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Pharmacist Involvement in AI-Supported Medication Decisions in Hospitals: Effects on Safety, Workflow, and Clinical Outcomes

A narrative review with Saudi and international evidence

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Abstract

Background: Hospitals are adopting machine learning (ML), rule-hybrid, and large language model (LLM) tools to support medication review and prescribing. Pharmacists sit at the point where these outputs become clinical action, yet the effects of their involvement on safety, workflow, and patient outcomes have not been synthesized, and Saudi evidence is scarce.

Objective: To summarize what is known about pharmacist involvement in AI-supported medication decisions in hospital settings, and to compare Saudi/Middle Eastern evidence with international evidence.

Methods: Structured narrative review. PubMed and Consensus were searched purposively on 21 November 2026 (2018–2026). Twenty sources were retained and tagged by setting (Saudi, GCC–MENA, international). Data were extracted from published records and synthesized by domain: safety, workflow, clinical outcomes, and acceptance.

Results: Pharmacist-supervised AI prioritization and co-pilot designs improved error and problem detection in prospective, simulated, or crossover studies (for example, area under the curve 0.81 versus 0.65 for conventional alerts; sensitivity 98% versus 55% for pharmacist review alone) and shortened review time by about half in one study. A randomized simulation showed the other side:

accuracy fell to 26.1% when AI advice was wrong, and users accepted 73.9% of incorrect recommendations. No completed study reported patient-level clinical outcomes; one cluster-randomized trial is registered. Saudi evidence consists of perception surveys and a conventional alert-override audit, with no outcome study of AI-supported decisions.

Conclusions: Pharmacist involvement appears to improve detection and efficiency but is not a guaranteed safeguard against automation bias. Hospitals should position pharmacists as validators, supervised reviewers, and monitors of AI performance, and Saudi centers should generate outcome evidence.

Keywords: clinical pharmacy; artificial intelligence; clinical decision support; medication safety; automation bias; Saudi Arabia

1. Introduction

Medication errors and preventable adverse drug events remain a leading source of hospital harm, and rule-based clinical decision support (CDS) has delivered mixed results because of alert fatigue (Alruwaili et al., 2026). Machine learning, hybrid rule–ML scoring, and, more recently, large language models promise more selective support: ranking prescriptions by risk, flagging likely errors, and drafting reviews of complex charts (Chalasani et al., 2023; Hamishehkar & Shahidi, 2025). Pharmacists are the profession that verifies orders, so the way they interact with these tools largely decides whether AI output becomes a safer decision or an unexamined default. The American Society of Health-System Pharmacists (ASHP) holds that the pharmacy workforce should lead the design, validation, implementation, and ongoing evaluation of AI that touches the medication-use process (Bastow et al., 2025).

Two gaps motivate this review. First, a systematic review of ML models for detecting inappropriate hospital orders found 13 studies, 12 at high risk of bias (Johns et al., 2024), so the evidence on pharmacist–AI interaction is thin and uneven. Second, the Middle East literature on AI in pharmacy is dominated by surveys of perceptions rather than evaluations of effect (Alhomoud, 2026). For Saudi hospitals working toward national and international accreditation, this leaves open how pharmacists should be placed in AI-supported workflows.

Objective. To synthesize evidence on how pharmacist involvement in AI-supported medication decisions affects (a) medication safety, (b) pharmacy workflow, and (c) clinical outcomes, and to benchmark Saudi/regional evidence against the international literature.

2. Methods

Design and reporting. A structured narrative review informed by the SANRA quality criteria. It is not a systematic review, and no PRISMA flow diagram is reported because records were not screened exhaustively.

Search. On 21 November 2026, PubMed and Consensus were searched for 2018–2026 using combinations of pharmacist, clinical decision support, artificial intelligence, machine learning, large language model, medication error, alert fatigue, automation bias, hospital, Saudi Arabia, and Middle East. Reference lists were not hand-searched.

Selection. Sources were retained if they addressed AI, ML, or LLM support for medication review, verification, or prescribing in a hospital pharmacy context, or pharmacists' acceptance of such tools, and reported safety, workflow, outcome, or acceptance findings. Irrelevant database hits (for example, global burden-of-disease analyses) were excluded. A conventional (non-AI) Saudi alert-override audit was retained as regional context. Relevance was graded as high, moderate, or background by the author.

Extraction and appraisal. Design, setting, sample, comparator, and main numerical results were extracted from the published records (abstracts and metadata); full texts were not systematically read. Sources were tagged Saudi, GCC–MENA, or international. Quality was judged qualitatively by design, comparator, and sample, without a formal risk-of-bias tool. Figures were drawn only from numbers reported in the sources.

3. Results

3.1 Evidence base

Twenty sources were retained: 12 primary studies (including one trial protocol), 6 reviews, and 2 statements or commentaries. Table 1 lists the 17 sources that carry data used below; the remaining three (Bastow et al., 2025; Chalasani et al., 2023; Hamishehkar & Shahidi, 2025) provide background. Only three sources were Saudi (all cross-sectional or retrospective audits) and one

covered the Middle East. Most outcome-bearing evidence came from France, China, the United States, and simulated settings (Table 1).

Table 1. Characteristics and main findings of sources contributing data to the synthesis.

Study	Setting	Design and sample	Key findings	Main limitation
Corny et al. (2020)	International (France)	Development/validation of hybrid ML + rules score; 10,716 patients (133,179 orders) for training, 412 patients (3,364 orders) for validation	AUROC 0.81 and AUPRC 0.75 versus 0.65/0.56 for CDS alerts and 0.68/0.56 for multicriteria query	Single hospital; pharmacist review as reference
Levivien et al. (2022)	International (France)	Randomized single-blinded comparison; 420 prescriptions (107 low-score, 313 high-score)	Severe DRPs 2.8% (low) vs 15.3% (high), $p = 0.0248$; tool ruled out 55% of prescriptions; detected 94% of severe DRPs vs 20% for CDS	Single center; low-risk subset small
Ong et al. (2025)	International (country not stated)	Prospective crossover; 91 error scenarios from 40 vignettes, 16 specialties; retrieval-augmented LLM	Pharmacist + LLM accuracy 61%; 1.5-fold gain over pharmacist alone for serious-harm errors	Vignettes, not live orders
Liu Z et al. (2026)	International (China)	Two-period crossover; 2 pharmacists, 213 outpatient prescriptions; local LLM	Accuracy 97.2% vs 82.6%; sensitivity 98% vs 55%; review time 1.12 vs 2.33 min (about 52% less)	Two reviewers; retrospective prescriptions
Surdilla et al. (2026)	International (country not stated)	Randomized simulation; 77 participants (23 pharmacists, residents, students); LLM advice	Adjusted OR 1.58 for accuracy; 80.2% accuracy with correct AI, 26.1% with incorrect AI; 73.9% of wrong advice accepted	Simulation; mixed experience levels
Liu X et al. (2023)	International (USA)	Qualitative; 13 critical care pharmacists, 104 case evaluations of AI vancomycin dosing	Empiric dose differed from AI in 85% (88/104); 78% (69/88) stayed discrepant after AI shown; distrust, limited data integration	Single institution; small sample
Chen et al. (2024)	International (academic hospital; country not stated)	Retrospective; 1,206,895 outpatient prescriptions, 28,536 ML alerts	Alert rate 2.36%; 48.88% accepted; 470 errors intercepted (16.4 per 1,000 alerted orders)	No comparator; single center
Lin et al. (2025)	International (China)	Pre–post; about 5.2 and 5.8 million orders in a 3,200-bed hospital	Orders with alerts 2.52% to 2.30%; patients with alerts 30.34% to 28.08%	Before–after; modest absolute change
Stottlemyer et al. (2025)	International (USA)	Cluster-randomized trial protocol; 38 clusters, 8 hospitals	Pharmacist-led, analytics-triggered intervention vs passive alert; primary outcome major adverse kidney events at 30 days	Protocol; no results yet

Study	Setting	Design and sample	Key findings	Main limitation
Johns et al. (2024)	International (review)	Systematic review (PRISMA); 13 studies of ML/DL models for inappropriate orders	12 of 13 at high risk of bias; heterogeneous data and endpoints	Few original studies
Alqahtani et al. (2025)	International (review)	Systematic review; 30 articles on AI in clinical pharmacy	Applications: adverse event detection, decision support, verification; calls for prospective multicenter studies	Descriptive synthesis
Alruwaili et al. (2026)	International (review; Saudi-affiliated author)	Structured narrative review; 75 studies	AI is both safety enhancer and source of new risk; persistent alert fatigue; need for governance	Narrative design
Zavaleta-Monestel et al. (2026)	International (editorial)	Commentary on AI-enabled prescription verification	Alert suppression can turn safety into inference from "algorithmic silence"; automation bias, data drift, shared accountability	Opinion; no data
Naeem et al. (2022)	Saudi (KAMC, Jeddah)	Retrospective audit; 11,350 red CDS alerts overridden by physicians and pharmacists (Sep–Dec 2020)	Interaction alerts 57%, dose 41%, allergy 2%; appropriate action least likely for dose alerts; refinements could remove 32% of irrelevant alerts	Conventional CDS, not AI; single site
Khaled et al. (2026)	Saudi (Aseer)	Cross-sectional; 117 community pharmacists	71.6% expect AI to reduce errors; 58.9% do not expect replacement; 51.6% of aware report sufficient knowledge	Community setting; convenience sample
Alghitran et al. (2025)	Saudi (Riyadh)	Cross-sectional; 1,022 pharmacists; ChatGPT focus	Positive attitude 64.1%; regular use 24.3%; ethical concerns 64%; no formal training 92%	Self-report; generative chatbot only
Alhomoud (2026)	GCC–MENA (Middle East)	Scoping review (PRISMA-ScR); 15 studies, 8,117 participants	93.3% cross-sectional surveys; benefits perceived, routine use and effectiveness data limited	Perception-dominated evidence

Note. AUROC = area under the receiver operating characteristic curve; AUPRC = area under the precision–recall curve; CDS = clinical decision support; DRP = drug-related problem; LLM = large language model; ML = machine learning; KAMC = King Abdulaziz Medical City. DOIs are given in the References.

3.2 Medication safety

Pharmacist-supervised AI improved detection in the studies that compared it with conventional tools or with pharmacists working alone. A hybrid ML and rule-based score that ranked prescriptions for pharmacist review outperformed rule-based CDS alerts and a multicriteria query on both discrimination measures (Corny et al., 2020). In routine use, severe drug-related problems

were found in 2.8% of low-score prescriptions and 15.3% of high-score ones, and the tool allowed 55% of prescriptions to be ruled out of manual review (Levivien et al., 2022). Figure 1 summarizes these two studies.

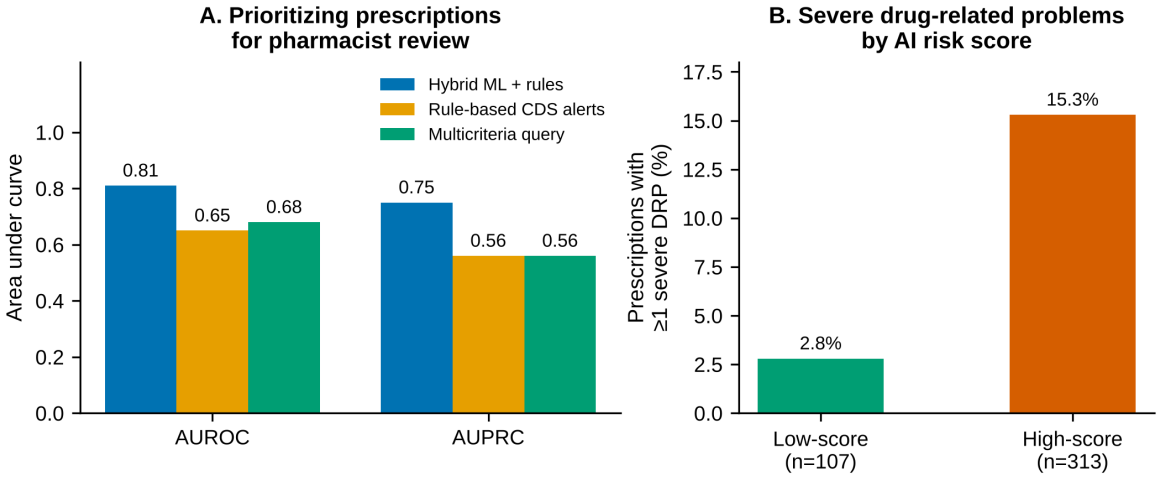


Figure 1. AI-based prioritization of prescriptions for pharmacist review. (A) Discrimination of a hybrid machine learning and rule-based score versus conventional approaches in 412 validation patients (Corny et al., 2020). (B) Share of prescriptions with at least one severe drug-related problem (DRP) in low- and high-score groups in 420 prescriptions (Levivien et al., 2022). AUROC = area under the receiver operating characteristic curve; AUPRC = area under the precision–recall curve.

LLM-based designs showed a similar pattern. In vignette testing, a pharmacist working with an LLM co-pilot detected serious-harm errors 1.5 times as accurately as the pharmacist alone, although overall co-pilot accuracy was 61% (Ong et al., 2025). In a crossover of 213 outpatient prescriptions, a locally deployed LLM raised pharmacist sensitivity from 55% to 98% without a significant change in specificity (Liu Z et al., 2026; Figure 2A). A deployed ML alert system in an outpatient setting intercepted 16.4 errors per 1,000 alerted orders, with nearly half of alerts accepted (Chen et al., 2024).

The same body of work shows that pharmacist involvement does not by itself protect against bad advice. In a randomized simulation with 77 pharmacists and trainees, AI assistance raised overall accuracy (adjusted OR 1.58), but accuracy was 80.2% when the AI was right and 26.1% when it was wrong; participants accepted 73.9% of incorrect recommendations, and accuracy was 21.7% when they disagreed with the AI (Surdilla et al., 2026; Figure 2B). Commentary on AI-enabled verification warns that when low-risk orders are deprioritized or alerts suppressed, “no alert” becomes an implicit assurance of safety, with automation bias, data drift, and diffuse accountability as the main hazards (Zavaleta-Monestel et al., 2026).

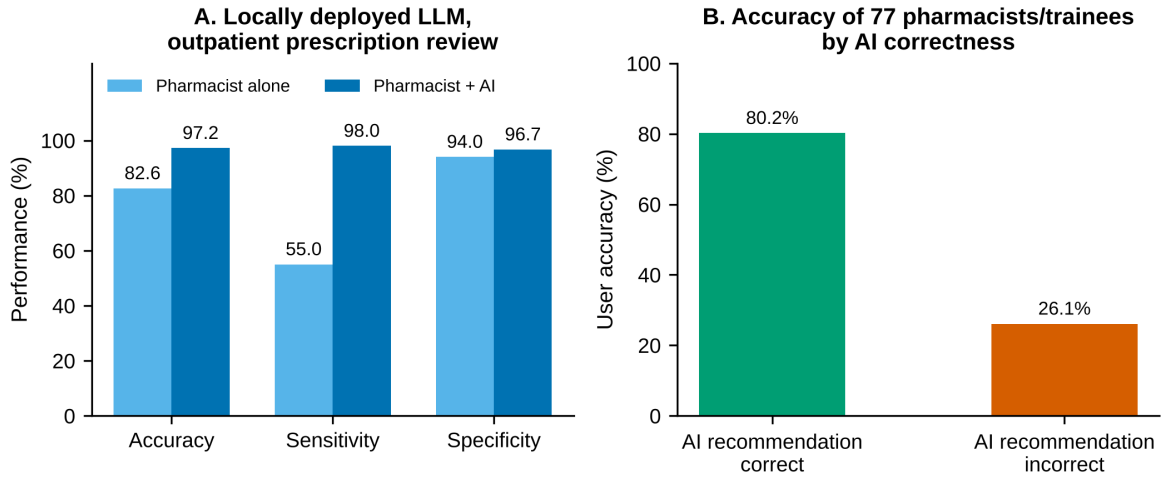


Figure 2. Human–AI performance in pharmacist medication review. (A) Accuracy, sensitivity, and specificity of two pharmacists reviewing 213 outpatient prescriptions alone and with a locally deployed large language model (Liu Z et al., 2026). (B) Accuracy of 77 pharmacists and trainees by whether the AI recommendation was correct (Surdilla et al., 2026).

3.3 Workflow

Workflow effects were reported mainly as time and alert burden. Collaborative LLM review cut mean review time per prescription from 2.33 to 1.12 minutes, about 52% (Liu Z et al., 2026), and risk-based triage removed more than half of prescriptions from manual review (Levivien et al., 2022). Alert burden fell only slightly after a CDSS was introduced in a 3,200-bed hospital: orders with alerts decreased from 2.52% to 2.30% and patients with alerts from 30.34% to 28.08% (Lin et al., 2025). Acceptance of ML alerts was 48.88% (Chen et al., 2024), which implies that about half were still judged not actionable.

Pharmacist acceptance is a limiting factor. Critical care pharmacists reviewing an AI vancomycin-dosing tool favored it in principle, yet their empiric doses differed from its recommendation in 85% of cases and 78% of those discrepancies persisted after seeing the recommendation, citing distrust, lack of dynamic evaluation, and incomplete data integration (Liu X et al., 2023). Together with the simulation data above, this suggests two opposite failure modes: reflexive rejection in domains where trust is low, and reflexive acceptance where AI is presented as a verification aid.

3.4 Clinical outcomes

No completed study in the evidence base reported patient-level outcomes such as adverse drug events, acute kidney injury, length of stay, or mortality attributable to pharmacist-supervised AI. Most outcomes were process measures (alerts, interventions, accuracy, time). A multi-hospital cluster-randomized trial now under way compares a passive electronic alert with a pharmacist-led, tiered intervention driven by predictive analytics for drug-associated acute kidney injury, with major adverse kidney events at 30 days as its primary outcome (Stottlemyer et al., 2025). Reviews

consistently call for prospective, multicenter studies with standardized clinical endpoints, external validation, and cost-effectiveness analysis (Alqahtani et al., 2025; Johns et al., 2024).

3.5 Saudi and regional evidence

Saudi data describe readiness rather than effect. Among 1,022 pharmacists in Riyadh, 78.7% were familiar with AI in pharmacy and 64.1% held positive attitudes toward ChatGPT, but only 24.3% used AI tools regularly, 64% raised ethical concerns, and 92% reported no formal training (Alghitran et al., 2025). Among 117 community pharmacists in Aseer, 71.6% expected AI to reduce errors and 58.9% did not expect it to replace pharmacists (Khaled et al., 2026; Figure 3). A scoping review of 15 Middle Eastern studies reached the same conclusion: positive attitudes, little routine use, and no effectiveness data (Alhomoud, 2026).

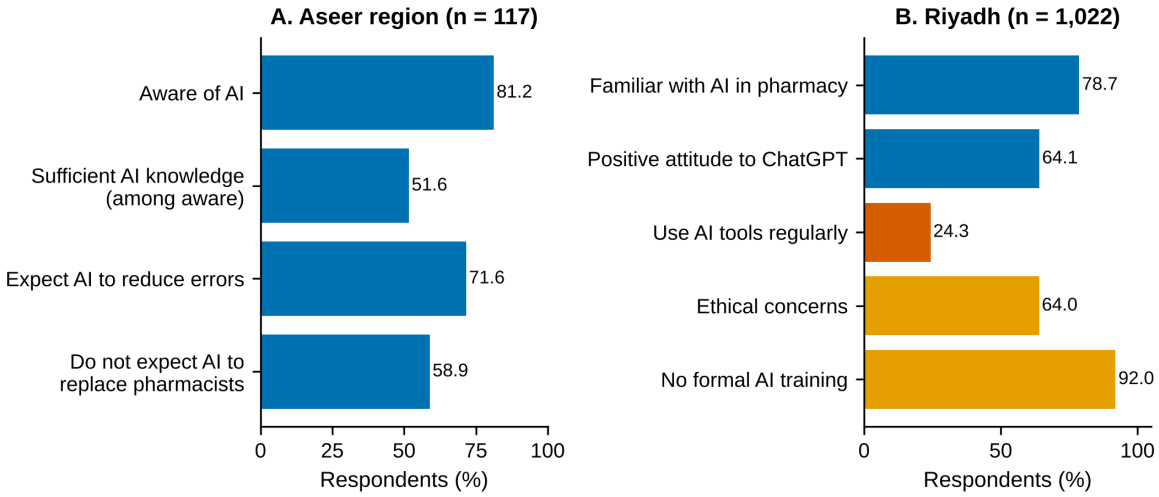


Figure 3. Saudi pharmacists' awareness, attitudes, and use of AI. (A) Community pharmacists in the Aseer region (Khaled et al., 2026). (B) Pharmacists in Riyadh, ChatGPT-focused survey (Alghitran et al., 2025). Percentages are of respondents; "sufficient knowledge" is among those aware of AI. Surveys used different instruments and are not directly comparable.

The only Saudi source touching hospital decision support evaluated conventional CDS: in an inpatient audit at King Abdulaziz Medical City, Jeddah, interaction alerts (57%) and dose alerts (41%) dominated 11,350 overridden red alerts, appropriate responses were least likely for dose alerts, and revising the alert set could remove about 32% of irrelevant alerts (Naeem et al., 2022).

This is the alert-fatigue problem that AI triage aims to address, but it was not tested with AI in Saudi hospitals. Table 2 consolidates the evidence by domain.

Table 2. Summary of evidence on pharmacist involvement in AI-supported medication decisions, by domain.

Domain	Key sources	Direction of findings	Strength and confidence
Error and DRP detection	Corny et al. (2020); Levivien et al. (2022); Ong et al. (2025); Liu Z et al. (2026)	Improved detection versus conventional alerts or pharmacist alone	Moderate for process measures; single-site, simulated, or crossover designs
Automation bias and over-reliance	Surdilla et al. (2026); Zavaleta-Monestel et al. (2026)	Accuracy 26.1% when AI wrong; 73.9% of wrong advice accepted	Low to moderate; one randomized simulation plus commentary
Review time and triage	Liu Z et al. (2026); Levivien et al. (2022)	About 52% less review time; 55% of prescriptions ruled out	Low to moderate; short horizons
Alert burden and acceptance	Lin et al. (2025); Chen et al. (2024); Naeem et al. (2022)	Small reduction in alert rate; acceptance about 49%; high override in Saudi CDS audit	Low; before–after and retrospective
Pharmacist trust and readiness	Liu X et al. (2023); Alghitran et al. (2025); Khaled et al. (2026); Alhomoud (2026)	Positive attitudes, low routine use, training gaps, selective distrust	Low; mostly self-report
Patient-level clinical outcomes	Stottlemyer et al. (2025); Alqahtani et al. (2025); Johns et al. (2024)	No completed outcome data; one trial registered	Very low; evidence gap

Note. Strength ratings are the author's qualitative judgments from design, comparator, and sample, not a formal GRADE assessment.

4. Discussion

Principal findings. Pharmacist-supervised AI consistently improved detection and efficiency in the studies that tested it, but the evidence is mainly process-level, short-term, and drawn from a few single sites and simulations. The simulation data add an essential caution: a pharmacist in the loop adds value only while the pharmacist remains an independent check. When the AI was wrong, accuracy fell to about one in four, so the benefit seen when AI is right comes with a matching cost when it is wrong (Surdilla et al., 2026). The studies that show the largest gains (Corny et al., 2020; Levivien et al., 2022; Liu Z et al., 2026) also use AI as a prioritizer or pre-screen feeding a pharmacist, not as an autonomous verifier.

Saudi versus international picture. International work has moved from model development to prospective evaluation and, in one case, a randomized trial (Stottlemyer et al., 2025). Saudi work is at the readiness stage: awareness and enthusiasm are high, regular use is low, and training is largely absent (Alghitran et al., 2025; Khaled et al., 2026). The Saudi alert-override audit (Naeem

et al., 2022) shows the local need that smarter triage could address, but local data on AI-supported decisions are lacking. The pattern matches the regional scoping review (Alhomoud, 2026), so the gap is regional, not confined to one survey.

Implications for practice. The evidence supports a defined pharmacist role across the AI lifecycle (Table 3). The roles follow ASHP's position that pharmacists should help validate AI, define when it is used, and monitor it (Bastow et al., 2025), and respond to the governance risks identified by Alruwaili et al. (2026) and Zavaleta-Monestel et al. (2026). The Table 3 roles are the author's interpretation of these sources, not tested protocols.

Table 3. Proposed pharmacist roles in AI-supported medication decisions, mapped to supporting evidence.

Stage	Pharmacist role	Supporting evidence
Selection and validation	Co-define the use case; test accuracy, hallucination, and local-data performance before go-live	Hallucination fell from 19.7% to 4.7% with knowledge augmentation (Liu Z et al., 2026); 12/13 models at high risk of bias (Johns et al., 2024)
Deployment design	Use AI to prioritize and pre-screen; keep a pharmacist decision for every released order; avoid silent suppression	Risk-based triage worked as a prescreen (Levivien et al., 2022); suppression creates "algorithmic silence" (Zavaleta-Monestel et al., 2026)
Daily use	Record agreement and overrides with reasons; review AI rationales critically; escalate disagreements	Wrong advice accepted 73.9% of the time (Surdilla et al., 2026); distrust drives rejection (Liu X et al., 2023)
Monitoring	Track alert acceptance, interventions, missed events, and data drift; audit overrides	Acceptance about 49% (Chen et al., 2024); override audit identified 32% removable alerts (Naeem et al., 2022)
Education and governance	Train pharmacists in AI limits and bias; assign accountability among pharmacy, prescribers, and IT	92% reported no formal training (Alghitran et al., 2025); shared accountability risk (Zavaleta-Monestel et al., 2026)
Outcome evaluation	Measure adverse drug events, kidney injury, length of stay, and cost with controlled designs	No outcome data yet; trial under way (Stottlemyer et al., 2025)

Note. Roles are the author's synthesis. Local accreditation and Ministry of Health requirements should be checked before adoption.

Research priorities. Saudi hospitals could contribute pragmatic before–after or stepped-wedge studies of AI-assisted pharmacist review, with outcome measures that include adverse drug events, intervention acceptance, and review time, and with subgroup reporting by pharmacist experience, because benefit differed between students and senior residents in the simulation study (Surdilla et al., 2026).

5. Strengths and Limitations

Strengths include the pairing of Saudi and international evidence, a clear domain structure, and figures built only from reported numbers. Limitations are substantial. The review is narrative, searched purposively in two sources without hand-searching, and screened by one reviewer, so relevant studies may be missing. Data were taken from published records, not full texts, and quality was not scored with a formal tool. The evidence is heterogeneous (production alerts, simulations, vignettes, surveys), so effects could not be pooled and cross-study comparison is indicative only. Several sources are recent and have few citations, and some did not state the study country. Two figures draw on single small studies. Findings may not transfer to Saudi hospital workflows.

6. Conclusion

Pharmacist involvement in AI-supported medication decisions improves error detection and shortens review in early studies, but it does not remove the risk of over-reliance, and no completed study shows better patient outcomes. Saudi evidence is limited to attitudes and conventional alert audits. Hospitals adopting these tools should place pharmacists in validation, supervised review, and monitoring roles, and should measure patient-level outcomes locally.

Declarations

Ethics approval and consent: Not applicable; this review used published literature only.

Funding: Not applicable

Conflicts of interest: not applicable

Data availability: All data are from the cited publications; figure data are in Tables 1 and 2 and the cited sources.

AI transparency: An AI assistant (Claude, Anthropic) helped with literature retrieval, data extraction, figure generation, and drafting. The author is responsible for verifying all content before submission.

References

Alghitran, A., AlOsaimi, H. M., Albuluwi, A., Almalki, E. O., Aldowayan, A. Z., Alharthi, R., Qattan, J. M., Alghamdi, F., AlHalabi, M., Almalki, N. A., Alharthi, A., Alshammari, A., & Kanan, M. (2025). Integrating ChatGPT as a tool in pharmacy practice: A cross-sectional exploration among pharmacists in Saudi Arabia. *Integrated Pharmacy Research & Practice, 14*, 31–43. https://doi.org/10.2147/IPRP.S500689

Alhomoud, F. (2026). Artificial intelligence in pharmacy practice in the Middle East: A scoping review of applications, adoption, barriers, and future directions. *Frontiers in Digital Health, 8*, Article 1951084. https://doi.org/10.3389/fdgth.2026.1951084

Alqahtani, S. S., Menachery, S. J., Alshahrani, A., Albalkhi, B., Alshayban, D., & Iqbal, M. Z. (2025). Artificial intelligence in clinical pharmacy: A systematic review of current scenario

and future perspectives. *Digital Health, 11*, Article 20552076251388145. https://doi.org/10.1177/20552076251388145

Alruwaili, M. F., Paul-Chima, U. O., & Nneoma, U. C. (2026). Integrating clinical decision support systems, nursing vigilance, and physician prescribing patterns to reduce preventable adverse drug events: A structured evidence-based narrative review on human–AI interface in medication safety. *Frontiers in Digital Health, 8*, Article 1831150. https://doi.org/10.3389/fdgth.2026.1831150

Bastow, S., Greszler, C., Hartell, E., Kalichira, A., Mathew, S., Rhodes, D., Zhan, S., & Anderson, S. V. (2025). ASHP statement on artificial intelligence in pharmacy. *American Journal of Health-System Pharmacy, 82*(19), e853–e858. https://doi.org/10.1093/ajhp/zxaf107

Chalasani, S. H., Syed, J., Ramesh, M., Patil, V., & Pramod Kumar, T. M. (2023). Artificial intelligence in the field of pharmacy practice: A literature review. *Exploratory Research in Clinical and Social Pharmacy, 12*, Article 100346. https://doi.org/10.1016/j.rcsop.2023.100346

Chen, C. Y., Chen, Y. L., Scholl, J., Yang, H. C., & Li, Y. J. (2024). Ability of machine-learning based clinical decision support system to reduce alert fatigue, wrong-drug errors, and alert users about look alike, sound alike medication. *Computer Methods and Programs in Biomedicine, 243*, Article 107869. https://doi.org/10.1016/j.cmpb.2023.107869

Corny, J., Rajkumar, A., Martin, O., Dode, X., Lajonchère, J. P., Billuart, O., Bézie, Y., & Buronfosse, A. (2020). A machine learning–based clinical decision support system to identify prescriptions with a high risk of medication error. *Journal of the American Medical Informatics Association, 27*(11), 1688–1694. https://doi.org/10.1093/jamia/ocaa154

Hamishehkar, H., & Shahidi, M. (2025). Impact of artificial intelligence on the future of clinical pharmacy and hospital settings. *Journal of Research in Pharmacy Practice, 14*(3), 87–97. https://doi.org/10.4103/jrpp.jrpp_51_25

Johns, E., Alkanj, A., Beck, M., Dal Mas, L., Gourieux, B., Sauleau, E. A., & Michel, B. (2024). Using machine learning or deep learning models in a hospital setting to detect inappropriate prescriptions: A systematic review. *European Journal of Hospital Pharmacy, 31*(4), 289–294. https://doi.org/10.1136/ejhpharm-2023-003857

Khaled, A., Almaghaslah, D., Orayj, K., Siddiqua, A., Kandasamy, G., & Bazan, N. S. (2026). Navigating the future: Community pharmacists' attitudes towards AI integration in pharmacy services: A cross-sectional study in Aseer, Saudi Arabia. *PeerJ, 14*, Article e21246. https://doi.org/10.7717/peerj.21246

Levivien, C., Cavagna, P., Grah, A., Buronfosse, A., Courseau, R., Bézie, Y., & Corny, J. (2022). Assessment of a hybrid decision support system using machine learning with artificial intelligence to safely rule out prescriptions from medication review in daily practice. *International Journal of Clinical Pharmacy, 44*(2), 459–465. https://doi.org/10.1007/s11096-021-01366-4

Lin, M., He, Y., He, P., Jiang, H., Luo, H., Dai, H., & Yu, L. (2025). Development and implementation of a clinical decision support system to enhance efficiency and accuracy in medication prescription review in a tertiary care hospital: A retrospective hospital CDSS register study. *Journal of Multidisciplinary Healthcare, 18*, 1043–1051. https://doi.org/10.2147/JMDH.S505889

Liu, X., Barreto, E. F., Dong, Y., Liu, C., Gao, X., Tootooni, M. S., Song, X., & Kashani, K. B. (2023). Discrepancy between perceptions and acceptance of clinical decision support systems: Implementation of artificial intelligence for vancomycin dosing. *BMC Medical Informatics and Decision Making, 23*, Article 157. https://doi.org/10.1186/s12911-023-02254-9

Liu, Z., Ding, Y., Chen, J., Yan, Z., Cheng, X., Zhou, W., Fu, P., & Wang, Z. (2026). Locally deployed large language models for AI-assisted outpatient prescription review: Crossover study. *JMIR Medical Informatics, 14*, Article e97520. https://doi.org/10.2196/97520

Naeem, A., Alwadie, A. F., Alshehri, A. M., Alharbi, L. M., Nawaz, M. U., AlHadidi, R. A., Alshammari, R. S., Alsufyani, M. A., Babsail, L. O., Alshamrani, S. A., Alkatheeri, A. A., Alshehri, N. F., Alzahrani, A. M., & Alzahrani, Y. A. (2022). The overriding of computerized physician order entry (CPOE) drug safety alerts fired by the clinical decision support (CDS) tool: Evaluation of appropriate responses and alert fatigue solutions. *Cureus, 14*(11), Article e31542. https://doi.org/10.7759/cureus.31542

Ong, J. C. L., Jin, L., Elangovan, K., Lim, G. Y. S., Lim, D. Y. Z., Sng, G. G. R., Ke, Y. H., Tung, J. Y. M., Zhong, R. J., Koh, C. M. Y., Lee, K. Z. H., Chen, X., Ch'ng, J. K., Than, A., Goh, K. J., Lim, C. P., Ng, T. M., Liu, N., & Ting, D. S. W. (2025). Large language model as clinical decision support system augments medication safety in 16 clinical specialties. *Cell Reports Medicine, 6*(10), Article 102323. https://doi.org/10.1016/j.xcrm.2025.102323

Stottlemyer, B. A., Kellum, J. A., Bihorac, A., Ozrazgat-Baslanti, T., Murugan, R., Chang, C. H., Amatullah, N., Tran, T. L., Lukan, C. J., Elder, M. M., Adiyeke, E., Ren, Y., Ricketts, D., Emanuele, B., Rashidi, P., & Kane-Gill, S. L. (2025). Multi-hospital electronic decision support for drug-associated acute kidney injury (MEnD-AKI): Study protocol for a randomized clinical trial. *Contemporary Clinical Trials, 157*, Article 108055. https://doi.org/10.1016/j.cct.2025.108055

Surdilla, D., Michaels, B., Michael, C., Wimer, D., He, Y., Baptiste, N., & Coralic, Z. (2026). Impact of AI assistance on pharmacist and pharmacy trainee accuracy and automation bias during medication order verification: A randomized simulation trial. *American Journal of Health-System Pharmacy*. Advance online publication. https://doi.org/10.1093/ajhp/zxag259

Zavaleta-Monestel, E., Mora-Jiménez, J., & Arguedas-Chacón, S. (2026). When silence signals safety: Governance and responsibility in AI-enabled prescription verification. *Cureus, 18*(2), Article e103272. https://doi.org/10.7759/cureus.103272