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Review Article

Artificial Intelligence in Pharmacy Practice: Transforming Medication Safety, Clinical Decision-Making, and Patient-Centered Care

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ABSTRACT

Background: Artificial intelligence (AI) is moving from experimental research into routine healthcare workflows, creating new opportunities for pharmacists to improve medication safety, clinical decision-making, pharmacovigilance, adherence, and patient engagement. Objective: This review examines the emerging role of AI across pharmacy practice, with emphasis on medication safety, clinical decision support, patient-centered care, workflow optimization, pharmacovigilance, and implementation governance. Methods: A focused narrative review was developed from peer-reviewed literature indexed in PubMed/MEDLINE and recent guidance from international health and regulatory organizations. Priority was given to evidence published from 2019 through August 2026, while seminal earlier work was retained when needed to explain core AI concepts. Results: Current evidence indicates that machine learning, natural language processing, computer vision, and generative AI can support prescription screening, drug–drug interaction detection, adverse drug event prediction, medication reconciliation, pharmacovigilance, medication counseling, adherence support, and clinical information retrieval. Recent pharmacy-specific reviews show that real-world applications remain concentrated on workflow and screening tasks, while prospective evidence for direct patient outcomes is comparatively limited. Generative AI and large language models may expand pharmacist access to information and communication support, but hallucination, outdated knowledge, bias, privacy, automation bias, and unclear accountability remain important safety concerns. Conclusion: AI should be implemented as a pharmacist-augmented technology rather than a substitute for professional judgment. Safe adoption requires validated use cases, human oversight, representative data, transparent performance monitoring, interoperability, cybersecurity, governance, and competency-based education. The future of pharmacy

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practice is likely to involve human–AI collaboration in which pharmacists retain responsibility for clinical interpretation, shared decision-making, and patient-centered care.

INTRODUCTION

Artificial intelligence (AI) refers broadly to computational systems capable of performing tasks that traditionally require aspects of human intelligence, including pattern recognition, prediction, classification, language processing, and decision support. Machine learning (ML), deep learning, natural language processing (NLP), computer vision, and generative AI represent different technical approaches within the broader AI ecosystem. In healthcare, the value of AI is increasingly linked not simply to automation, but to the ability to transform large and heterogeneous datasets into information that can support clinical action [1–5].

Pharmacy practice is particularly data-rich. Pharmacists routinely interpret medication histories, prescriptions, laboratory values, adverse-event reports, dispensing records, clinical notes, formulary information, and patient-reported outcomes. These data are often distributed across electronic health records (EHRs), pharmacy information systems, computerized provider order-entry systems, medication administration records, and external databases. AI therefore has a plausible role at multiple points in the medication-use process, from prescribing and verification to dispensing, monitoring, adherence, and follow-up. Recent pharmaceutical research has also explored AI and computational modeling in nanomedicine, illustrating the broader expansion of AI across pharmaceutical science [41].

Recent pharmacy literature suggests that AI adoption is growing, but the evidence base remains uneven. A 2025 scoping review of current pharmacy practice identified applications mainly involving identification of atypical or inappropriate medication orders, screening services, and adherence or quality-use-of-medicines support, while direct evidence of improved patient outcomes remained limited [6]. A 2025 systematic review of clinical pharmacy applications similarly identified adverse drug event detection, prescription verification, clinical decision support, pharmacometrics, medication therapy management, and prediction of therapeutic response as important areas of development [7]. More recent 2026 reviews have further emphasized drug-interaction detection, medication-error identification, pharmacovigilance, AI-enabled clinical decision support, and large language model applications [8,9].

The central question for pharmacy is therefore not whether AI will enter practice, but how it can be introduced safely and meaningfully. Pharmacists have a distinctive role in evaluating medication appropriateness, balancing benefit and risk, identifying drug-related problems, communicating with patients, and coordinating medication-related decisions across healthcare settings. AI can extend these capabilities by rapidly processing information, prioritizing cases, and identifying patterns that may be difficult to detect manually. However, AI outputs can also be wrong, poorly calibrated, biased, or difficult to explain. The pharmacist must therefore remain an accountable clinical professional rather than becoming a passive recipient of algorithmic recommendations.

This review discusses the principal applications, opportunities, limitations, governance requirements, and future directions for AI-enabled pharmacy practice, with particular attention to medication safety, clinical decision-making, and patient-centered care.

SCOPE AND APPROACH OF THE REVIEW

This article is a narrative review rather than a systematic review or meta-analysis. A focused literature search was undertaken using PubMed/MEDLINE and authoritative organizational sources, including the World Health Organization (WHO), U.S. Food and Drug Administration (FDA), and National Institute of Standards and Technology (NIST). Priority was given to peer-reviewed publications from 2019 through August 2026, with additional seminal publications included when necessary to explain foundational AI concepts. Search concepts included artificial intelligence, machine learning, pharmacy practice, clinical pharmacy, medication safety, adverse drug events, pharmacovigilance, drug–drug interactions, clinical decision support, large language models, ChatGPT, medication adherence, and patient-centered care.

The evidence was synthesized thematically rather than quantitatively. Particular attention was given to recent pharmacy-specific reviews, systematic reviews, empirical evaluations of generative AI, and current governance frameworks. Because AI technologies evolve rapidly, performance results from a specific model or software version should not be assumed to apply to later versions or to different clinical environments. The review therefore emphasizes implementation principles and clinically meaningful outcomes rather than treating individual model accuracy as a sufficient measure of usefulness.

AI TECHNOLOGIES RELEVANT TO PHARMACY PRACTICE

Machine learning and predictive analytics

ML algorithms learn relationships from data and can be used for classification, prediction, clustering, and risk estimation. In pharmacy practice, supervised ML can estimate the probability of an adverse drug event, identify prescriptions likely to contain errors, predict medication nonadherence, or prioritize patients for pharmacist review. Recent systematic evidence indicates that logistic regression, random forests, and gradient-boosting approaches are commonly used in adverse drug event prediction, although external validation and handling of class imbalance remain important weaknesses in the literature [10].

Deep learning

Deep learning uses multilayer neural networks to model complex relationships. It is especially useful when the input data are high dimensional, such as clinical text, images, physiologic signals, and molecular structures. Deep-learning approaches have been applied to adverse-event extraction from clinical text and to drug–drug interaction prediction [11,12]. Their major limitation in practice is that high predictive performance does not automatically establish clinical utility or explainability.

Natural language processing

NLP converts unstructured text into machine-readable information. Pharmacy applications include extracting medication names and doses from clinical notes, identifying adverse reactions in narrative records, summarizing medication histories, screening literature, and supporting pharmacovigilance. NLP can reduce the manual burden of reviewing large volumes of text, but terminology ambiguity, negation, abbreviations, documentation quality, and multilingual variation can affect reliability [13].

Generative AI and large language models

Generative AI can produce or transform text, summarize information, answer questions, and interact conversationally. Large language models (LLMs) are increasingly being evaluated for medication counseling, clinical question answering, documentation, education, and decision support. Recent studies indicate potential value, but also substantial variability in factual accuracy and safety. A 2026 systematic review of ChatGPT-class models in medication-related tasks identified evaluation domains including drug–drug interaction assessment, patient counseling, clinical pharmacotherapy, and pharmacovigilance, while emphasizing the need for rigorous validation [14]. LLM outputs should therefore be treated as draft information requiring pharmacist verification rather than authoritative prescribing or dispensing instructions.

Knowledge graphs and hybrid systems

Knowledge graphs represent relationships among medicines, diseases, adverse effects, genes, laboratory parameters, and clinical concepts. Combining LLMs with curated knowledge sources may reduce unsupported responses by grounding generation in validated information. Hybrid architectures are particularly attractive for pharmacy because they can combine the language flexibility of generative models with structured medication knowledge, interaction rules, and institutional formularies.

ARTIFICIAL INTELLIGENCE AND MEDICATION SAFETY

Medication safety is one of the strongest use cases for AI because medication-related decisions involve large numbers of interacting variables. AI may support error detection at several stages: prescribing, transcription, verification, dispensing, administration, monitoring, and follow-up.

Prescription screening and prioritization

AI can screen prescriptions for dose anomalies, duplicate therapy, contraindications, high-risk combinations, renal or hepatic dosing concerns, and other patterns associated with pharmacist intervention. The principal advantage is prioritization: instead of treating every alert as equally important, a model may estimate which orders deserve immediate clinical review. Pharmacy-specific evidence shows that identification of atypical or inappropriate medication orders is among the most frequently studied AI applications [6].

Drug–drug interaction detection

Traditional interaction databases are rule-based and can generate large numbers of alerts. ML and graph-based approaches attempt to identify interaction relationships using drug structure, biological information, adverse-event data, and knowledge networks [15–18]. Such systems may improve prioritization and reduce alert fatigue, but they should complement rather than replace established interaction databases and pharmacist assessment.

Medication reconciliation

Medication reconciliation requires integration of information from multiple sources and identification of discrepancies. NLP and predictive models may assist by extracting medication information from notes and records, matching medicines across lists, and prioritizing clinically significant discrepancies. Human review remains essential because apparent discrepancies may represent intentional changes, temporary medicines, historical medications, or documentation artifacts.

Adverse drug event prediction

AI-based prediction of adverse drug events is an active research area. A 2024 systematic review and meta-analysis examined ML models using EHR data, while a 2026 systematic review found that many models achieved moderate-to-high internal discrimination but relatively few underwent external validation [10,19]. This distinction is crucial: a model that performs well in one hospital dataset may fail after deployment because of differences in prescribing patterns, patient populations, documentation, laboratory measurement, or disease prevalence.

Reducing medication-alert burden

AI can potentially optimize computerized medication alerts by predicting which alerts are likely to result in meaningful clinical action. A 2024 scoping review identified AI-based alert optimization as an emerging strategy [20]. The objective should not be to minimize the number of alerts indiscriminately, but to increase the proportion that are clinically relevant while preserving sensitivity for serious risks. Pharmacists should participate in defining alert thresholds, evaluating false negatives, and monitoring unintended consequences.

AI-ENABLED CLINICAL DECISION-MAKING IN PHARMACY

Clinical decision-making in pharmacy integrates patient-specific characteristics, pharmacology, evidence, guidelines, local policy, and clinical judgment. AI can augment this process by rapidly synthesizing information and generating risk estimates or candidate options.

Clinical decision support

AI-enabled clinical decision support systems (AI-CDSS) can analyze structured and unstructured patient information and provide recommendations or risk scores. Their potential applications include antimicrobial dosing, anticoagulation management, renal-dose adjustment, therapeutic drug monitoring, and identification of patients who require pharmacist intervention. A key principle is that AI-CDSS should present evidence and uncertainty in a form that allows the pharmacist to understand why a recommendation was generated.

Pharmacokinetics and pharmacometrics

AI and ML may support pharmacokinetic prediction and individualized dosing by learning relationships among patient characteristics, drug exposure, laboratory measurements, and outcomes. Such systems may become valuable for medicines with narrow therapeutic indices. Nevertheless, model predictions must be evaluated against validated pharmacokinetic principles and therapeutic drug monitoring, particularly when patient characteristics fall outside the training population.

Precision medicine and pharmacogenomics

AI can integrate genetic, clinical, demographic, and medication data to support individualized therapy. Pharmacogenomic information may help identify patients with altered metabolism or response to selected medicines, while ML can assist in interpreting complex multi-variable datasets. The clinical value depends on the quality and clinical validity of the underlying genomic associations and on appropriate integration into medication-use workflows [21].

Literature and evidence retrieval

Pharmacists face an expanding volume of clinical evidence. NLP and LLMs can assist with literature summarization, extraction of study characteristics, and generation of draft evidence summaries. However, generative systems can produce fabricated citations or inaccurately summarize evidence. Evidence retrieval tools should therefore be designed to expose source documents and allow pharmacists to verify claims.

Human–AI collaboration

The emerging evidence favors a co-pilot model rather than autonomous decision-making. In a 2025 study evaluating an LLM-based clinical decision support approach across multiple specialties, pharmacist-plus-LLM collaboration outperformed pharmacist-alone and LLM-alone configurations for the evaluated medication-chart task [22]. Although such findings are promising, they should not be generalized to all clinical contexts. The practical lesson is that AI may be most useful when it increases human capacity while preserving professional review.

PHARMACOVIGILANCE AND MEDICATION SURVEILLANCE

Pharmacovigilance traditionally relies heavily on spontaneous reporting systems, case-series assessment, signal detection, and epidemiologic studies. AI can augment these processes by processing large datasets from EHRs, claims, clinical notes, biomedical literature, patient reports, and other sources.

NLP can identify suspected adverse reactions in free text, while ML can rank drug-event associations for further evaluation. A 2022 scoping review demonstrated broad use of ML in pharmacovigilance, while a 2025 systematic review specifically examined AI approaches for predicting adverse drug reactions in hospitalized patients [23,24]. A 2024 review also highlighted deep learning and NLP for extraction of adverse drug events from clinical text [11].

For pharmacists, the value of AI-enabled pharmacovigilance is not simply faster signal generation. The larger opportunity is earlier recognition of clinically important patterns and better targeting of manual review. However, pharmacovigilance models may be affected by confounding, reporting bias, missing data, indication effects, and changes in prescribing behavior. AI-generated signals should therefore enter an established pharmacovigilance workflow rather than being treated as confirmed causal relationships.

AI IN PATIENT-CENTERED PHARMACY CARE

Patient-centered care requires communication, shared decision-making, attention to preferences, health literacy, and consideration of social and practical barriers to medication use. AI can support these functions, but the patient–pharmacist relationship should remain central.

Medication counseling

Conversational AI can provide preliminary explanations of dosing schedules, common adverse effects, administration instructions, and questions patients may wish to discuss with a pharmacist. However, medication counseling is a high-stakes domain. A response can appear fluent while containing an incorrect dose, contraindication, interaction, or unsupported recommendation. Pharmacists should therefore use AI-generated counseling content only when the underlying information is verifiable and the final message is reviewed.

Medication adherence

AI can combine dispensing history, patient-reported information, digital reminders, and behavioral patterns to identify patients at risk of nonadherence. Interventions can then be targeted toward practical barriers such as regimen complexity, misunderstanding, cost, adverse effects, or forgetfulness. Importantly, prediction alone does not improve adherence; it must trigger an effective pharmacist or care-team intervention.

Patient education and health literacy

AI can translate technical information into simpler language and generate alternative explanations. This may improve accessibility, but translation and simplification must preserve clinically important meaning. Pharmacists should verify language, cultural appropriateness, and medication-specific accuracy.

Remote and digital pharmacy services

Telepharmacy and digital health platforms can extend access to medication counseling and follow-up. AI may assist with triage, documentation, and identification of patients who require human review. WHO's current digital-health strategy emphasizes interoperability, evidence-based implementation, equitable access, and alignment with health-system needs [25,26]. AI-enabled pharmacy should therefore be integrated into broader digital-health infrastructure rather than developed as isolated tools.

AI IN COMMUNITY, HOSPITAL, AND AMBULATORY PHARMACY

The implementation priorities for AI differ across practice settings. In community pharmacies, applications may include prescription triage, dispensing workflow support, inventory forecasting, adherence identification, patient education, and screening services. Hospital pharmacies may benefit from medication-order review, high-risk medication surveillance, antimicrobial stewardship support, medication reconciliation, pharmacovigilance, and clinical prioritization. Ambulatory and primary-care pharmacy services may use AI for chronic-disease medication management, adherence risk prediction, and longitudinal monitoring.

A 2025 scoping review found that existing pharmacy-practice evidence remains concentrated in workflow and screening applications, suggesting that the profession is still transitioning from operational AI toward outcome-focused clinical AI [6]. The next stage should therefore emphasize measurable clinical outcomes: medication errors prevented, adverse events avoided, clinically relevant interventions, adherence improvement, hospitalization reduction, patient experience, and cost-effectiveness.

RISKS, LIMITATIONS, AND ETHICAL CHALLENGES

Hallucination and factual error

Generative AI can produce plausible but incorrect statements. In pharmacy, this creates direct patient-safety risks. LLMs should not be assumed to possess reliable current knowledge of drug labeling, local formularies, institutional protocols, or patient-specific contraindications.

Bias and inequity

AI systems can reproduce or amplify biases in training data. Underrepresentation of particular populations may result in poorer performance for those groups. WHO emphasizes data quality, external validation, transparency, and safeguards against bias in health AI [27]. Equity must therefore be assessed before and after implementation.

Automation bias and deskilling

Clinicians may over-trust algorithmic recommendations, especially when systems appear authoritative. Conversely, excessive reliance on automation may weaken independent clinical reasoning. Pharmacy education should therefore teach appropriate skepticism, verification, and recognition of model limitations.

Privacy and cybersecurity

AI systems may process highly sensitive health and medication information. Data minimization, access control, encryption, auditability, secure integration, and appropriate consent or legal basis are necessary. Cloud-based generative AI tools require particular caution because users may inadvertently enter identifiable patient information into systems not approved for clinical use.

Explain ability and accountability

When an AI system influences a medication decision, clinicians need to know the intended use, relevant inputs, performance characteristics, limitations, and escalation procedures. The NIST AI Risk Management Framework emphasizes trustworthy AI risk management across design, development, deployment, and evaluation [28,29]. The FUTURE-AI international consensus framework similarly emphasizes fairness, universality, traceability, usability, robustness, and explainability [30].

Interoperability and data quality

Poorly standardized data can undermine AI performance. Medication names, units, laboratory values, diagnoses, and patient identifiers may be represented differently across systems. AI implementation should therefore be linked to data-governance and interoperability programs.

Model drift

Clinical practice changes, formularies change, patient populations change, and AI models may become less reliable over time. Continuous monitoring is essential, particularly for models that learn from real-world data. Regulatory approaches increasingly recognize the need to manage planned changes and monitor AI-enabled systems throughout their lifecycle [31].

REGULATORY AND GOVERNANCE CONSIDERATIONS

AI in pharmacy operates within overlapping professional, institutional, privacy, medical-device, and medicines-regulatory frameworks. The exact requirements vary by jurisdiction and by the intended use of the software. Tools that merely assist information retrieval may be governed differently from software that makes or drives clinical decisions.

WHO recommends that health AI be subject to appropriate safety and effectiveness assessment, transparency, documentation, external validation, data-quality controls, privacy protection, and stakeholder engagement [27]. FDA policy similarly emphasizes lifecycle oversight for AI/ML-enabled medical devices, including mechanisms for managing changes after deployment [31,32]. NIST provides a voluntary framework for managing AI risks, while its generative-AI profile provides additional guidance for risks associated with generative systems [28,29].

For pharmacy organizations, governance should include at least: (1) clearly defined intended use; (2) identification of the accountable clinical owner; (3) validation in the local population; (4) documented limitations and contraindicated uses; (5) human-review requirements; (6) privacy and cybersecurity assessment; (7) performance monitoring; (8) incident reporting; (9) change control; and (10) periodic reassessment of clinical benefit.

IMPLEMENTATION FRAMEWORK FOR PHARMACY PRACTICE

A practical implementation pathway can be organized into seven stages.

Stage 1—Define the clinical problem. The organization should identify a specific medication-related problem and determine whether AI is genuinely needed. AI should not be introduced merely because it is technologically available.

Stage 2—Define the intended use and risk level. The team should specify who will use the output, what decision it supports, what happens when the model is uncertain, and which decisions remain exclusively human.

Stage 3—Validate locally. Performance should be evaluated using representative patients and real workflow conditions. Important measures include sensitivity, specificity, calibration, positive and negative predictive values, false-alert rates, clinician workload, and clinically meaningful outcomes.

Stage 4—Integrate into workflow. AI should be placed at the point where it can reduce burden or improve decisions without creating duplicate documentation. Human escalation pathways must be explicit.

Stage 5—Train pharmacists and staff. Competency should include AI literacy, interpretation of performance metrics, prompt and information hygiene for generative tools, privacy, bias recognition, and verification of AI outputs.

Stage 6—Monitor after deployment. Organizations should track performance, errors, overrides, alert fatigue, disparities, and patient outcomes. Model updates should trigger reassessment.

Stage 7—Evaluate value. Adoption should ultimately be justified by patient, professional, operational, and economic outcomes rather than by model accuracy alone.

PHARMACY EDUCATION AND PROFESSIONAL COMPETENCY

AI literacy is becoming a professional competency for pharmacists. Education should move beyond teaching how to operate a chatbot. Students and practicing pharmacists need to understand basic ML concepts, dataset limitations, model evaluation, bias, privacy, cybersecurity, clinical validation, and responsible use.

Generative AI is already being explored in pharmacy education, including reflective writing, clinical problem solving, and student learning [33–35]. These developments create opportunities to teach students how to use AI as a learning aid while preserving independent reasoning. Assessment methods should emphasize verification, source appraisal, clinical justification, and communication rather than the ability to generate fluent text.

Professional organizations and pharmacy schools should consider competency frameworks covering: AI fundamentals; data governance; clinical decision support; human–AI collaboration; ethical and legal considerations; patient communication; and post-deployment monitoring. Pharmacists should also participate in multidisciplinary AI governance committees because medication-use expertise is essential when algorithms affect prescribing, dispensing, administration, or monitoring.

ECONOMIC AND WORKFORCE IMPLICATIONS

AI may reduce time spent on repetitive information-processing tasks, but implementation itself requires investment in software, integration, cybersecurity, validation, training, and ongoing monitoring. Economic evaluations should therefore include total implementation cost rather than comparing software price with pharmacist labor alone.

The workforce effect is likely to be a redistribution of tasks rather than simple replacement. Routine screening, documentation, and information retrieval may become more automated, allowing pharmacists to spend more time on complex medication management, patient counseling, care coordination, and clinical problem solving. This transition will require redesign of roles and performance measures.

A key risk is unequal access. Large health systems may have greater ability to implement validated AI than small community pharmacies or resource-limited settings. WHO's digital-health strategy emphasizes equitable access and country-specific implementation capacity [25,26]. Pharmacy AI programs should therefore consider affordability, interoperability, workforce capacity, and accessibility from the beginning.

FUTURE DIRECTIONS

The next phase of AI in pharmacy practice is likely to be characterized by multimodal and interoperable systems rather than isolated algorithms. An AI platform may combine medication lists, laboratory results, clinical notes, patient-reported outcomes, pharmacogenomic information, and real-time dispensing data. Knowledge-grounded LLMs may provide conversational interfaces to validated medication resources, while predictive models identify patients requiring pharmacist intervention. This broader convergence of computational methods with pharmaceutical formulation research further supports an interdisciplinary approach to AI-enabled pharmacy practice [41,42].

Federated learning and privacy-preserving analytics may allow institutions to collaborate without centralizing sensitive patient-level data. Explainable AI may improve the usability of risk predictions, although explanations themselves must be evaluated for accuracy and clinical usefulness. Digital twins and individualized predictive models may eventually support longitudinal medication optimization, but these applications remain research-oriented and require substantial validation.

Future research should prioritize prospective and multicenter evaluations with patient-centered endpoints. Studies should report external validation, calibration, subgroup performance, workflow impact, implementation fidelity, and economic outcomes. For LLMs, evaluations should include factuality, citation accuracy, harmful recommendations, reproducibility, and performance across medication classes and clinical scenarios. The field should move from demonstrations of what AI can do toward evidence of what AI improves.

Importantly, the strongest future model is likely to be collaborative. AI can rapidly analyze information, but pharmacists provide contextual judgment, ethical reasoning, patient communication, and responsibility for medication-related decisions. The goal should therefore be augmentation of professional capability rather than replacement of the pharmacist.

DISCUSSION

AI has reached a stage at which its relevance to pharmacy practice is no longer hypothetical. Evidence now spans prescription screening, adverse-event prediction, pharmacovigilance, drug–drug interaction prediction, medication counseling, adherence support, and clinical decision support [6–9,14,20,22–24]. Nevertheless, the evidence also reveals a gap between technical feasibility and demonstrated improvement in patient outcomes.

Three themes emerge. First, AI is most immediately valuable when it reduces information-processing burden and prioritizes pharmacist attention. This includes screening large numbers of medication orders and identifying patients at increased risk. Second, patient-facing generative AI requires substantially stronger safeguards because an incorrect output can be directly acted upon by a patient. Third, implementation quality is as important as model performance. A high-performing model that is poorly integrated, insufficiently monitored, or distrusted by pharmacists may provide little real-world benefit.

The profession should consequently resist both excessive enthusiasm and excessive resistance. AI is neither inherently safe nor inherently unsafe. Its clinical value depends on the problem, data, model, workflow, users, governance, and consequences of error. A mature pharmacy AI strategy should therefore begin with medication-use problems and patient outcomes, not with a particular technology.

The pharmacist's role is likely to become more, rather than less, important in an AI-enabled medication system. Pharmacists will need to interpret algorithmic outputs, identify clinically implausible recommendations, explain decisions to patients, manage exceptions, and participate in the governance of clinical AI. This transition aligns with the broader concept of human–AI convergence in medicine, in which technology handles data-intensive tasks while clinicians retain contextual and relational responsibilities [1,2].

Table 1. Major applications of artificial intelligence in pharmacy practice

Pharmacy domain	Potential AI application	Expected benefit	Key safety consideration
Prescription review	Risk-based screening of dose, duplication, contraindication, and high-risk orders	Prioritizes pharmacist review	False negatives; local validation
Drug–drug interactions	ML/graph-based interaction prediction and alert prioritization	Improves signal prioritization	Incomplete interaction knowledge; alert fatigue
Medication reconciliation	NLP extraction and discrepancy detection	Reduces manual information processing	Intentional vs unintentional discrepancies
Adverse drug events	Predictive risk models using EHR data	Earlier identification of high-risk patients	Limited external validation; dataset shift
Pharmacovigilance	NLP/ML signal detection from clinical text and reports	Faster signal generation	Confounding and reporting bias
Clinical decision support	Patient-specific recommendations and risk estimates	Supports evidence-informed decisions	Automation bias; explainability
Medication counseling	Conversational drafting and patient education	Accessible information and communication support	Hallucination; unsafe advice

Adherence	Risk prediction and targeted reminders	Targets pharmacist interventions	Privacy; prediction without effective intervention
Workflow	Triage, documentation, inventory and operational forecasting	Efficiency and workload reduction	Over-automation and role redesign
Education	Case generation, feedback and learning support	Personalized learning	Accuracy, assessment integrity, overreliance

Table 2. Minimum governance requirements for AI implementation in pharmacy practice

Governance element	Minimum requirement	Suggested monitoring metric
Intended use	Document clinical purpose, users, inputs, outputs, exclusions	Use outside intended purpose
Validation	Test on representative local data before deployment	Sensitivity, specificity, calibration
Human oversight	Define mandatory pharmacist review and escalation	Override and escalation rates
Equity	Assess subgroup performance and access	Performance gaps across populations
Privacy	Use approved systems; minimize identifiable data	Privacy incidents and access logs
Cybersecurity	Secure interfaces, authentication, audit trails	Security events
Model monitoring	Monitor drift and performance after deployment	Performance over time
Change control	Review material model/software updates	Update-related performance changes
Patient safety	Define incident reporting and response	AI-related near misses/adverse events
Value	Assess clinical, operational and economic outcomes	Errors prevented, time saved, patient outcomes

CONCLUSION

Artificial intelligence offers a substantial opportunity to strengthen modern pharmacy practice by improving medication-safety surveillance, clinical decision support, pharmacovigilance, workflow prioritization, medication counseling, and patient engagement. Current evidence supports a promising but still developing role for AI, with stronger evidence for operational and screening applications than for long-term patient outcomes.

Safe and effective adoption requires a pharmacist-centered model in which AI augments rather than replaces professional judgment. Local validation, transparent intended use, representative data, privacy and cybersecurity controls, human oversight, continuous monitoring, and competency-based education are essential. Future research should emphasize prospective, multicenter, patient-centered, and economic outcomes, particularly for generative AI and AI-enabled clinical decision support.

The future of pharmacy practice should therefore be framed not as pharmacists versus AI, but as pharmacists with appropriately governed AI. The most valuable systems will be those that reduce cognitive and administrative burden while preserving clinical accountability, patient autonomy, professional judgment, and the therapeutic relationship.

DECLARATIONS

Ethics Approval and Consent to Participate

Not applicable. This article is a narrative review of published literature and publicly available guidance and does not involve new human or animal research.

Human and Animal Rights

Not applicable. No human participants or animals were directly involved in this review.

Consent for Publication

Not applicable.

Conflict of Interest

The authors should disclose any financial or non-financial conflicts of interest. If none exist, use the journal's required wording: "The authors declare no conflict of interest, financial or otherwise."

AI USE DISCLOSURE

For manuscript preparation, AI-assisted tools were used for editorial and drafting assistance. The authors are responsible for verifying all scientific statements, references, interpretations, and final content. If AI tools were used to generate or substantially modify the submitted graphical abstract or figures, the disclosure should be revised to accurately describe that use in accordance with the target journal's policy.

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