% to 0.044% of prescriptions after implementation, with the pharmacist's median dispensing time per prescription falling from 60 to 23 seconds (Takase et al., 2022). Similar reductions in dispensing errors and improvements in turnaround time have

been reported following the introduction of robotic-arm dispensing systems and Six Sigma-guided automation projects in outpatient pharmacy settings (Alahmari et al., 2022; Almalki et al., 2023; Sallam, 2024), and case studies from retail pharmacy chains have documented measurable gains in operational efficiency and service delivery following robotic dispensing adoption (Basile et al., 2024). Beyond error reduction, robotic systems free pharmacists and technicians from repetitive manual tasks, allowing more time to be redirected toward clinical verification, medication therapy management, and direct patient counselling.

3.7 Medication Adherence Monitoring

Roughly half of patients with chronic disease do not take medications as prescribed, contributing substantially to preventable morbidity, mortality, and healthcare costs. AI-enabled adherence technologies span several modalities: electronic pill bottles and blister packs that record opening events; ingestible sensors that transmit ingestion confirmation via an external monitor; wearable accelerometer- and computer-vision-based systems that detect medication-taking gestures; and predictive analytics that identify patients at elevated risk of non-adherence so that pharmacist outreach can be proactively targeted rather than reactive. Conversational AI adds a further layer, allowing patients to receive tailored reminders, ask medication questions, and obtain motivational support outside of scheduled clinical encounters (Chalasani et al., 2023).

3.8 Chatbots, Virtual Assistants, and Patient Counselling

Conversational AI systems—ranging from rule-based scripted chatbots to sophisticated LLM-powered assistants—are increasingly deployed in both community and hospital pharmacy settings to support patient counselling, triage routine medication questions, and extend pharmacist availability beyond staffed hours. Reported use cases include chatbots that provide generic medicine information for paediatric populations, tools that help patients identify pharmaceutical products, and platforms that deliver personalized lifestyle and medication-usage advice. A recent comparative study evaluating a general-purpose LLM (ChatGPT-4.5) against practising pharmacists in over-the-counter counselling scenarios found that the model could generate largely appropriate recommendations across several therapeutic categories, though pharmacists retained an advantage in nuanced, patient-specific judgment and in recognizing red-flag symptoms warranting referral (Al-Safadi et al., 2026). Purpose-built healthcare chatbots that integrate secure, decentralized communication protocols have similarly been developed to provide personalized medication answers while addressing data-privacy requirements specific to health information (Pap & Oniga, 2024). Despite this promise, adoption of generative AI in pharmacy remains uneven internationally; a comparative study in an internet-restricted country found meaningful gaps in both access to, and pharmacist knowledge of, generative AI

tools, underscoring that infrastructure and digital literacy—not only technological capability—shape real-world uptake (Kahwaji et al., 2026).

3.9 Community Pharmacy Operations and Workflow Optimization

Beyond clinical applications, AI supports the day-to-day operational functions of community pharmacies, including automated triage of routine customer queries, personalized refill reminders generated from predictive purchasing models, and administrative tasks such as meeting transcription and literature summarization for continuing education (Chalasani et al., 2023). Large retail pharmacy chains have partnered with telehealth platforms to enable AI-mediated video consultations, further blurring the boundary between dispensing, counselling, and virtual primary care.

3.10 Pharmaceutical Supply Chain and Inventory Management

AI-driven predictive analytics are increasingly applied to pharmaceutical supply chain management, addressing persistent challenges of demand volatility, cold-chain complexity, and drug shortages. Machine learning models—including long short-term memory (LSTM) networks, gradient-boosted tree ensembles such as XGBoost, and hybrid autoregressive-AI approaches—combine historical sales data with prescribing trends, seasonality, and epidemiological signals to forecast demand more accurately than traditional statistical methods, enabling optimized safety-stock levels, automated reorder points, and reduced expiry-related waste (Khan, 2025). At the point of care, such forecasting reduces the frequency of stockouts for essential medicines while minimizing excess inventory of costly or temperature-sensitive products, supporting both patient access and pharmacy financial sustainability.

3.11 Generative AI and Large Language Models

The emergence of large language models represents the newest and most rapidly evolving application domain. Beyond patient counselling, LLMs are being explored for drafting clinical documentation, summarizing medication histories, supporting pharmacy education through simulated formulation-training exercises, and assisting with literature review and evidence synthesis (Al-Safadi et al., 2026). Early evaluations suggest that general-purpose LLMs can perform creditably on constrained, well-defined pharmacy tasks such as OTC counselling and basic interaction checks, but their performance on complex, high-stakes clinical decisions remain inconsistent, and hallucination—the generation of plausible but incorrect information—poses a distinct safety risk that has not been fully characterized in pharmacy-specific contexts (Mondal et al., 2025). As a result, current expert commentary consistently frames generative AI as a productivity and communication aid to be used under pharmacist supervision rather than as an autonomous clinical decision-maker (Wong et al., 2025).

Table 1. Summary of Key Artificial Intelligence Applications in Pharmacy Practice

Domain	Representative AI Technologies	Illustrative Use Cases	Key Source(s)
Drug discovery & development	Deep learning, graph neural networks, generative models	Target identification, lead optimization, de novo molecular design	Ferreira & Carneiro, 2025
Clinical decision support	Hybrid ML/rule-based systems	Flagging inappropriate orders, dosing errors, contraindications	Sutton et al., 2020; Chalasani et al., 2023
Pharmacovigilance / ADR detection	NLP, knowledge graphs, decision trees	Predicting unknown ADRs; mining clinical notes and social media	Bean et al., 2017; Oyeboode & Orji, 2023
Drug–drug interaction screening	Similarity- and network-based ML; LLMs	QTc-prolongation alerts; automated interaction checking	Domíán et al., 2025; Mondal et al., 2025
Precision dosing & pharmacogenomics	Reinforcement learning, Bayesian PK/PD models	Vancomycin/warfarin dosing; genotype-guided therapy	Taherdoost & Ghofrani, 2024
Robotic dispensing	Computer vision, barcode verification robotics	Automated storage, retrieval, and packaging of medications	Takase et al., 2022; Alahmari et al., 2022
Medication adherence	Sensors, wearables, predictive analytics	Ingestible sensors, smart blister packs, risk-based outreach	Chalasani et al., 2023
Patient counselling / chatbots	Conversational AI, LLMs	OTC counselling, refill reminders, symptom triage	Al-Safadi et al., 2026; Pap & Oniga, 2024
Supply chain management	LSTM, XGBoost, hybrid forecasting	Demand forecasting, inventory optimization, shortage mitigation	Khan, 2025

4. Benefits of Artificial Intelligence in Pharmacy Practice

Across the application domains reviewed above, four recurring categories of benefit emerge from the literature: improved medication safety, enhanced operational efficiency, more personalized pharmacotherapy, and stronger patient engagement.

4.1 Improved Medication Safety and Error Reduction

The most consistently reported benefit of AI adoption in pharmacy is a reduction in medication errors across the prescribing, dispensing, and administration stages. Hybrid AI-based decision support tools have demonstrated superior sensitivity and precision in flagging high-risk prescriptions relative to conventional alert systems, while simultaneously reducing the false-alert burden that contributes to pharmacist alert fatigue. Robotic dispensing systems have documented reductions in preventable dispensing errors of over 75% in some settings, alongside near-elimination of the most clinically consequential error types—wrong-drug and wrong-strength dispensing (Takase et al., 2022). Machine-learning-based screening protocols for high-alert medications have achieved detection rates exceeding 98% for prescription mismatches in test datasets, substantially outperforming manual double-checking alone.

4.2 Enhanced Efficiency and Workflow Optimization

AI-enabled automation consistently reduces the time pharmacists and technicians spend on repetitive, low-complexity tasks, freeing capacity for higher-value clinical activities. Reported gains include dispensing-time reductions of more than 60% following robotic automation (Takase et al., 2022), improved traceability and real-time error identification in high-volume outpatient dispensing, and streamlined literature review, documentation, and inventory management supported by AI-based forecasting and generative tools. In supply chain contexts, AI-enabled demand forecasting has been associated with substantial reductions in logistical losses and

inventory costs relative to traditional forecasting methods (Khan, 2025).

4.3 Personalized and Precision Pharmacotherapy

By integrating pharmacogenomic, pharmacokinetic, and real-world outcome data, AI enables a shift from population-averaged dosing toward genuinely individualized therapy. Reinforcement-learning-based dosing platforms in oncology have achieved dose reductions relative to standard-of-care while maintaining therapeutic response, and machine-learning dosing models for narrow-therapeutic-index drugs have outperformed traditional pharmacokinetic nomograms in achieving target drug concentrations. In pharmacogenomics, AI-augmented multi-omic integration has been shown to meaningfully improve the explained variance of dose-prediction models—for example, incorporating gene-expression data alongside genomic variants has improved warfarin dose prediction accuracy by eight to twelve percentage points relative to genomic data alone—illustrating the tangible clinical value of AI's capacity to synthesize heterogeneous biological data streams (Taherdoost & Ghofrani, 2024).

4.4 Cost Savings and Resource Optimization

Economic evaluations of AI-supported medication therapy management programs have reported substantial reductions in total cost of care alongside decreased emergency department utilization and hospital admissions among high-risk patient populations, translating into favourable returns on investment for payers and health systems. Supply chain applications similarly report meaningful reductions in inventory carrying costs and waste from expired stock, alongside improved forecast accuracy that mitigates the financial and clinical costs of drug shortages (Khan, 2025).

4.5 Improved Patient Engagement and Adherence

Conversational AI and remote monitoring technologies have been associated with meaningful improvements in medication adherence, particularly among patients managing chronic

conditions such as diabetes, hypertension, and tuberculosis. Chatbot-mediated reminders and motivational support have been linked to adherence improvements reported in some populations to exceed 80%, and smart adherence devices incorporating real-time reminders have demonstrated adherence

rates substantially higher than standard-of-care controls in randomized evaluations. These tools extend pharmacist reach beyond the physical dispensing counter, enabling continuous, low-intensity support between clinical encounters.

Table 2. Reported Quantitative Benefits of AI Implementation in Pharmacy Settings

Application	Reported Outcome	Comparator	Source
Robotic dispensing (hospital)	Prevented dispensing errors fell from 0.204% to 0.044%; dispensing time fell from 60s to 23s	Pre-implementation manual dispensing	Takase et al., 2022
High-alert drug screening	Over 98% of prescription mismatches correctly identified	Manual double-checking	Chalasani et al., 2023 (review)
Hybrid ML/rule-based CDSS	AUROC 0.81 for high-risk medication detection; reduced false alerts	Conventional rule-based CDSS (AUROC 0.65)	Chalasani et al., 2023 (review)
Multi-omic warfarin dosing	8–12 percentage-point gain in explained variance for dose prediction	Genomic variants alone	Taherdoost & Ghofrani, 2024
AI-based medication therapy management	~19% reduction in total cost of care; reduced ED visits and admissions	Pre-intervention baseline	Chalasani et al., 2023 (review)
AI-enabled supply chain forecasting	Improved forecast accuracy; reduced logistical losses and inventory costs	Traditional statistical forecasting	Khan, 2025

5. Challenges and Limitations

Despite tangible benefits, the literature is consistent in identifying significant barriers to the safe, equitable, and sustained adoption of AI in pharmacy practice. These challenges span technical, ethical, regulatory, and professional dimensions.

5.1 Data Privacy and Security

AI systems in pharmacy depend on large volumes of sensitive patient data—medication histories, laboratory results, and genomic information—raising substantial privacy and security concerns. Health information is a frequent target of data breaches, and patients may be unaware of or object to the secondary use of their data for AI model training. The widely cited case in which a major technology company's health AI subsidiary received identifiable data on 1.6 million patients from a national health service without adequate individual consent illustrates the reputational and regulatory risk that inadequate data governance can create, and has informed subsequent tightening of consent and data-sharing requirements across multiple jurisdictions (Hou et al., 2026).

5.2 Algorithmic Bias and Health Equity

AI models trained on non-representative datasets risk perpetuating or amplifying existing healthcare disparities. Racial and ethnic minorities, women, and patients from low-resource settings are frequently under-represented in the clinical and genomic datasets used to train pharmacy-relevant AI tools, which can degrade model performance for these groups or, more troublingly, encode and reproduce systemic biases already present in historical care patterns—for example, models trained on prescribing records that reflect documented disparities in opioid analgesia by race risk recommending similarly disparate treatment going forward. Regulatory audits of AI-enabled medical products have found that a substantial proportion of cleared products were validated using clinical data lacking adequate demographic or technical reporting,

limiting the ability of pharmacists and regulators to assess whether a given tool performs equitably across the populations it will serve.

5.3 Data Quality, Integration, and Interoperability

The performance of any AI system is bounded by the quality and completeness of its training and input data. Healthcare data are frequently siloed across institutions, recorded in heterogeneous formats, and subject to missingness, transcription error, and inconsistent coding standards. Text, numeric, imaging, and video data must often be integrated within a single analytic pipeline, a task that remains among the most persistent technical obstacles in medical AI development. Overfitting—where a model learns spurious associations from a dataset with too many variables relative to observed outcomes—further threatens the reliability of models trained on the modestly sized, single-institution datasets that characterize much current pharmacy AI research (Ranchon et al., 2023; Simpson & Qasim, 2025).

5.4 Clinical Validation and Evidence Gaps

A recurring theme across scoping and systematic reviews is that the great majority of AI applications in pharmacy remain at the proof-of-concept or retrospective-validation stage, with comparatively few tools evaluated in prospective, randomized, or real-world implementation studies. Models developed using single-institution data may capture local prescribing cultures, formulary restrictions, and pharmacist intervention behaviours that limit generalizability to other healthcare systems, and pharmacist intervention thresholds themselves vary by local policy and staffing model in ways that are difficult for externally developed algorithms to anticipate (Ranchon et al., 2023). Without robust prospective evidence linking AI-supported interventions to improved patient outcomes—rather than solely to process measures such as alert accuracy—clinicians, payers, and regulators face genuine uncertainty about which tools merit routine adoption.

5.5 Ethical, Legal, and Regulatory Considerations

The introduction of AI into clinical decision-making raises unresolved questions of accountability: when an AI-assisted recommendation contributes to patient harm, it remains unclear whether liability should rest with the prescribing clinician, the supervising pharmacist, the institution, or the algorithm's developer. Existing regulatory frameworks—including the U.S. Food and Drug Administration's evolving guidance on AI/ML-based software as a medical device, the Health Insurance Portability and Accountability Act (HIPAA), and the European Union's General Data Protection Regulation and AI Act—provide partial but incomplete coverage of these questions, and regulatory approaches remain fragmented across jurisdictions. Bias audits, where conducted, are typically limited to the model-development and validation phases rather than continuous post-deployment monitoring, leaving a substantial portion of a model's real-world lifecycle without formal oversight. A qualitative synthesis of healthcare AI ethics literature further identifies transparency, informed consent, and the erosion of the traditional clinician–patient relationship as recurring ethical concerns that have not yet been adequately operationalized into practice standards (Hou et al., 2026).

5.6 Workforce, Trust, and Professional Identity

Pharmacists' willingness to adopt AI tools is shaped not only by evidence of clinical benefit but by trust, workflow fit, and professional identity concerns. Surveys of pharmacist knowledge and adoption of generative AI have found meaningful gaps even where infrastructure exists, and considerably larger gaps in settings with restricted internet access, indicating that technological availability alone does not guarantee uptake (Kahwaji et al., 2026). A persistent social concern, echoed across the literature, is the fear that AI will displace pharmacy jobs, a belief the evidence to date does not support but which nonetheless shapes attitudes toward adoption. Practically, successful implementation also depends on factors extending beyond the technology itself: the quality and structure of existing electronic health record systems, the degree to which AI tools alter established clinician–patient relationships, and the practical difficulties of integrating new systems with legacy pharmacy software and workflows.

Table 3. Key Challenges to AI Adoption in Pharmacy Practice and Potential Mitigation Strategies

Challenge	Description	Potential Mitigation Strategies
Data privacy & security	Sensitive patient and genomic data required for training and operation of AI tools	Robust consent frameworks; data minimization; federated learning; compliance with HIPAA/GDPR
Algorithmic bias	Under-representation of minority and low-resource populations in training data	Diverse and representative datasets; routine bias audits; subgroup performance reporting
Data quality & interoperability	Siloed, heterogeneous, and incomplete healthcare data across systems	Standardized data formats; interoperable EHR architecture; data governance policies
Limited clinical validation	Predominance of retrospective, single-institution evidence	Prospective multicenter trials; real-world post-deployment monitoring
Accountability & liability	Unclear responsibility when AI-assisted decisions cause harm	Clear regulatory guidance; documented human-in-the-loop oversight requirements
Workforce trust & readiness	Limited AI literacy and fear of professional displacement	AI curricula in pharmacy education; transparent tool design; continuous professional development

6. Future Perspectives

The trajectory of AI in pharmacy practice suggests several converging directions for the coming decade, each of which carries implications for pharmacists, educators, regulators, and health systems.

6.1 Explainable and Trustworthy AI

As AI tools move from advisory to increasingly autonomous roles in medication-related decision-making, the demand for explainable AI—models whose reasoning can be interrogated and understood by clinicians rather than treated as an opaque "black box"—is expected to intensify. Explainability is likely to become a prerequisite for regulatory clearance and clinical trust alike, particularly for high-stakes applications such as precision dosing and ADR prediction, where pharmacists must be able to justify a recommendation to patients and colleagues.

6.2 Deeper Integration of Multi-Omic and Real-World Data

Future pharmacogenomic and precision-dosing tools are likely to move beyond single-layer genomic data toward integrated

multi-omic frameworks that combine genomics, transcriptomics, proteomics, and metabolomics with continuous real-world data from wearables and remote monitoring devices (Taherdoost & Ghofrani, 2024; Judijanto, 2026). Coupled with model-informed precision dosing and emerging "digital twin" approaches that simulate an individual patient's physiology, this integration promises dosing recommendations that are dynamically updated as a patient's condition evolves, rather than fixed at the point of prescribing.

6.3 Regulatory Evolution and Global Harmonization

Regulatory frameworks governing AI-enabled medical software are actively evolving, with agencies increasingly moving toward lifecycle-based oversight that accounts for models which continue to learn and change after initial approval, rather than treating AI tools as static, one-time-approved devices. Greater international harmonization—reducing the current fragmentation across FDA, EU AI Act, and other national frameworks—would reduce duplicative

validation burden and accelerate the safe cross-border deployment of validated pharmacy AI tools.

6.4 Education, Workforce Preparedness, and "Pharmacointelligence"

A recurring theme in the literature is the need to formally integrate AI and machine learning literacy into pharmacy curricula, ensuring that graduating and practising pharmacists alike can critically evaluate, supervise, and contextualize AI-generated recommendations. Some authors have proposed the term "pharmacointelligence" to describe this deliberate integration of AI and related advanced technologies into pharmacy practice with the explicit goal of improving patient care and safety, positioning the pharmacist as an active supervisor and validator of algorithmic output rather than a passive consumer of it (Chalasani et al., 2023). Continuing-education programs, updated accreditation standards, and structured post-deployment feedback loops between practising pharmacists and AI developers will likely be necessary to sustain this evolving professional competency.

6.5 Toward Collaborative, Agentic Pharmacy Systems

Looking further ahead, the convergence of generative AI, robotic automation, and real-time clinical data integration points toward increasingly collaborative "AI co-pilot" models of pharmacy practice, in which an AI system continuously monitors incoming orders against a comprehensive clinical knowledge base, pre-drafts verification and counselling materials, and escalates only genuinely ambiguous or high-risk cases for pharmacist judgment. Realizing this vision safely will depend on the resolution of the data, validation, regulatory, and trust challenges outlined in Section 5, underscoring that technological capability alone is not a sufficient condition for responsible clinical adoption.

7. CONCLUSION

Artificial intelligence has moved from a peripheral curiosity to a substantive force reshaping pharmacy practice across the full medication-use continuum—from computational drug discovery through clinical decision support, pharmacovigilance, precision dosing, robotic dispensing, and direct patient engagement via conversational AI. The evidence reviewed here demonstrates measurable, and in some domains substantial, benefits for medication safety, operational efficiency, personalization of therapy, and patient adherence. At the same time, the literature is unambiguous that these gains remain unevenly distributed, insufficiently validated in prospective and diverse populations, and constrained by unresolved questions of data privacy, algorithmic bias, legal accountability, and workforce readiness. The path forward is not one in which AI displaces the pharmacist, but one in which pharmacists take on an expanded role as informed supervisors, validators, and ethical stewards of AI-generated recommendations—a competency that pharmacy education, professional bodies, and regulators must now actively cultivate. Achieving the full, safe potential of AI in pharmacy practice

will require sustained investment in data infrastructure, rigorous prospective evaluation, transparent and equitable model development, and a workforce equipped to critically engage with these rapidly evolving tools.

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About the Corresponding Author



Avinash Bajpai is an Assistant Professor at I.T.S College of Pharmacy, Muradnagar, Ghaziabad, Uttar Pradesh, India. He is actively involved in teaching, academic activities, and pharmaceutical education. His professional interests include pharmacy education, research, and the advancement of knowledge in pharmaceutical sciences through academic and scholarly contributions.