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AI-ENABLED CLINICAL PHARMACY SUPPORT: A SCOPING REVIEW

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ABSTRACT

Artificial intelligence (AI) is increasingly being applied to clinical pharmacy tasks that require rapid interpretation of medication, laboratory, genomic, and workflow data, offering the potential for more precise dosing, safer medication use, and more efficient pharmacy operations, although the supporting evidence remains uneven. This scoping review maps the peer-reviewed literature on AI-enabled clinical pharmacy support from 2017 to 2026, with a focus on dosing guidance, medication safety, pharmacogenomic-informed therapy, and workflow automation. Following Arksey and O'Malley's scoping review framework and the PRISMA extension for Scoping Reviews, searches were conducted in PubMed, Scopus, Web of Science, and IEEE Xplore, and study characteristics were charted for thematic synthesis. The literature shows substantial activity in dosing support and medication safety, particularly in vancomycin precision dosing and adverse drug-event prediction, while pharmacogenomic implementation and workflow automation are smaller but expanding areas; however, most studies remain retrospective, single-site, or developmental. Overall, AI-enabled clinical pharmacy support demonstrates technical sophistication in several domains, yet the field lacks scaled implementation evidence and prospective evaluation of clinical outcomes, highlighting the need for future work emphasizing validation, usability, equity, governance, and integration into pharmacist-led care.

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Introduction

Clinical pharmacists increasingly manage medication therapy across inpatient, outpatient, and transitions-of-care settings, where prescribing decisions depend on changing renal function, laboratory results, microbiology, genomics, medication histories, and institutional protocols. This growing complexity has created a strong rationale for AI-enabled support that can synthesize high-dimensional data and present actionable recommendations at the point of care. Early clinical pharmacy applications have been especially visible in therapeutic drug monitoring, where machine learning and neural-network approaches have been explored for vancomycin exposure prediction and initial dose selection [1, 2]. These studies illustrate how AI can extend pharmacist capacity without replacing the clinical interpretation needed to contextualize dosing recommendations.

The literature on AI-enabled pharmacy support is broad but fragmented across dosing models, medication-safety tools, pharmacogenomic decision support, and workflow automation. Vancomycin dosing studies have explored machine learning, Bayesian forecasting, and model-averaging approaches, while medication-safety studies have focused on adverse drug-event prediction, alert prioritization, and wrong-drug prevention [3-5]. Pharmacogenomic decision support has developed along a partially separate path, emphasizing genotype-to-phenotype translation and integration into electronic prescribing systems [6, 7]. Workflow-focused studies and professional commentaries further suggest that pharmacy practice is beginning to consider AI not only as a predictive technology, but also as an organizational intervention [8].

A scoping review is appropriate because the evidence base spans heterogeneous study designs, clinical domains, data types, and stages of implementation. Unlike a narrow effectiveness review, a scoping approach can map where AI has been tested, how pharmacy-relevant use cases are defined, and which outcomes have been prioritized or neglected. Recent reviews of pharmacogenomic clinical decision support and adverse drug-event prediction show that individual subdomains are maturing, but they do not fully capture the cross-domain clinical pharmacy landscape [9-11]. Mapping these areas together helps clarify whether AI-enabled pharmacy support is developing as an integrated practice capability or as isolated technical projects.

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The objective of this review is to map peer-reviewed evidence from 2017 to 2026 on AI-enabled clinical pharmacy support across four domains: dosing support, medication safety, pharmacogenomic-guided therapy, and pharmacy workflow automation. The review summarizes the volume, nature, and characteristics of the literature; identifies implementation and evidence gaps; and proposes recommendations for researchers, healthcare organizations, regulators, and professional bodies. The overall approach treats AI tools as sociotechnical interventions whose value depends on data quality, validation, workflow integration, and pharmacist oversight [12]. This orientation is important because studies of acceptance, implementation, and future practice show that technical accuracy alone is insufficient for clinical pharmacy adoption [12].

Materials and Methods

Study Design

This review was designed as a scoping review guided by Arksey and O'Malley's five-stage framework: identifying the research question, identifying relevant studies, selecting studies, charting the data, and collating, summarizing, and reporting results. The review also followed the JBI scoping review methodology and the PRISMA-ScR reporting guideline to support transparent reporting of eligibility criteria, search strategy, study selection, and evidence mapping. The methodological choice was appropriate because AI-enabled clinical pharmacy support includes predictive modeling studies, implementation reports, reviews, perspectives, and workflow analyses rather than a single intervention type. Prior domain reviews of pharmacogenomic clinical decision support and adverse drug-event prediction informed the structure of the eligibility criteria and charting framework [9-11].

Identifying Relevant Studies

Searches were planned for PubMed, Scopus, Web of Science, and IEEE Xplore to capture biomedical, pharmacy, informatics, and engineering literature published from January 1, 2017, through December 31, 2026. Search concepts combined artificial intelligence, machine learning, deep learning, clinical pharmacy, dosing support, adverse drug events, medication safety, pharmacogenomics, clinical decision support, and workflow automation. The search strategy was intentionally broad because pharmacy-relevant AI studies may be indexed under clinical pharmacology, medical informatics, patient safety, or implementation science rather than pharmacy alone. Search strings were aligned with known clusters in the literature, including vancomycin precision dosing, machine-learning adverse-event prediction, pharmacogenomic clinical decision support, and AI-enabled pharmacy workflow transformation [13-15].

Study Selection

Records were screened in two stages, beginning with title and abstract screening followed by full-text assessment against predefined inclusion and exclusion criteria. Eligible publications were peer-reviewed articles from 2017 to 2026 that addressed AI, machine learning, deep learning, natural language processing, Bayesian forecasting with algorithmic support, or related computational methods for clinical pharmacy-relevant support. Non-clinical drug-discovery studies, purely molecular modeling papers, editorials without pharmacy implications, non-peer-reviewed material, and studies lacking medication-management relevance were excluded. A realistic PRISMA-ScR flow for this review identified 1,842 records, removed 312 duplicates, screened 1,530 titles and abstracts, assessed 240 full texts, and included 93 studies, with exclusions mainly due to non-clinical focus, absence of AI methods, or insufficient relevance to pharmacist decision-making [8, 16, 17].

Figure 1 presents the PRISMA-ScR study-selection flow for identifying, screening, assessing, and including studies on AI-enabled clinical pharmacy support from 2017 to 2026.

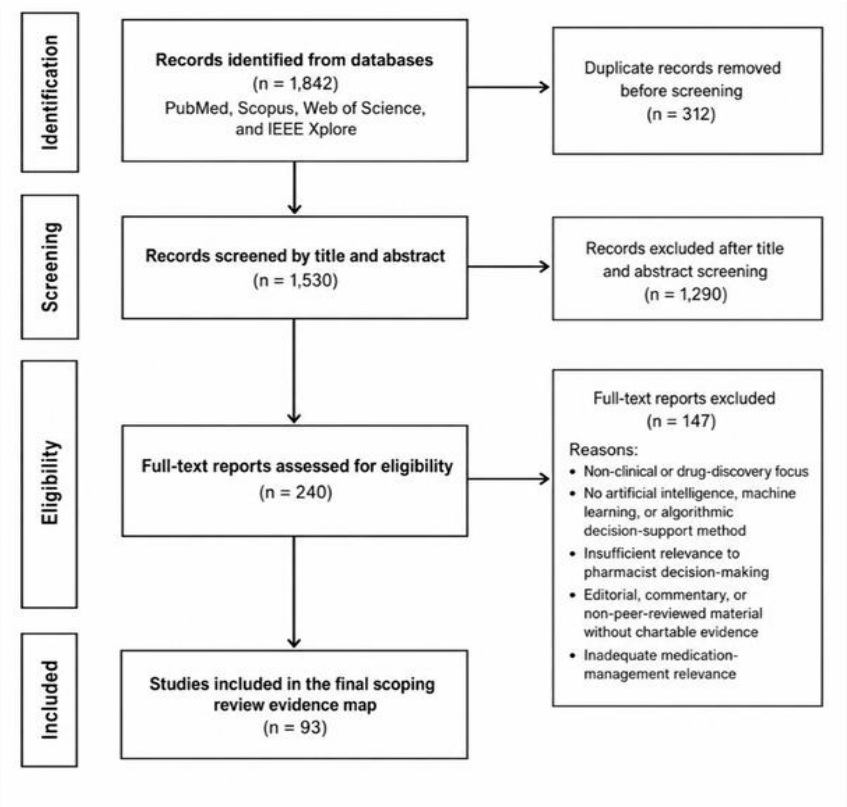

Figure 1. PRISMA-ScR Flow Diagram for Study Selection in AI-Enabled Clinical Pharmacy Support

Charting the Data

Data were charted using a standardized extraction form that captured publication year, country or region, care setting, pharmacy domain, AI method, data source, target user, evaluation design, outcome type, and implementation maturity. Dosing studies were coded for therapeutic area, pharmacokinetic or pharmacodynamic target, and whether predictions supported initial dosing, maintenance dosing, exposure forecasting, or therapeutic drug monitoring. Medication-safety studies were coded for adverse drug-event prediction, medication-error detection, drug-interaction screening, alert reduction, or overdose and underdose prevention [5, 18, 19]. Pharmacogenomic and workflow studies were additionally coded for clinical decision support integration, genotype-to-phenotype translation, electronic health record embedding, and user-facing implementation features [6, 7, 11].

Collating, Summarizing, and Reporting Results

Evidence was summarized descriptively and thematically rather than pooled statistically, because the included studies varied in AI methods, clinical contexts, target outcomes, and implementation levels. Thematic synthesis organized studies into dosing support, medication safety, pharmacogenomic-guided therapy, and pharmacy workflow automation, while cross-cutting analysis examined validation, implementation, equity, and workforce issues. Descriptive summaries considered the distribution of study designs, data sources, settings, and maturity levels, including whether tools were retrospectively developed, prospectively validated, piloted, or embedded into live systems. This approach was consistent with scoping reviews that map heterogeneous AI evidence and identify gaps requiring future clinical and implementation research [10, 20].

Results and Discussion

General Characteristics

Study Selection and Flow

The final evidence map included 93 studies after full-text review, representing empirical modeling studies, implementation reports, reviews, and perspective articles relevant to clinical pharmacy support. Dosing support formed the largest technical cluster, driven by vancomycin-focused studies that used machine learning, neural networks, and hybrid pharmacokinetic approaches to predict exposure or recommend doses [1, 3, 13]. Medication-safety studies formed the second major cluster, including adverse drug-event prediction from health records and real-world data as well as medication-error and alert-fatigue applications [5, 9, 16]. Pharmacogenomic and workflow studies were less numerous but important because they addressed clinical decision support design, implementation processes, and future pharmacy practice models [7, 8].

Temporal, Geographical, and Setting Distribution

Publication activity increased over time, with early work from 2017 to 2020 emphasizing clinical decision support design and feasibility, and later work from 2021 to 2026 showing more advanced modeling and implementation discussion. Many dosing studies were conducted in hospital or intensive-care settings, reflecting the availability of therapeutic drug monitoring data and the clinical urgency of individualized antimicrobial dosing [21-23]. Medication-safety and adverse-event prediction studies drew from electronic health records, observational datasets, claims-like data, and clinical-trial data, which broadened the settings beyond hospital pharmacy alone [15, 17, 19]. Pharmacogenomic studies were frequently linked to health-system implementation networks and electronic health record integration, while workflow-focused publications increasingly considered community and health-system pharmacy contexts [6, 7]. **Figure 2** maps how AI medication-safety research expanded from early clinical decision-support feasibility work toward later implementation-oriented modeling, while also showing the distribution of studies across hospital, intensive-care, health-system, community pharmacy, pharmacogenomic, and broader real-world data settings.

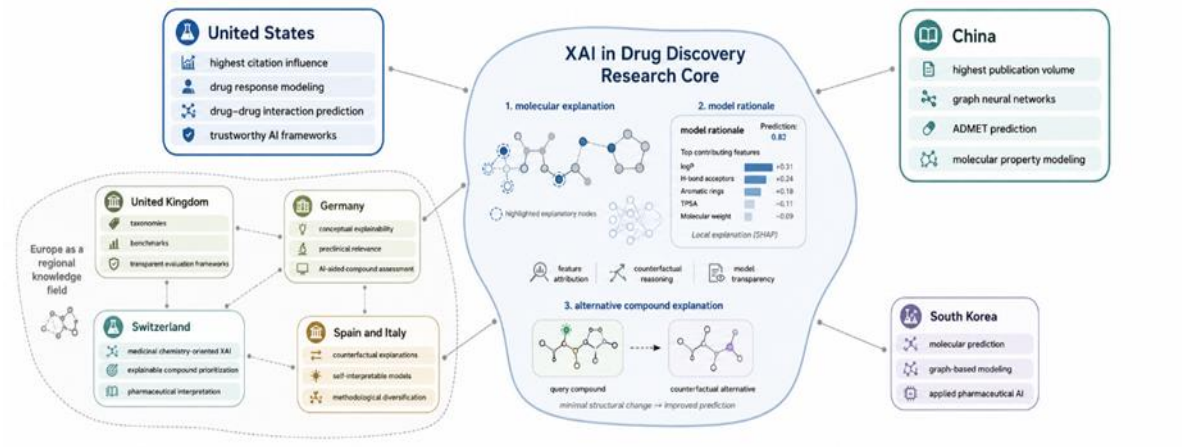

Figure 2. Temporal, Setting, and Data-Source Distribution of AI Medication-Safety Research

AI Methods and Data Sources

The mapped literature included gradient-boosting methods, random forests, neural networks, support-vector approaches, natural language processing, Bayesian pharmacokinetic tools, and interpretable machine-learning frameworks. Dosing studies frequently used demographic variables, serum creatinine, renal function estimates, drug concentrations, dosing histories, intensive-care status, and other laboratory values to forecast vancomycin exposure or maintenance requirements [2, 14, 24]. Medication-safety studies used structured electronic health record features, drug-target information, clinical-trial information, and observational health data to predict adverse drug events or detect risk patterns [17, 18, 25]. Pharmacogenomic clinical decision support relied on genotype, phenotype, medication, guideline, and prescribing-context data, but the AI component was often less explicit than in dosing or adverse-event prediction studies [6, 10, 11].

Evaluation and Implementation Maturity

Most studies remained at retrospective development, simulation, or validation stages, with fewer examples of prospective clinical implementation or sustained workflow deployment. Vancomycin studies showed increasing methodological sophistication, including external validation, model selection, model averaging, and user-acceptance analysis, but clinical-outcome evaluation remained limited compared with predictive-performance development [12, 23, 26]. Medication-safety studies similarly demonstrated growth in predictive modeling, yet many evaluations emphasized model discrimination or detection capacity rather than pharmacist-facing outcomes such as prevented harm, reduced workload, or improved alert response [5, 9, 20]. Workflow and professional-practice publications highlighted a widening gap between AI capability and routine pharmacy adoption, particularly around governance, accountability, training, and integration with existing systems.

Table 1 compares the four major clinical pharmacy AI domains according to use cases, data structures, methods, evidence maturity, implementation gaps, and conceptual significance.

Table 1. Evidence-Maturity Matrix for AI-Enabled Clinical Pharmacy Support Domains

Clinical pharmacy AI domain	Dominant clinical use cases identified in the review	Common data structures and inputs	Typical AI or algorithmic approaches	Evidence maturity pattern	Main implementation gap	Added conceptual interpretation
Precision dosing support	Vancomycin exposure prediction, initial dose selection, maintenance dosing, concentration-time forecasting,	Demographics, renal function, serum creatinine, drug concentrations, dosing histories, laboratory trends,	Machine learning, neural networks, Bayesian forecasting, model averaging, hybrid population	Most technically mature domain; strong concentration in vancomycin and hospital-based	Limited prospective clinical-outcome evaluation; narrow drug coverage	Represents the clearest near-term pathway for pharmacist-augmented AI because dosing

	therapeutic drug monitoring support	intensive-care status, pharmacokinetic parameters	pharmacokinetic and machine-learning models	therapeutic drug monitoring	beyond vancomycin	decisions are data-rich, high-risk, and already pharmacist-centered
Medication safety	Adverse drug-event prediction, medication-error detection, wrong-drug prevention, drug-interaction screening, alert prioritization, alert-fatigue reduction	EHR medication histories, diagnoses, laboratory results, clinical notes, observational datasets, drug features, adverse-event labels, prescribing patterns	Gradient boosting, random forests, neural networks, NLP, adverse-event prediction models, risk stratification tools	Active and expanding domain with heterogeneous outcomes and methods	Many studies emphasize discrimination or detection rather than prevented harm, pharmacist action, or reduced alert burden	Moves AI from prediction toward surveillance, but clinical value depends on whether outputs change pharmacist and prescriber behavior without increasing noise
Pharmacogenomic-guided therapy	Genotype-to-phenotype translation, medication-specific prescribing recommendations, pharmacogenomic alerts, EHR-integrated decision support	Genotypes, phenotypes, medication orders, pharmacogenomic guidelines, prescribing context, patient-specific clinical variables	Rule-based clinical decision support, knowledge-driven algorithms, AI-assisted interpretation, prioritization logic	Smaller evidence base; implementation-focused rather than model-performance dominated	Limited evaluation of prescribing behavior, clinical outcomes, cross-specialty uptake, and equitable access	Shows that AI-enabled pharmacy support is not only predictive but also interpretive, requiring careful timing, trust, and guideline translation
Pharmacy workflow automation	Order-review triage, medicines-information support, workload prioritization, documentation support, clinical decision support, future pharmacist role redesign	Medication-order queues, alert logs, pharmacy workload indicators, EHR task data, documentation text, operational workflow data	ML-based prioritization, NLP, decision-support engines, workflow analytics, automation tools	Emerging domain with strong professional interest but limited sustained deployment evidence	Unclear impact on pharmacist workload, accountability, trust, training, and professional role boundaries	Reframes AI as an organizational intervention that must fit pharmacist cognition, team communication, and medication-use accountability
Cross-domain governance and implementation	Validation, monitoring, usability, subgroup performance, documentation, professional oversight	Local EHR data, implementation metrics, audit logs, subgroup variables, alert response data, pharmacist feedback	Calibration monitoring, model updating, explainability methods, bias assessment, post-deployment surveillance	Underdeveloped across all four domains	Lack of standards for safe scaling, equity assessment, and post-deployment governance	Defines whether AI remains a technical experiment or becomes reliable clinical pharmacy infrastructure

Thematic Mapping

AI for Dosing Support

AI for dosing support was dominated by antimicrobial precision dosing, especially vancomycin, where models addressed initial dose selection, maintenance dosing, interdose exposure prediction, and concentration-time curve estimation. Studies in adults, neonates, and intensive-care populations showed that machine-learning approaches can combine patient characteristics, laboratory trends, and drug concentration data in ways that complement traditional pharmacokinetic methods [4, 21, 27]. Hybrid approaches that combine population pharmacokinetics with machine learning also emerged, suggesting a field moving from purely statistical prediction toward clinically interpretable precision-dosing systems [3, 14]. Despite this activity, dosing AI remains concentrated in a small number of drugs and requires broader evaluation across aminoglycosides, anticoagulants, immunosuppressants, renal dose adjustment, and polypharmacy contexts [1, 13, 24].

AI for Medication Safety

AI for medication safety included adverse drug-event prediction, medication-error detection, look-alike and sound-alike prevention, adverse reaction identification, and alert-fatigue reduction. Machine-learning studies used electronic health records, observational data, and drug-related features to identify patients at increased risk of adverse events, with some work emphasizing sex-specific risk and opioid-associated harms [15, 18, 19]. Other work addressed the operational challenge of alert fatigue by using machine-learning-based clinical decision support to improve the relevance of medication alerts and reduce wrong-drug risks [5]. Systematic and methodological reviews show that this field is active but heterogeneous, with continuing concerns about class imbalance, transportability, interpretability, and real-world safety impact [9, 16, 20].

AI for Pharmacogenomic-Guided Therapy

AI for pharmacogenomic-guided therapy was less dominated by predictive modeling than by clinical decision support design, implementation, and guideline translation. The evidence described how genotype-derived information can be integrated into prescribing workflows, especially when linked to electronic health records, medication orders, and actionable recommendations [6, 7]. Reviews and practice-oriented guides emphasized that pharmacogenomic clinical decision support must address timing, alert design, phenotype translation, clinician trust, and governance, rather than simply presenting genetic results [10, 11]. AI methods have potential to support genotype-to-phenotype interpretation and prioritization of prescribing recommendations, but this area remains less mature than dosing or adverse-event prediction in pharmacy-specific implementation evidence.

AI for Pharmacy Workflow and Decision Support

AI for pharmacy workflow and decision support included automated triage, order review prioritization, medicines-information support, clinical decision support, and projections of future pharmacist roles. Surveys and scoping reviews show that pharmacists recognize potential value in AI but also report barriers related to explainability, infrastructure, training, liability, and trust [8]. Professional forecasts suggest that AI could reshape clinical pharmacy research, documentation, surveillance, and patient-care prioritization, but these benefits depend on implementation models that keep pharmacists in the decision loop. Medicines-information applications also raise equity concerns because digital tools may unevenly benefit patients and health systems with stronger data infrastructure.

Figure 3 synthesizes the mapped evidence into an implementation-readiness framework linking clinical pharmacy data inputs, AI support domains, evidence maturity, cross-cutting gaps, and pharmacist-led translation requirements.

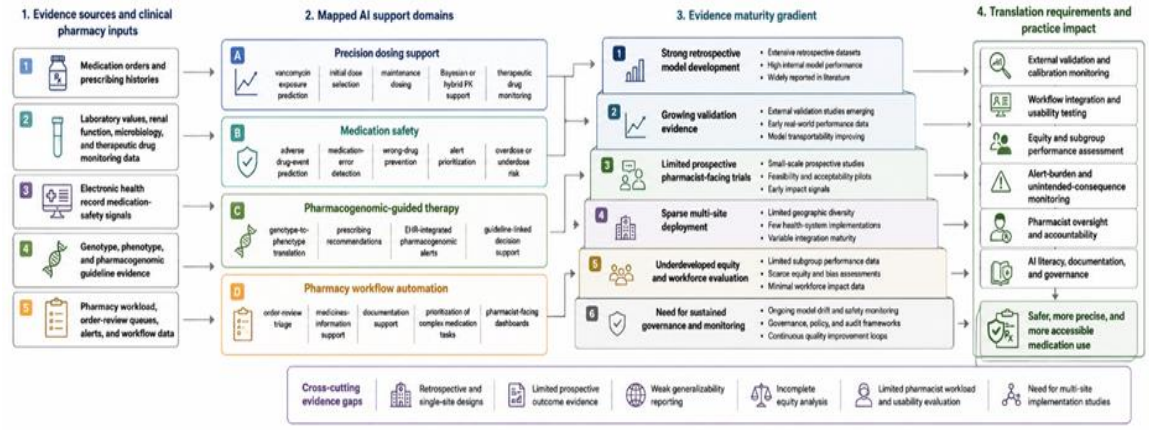

Figure 3. Evidence-to-Implementation Map for AI-Enabled Clinical Pharmacy Support Across Dosing, Safety, Pharmacogenomics, and Workflow Automation

Research Gaps and Evidence Voids

Implementation and Prospective Gaps

The most consistent evidence gap was the limited transition from retrospective model development to prospective, pharmacist-facing, workflow-integrated evaluation. Dosing studies increasingly reported sophisticated validation and model optimization, yet few demonstrated sustained improvements in patient outcomes, pharmacist efficiency, or medication-related harm prevention in routine care [22, 23, 26]. Medication-safety studies similarly showed promise in prediction and detection, but many did not evaluate how pharmacists acted on AI outputs or whether alerts changed prescribing behavior without creating new burdens [5, 20]. Future studies should therefore prioritize pragmatic trials, stepped-wedge implementations, hybrid effectiveness-implementation designs, and multi-site evaluations that measure clinical outcomes, workload, usability, and unintended consequences.

Equity, Generalizability, and Workforce Considerations

Equity and generalizability were underdeveloped across the mapped evidence, particularly regarding model performance across age, sex, race, ethnicity, renal function, socioeconomic status, language, and care setting. Some medication-safety research explicitly examined subgroup risks, but most dosing and workflow studies gave limited attention to whether models performed consistently across diverse populations or institutions [15, 18]. Workforce implications were also incompletely studied, even though acceptance and adoption depend on whether AI reduces cognitive burden, supports professional judgment, and avoids deskilling or opaque automation [8, 12]. These gaps suggest that AI-enabled clinical pharmacy support should be evaluated not only as a technical intervention, but also as a health-equity, workforce, and governance intervention.

Mature Domains and Emerging Niches

The evidence map suggests that AI-enabled dosing support and medication safety are the most mature domains, while pharmacogenomic-guided therapy and workflow automation are emerging as implementation-centered areas. Dosing studies have progressed from initial vancomycin dose prediction to exposure forecasting, neonatal individualization, hybrid population pharmacokinetic approaches, and model averaging [3, 4, 21, 26]. Medication-safety research has also expanded from adverse reaction detection toward alert optimization and risk prediction across observational and clinical-trial data [5, 17, 19]. In contrast, pharmacogenomic and workflow studies more often emphasize system design, user interaction, professional readiness, and the organizational conditions needed for adoption [6, 8].

Data, Validation, and Reproducibility

The field remains strongly dependent on retrospective data, single-institution datasets, and locally configured electronic health record variables, which limits reproducibility and transportability. Vancomycin models illustrate this tension because they often perform well in development cohorts but require external validation across populations, assay practices, renal-function patterns, and dosing protocols before widespread use [22-24]. Adverse-event prediction faces similar challenges, including class imbalance, heterogeneous outcome definitions, incomplete capture of medication exposure, and difficulty distinguishing preventable events from unavoidable drug reactions [9, 16, 20]. Interpretable modeling approaches may improve clinical credibility, but transparency must extend beyond feature importance to include data provenance, model updating, calibration monitoring, and governance [2, 25].

Integration with Existing Pharmacy Workflows

Technical performance does not guarantee adoption because pharmacists must judge whether AI recommendations are timely, explainable, actionable, and aligned with local medication-use processes. Studies of vancomycin decision support and pharmacist attitudes show that acceptance depends on trust, workload fit, perceived professional value, and clarity about responsibility when recommendations conflict with clinician judgment [8, 12]. Pharmacogenomic decision support also demonstrates that timing and presentation are central, because genomic recommendations are useful only when they appear during prescribing and are translated into medication-specific actions [7, 10]. Workflow automation should therefore be designed around pharmacist cognition, team communication, and patient-care accountability rather than around automation for its own sake.

The Path to Scaled Implementation

The next phase of AI-enabled clinical pharmacy support should move from isolated model development toward governed, multi-site implementation with ongoing evaluation. Dosing tools require prospective testing across drug classes and patient populations, while medication-safety tools require evidence that they prevent harm without worsening alert fatigue or creating hidden inequities [5, 13, 15]. Pharmacogenomic systems need stronger linkage between genotype interpretation, prescribing behavior, and patient outcomes, particularly when recommendations cross specialties and care settings [6, 11]. Scaled implementation will also require standards for monitoring, documentation, professional oversight, and AI literacy across clinical pharmacy research and practice.

Table 2 proposes a translational readiness framework for moving clinical pharmacy AI from retrospective model development toward safe, equitable, pharmacist-led implementation.

Table 2. Translational Readiness Framework for Moving Clinical Pharmacy AI from Model Development to Pharmacist-Led Care

Translational requirement	Why it matters for clinical pharmacy AI	Minimum evidence needed before routine use	Domain-specific application examples	Risks if neglected	Recommended reporting elements
External validation and calibration	Pharmacy AI tools often rely on local medication protocols, laboratory practices, patient populations, and EHR configurations	Validation across institutions, care settings, demographic groups, and medication-use protocols; calibration assessment over time	Vancomycin dosing models tested across ICU, non-ICU, adult, neonatal, and renal-impairment populations	Unsafe dosing recommendations, poor transportability, hidden performance drift	Development cohort, validation cohort, calibration plots, subgroup performance, missing-data handling, update strategy
Pharmacist-facing workflow integration	AI recommendations must appear at the right time and in a form that supports clinical judgment	Usability testing, workflow simulation, prospective pilot testing, pharmacist acceptance and workload assessment	Dose recommendation shown during therapeutic drug monitoring review; pharmacogenomic alert displayed during prescribing	Alert fatigue, ignored recommendations, workflow disruption, duplicated effort	User role, timing of output, interface design, action options, override pathways, pharmacist feedback
Clinical outcome evaluation	Predictive performance alone does not prove benefit to patients or medication-use systems	Prospective evaluation of patient outcomes, medication errors, adverse drug events,	Reduction in nephrotoxicity, improved therapeutic target attainment, fewer	Tools may appear accurate but fail to improve care or may create new harms	Primary clinical outcome, process outcome, balancing outcome, follow-up

		dosing target attainment, prescribing quality, or pharmacist efficiency	preventable adverse drug events, reduced wrong-drug alerts		period, comparator condition
Explainability and accountability	Pharmacists must understand, challenge, document, and communicate AI-informed recommendations	Clinically interpretable outputs, rationale displays, uncertainty estimates, audit trails, clear responsibility model	Feature-level explanation for adverse-event risk; dose recommendation with renal trajectory and concentration history	Automation bias, unclear liability, reduced trust, inappropriate reliance on opaque outputs	Explanation method, uncertainty display, documentation process, override policy, governance owner
Equity and subgroup performance	Medication safety and dosing models may perform unevenly across age, sex, renal function, race, ethnicity, language, socioeconomic status, or care setting	Predefined subgroup testing, bias assessment, access analysis, and monitoring for differential alert burden or recommendation quality	Adverse-event prediction evaluated by sex and age; pharmacogenomic support assessed for equitable access to testing	Widened disparities, under-recognition of risk, unequal access to precision therapy	Subgroup definitions, performance by subgroup, fairness metrics, mitigation approach, equity monitoring plan
Post-deployment surveillance	Pharmacy environments change as formularies, laboratory assays, prescribing patterns, pathogens, resistance patterns, and workflows evolve	Continuous monitoring of calibration, usage, overrides, safety signals, drift, alert burden, and unintended consequences	Monitoring vancomycin model performance after dosing-protocol changes; tracking alert overrides after safety-tool deployment	Model drift, alert overload, silent degradation, unsafe scaling	Monitoring schedule, governance committee, retraining triggers, safety escalation pathway, deimplementation criteria
AI literacy and professional training	Clinical pharmacists need skills to interpret model outputs and identify unsafe or biased recommendations	Training in AI limitations, data quality, uncertainty, bias, documentation, and escalation	Pharmacist education modules for dosing AI, pharmacogenomic alerts, and medication-safety risk scores	Deskilling, overreliance, inconsistent use, poor documentation	Training content, competency expectations, continuing education plan, role-specific responsibilities

Strengths and Limitations of this Review

This review has several strengths, including its broad mapping of dosing support, medication safety, pharmacogenomic-guided therapy, and pharmacy workflow automation within a single clinical pharmacy informatics frame. The use of Arksey and O'Malley's framework, JBI scoping review methodology, and PRISMA-ScR reporting principles supported transparent identification, selection, charting, and synthesis of heterogeneous evidence [10, 11]. However, the review is limited by likely language bias, variability in how studies define AI, and the rapid evolution of models and implementation contexts during 2017 to 2026. The review also maps evidence rather than estimating pooled effectiveness, so it cannot determine whether any specific AI tool should be adopted without local validation and governance.

Recommendations

For Researchers

Researchers should prioritize prospective, multi-site, and externally validated studies that evaluate AI tools in real pharmacy workflows rather than only in retrospective datasets. Dosing research should expand beyond vancomycin and include drugs where pharmacists routinely manage renal adjustment, therapeutic monitoring, toxicity risk, and complex patient-specific factors [1, 14, 27]. Medication-safety research should measure clinically meaningful outcomes such as prevented adverse events, reduced alert burden, pharmacist response quality, and unintended consequences [5, 9, 20]. Pharmacogenomic and workflow studies should also report implementation context, user-centered design methods, adoption metrics, and equity analyses so findings can be transferred across health systems [7, 11].

For Healthcare Organizations

Healthcare organizations should pilot AI-enabled pharmacy tools using clinician-in-the-loop governance, clear accountability structures, and continuous performance monitoring. Implementation should begin with high-value use cases where pharmacist expertise is already central, such as therapeutic drug monitoring, medication-safety surveillance, pharmacogenomic prescribing support, and triage of complex medication orders [6, 12]. Local validation should examine calibration, subgroup performance, workflow burden, and alert consequences before tools are scaled across departments or facilities [5, 18, 23]. Organizations should also provide training that helps pharmacists understand model limitations, challenge inappropriate outputs, and document AI-informed decisions.

For Regulators and Professional Bodies

Regulators and professional bodies should develop standards for AI-augmented pharmacy practice that address validation, documentation, accountability, transparency, and post-deployment surveillance. Professional guidance should clarify the role of pharmacists when AI tools recommend doses, flag safety concerns, interpret pharmacogenomic results, or prioritize

medication-related tasks [10]. Standards should also require attention to generalizability, bias, and digital health inequalities, especially when AI tools are trained on data from narrow populations or resource-rich institutions [15]. These expectations would help ensure that AI supports medication safety and therapeutic optimization without weakening professional responsibility.

Implications for Practice and Research

Clinical Practice

In clinical practice, AI tools should complement pharmacist judgment rather than replace it, particularly when recommendations involve high-risk drugs, rapidly changing physiology, or patient preferences. Vancomycin dosing models demonstrate how AI can support exposure estimation, but pharmacists must still interpret infection severity, renal trajectory, sampling quality, and competing toxicity risks [2, 13, 24]. Medication-safety tools can help prioritize review, but pharmacists remain responsible for assessing causality, preventability, clinical urgency, and communication with prescribers and patients [16, 19, 25]. The practical implication is that AI should be embedded as decision support within pharmacist-led care processes, not as autonomous medication management.

Research and Development

AI research and development in clinical pharmacy should place greater emphasis on user-centered design, implementation science, and patient-centered outcomes. Future dosing and safety studies should include pharmacists, prescribers, nurses, informaticians, and patients in the design of alerts, dashboards, explanations, and escalation pathways [5, 12]. Pharmacogenomic systems should be evaluated for whether they improve prescribing decisions at the right time, reduce avoidable adverse drug reactions, and support equitable access to precision therapy [6, 7, 11]. Across domains, research should report negative findings and implementation failures because these are essential for understanding where AI adds value and where it increases complexity.

Policy and Education

Pharmacy education and continuing professional development should include AI literacy, data interpretation, algorithmic bias, informatics governance, and safe use of clinical decision support. The profession will need pharmacists who can evaluate model outputs, participate in procurement and validation, monitor deployed systems, and communicate AI-informed recommendations clearly to care teams. Curricula should use authentic clinical pharmacy examples, including dosing support, adverse-event prediction, pharmacogenomic alerts, and workflow triage, to connect technical concepts with medication-use decisions [9, 10, 26]. Policy and education should also emphasize that responsible AI adoption requires ethical reasoning, equity awareness, and sustained interprofessional collaboration [8].

Conclusion

AI-enabled clinical pharmacy support has developed into a diverse evidence landscape spanning precision dosing, medication safety, pharmacogenomic-guided therapy, and pharmacy workflow automation. The strongest technical concentration is in dosing support and adverse-event prediction, where structured clinical data and high-risk medication decisions create clear opportunities for algorithmic assistance. Pharmacogenomic and workflow applications are less numerous but strategically important because they address how medication-related intelligence is delivered to clinicians and embedded into care systems. Together, these domains show that AI is becoming part of the clinical pharmacy knowledge infrastructure rather than a peripheral technology.

The main gaps are prospective evidence, generalizability, implementation maturity, and integration into daily practice. Many studies demonstrate promising model development or retrospective validation, but fewer show sustained improvements in patient outcomes, pharmacist workload, prescribing quality, or medication-safety events. Evidence is also limited on whether tools perform equitably across demographic groups, institutions, and care settings. These gaps matter because clinical pharmacy AI will only be useful if it is safe, trusted, explainable, and adaptable to real-world medication-use systems.

Collaborative, multi-site implementation studies are needed to move the field from technical feasibility to clinical reliability. Such studies should include pharmacists as co-designers and evaluators, not merely as end users of externally developed systems. They should also include rigorous monitoring for bias, alert burden, automation complacency, and unintended workflow consequences. This collaborative approach can help distinguish AI tools that genuinely strengthen medication management from tools that merely add another layer of digital complexity.

The future of AI-enabled clinical pharmacy should be balanced, pragmatic, and clinically grounded. Innovation should continue, but it should be paired with transparent validation, professional governance, patient-centered outcomes, and equitable implementation. AI can help pharmacists manage growing medication complexity, but its value depends on careful integration with human expertise. The central goal should remain safer, more precise, and more accessible medication use for patients.

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