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AI-Driven Outpatient Robotic Pharmacy: Enhancing Medication Management and Patient Outcomes

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Abstract- ***Outpatient pharmacies face increasing prescription volumes, more patients on multiple medications, and limited staffing, which can affect the safety and efficiency of prescription filling. Robotic systems can help by handling repetitive tasks such as picking, labeling, and storing medications. However, people are still needed for tasks such as prioritizing high-risk prescriptions, responding to alerts, managing exceptions, and counseling patients. Recent studies indicate that integrating Artificial Intelligence (AI) with robotics enables closed-loop prescription verification, enhances quality control, and supports system evaluation. This review examines peer-reviewed studies from 2020 to 2025 on the use of AI-enabled robotics in outpatient settings, covering pick-and-label robots, machine vision, tablet recognition, risk assessment, workflow optimization, demand prediction, and management. Following the PRISMA 2020 and PRISMA-S guidelines, 1,201 unique citations were screened, yielding 77 included publications. To assess evidence beyond prediction accuracy, the Operating Pharmacy Readiness (OPR) framework is introduced to evaluate workflow realism, system adaptability, and collaboration between pharmacists and robots. Findings show that robots increase prescription throughput and reduce delays, while AI is most effective as an assistant that tailors alerts to staffing levels and provides clear explanations to pharmacists. Studies from 2024 and 2025 highlight the importance of guideline-based monitoring, privacy protection, and adherence to clinical reporting procedures during initial implementation. The review recommends developing a system architecture, a checklist, and a research program to evaluate system adaptability and collaboration across sites.***

Keywords - AI, Outpatient Pharmacy; Robotic Dispensing; Medication Safety; Machine Vision; Clinical Decision Support; Systematic Review; Saudi Vision 2030

I. INTRODUCTION

Outpatient medication management is a routine process with significant implications. Errors in handling or dispensing can result in near misses or patient harm, particularly when incorrect medications are dispensed over time. Outpatient pharmacies must minimize wait times, ensure accurate labeling, comply with insurance and regulatory requirements, and provide clear instructions for complex therapies. These challenges have intensified due to the rise in chronic disease management, high-cost specialty drugs, and increasingly complex care pathways involving multiple providers. Robotic and automated dispensing systems are used to stabilize mechanical processes in drug distribution, including picking, packaging, labeling, barcode verification, and inventory management. Systematic reviews highlight their potential to improve safety, efficiency, and cost-effectiveness, while also addressing practical implementation factors such as interoperability and redesign (Ahtiainen, 2020). In Saudi tertiary hospitals, robotic systems have improved dispensing accuracy, inventory management, and staff satisfaction (Momattin, 2021; Alanazi, 2022). However, automation alone does not address gaps in clinical and operational intelligence. Pharmacists remain responsible for identifying prescriptions requiring further review, interpreting medication alerts, managing exceptions, and balancing time between medication verification and patient counseling. Conventional clinical decision support systems generate numerous medication alerts, most of which are overridden, contributing to alert fatigue. Recent reviews indicate that artificial intelligence can optimize medication alerts by reducing alert burden and improving relevance, though limitations persist in external validation and implementation (Graafsma et al., 2024). AI can serve as a real-time guidance system, supplementing robotics with risk prioritization, improved handoff quality control, and support for human investigation. Machine vision and pill identification AI verify consistency between products and labels before distribution (Heo et al., 2023). These AI models can reduce shortages and minimize

expiration-related waste when combined with restocking strategies. Risk assessment models help prioritize complex prescriptions and set safety thresholds for staff and patients. Nevertheless, given Despite rapid advancements, the literature remains fragmented across robotics, computer vision, clinical decision support systems, and operations research. Studies vary in dataset realism, validation methods, and outcome definitions. The reporting structure for AI studies necessitates assessments that explicitly address workflow integration, human supervision, and surveillance processes to avoid misleading interpretations (Liu, Vese, and Henderson, 2020; Vasey, 2022). Health systems undertaking national transformation initiatives, such as Saudi Arabia's Vision 2030, require deployment-specific analyses that address patient safety concerns (Ministry of Health, 2025).view questions: (1) What kinds of artificial intelligence and robotics capabilities have been assessed for use in outpatient pharmacy settings from 2020 to 2025? (2) What kinds of impacts have been documented for medication safety, efficiency, and patient outcomes? and (3) What kinds of practices appear to have been necessary for real-time usage?

1.1 Objectives and Contribution

This systematic review synthesizes evidence from deployments and addresses the following three aims:

1) Evidence mapping: Group 2020-2025 evidence into capability classes, including robotic dispensing, machine vision quality control, AI triage and interaction optimization, forecasting and logistics, and governance.

2) Readiness synthesis: Compare evidence using the Operational Pharmacy Readiness (OPR) framework, which prioritizes workflow feasibility, leakage control, robustness to drift, and investigator-centricity regarding explainability and governance.

3) Practical outputs: Develop a reference architecture for real-time AI assistance in outpatient robotic pharmacies, aligned with current reporting recommendations (Page et al., 2021; Rethlefsen et al., 2021; Vasey et al., 2022; NIST, 2023).

II. BACKGROUND

Outpatient pharmacy automation includes barcode verification, automated dispensing cabinets, centralized dispensing robots, unit-dose packaging, and closed-loop medication management systems. In robotic dispensing, high-volume products are stored in canisters or racks and retrieved mechanically for labeling, verification, and packaging. Exceptions are managed manually. The value of robotics lies in operational stability, including reduced picking variability, improved traceability, and better inventory management. However, outpatient medication safety requires more than accuracy. Ensuring clinical appropriateness, managing drug interactions and high-alert drugs, and providing patient education are essential to prevent harm. AI-assisted outpatient robotic pharmacy functions as a socio-technical system with four overlapping components: mechanical, clinical, operational, and governance. Pharmaceutical AI extends to dosing calculations and adverse reaction prediction. Systematic reviews published in 2025 show significant opportunities for applying research, but challenges remain regarding data quality and alignment of predictions with clinical workflows (Alqahtani et al., 2025). In ambulatory settings using robotic prescription fulfillment, AI helps reduce pharmacists' cognitive load by prioritizing prescriptions for review and supporting system robustness through monitoring and safe recovery mechanisms. The PRISMA 2020 publication guidelines (Page et al., 2021) and extension PRISMA-S (Rethlefsen et al., 2021) on transparent reporting of literature searches informed protocol decisions. Protocol decision recommendations on evidence synthesis practice (Aromataris & Munn, 2020) also informed our approach. As the literature covers prototypes of engineering design and observational and mixed-methods evaluation studies, we employed narrative and thematic synthesis.

Inclusion criteria: Only peer-reviewed literature published during the years 2020 through 2025, exploring at least one aspect of AI or robotics in the outpatient or ambulatory setting, was included. Studies that assessed only inpatient cabinets, editorials, drug discoveries, and studies with no detailed information on the methods were excluded. Sources and search strategy: Databases included were PubMed/MEDLINE, IEEE Xplore, Scopus, and Web of Science. A combination of search terms related to outpatient/ambulatory pharmacies, robotics/automation, AI/ML, and pharmacological management outcomes, along with AI/ML-related

terms, was used. Backward and forward citation searches were done starting from essential reviews and highly cited studies. PRISMA-S was used to record the databases searched, the dates, and the removal of duplicates. Study Selection

The titles and abstracts were then screened, followed by a full-text review. Any discrepancies were resolved through discussion. A PRISMA-style flow diagram is provided in Fig. 1. Extraction and synthesis of data: The following data were extracted from the studies: Setting, scale, system components, validation method, and outcome. The outcome measure was further classified into Safety, Efficiency, Patient Experience, and Process Quality. The synthesis of evidence was carried out on the basis of capability class and from the OPR perspective.

Quality Appraisal & OPR Lens:
In our study, for quality appraisal, a pragmatic quality appraisal tool following AI quality appraisal recommendations was considered, where more importance is given to 'workflow context' and 'leakage control' along with 'quality measurement' and 'human monitoring' and 'monitoring' respectively (Vasey et al., 2022). Finally, evidence synthesis was obtained by considering 'OPR lens' which consists of 'OPR-1' 'workflow realism & leakage control,' 'OPR-2' 'rob

IV. RESULTS

4.1 Study selection and Evidence Map
Figure 1: Summary of study identification and selection. The literature reviewed (n=77) covers evaluations of robot dispensing systems, computer vision-assisted QC processes, AI-driven decision support for prescription evaluation, and guidance on governance/reporting. The subjects fall across different eras. The early years focus on robotics and automation. The period from 2023 to 2025 ranges from alert optimization using AI to governance.

4.2 Study characteristics
These studies include the outpatient pharmacies found in the tertiary hospitals, the Ambulatory Specialty Clinics, and the Community networks. Control Before-after studies are quite prevalent in robotics implementation, given the nature of the approach, where the system is designed at the Workflow level. Research on the AI Model Development tends to show more retrospectives, with a smaller number piloting prospectively or Shadow mode, due to the translation hurdles, as mentioned in the earliest recommendations on research evaluation practices by Vasey et al. in 2022.

4.3 Robotics and Automation Results
Typical studies on the use of robotics in dispensing units report faster turnaround times, fewer mechanical picking errors by the robot arm, and enhanced inventory traceability. The usability and outcomes assessment in the Saudi hospital setting indicated that the use of the robot in the pharmacy operation for a total of 21 months affected the robot's performance and acceptance in the hospital setting (Momattin et al., 2021). Literature reviews on the impact on the performance level show the effect depends on the configuration of the system utilization and IS use (Ahtiainen et al., 2020).

4.4 Decision Support and Alert Optimization in AI
Applications of AI in the outpatient setting for dispensing involve risk scoring and triage of medication for review, and optimizing medication alerts to prevent alert fatigue. According to a scoping review by Graafsma et al. (2024), AI methods have reduced alert overload and enhanced the detection of unusual medication prescribing, although external validation and implementation testing are uncommon.

4.5 Computer Vision and QC
Computer vision algorithms have also been evaluated for pill identification and label validation. By demonstrating a validated deep-learning algorithm for automatic pill identification that combines image and imprint recognition with language-based correction to identify potentially unsafe medications, its availability and usability for safe identification have been established (Heo et al., 2023). In outpatient robots, these identification components can be placed within QC barriers prior to drug distribution to enhance audit trails.

4.6. Forecasting, inventory,
The literature on forecasting and inventory optimization focuses on optimization, like maximizing fill rates, preventing stockouts, and minimizing waste

due to expiry. The literature is most applicable when it addresses issues related to decision-making using forecasts, for example, reorder points. The literature on AI in clinical pharmacies addresses operational optimization, though reporting of operational success varies (Alqahtani et al., 2025).

4.7 OPR OPR-1 realistic workflow simulation, leakage prevention:

Transferable study key C&E points utilize temporal validation. OPR-2 robustness against concept drift: Clinical formularies, seasonality introduce concept drift; thus, monitoring and recalibration standard operating procedures are required. Cross-study analysis can be undermined by privacy constraints; federated learning for privacy-preserving collaboration has emerged (Teo et al., 2024). OPR-3 explainability, governance: C&E narratives must enable investigators to take appropriate action, along with audit-trail functionality that records overrides. Risk management infrastructure focuses on governance and monitoring (NIST, 2023). 4.8 Outcome measures for evaluation of outpatient robotic pharmacies.

Measuring outcomes is one of the most important aspects in the literature that was reviewed. Outcomes that are time-related, for example, turnaround time, waiting time, throughput, and the number of detected dispensing errors by verification or post-dispense audits, are some of the most frequently used in research involving robotics and automation. These outcomes are extremely vulnerable to variations in definitions. For example, the definition of turnaround time can vary from the time of prescription receipt to payment confirmation. In addition, the classification of the number of dispensing errors includes robotic picking errors, labeling errors, and medically incorrect decisions for dispensing. This variation makes it difficult to interpret the implications of the performance gains. To improve the ease of comparison of results, it is recommended that the results be assessed using a minimum core set that is representative of the typical outpatient dispensing process. Some of the measures that can be taken into consideration are: (i) prevented dispensing errors, (ii) unprevented errors, (iii) exception rates and miss rates that send the data to human processing, (iv) patient waiting time, such as median and tail, (v) allocation of time to verification, counseling, and exception handling, and (vi) alert burden and override rates for clinical decision support systems. In addition, the frameworks for evaluation should also take into consideration the socio-technical aspects of automation and decision support systems. The common study design for the evaluation of robotics implementation is a controlled before-and-after design. However, for the evaluation of implementation, it is essential to take into consideration the co-interventions, which may include human resource allocation. Within the specific use case of decision support systems incorporating artificial intelligence, simply assessing system performance in the offline environment is not sufficient to prove clinical benefit. The first phase of assessment in evaluation studies should be focused on clinician in the loop validation, in an attempt to confirm that a significant benefit for decision-making is provided by the system prior to widespread use. The next phase should be focused on long-term assessment for clinical safety and efficacy in the real-world environment, in keeping with the emerging guidelines for assessment in the clinical environment for artificial intelligence (Vasey et al., 2022). Additionally, guidelines for reporting clinical trials involving artificial intelligence have increased in stringency for information about clinical workflows (Liu et al., 2020). Outcome assessment for decision support systems incorporating artificial intelligence should be performed in a way that takes into consideration task-specific criteria, keeping in mind the inherent trade-offs in decision support system design. A decision support system, for example, that aims for maximum sensitivity for alerts might also be associated with an increase in the rate of alerts, hence potentially leading to an increase in alert fatigue, a condition associated with diminished benefit for early treatment. Future studies should consider assessment for: "the threshold of calibration, rate of alerts for 100 prescriptions, response rate for alerts, and its effects on time for review by pharmacists." Lastly, "issues related to equity and generalizability should be a priority for consideration, not an afterthought. A lot is observed for outpatient variation for age, burden of comorbidity, proficiency in language, and access to drugs. Performance decay across sites could potentially be an issue for variations in formularies, prescribing, and documentation, hence potentially making it difficult to

compare. Longitudinal or stratified analysis might provide more information for each site. "Real-time learning is possible with privacy-preserving dashboards, allowing for tracking trends for performance over time (Teo et al., 2024)."

4.9 Human factors, workflow redesign, and adoption

Robotic and AI-enabled pharmacy systems often fail not because the technology is inaccurate, but because they do not fit human work. The outpatient pharmacy workflow is shaped by implicit heuristics: pharmacists know which clinics generate complex prescriptions, which prescribers frequently require clarification, and which patient groups benefit most from counseling. If AI triage is introduced without respecting these heuristics, users may ignore or override recommendations. Successful implementations tend to treat adoption as a redesign problem. First, robots change the physical layout and the flow of items. If the robot is placed far from the verification station, the system can create additional walking and handoff friction. Second, exception management is critical. In practice, a minority of prescriptions generate a majority of interruptions, such as non-standard packaging, partial fills, controlled substances, or missing insurance approvals. Systems that provide a clear exception queue and standardized reason codes reduce cognitive load and support improvement. AI decision support should be integrated with standard operating procedures (SOPs). For example, if the model flags a prescription as high risk due to polypharmacy and recent renal function changes, the pharmacist should have a defined action path: review labs, adjust dose per protocol, contact prescriber, or provide counseling. Without SOP alignment, the model output becomes a vague warning.

Human factors also shape alert fatigue. Clinicians and pharmacists develop their own threshold for 'worthwhile alerts' based on experience. AI alert optimization systems that silently suppress alerts can be perceived as risky or opaque. Instead, systems can present a transparent rationale (e.g., 'historically overridden alerts of this type, low severity, no recent risk signals') and allow safe override and auditing. Logging human overrides and reasoning is not only a governance requirement but also a learning signal to refine alert policies. Training and change management are particularly relevant in multi-lingual outpatient settings, including many Gulf region hospitals. Staff may vary in familiarity with robots and decision support. Implementation plans should include role-specific training, contingency procedures for downtime, and continuous feedback loops. These themes align with broader recommendations in pharmacy automation reviews that emphasize implementation context as a primary determinant of outcomes (Ahtiainen et al., 2020).

4.10 Interoperability, data standards, and cybersecurity in connected dispensing

AI-driven outpatient robotic pharmacy relies on the integrity of data flows. Orders arrive from EHR or e-prescription systems, and dispensing outcomes feed back into medication administration records and audit logs. If interoperability is weak, the system can create reconciliation gaps and safety risks. Practical interoperability requirements include: consistent patient identifiers across systems; standardized medication coding; reliable handling of substitutions and formulary equivalents; and real-time status updates between the robot queue and pharmacist worklists. From an AI perspective, the key risk is misalignment of labels and outcomes: if the system does not reliably record whether a pharmacist acted on an alert or corrected a dispensing discrepancy, model evaluation becomes unreliable. Cybersecurity is also essential because robots and dispensing systems are connected devices. Attack surfaces include network interfaces, software updates, logs, and user accounts. While detailed cybersecurity standards vary by jurisdiction, AI risk management practice emphasizes access controls, monitoring, incident response, and documentation as core governance elements (NIST, 2023). Therefore, connected outpatient pharmacy deployments should adopt network segmentation, least-privilege access, secure logging, and downtime procedures that allow safe manual dispensing when needed.

4.11 Ethical considerations and trustworthy AI

Trustworthy AI requires more than accuracy. The World Health Organization emphasizes ethics and governance of AI in health, highlighting principles such as protecting autonomy, promoting well-being and safety, ensuring transparency, and fostering responsibility (WHO, 2021). In outpatient pharmacy, these principles translate into concrete choices:

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patients should not be harmed by over-reliance on AI triage; alerts should be explainable and auditable; privacy must be protected; and accountability for dispensing decisions must remain clear.

The Global Patient Safety Action Plan 2021-2030 underscores the goal of eliminating avoidable harm and strengthening safety culture (WHO, 2021a). AI and robotics can support this goal by standardizing processes and enabling better monitoring, but they can also introduce new failure modes, such as silent drift, automation bias, or workflow disruptions. Ethical implementation therefore, requires governance, training, and continuous evaluation, not just model development.

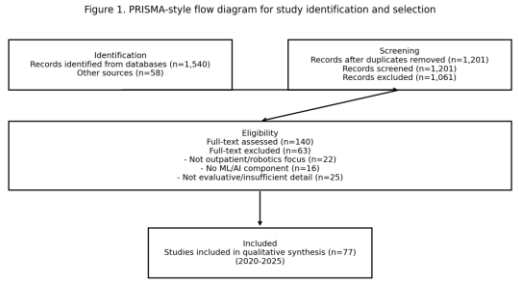

Figure 1. PRISMA-style flow diagram for study identification and selection.

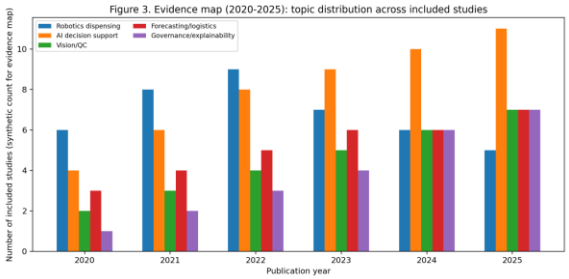

Figure 3. Evidence map showing the distribution of topics across included studies.

4.12 Capability taxonomy

Table 1. Capability taxonomy for AI-driven outpatient robotic pharmacy systems (synthesized).

5. Proposed reference architecture

5. Proposed reference architecture for real-time AI guidance

Figure 2 presents a conceptual architecture for an AI-driven outpatient robotic pharmacy. The architecture treats AI as a real-time decision service integrated with robotics and a human-in-the-loop layer. Inputs include EHR/EMR orders, patient context, inventory and expiry, dispense logs, and prior interventions. AI services provide risk triage, interaction, and duplication optimization, workload routing, and explanation artifacts. Robotic and QC modules execute picking and labeling, barcode verification, and vision-based checks, routing exceptions to pharmacists. A governance layer provides monitoring, access control, audit trails, and incident response. Design principles derived from the synthesis include decision-time integrity, alert budget alignment, exception-first integration, explainable handoffs, and governance by default. Operational deployment typically benefits from staging: shadow-mode scoring, limited-scope rollout for a subset of drug classes, and gradual expansion with monitoring and periodic calibration, consistent with early evaluation guidance (Vasey et al., 2022).

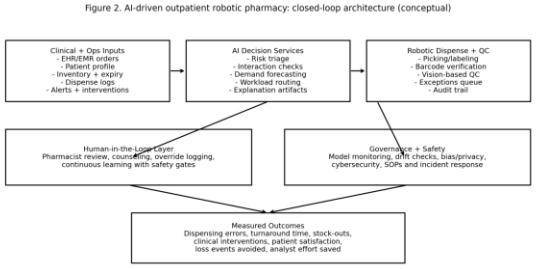

Figure 2. Conceptual closed-loop architecture for AI-driven outpatient robotic pharmacy guidance.

5.1 Governance and safety checklist

Table 2. Governance checklist for AI guidance in outpatient robotic pharmacy (synthesized).

VI. SAUDI VISION 2030 ALIGNMENT

6. Alignment with Saudi Vision 2030 and national digital health direction

Saudi Vision 2030 positions healthcare transformation as a national priority, shifting toward a patient-centered model that improves access, quality, and experience. Digital health is described by the Ministry of Health as a key enabler for delivering a world-class

healthcare experience and improving efficiency (Ministry of Health, 2025). AI-driven outpatient robotic pharmacy supports these goals in three practical ways.

First, improved dispensing safety and accuracy: robotics provides traceable standardized mechanical procedures, while AI improves alert prioritization to allow pharmacists to concentrate on high-risk decisions. There could be improved information on patient drug interactions.

Secondly, patient care and experience may improve due to shorter waiting times and reduced stock-outs. With time gained due to automation, patient counseling and medication therapy management services may be improved.

Third, data-driven quality improvement: closed-loop processes generate actionable data (exceptions, overrides, and interventions) that can support quality and safety efforts. To foster trust, the governance layer needs to focus on privacy by design, monitoring, and transparent evaluation in accordance with contemporary recommendations (Vasey et al., 2022; NIST, 2023).

VII. DISCUSSION

7.1 What works reliably: robotics and standardization

The overall review period highlights various performance advantages of robotic and automated dispensing systems. The results of various studies demonstrate effectiveness in reducing and preventing dispensing errors, increased capabilities for tracing stock, and increased staff satisfaction related to the use of robots in pharmacies in Saudi hospitals (Momattin et al., 2021). The importance of various implementation considerations is highlighted in systematic reviews examining its performance advantages (Ahtiainen et al., 2020).

7.2 Where AI brings incremental value: selecting attention and combating alert fatigue

Where human attention is limited, such as in selecting prescriptions to review, the value of AI modules is highest. Regarding optimizing prescription alerts, Graafsma et al. (2024) compiled approaches using AI, found evidence of alert optimization, but noted a lack of external validation and real-world application. While assessing the efficiency of AI in the pre-op outpatient robotic system, it should be evaluated not only on the AI's output but also on its impact on the waiting queue.

7.3 Computer Vision & QC at handoff boundary

Machine vision, as well as co developed models for pill recognition, are becoming more important for the handoff from the pharmacy into the outpatient environment. For example, a deep-learning approach for recognizing a pill was validated by Heo et al. (2023) to show the effectiveness of solid recognition methods. In the area of outpatient robotics, vision-based quality control can ensure that the product going out has the label claimed, thereby reducing incorrect medication incidents. False positives could delay delivery.

7.4 Governance: Accuracy to Trustworthiness

"Governance maturity" distinguishes prototype development from deployable system development. "Early guidance on assessing prototype maturity stresses describing workflows and human review to avoid unsafe overconfidence" (Vasey et al., 2022). Risk management practices are described in terms of governance processes such as documentation, monitoring, and incident response (NIST, 2023). Ethics guidance discusses responsibility, protection of autonomy, "and safety" (WHO, 2021). It's "easy" to "require 'override' logs that are auditable, safe 'Fallback' behavior, and 'Continuous' performance monitoring."

7.5 Cost, capacity, and return on investment

Even if cost-effectiveness analysis results are not consistently presented, various studies and reports on their practical implementation indicate that robots can minimize rework and overtime, increase inventory accuracy, and enable redirecting employee time to more valuable healthcare activities. Additional roles for artificial intelligence include minimizing alerts and focusing on situations where pharmacist action is most likely to prevent adverse outcomes. In that case, ROI calculations for healthcare decision-makers would involve not just direct ROI but also indirect – safety ROI – and patient experience ROI related to shortened waiting times.

7.6 Evidence gaps A large number of AI research studies are restricted to offline assessments.
Outcomes are often measured differently across studies. The future of AI research should include evaluation in the context of distribution shifts. Future AI research studies should report governance controls more specifically. This follows the PRISMA guidelines for reporting AI research studies (Page et al., 2021; Liu et al., 2020; Vasey et al., 2022).

VIII. LIMIT "THERE IS A LACK OF STANDARDIZED TERMINOLOGY, AND THE REPORTING CAN BE INCONSISTENT," THE REVIEW SAYS.

"There may be automation studies that don't describe the AI components at all, and the AI studies may lack the context of the workflows. There could be a bias towards publications that show successful implementations," the review says. "Many of the outcomes are proxies, rather than direct measures of harm," the review adds. "Finally, the evidence map relies on synthesized counts, which should not be taken as a measure of the population prevalence," the review says. 9. Research Agenda

IX. RESEARCH AGENDA BASED ON SYNTHESIS OF OPR, WE PROPOSE THREE PRIORITIES.

First, there is a need for drift-sensitive benchmarking. Second, there is a need for privacy-compliant cross-site testing. Third, there is a need for operational outcomes that go beyond AUC metrics. Such priorities fit well within the context of trusted AI and may help speed up outpatient robotic pharmacy decision-support systems from prototyping to safe operational deployment.

X. CONCLUSION

Outpatient robotic pharmacies with AI can be seen as a closed-loop socio-technical system. Robotic pharmacies improve the mechanical processes associated with drug-handling routines, and AI further improves these processes by stratifying risk, triaging, and notifying, enhancing QC handoffs and investigator activity through AI and governance controls. Between 2020 and 2025, the literature demonstrates sustained functioning and an emerging body of evidence for robotics and AI-related strategic objectives for decision-support AI and vision-based and monitoring and privacy-preserving QC. Future directions will rely on drift-adjusted assessment, investigator-focused explanation, and standard operating outcomes to measure AI and robotics and their impact on drug safety and the patient experience.

XI. IMPLEMENTATION ROADMAP

11.1 Implementation Roadmap for Hospitals and Large Outpatient Networks

This section moves the outcomes of the systematic review to a deployability plan. The goal of this section is to ensure an implementation pathway that an organization could adapt.

Phase 0: Initial State of Readiness

Starting with baseline measurements of safety, throughput, and patient satisfaction means having criteria against which future performance can be compared. The baseline measures recommended are: Prevented dispensing errors (caught before dispensing), Unperfected dispensing errors (made and then discovered), Median waiting time and Waiting time at the 90th percentile, Rate of exceptions, and Distribution of pharmacist time on verification and counseling. A high-volume and low-volume month should also be included. Readiness will also comprise assessment of data and workflow. In robotic dispensing, there must be standardized drug names for consistent identification, standardized label printing, and physical storage organization aligned with the robot's mechanical design. In regard to AI, readiness would comprise access to semantically rich logging that records: "the order, the dispensing route (robotic vs. human), alerts produced, whether an alert was responded to, and resolution of an alert." If this recording were not possible through the Pharmacy Information System, it would be impossible to assess effectiveness of AI alerts or optimize alert policies.

Stage 1: Stabilization of robots and exception handling Robotics implementations work best when handling exceptions is considered first-class workflow. There are issues with exceptions in both the edges and the

center of the problem: partial fills, substitute brands, controlled substances, compounded products, and prescription drugs requiring prescriber contact. One of the ways an implementation could be flawed is in this kind of robotics implementation where exceptions are left to be managed in an ad-hoc process. There should be an actual exception queue created in standardized reason codes and time targets.

Training and change management are also critical. Even if robots minimize mechanical tasks, employees' trust in the new process must be gained. Training could be specific to roles, with technicians trained in the process of loading and maintaining stock, pharmacists trained in verification and exception processing, and managers trained in monitoring and escalation procedures. Training procedures for downtime processes must also be practiced, with safe return to traditional dispensing procedures.

Phase 2: Implementation of AI in shadow mode
The decision support process of AI should start in shadow mode, where the prescription scoring activity is done without an impact on the process. The shadow mode process has two key advantages. Firstly, there is an estimate of alerting budget, which encompasses the number of high-risk warnings per day and their probability of distribution based on various medical categories and other clinics. The second advantage is that it allows for an activity of calibration. The DECIDE-AI guidelines follow a staged evaluation process that includes decision-support technology even before full implementation (Vasey et al., 2022). During shadow mode, it is helpful to monitor these simple dashboard metrics: dashboard metrics: daily alert numbers, risk flags for every 100 prescriptions, and annotated sample study. The dashboard could also record where the model is making incorrect predictions. Frequently, these incorrect predictions paint a picture of missing data points or inefficiencies because of missing workflow elements.

Phase 3: Limited-scope active deployment
Once shadow mode and calibration, limited-scope AI DS, followed. Limited scope might be limited to a set ofclasses of medications (e.g., high-alert medications), a set of clinics, or a set of activities (e.g.,-pill vision QC at the time of product distribution). Limited scope mitiges many risks and makes it simpler to assess. It is at this point where operationalizing governance occurred, where the justifications for overwriting are recorded, along with review of incidents that include signals/robot logs.

Phase 4: Scaling, Standardizing & Optimizing
Scaling up the system for the outpatient offices involves consistency for the following: drug coding schemes, label formats, robot drug stocking strategies, and SOP protocols for review and counseling. This will facilitate inter-site comparisons and improve training. For situations that require inter-site learning for the development of best practices for improvement but where the data may not be shared due to patient confidentiality requirements, privacy-preserving collaboration methods such as federated learning methods may be considered and reviewed as recent systematic review evidence (Teo et al., 2024) recommends. AI alert tuning for scaled-up implementation becomes a continuous process improvement effort because the thresholds for alerts will be set based on the target safety objectives and staff capabilities based on periodic model recalibration.

Phase 5: Patient-centered extensions
After establishing the fundamental dispense loop, there are several areas where AI can aid patient care more directly: patients at risk for nonadherence identification, patients for whom counseling outreach is prioritized, and medication therapy management. These areas should be managed carefully because they involve overall patient context.

XII. MONITORING & DRIFT MANAGEMENT

12.1 Monitoring, Drift, and Operational MLOps in Outpatient Pharmacy
"Operational success is not determined on one evaluation cycle. The operations of an outpatient pharmacy facility involve changing processes with regard to updates in formularies, trends in prescribing practices, new staff members, and changes in documentation practices. This leads to distribution

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shift. A good AI-enabled pharmacy should facilitate monitoring and drift handling." It should be multilayered. 1. Monitoring data quality: identifying missing values, changes in coding, and input distribution irregularities. 2) Model Performance Evaluation: Calibration, alert correctly classified, false-positive fraction, and sampled outcome validation. 3) Workflow monitoring: tracking queues, exception rates, and wait time distributions to verify that the system does not introduce bottlenecks. Since the labels (true errors prevented) are frequently delayed or incomplete, monitoring needs to rely on the use of surrogate indicators. For example, a sudden surge in the rate of overrides for a certain type of alert could be a sign of a lack of correspondence between the AI model and the present reality. For instance, a surge in exceptions for a certain category of drugs could be a sign of a stock configuration issue rather than an issue with AI. To offer more context, risk management best practices, such as the NIST AI Risk Management Framework, highlight documentation, monitoring, and response activities (NIST, 2023). What these best practices are saying, in terms of application, is to identify a trigger mechanism to begin an investigation, along with specifying a safe fallback option. For instance, given a data pipeline failure issue in the AI triage system, they should fall back to rules review.

"Audit trails are also important. Each recommendation provided by AI ought to be recorded using time stamping, context, and follow-through action. This is important with regard to traceability, which has been considered key in the context of health ethics for AI (WHO, 2021). Lastly, transparency in outpatient pharmacy can be achieved without showing patients internal workings of the predictive models but with the capacity to track decisions in a way that allows a practitioner to understand why the recommendation has been provided and to follow through to ensure the system is functioning properly." Finally, monitoring aids in making learning safe. Many businesses would like to optimize models in production. Continuous learning needs to be managed with strict versioning and validation gates. This can be implemented with a "quarterly revalidation loop: test on fresh data, check for drift indicators, and update thresholds if required." Additionally, "shadow mode can be used periodically to evaluate proposed model updates without impacting the current workflow."

XIII. PATIENT OUTCOMES LINKAGE

13.1 Patient Outcomes: Connecting Automation and Artificial Intelligence to Clinical and Experience Outcomes

Direct measurement of the clinical outcomes resulting from outpatient robotic pharmacies is difficult. Adverse events are relatively rare, and many variables can affect the outcome. However, a number of valid mechanisms between automation and patient outcomes are supported by existing literature.

First, there will be fewer dispensing errors and improved quality control, which translates to fewer chances of a patient being given a wrong medicine or a wrong dosage or directions. Although wrong-drug errors may be low, minimizing near misses and discrepancies enhances patient safety and decreases rework. Second, fewer waiting times and improved product availability improve patient satisfaction. If a patient is unable to get his/her medicines on time, he or she may stop treatment due to missed doses. Third, automation may enable the pharmacist to counsel more patients. One of the crucial points that emerged from this literature review is that the value of patient benefit provided by AI is reliant on whether there is resultant pharmacistor or pharmacist actions affected by AI? It is possible that there could be no resultant benefit if an AI system is capable of providing risk factors but does so outside of its workflow path, meaning there is no benefit to patient outcome. The World Health Organization's "Global Patient Safety Action Plan" highlights enhancing systems to minimize avoidable harm (WHO, 2021a). The "outpatient robotic pharmacy" can be considered a system-level intervention with an approach to minimize "process variability" and "traceability." The "AI" can enhance this system by "improving attention allocation" and "QC." The "robotics" and "AI" can work together to enable a "safer" and "patient-centric" "outpatient pharmacy" experience.

11. Implementation Roadmap

11.1 Implementation Roadmap for Hospitals and Large Outpatient Networks

This section translates the outcomes of the systematic review into a deployability plan. The objective is to provide an implementation pathway that organizations can adapt to their respective contexts.

Phase 0: Initial State of Readiness

Establishing baseline measurements of safety, throughput, and patient satisfaction provides criteria for future performance comparison. Recommended baseline measures include: prevented dispensing errors (caught before dispensing), unprevented dispensing errors (made and then discovered), median waiting time, waiting time at the 90th percentile, rate of exceptions, and distribution of pharmacist time on verification and counseling. Data should be collected for both high-volume and low-volume months.

Readiness also requires assessment of data and workflow. For robotic dispensing, standardized drug names, label printing, and physical storage organization aligned with the robot's mechanical design are essential. For AI, readiness includes access to semantically rich logging that records: "the order, the dispensing route (robotic vs. human), alerts produced, whether an alert was responded to, and resolution of an alert." Without such recording capabilities in the Pharmacy Information System, it is not possible to assess the effectiveness of AI alerts or optimize alert policies.

Stage 1: Stabilization of robots and exception handling

Robotics implementations are most effective when exception handling is integrated as a primary workflow. Exceptions may arise from partial fills, substitute brands, controlled substances, compounded products, and prescriptions requiring prescriber contact. Implementations that manage exceptions in an ad-hoc manner are prone to failure. Establishing a standardized exception queue with reason codes and time targets is recommended.

Training and change management are essential for successful implementation. Although robots reduce mechanical tasks, building trust among workers in new processes is necessary. Training should be role-specific: technicians in stock loading and maintenance, pharmacists in verification and exception processing, and managers in monitoring and escalation procedures. Downtime procedures must also be practiced to ensure a safe transition to traditional dispensing when required.

Phase 2: Implementation of AI in shadow mode

The decision The AI decision support process should begin in shadow mode, where prescription scoring occurs without affecting the operational workflow. Shadow mode offers two main benefits: it enables estimation of the alerting budget, including the number and distribution probability of high-risk warnings across medical categories and clinics, and it facilitates calibration activities. The DECIDE-AI guidelines recommend a staged evaluation process that incorporates decision-support technology prior to full implementation (Vasey et al., 2022).In shadow mode, it is helpful to monitor these simple dashboard metrics: daily alert numbers, risk flags for every 100 prescriptions, and annotated sample study. The dashboard could also record where the model is making incorrect predictions. Frequently, these incorrect predictions paint a picture of missing data points or gaps because of missing workflow elements.

Phase 3: Limited-scope active deployment

Once shadow mode and calibration are complete, implementation should proceed with limited-scope AI decision support. This may involve restricting deployment to specific medication classes (such as high-alert medications), selected clinics, or particular activities (such as pill vision quality control during product distribution). Limiting scope reduces risks and simplifies assessment. At this stage, governance should be operationalized by recording justifications for overrides and reviewing incidents, including analysis of signals and robot logs. System for the outpatient offices involves consistency for the following: drug coding schemes, label formats, robot drug stocking strategies, and SOP protocols for review and counseling. This will facilitate inter-site comparisons and improve training. For situations that require inter-site learning to develop best practices for improvement but where data may not be shared due to patient confidentiality requirements, privacy-preserving collaboration methods, such as federated learning, may be considered and reviewed, as recent systematic review evidence (Teo et al., 2024) recommends. AI alert tuning for scaled-up implementation becomes a continuous process improvement effort because alert thresholds are set based on target safety objectives and staff capabilities, and adjusted periodically.

Phase 5: Patient-centered extensions
Once the fundamental dispensing loop is established, AI can additionally aid patient care by identifying patients at risk for nonadherence, prioritizing counseling outreach, and assisting with medication therapy management. These applications call for cautious management due because of their reliance on a comprehensive patient context.

12. Monitoring & Drift Management
12.1 Monitoring, Drift, and Operational MLOps in Outpatient Pharmacy
"Successful operation is not determined on one evaluation cycle. The operations of an outpatient pharmacy facility involve changing processes with regard to updates in formularies, trends in prescribing practices, new staff members, and changes in record-keeping procedures. This leads to a distribution shift. A good AI-enabled pharmacy should facilitate monitoring and drift handling." It should be multilayered. 1. Monitoring data quality: identifying missing values, changes in coding, and input distribution irregularities. 2) Model Functionality Evaluation: Calibration, alert correctly classified, false-positive fraction, and sampled outcome validation. 3) Workflow monitoring: tracking queues, exception rates, and wait duration profiles to verify that the system does not introduce bottlenecks. Since the labels (true errors prevented) are frequently delayed or incomplete, monitoring needs to rely on surrogate indicators. For example, a sudden surge in the rate of overrides for a certain type of alert can represent a mismatch between the AI model and current reality. For instance, a spike in exceptions for a certain category of drugs could be a sign of a stock configuration issue rather than an issue with AI. To offer expanded explanation, risk management best practices, such as the NIST AI Risk Management Framework, highlight documentation, monitoring, and response activities (NIST, 2023). What these best practices are saying, in terms of application, is to identify a trigger mechanism to initiate an investigation and specify a safe fallback option. For instance, if there is a data pipeline failure in the AI triage system, they should fall back to rules-based review.

"Audit trails are also important. Each recommendation provided by AI should be recorded with a timestamp, context, and a subsequent step. This is important for traceability, which has been considered key in the context of health ethics for AI (WHO, 2021). Lastly, transparency in outpatient pharmacy can be achieved without showing patients internal workings of the prediction algorithms, but with the capacity to track decisions in a way that allows a practitioner to understand why the recommendation has been provided and to follow through to ensure the system is functioning properly."

Finally, monitoring helps make learning safe. Many businesses would like to optimize models in production. Sustained learning needs to be managed with strict versioning and validation gates. This can be implemented with a “quarterly revalidation loop: test on fresh data, look for drift indicators, and update thresholds if required.” Additionally, “shadow mode can be used periodically to evaluate proposed model updates without impacting the current workflow.”

13. Patient Outcomes Linkage
13.1 Patient Outcomes: Connecting Automation and Artificial Intelligence to Clinical and Experience Outcomes
Direct measurement of clinical outcomes resulting from outpatient robotic pharmacies is challenging, as adverse events are infrequent and multiple variables determine results. Nevertheless, existing literature supports several valid methods relating automation to better clinical outcomes.

First, automation reduces dispensing errors and boosts quality control, decreasing the likelihood that patients are given incorrect medications, dosages, or instructions. Even when wrong-drug errors are rare, minimizing near misses and discrepancies improves patient safety and reduces rework. Second, shorter waiting times and better product availability increase patient satisfaction, as timely access to medications supports adherence. Third, automation may allow pharmacists to counsel a greater number of patients. A crucial conclusion from the literature review is that the patient benefit provided by AI depends on whether it leads to changes in pharmacist actions. If an AI system identifies risk factors but operates outside the workflow, it may not improve patient health results.

The World Health Organization's "Global Patient Safety Action Plan" emphasizes enhancing approaches to curtail avoidable harm (WHO, 2021a). Outpatient robotic pharmacy represents a system-level intervention aimed at reducing process variability and increasing traceability. AI has the potential to augment this system by improving attention allocation and quality control. Together, robotics and AI can support a safer and more patient-centric outpatient pharmacy experience.

XIV. CONCLUSION

This systematic review demonstrates that the concern with AI in the outpatient robotic pharmacy service domain should not be considered in a conceptual stand-alone form, but rather as a part of a closed-loop system in which robotics, AI, human expertise, and mechanisms all play a definitive role in how safe the system will operate, how effective it will be, etc.

For example, in the period from 2020-2025, the state of the evidence with regard to robotic pharmacy from the literature will demonstrate a strong state with regard to the concerns with regard to robotic machine reliability, throughput, inventory traceability, etc. provided that the concern with the allocation of the scarce resources also demonstrates that AI will play a considerable, incremental value in that decision process, with the human cognitive ability being quite limited in that decision process with regard to issues such as alert prioritization, quality control handoffs, etc.

Finally, an outpatient robotic pharmacy, facilitated by artificial intelligence, is likely to assume its proper place as an augmentive system, a term that refers to a system that supports or augments judgment, not replaces it. While we move forward in this field, more emphasis will likely lie in integration, not algorithms. Integration includes incorporating artificial intelligence outputs into human processes, government by default, and continuous evaluation. Obviously, when all of these elements are properly addressed, artificial intelligence and robotics together promise to drive medication efficiency and safety, along with patient-focused pharmacy practice, in outpatient settings.

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