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Artificial Intelligence in Pharmacy Practice: Applications, Challenges, and the Evolving Role of the Pharmacist

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ABSTRACT

Artificial intelligence (AI) has moved from a research concept to a working tool in healthcare, and pharmacy is one of the professions where its influence is growing fastest. Machine learning models now help detect medication errors, prioritise drug-interaction alerts, forecast inventory, support dosing decisions, and speed up the early stages of drug discovery. More recently, large language models have opened a new channel for patient counselling and drug-information retrieval. This review describes how AI is being applied across community, hospital and clinical pharmacy settings, summarises the evidence available for each application, and discusses the barriers that currently limit safe adoption, including algorithmic bias, limited explainability, data privacy, regulatory uncertainty and the tendency of generative models to produce confident but incorrect statements. The review argues that AI is best understood as a decision-support layer that extends, rather than replaces, pharmaceutical care, and that pharmacists must acquire basic data and AI literacy to supervise these systems responsibly. Priorities for future practice, education and research are outlined.

Keywords: *artificial intelligence; pharmacy practice; clinical pharmacy; medication safety; machine learning; large language models; pharmacovigilance; personalised medicine*

1. Introduction

Healthcare is generating data at a pace that no individual clinician can fully absorb. Electronic health records, laboratory systems, prescribing databases, wearable devices and genomic platforms all produce information that bears on how a medicine should be selected, dosed and monitored. Artificial intelligence, broadly defined as computer systems that perform tasks normally requiring human judgement, offers a way to turn this volume of data into usable guidance [1,2]. In medicine, the discussion has shifted in recent years from whether such systems can perform at a useful level to how they should be validated, governed and integrated into daily work.

Pharmacy practice is a natural setting for this shift. The profession has moved over several decades from a product-centred role, focused on compounding and dispensing, to a patient-centred role built around pharmaceutical care, in which the pharmacist takes responsibility for the outcomes of drug therapy [3]. Evidence supports the value of that role. Pharmacists who take part in ward rounds, for example, have been associated with a substantial reduction in preventable adverse drug events in hospital medical units [4]. At the same time, medication-related harm remains common. Early landmark work in hospitalised patients showed that adverse drug events occurred at a rate of roughly 6.5 per 100 admissions, and that a considerable share of them were preventable [5]. Pharmacists therefore work in a field where the clinical need is high, the data are abundant and the workload is heavy, which are exactly the conditions under which decision-support technology tends to be introduced.

The purpose of this review is to give pharmacy students, practitioners and educators a structured overview of AI in pharmacy practice. It covers the main technologies, the settings in which they are used, the strength of the supporting evidence, the limitations that practitioners should understand, and the implications for the pharmacist's professional role. The emphasis is on practice rather than on algorithm design.

2. Evolution of Pharmacy Practice and the Case for Intelligent Systems

Pharmacy practice has gone through three broad phases. In the first, the pharmacist was primarily a preparer and supplier of medicines. In the second, clinical pharmacy emerged, with pharmacists contributing drug-therapy expertise to prescribers and wards. In the third, which is still developing, pharmacists are expected to manage medication outcomes across care transitions, chronic disease programmes and public-health services. Each phase has widened the range of information that the pharmacist must handle.

Several pressures make intelligent systems attractive in this third phase. Polypharmacy is increasingly common in ageing populations, which multiplies the number of possible drug-drug and drug-disease interactions. Prescription volumes continue to rise while staffing is often constrained. Patients expect faster service and clearer explanations. Finally, the growing use of pharmacogenomic testing and biologic therapies means that dosing and selection decisions depend on more variables than traditional reference works can easily convey. Computational tools that can screen large datasets quickly and flag the cases that need human attention address a real gap [6,7].

It is important to separate older rule-based software from AI in the stricter sense. Classical clinical decision support applies fixed rules written by experts, such as a threshold for a drug interaction. Modern AI systems, by contrast, learn patterns from data and can improve with exposure to more examples. This difference matters for practice because learned models can capture relationships that rules miss, but they can also inherit hidden errors from the data used to train them.

3. Core AI Technologies Relevant to Pharmacy

3.1 Machine learning

Machine learning refers to algorithms that infer relationships from data rather than following explicit instructions. In supervised learning, a model is trained on examples with known outcomes, for instance prescriptions labelled as appropriate or inappropriate, and then asked to classify new cases. In unsupervised learning, the algorithm looks for structure without labels, such as clusters of patients with similar medication histories. Reinforcement learning, in which a system learns by trial and feedback, has been explored for dose optimisation. Reviews of machine learning in health care emphasise that model quality depends heavily on the representativeness and accuracy of the training data [8,9].

3.2 Deep learning

Deep learning uses multi-layered neural networks and is particularly effective with complex inputs such as images, signals and long sequences of clinical events. Studies using electronic health record data have shown that deep models can predict outcomes such as in-hospital mortality, readmission and length of stay from raw records, which hints at their potential for risk stratification of patients who need pharmacist review [10].

3.3 Natural language processing and large language models

A large share of clinically important information is stored as free text, including discharge summaries, prescriber notes and patient queries. Natural language processing allows software to read and organise this text. Large language models (LLMs) extend the approach, generating fluent answers to open questions after training on very large text collections. Evaluations indicate that such models can encode a considerable amount of clinical knowledge, although their reliability is uneven and their outputs require verification [11,12].

3.4 Robotics and automation

Although not AI in the strict sense, robotic dispensing, automated compounding and smart cabinets increasingly work alongside AI components such as demand forecasting and image-based verification. In practice, the term "AI in pharmacy" often covers this combined ecosystem of automation and learning systems.

4. Applications Across Pharmacy Settings

4.1 Medication safety and prevention of adverse drug events

Medication safety is the most mature application area. Scoping reviews have found that AI can contribute to patient safety by identifying likely adverse events, flagging unsafe prescribing patterns and predicting which patients are at the highest risk of harm [13]. A systematic evaluation of use cases for reducing adverse drug events grouped the work into areas such as identification of high-risk patients, detection of prescribing errors and prediction of drug-related complications, while also noting that few tools had been tested in routine care [14]. A systematic review of AI and patient safety outcomes reached a similar conclusion, reporting encouraging performance in development studies but limited evidence of improved patient outcomes in real deployments [15].

For pharmacists, the practical value lies in prioritisation. Rather than reviewing every order with equal intensity, a pharmacist can focus on the small subset that a model identifies as unusual or high risk. This is particularly useful in hospital settings, where the number of daily orders exceeds what can be examined in detail.

4.2 Clinical decision support and alert fatigue

Computerised prescribing systems have long included alerts for interactions, allergies and dose limits. Reviews of medication-related decision support show that these tools can reduce errors, yet clinicians frequently override alerts, many of which are considered low value [16,17]. Repeated, poorly

targeted alerts lead to alert fatigue, and experimental work has shown that override rates rise as the number and repetition of alerts increase [18]. AI offers a way to make alerts more selective. A model that takes into account patient context, such as renal function, concurrent drugs and prior overrides, can suppress alerts that are unlikely to matter and elevate those that are. Evidence for this approach is still emerging, and any such system needs prospective evaluation to confirm that it reduces noise without missing true hazards.

4.3 Dispensing, inventory and workflow management

In community and hospital pharmacies, AI-supported systems are used to forecast demand, optimise stock levels, reduce expiry-related waste and schedule staff. Image-recognition tools can assist in verifying tablets and packaging against the intended product, and automated systems can handle high-volume, repetitive dispensing tasks. The benefit for the pharmacist is time. When routine technical work is automated and checked by software, more of the working day can be spent on counselling, medication review and collaboration with prescribers. Frameworks that give pharmacists structured, secure access to patient data across care settings have also been proposed to support these functions [19]. Evidence on cost and safety benefits comes largely from implementation reports and local evaluations, so results may not transfer between institutions.

4.4 Patient counselling, adherence and community pharmacy services

Non-adherence is a major cause of poor treatment outcomes, and AI tools are being tested to predict which patients are likely to stop therapy and to tailor reminders accordingly. Conversational agents can answer routine questions about administration, missed doses or common side effects at any hour. Used carefully, they can extend the reach of the pharmacist, for example by handling simple queries and referring complex or alarming ones to a human. Their use in counselling raises distinct safety questions, which are discussed in Section 5.

4.5 Personalised medicine and pharmacogenomics

Individual response to drugs is shaped by genetics, age, organ function, co-medication and lifestyle. Machine learning is being applied to combine these variables to predict dose requirements and risk of toxicity, particularly for narrow-therapeutic-index drugs. Broader reviews of AI in medicine identify precision therapy as one of the areas where data-driven models are most likely to have lasting influence [20]. For pharmacists, who are often the professionals best placed to interpret pharmacogenomic reports for prescribers, this development strengthens an existing area of expertise rather than creating a new one.

4.6 Drug discovery, repurposing and development

The upstream pharmaceutical pipeline is where AI has attracted the most attention. Machine learning is used for target identification, virtual screening, property prediction and the design of new molecules, and a major review has summarised both the opportunities and the data-quality obstacles [21]. Deep learning has been used to identify potent kinase inhibitors within a few weeks of computational design and testing [22], and a neural-network approach led to the discovery of a structurally novel antibiotic with activity against resistant bacteria [23]. In structural biology, accurate prediction of protein structures from amino-acid sequences has provided a resource that supports target analysis across many diseases [24]. Although pharmacists in practice are not usually involved in these steps, they will increasingly encounter drugs developed with such methods and need to understand the strengths and uncertainties behind them.

4.7 Summary of applications

Table 1. Summary of AI applications in pharmacy practice.

Practice area	Typical AI function	Main benefit	Main limitation
Medication safety	Risk prediction, error detection	Prioritised review	Limited outcome data
Decision support	Context-aware alerts	Less alert fatigue	Needs prospective validation
Dispensing and inventory	Forecasting, image checks	Time and waste savings	Local evidence only
Counselling and adherence	Chatbots, risk prediction	Round-the-clock access	Accuracy and safety of advice
Personalised medicine	Dose and toxicity models	Individualised therapy	Data and equity gaps
Drug discovery	Screening, molecule design	Faster early development	Translation to clinic

5. Generative AI and Large Language Models in Pharmacy

No recent development has drawn more attention to AI in healthcare than the arrival of general-purpose language models. Early assessments described both substantial potential and clear risks when such a model is used as a medical assistant, including its ability to summarise information, draft patient-friendly explanations and answer clinical questions, and its tendency to make errors that are hard to detect because the language is fluent [25]. In one comparison of responses to patient questions posted on a public forum, evaluators often rated chatbot answers as more detailed and more empathetic than those written by physicians, which suggests a role in drafting and communication support [26]. Commentators on health-system adoption have noted that the more realistic near-term gains lie in administrative and documentation tasks, where mistakes are easier to catch, rather than in autonomous clinical decisions [27].

For pharmacy, plausible uses include drafting counselling leaflets in plain language, summarising a patient's medication list from several sources, supporting responses to drug-information queries, and assisting students with study material. A systematic review of such tools in education, research and practice highlighted the same benefits together with concerns about accuracy, bias, transparency and academic integrity [28]. The central technical hazard is hallucination, in which a model generates statements that sound authoritative but are not supported by evidence, a behaviour documented across natural-language generation systems [29]. In drug information, a fabricated dose, an invented interaction or a non-existent citation can cause real harm. Any LLM used in a pharmacy workflow should therefore be treated as a drafting aid whose output is checked by a qualified person against primary references, never as a final authority.

6. Challenges and Limitations

6.1 Bias and equity

Algorithms trained on historical data can reproduce the inequities embedded in that data. A widely cited analysis of a commercial algorithm used to allocate care-management resources found that it systematically underestimated the needs of Black patients, because it used healthcare cost as a proxy for health need [30]. The lesson for pharmacy is direct: a risk score used to target medication-review services could disadvantage groups who have historically had less access to care, even if no one intended it. Developers and users should examine performance across demographic subgroups before deployment, not only overall accuracy.

6.2 Explainability and trust

Many high-performing models are opaque. Explanation methods exist, but critics argue that the explanations they provide are approximations that may not reveal what the model actually relied on, and that they should not be treated as a guarantee of safety [31]. A multidisciplinary analysis of explainability in healthcare emphasises that technical, legal, medical and patient perspectives all bear on how much transparency is necessary [32]. Techniques that attribute a prediction to individual input features have become popular for this purpose [33], and they can help a pharmacist see why a patient was flagged. However, a pharmacist who cannot understand or challenge a recommendation is poorly placed to take professional responsibility for it, which is why the principle of keeping a human decision-maker in the loop remains important.

6.3 Privacy and data governance

AI systems depend on large quantities of sensitive personal data. Concerns include re-identification of supposedly anonymised records, secondary use of data without clear consent and the security of the platforms that store it [34]. Pharmacy data are particularly revealing, because dispensing histories can indicate diagnoses and lifestyle. Institutions should therefore ensure clear data-sharing agreements, secure storage and transparent communication with patients about how their information is used.

6.4 Ethical and professional accountability

The introduction of machine learning into care raises questions about informed consent, the allocation of responsibility when a system errs, and the risk that clinicians defer too readily to automated output [35,36]. Professional accountability cannot be delegated to software. The pharmacist who accepts a recommendation remains answerable for it, and the regulatory frameworks that govern pharmacy practice are likely to reinforce this expectation.

6.5 Regulation and validation

Regulatory systems are still adapting. International guidance has set out principles for the ethical use of AI in health, including protecting human autonomy, promoting transparency and ensuring accountability [37]. A growing number of AI-based medical devices have been authorised by regulators, but many were cleared on the basis of limited evidence and with little post-market reporting [38]. Calls for specific oversight of generative models in healthcare reflect their breadth and unpredictability [39]. For research, reporting standards such as the CONSORT-AI extension have been introduced so that trials of AI interventions describe the system, the data and the context of use clearly [40].

6.6 Implementation and workflow integration

A technically accurate model can still fail in practice if it does not fit into workflow, if staff are not trained to use it or if its performance drifts as patient populations and prescribing patterns change. Analyses of what it takes to deliver clinical impact with AI stress early involvement of end users, continuous monitoring after deployment and attention to the practical costs of maintenance [41]. Pharmacy managers considering adoption should plan for these elements in advance.

7. The Evolving Role of the Pharmacist

Concerns that AI will replace pharmacists are understandable but do not match the evidence reviewed above. Most current systems are narrow tools that perform specific tasks under supervision. What changes is the distribution of the pharmacist's time. As technical verification and routine queries are increasingly handled by automated systems, the pharmacist's distinctive contributions become more prominent: clinical judgement in complex or atypical cases, communication with patients who are anxious or have low health literacy, coordination across the care team and oversight of the tools themselves.

This shift implies several new competencies. Pharmacists will need a working understanding of how models are trained and validated, the ability to interpret performance measures such as sensitivity, specificity and calibration, and an awareness of typical failure modes. They should be able to judge whether a given tool has been tested in a population similar to their own, to recognise automation bias, and to report problems through appropriate channels. Curricula for pharmacy students should therefore include basic data science, digital health ethics and supervised practice with decision-support tools. Continuing professional development for practising pharmacists should cover the same ground.

Pharmacists also have a contribution to make to the development of AI. Because they understand dosing, interactions, adherence barriers and real-world medication use, they can help define meaningful clinical questions, evaluate outputs for plausibility and design safe workflows. Participation of pharmacists in governance committees that approve and monitor AI tools is a practical way of ensuring that medication safety considerations are represented.

8. Future Directions

Several directions appear likely to shape the next stage of development. First, prospective, multi-site studies that measure patient outcomes, rather than only model accuracy, are needed to show whether AI-assisted pharmacy services actually improve safety and cost-effectiveness. Second, tools should be tested for fairness across populations before wide use. Third, integration of pharmacogenomic, wearable and social-determinant data may allow more individualised dosing and adherence support, provided privacy safeguards keep pace. Fourth, methods that give grounded, referenced answers, for example by linking language models to curated drug-information databases, may reduce hallucination and make outputs easier to verify. Fifth, regulators and professional bodies should publish clear expectations on the use of AI in dispensing and counselling, including documentation and liability. Finally, practice-based research networks could provide a route for pharmacists to contribute real-world evidence on what works.

9. Conclusion

AI is steadily entering pharmacy practice, with the strongest current evidence in medication-safety screening and decision support, growing activity in workflow automation and counselling support, and a rapidly expanding pipeline in drug discovery. The technology has real promise, but also real limits, including bias, limited transparency, privacy risk, regulatory uncertainty and the unreliability of generative models when unchecked. The most defensible position is that AI should extend the capacity of pharmacists to deliver pharmaceutical care while professional responsibility stays with the human practitioner. Pharmacists who understand these tools and can evaluate them critically will be best placed to protect patients and to shape how the profession develops.

Conflict of Interest

The author declares no conflict of interest.

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