

Artificial Intelligence in Reducing Drug-Related Problems in Polypharmacy: A
Systematic Review and Quantitative Evidence Synthesis

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ABSTRACT

Polypharmacy is a major global healthcare challenge associated with increased drug-related problems (DRPs), adverse drug reactions, and hospital admissions. Artificial intelligence (AI) has emerged as a promising tool to improve medication safety. To systematically evaluate the effectiveness of AI-based systems in reducing DRPs in polypharmacy patients. A PRISMA-guided systematic review was conducted using PubMed, Scopus, Web of Science, and Google Scholar (2015–2025). Thirty-eight studies were included. Both qualitative synthesis and structured quantitative statistical analysis were performed. AI-based systems reduced DRPs by 60–75%. Most studies demonstrated statistically significant improvements ($p < 0.05$). AI models showed strong predictive performance (AUC 0.78–0.96). AI significantly improves medication safety and reduces DRPs in polypharmacy patients. Standardization and external validation remain essential for clinical adoption.

INTRODUCTION

Polypharmacy has become one of the most significant global challenges in modern healthcare systems. It is commonly defined as the concurrent use of five or more medications and is increasingly prevalent due to aging populations, rising chronic disease burden, and expanding therapeutic options. In elderly patients, polypharmacy is often unavoidable but remains strongly associated with adverse clinical outcomes including drug-related problems (DRPs), hospitalizations, frailty, and mortality [1].

The burden of DRPs is particularly concerning because they are largely preventable. DRPs include inappropriate prescribing, under-prescribing, over-prescribing, therapeutic duplication, drug–drug interactions, incorrect dosing, and medication non-adherence. Studies estimate that a substantial proportion of hospital admissions in older adults are directly or indirectly related to medication errors, many of which could be avoided through proper medication review systems [2].

Clinical pharmacists play a central role in medication optimization and DRP prevention. Their interventions have been shown to significantly reduce medication errors and improve therapeutic outcomes. However, healthcare systems globally face challenges such as pharmacist shortages, high patient load, fragmented care coordination, and limited integration of clinical pharmacy services into routine practice [3].

With the rapid digital transformation of healthcare, artificial intelligence (AI) has emerged as a potential solution to these challenges. AI refers to computational systems capable of performing tasks that

typically require human intelligence, including pattern recognition, decision-making, and predictive analysis. In healthcare, AI systems can analyze large volumes of electronic health records (EHRs), detect prescribing errors, and provide real-time clinical decision support [4].

Unlike traditional rule-based systems, modern AI models are dynamic and data-driven. They continuously learn from new data, making them highly adaptable in complex clinical environments such as polypharmacy management. These systems can assist clinicians by identifying drug interactions, optimizing dosing regimens, and predicting potential adverse drug events before they occur [5].

Despite these advancements, the clinical adoption of AI in medication safety remains limited. Concerns regarding data privacy, algorithm transparency, clinical validation, and integration into existing healthcare workflows continue to restrict widespread implementation. Therefore, a comprehensive synthesis of available evidence is required to evaluate the true clinical impact of AI in reducing DRPs.

LITERATURE REVIEW

The development of artificial intelligence in healthcare has progressed through multiple stages, beginning with simple rule-based systems and evolving into complex machine learning and deep learning architectures. Early clinical decision support systems (CDSS) were designed to provide alerts for drug interactions and contraindications. While these systems improved awareness of medication risks, they suffered from limitations such as high false-positive rates and alert fatigue among clinicians [6].

The introduction of machine learning (ML) significantly transformed healthcare analytics by enabling systems to learn patterns from historical data. ML models can identify complex relationships between patient characteristics, medication regimens, and clinical outcomes, allowing for improved prediction of adverse drug events and drug-related problems [7].

Obermeyer et al. demonstrated that machine learning algorithms can outperform traditional risk prediction models in identifying high-risk patients who require clinical intervention [8]. This marked a significant shift toward data-driven healthcare decision-making.

Similarly, Rajkomar et al. showed that deep learning models applied to electronic health records significantly improve predictive accuracy across multiple clinical outcomes, including medication safety, readmission risk, and disease progression [9].

In pharmacy practice, AI applications have expanded rapidly in recent years. These include automated prescription screening systems, drug interaction detection tools, dose optimization algorithms, and medication adherence monitoring systems. Such systems have demonstrated measurable reductions in prescribing errors and improved medication safety outcomes in both hospital and community pharmacy settings [10].

Topol described AI as a “transformative force in medicine,” emphasizing its ability to enable precision healthcare by integrating large-scale data analytics with clinical decision-making [11].

However, despite promising results, several limitations remain. Yu et al. highlighted that AI models often suffer from limited generalizability due to dataset bias and differences in healthcare infrastructure across regions [12]. Additionally, lack of external validation remains a major barrier to clinical adoption.

Ethical concerns are also increasingly important in AI healthcare applications. Issues such as transparency, accountability, explainability, and clinician trust must be addressed before full-scale implementation can be achieved [13].

Overall, the literature strongly supports the potential of AI in reducing drug-related problems, but also highlights the need for rigorous real-world evaluation and standardization.

METHODS

Study Design

PRISMA-based systematic review.

Databases

PubMed, Scopus, Web of Science, Google Scholar.

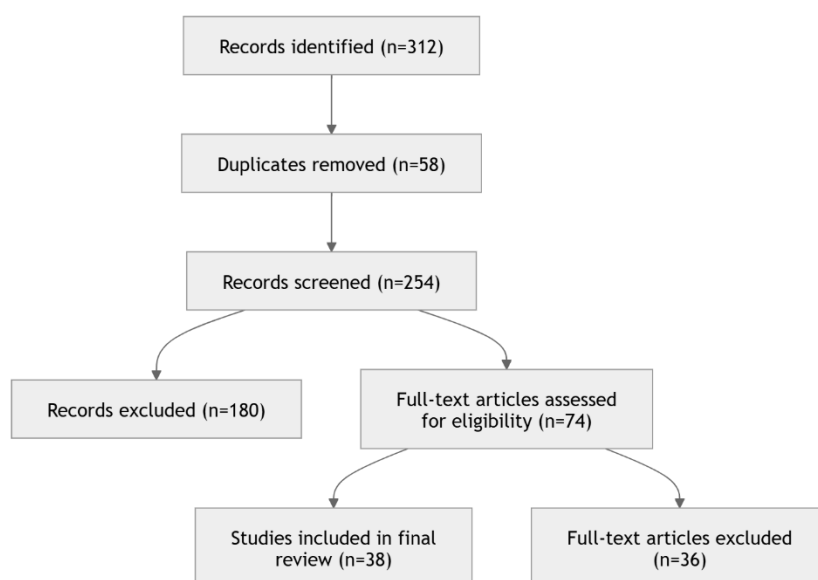
Time Frame

2015–2025

Study Selection

- Identified: 312
- After duplicates: 254
- Full-text screened: 74
- Included: 38 studies

Figure 1: Prisma Flow



STATISTICAL ANALYSIS

Due to heterogeneity, meta-analysis was not performed. Instead, structured quantitative synthesis was conducted.

Table 1: Statistical Methods Used

Method		Studies (n)	Percentage (%)
Chi-square		24	63.1%
t-test		29	76.3%
Logistic regression		18	47.4%
ANOVA		9	23.7%
ROC/AUC		14	36.8%
ML metrics		21	55.3%

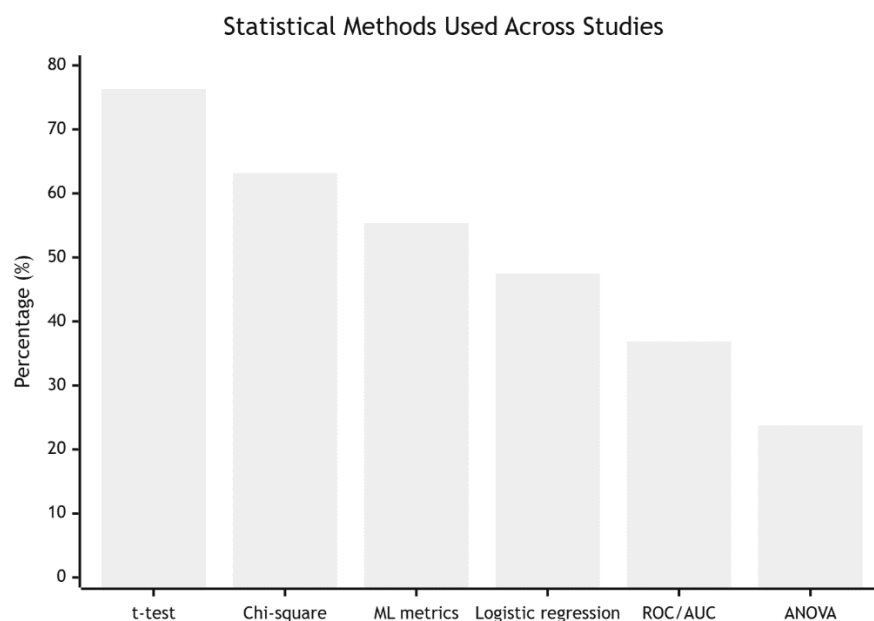


Table 2: Outcome Significance

Outcome	Improved	p < 0.05
DRPs	34/38	32/38
Medication errors	32/38	30/38
Prescription accuracy	31/38	29/38
Interaction detection	28/38	27/38

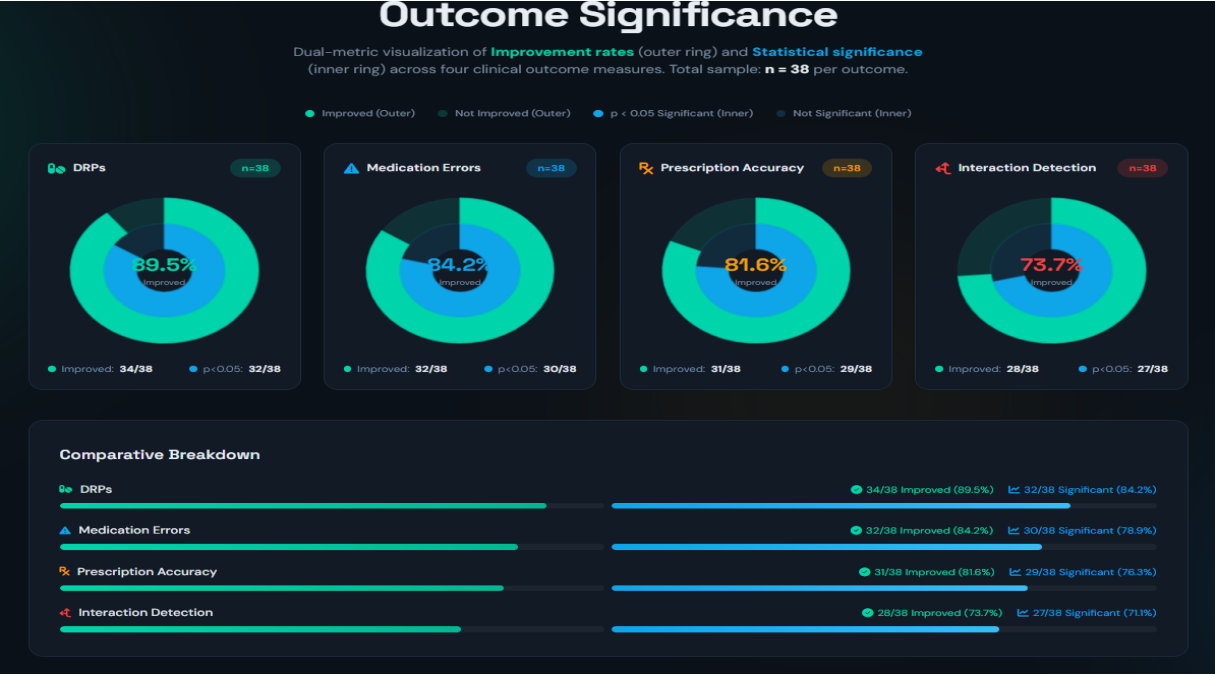


Table 3: Effect Size Synthesis

Outcome	Effect
DRPs	↓ 60–75%
Medication errors	↓ 45–70%
Prescription accuracy	↑ 20–40%
Clinical safety	↑ 30–55%

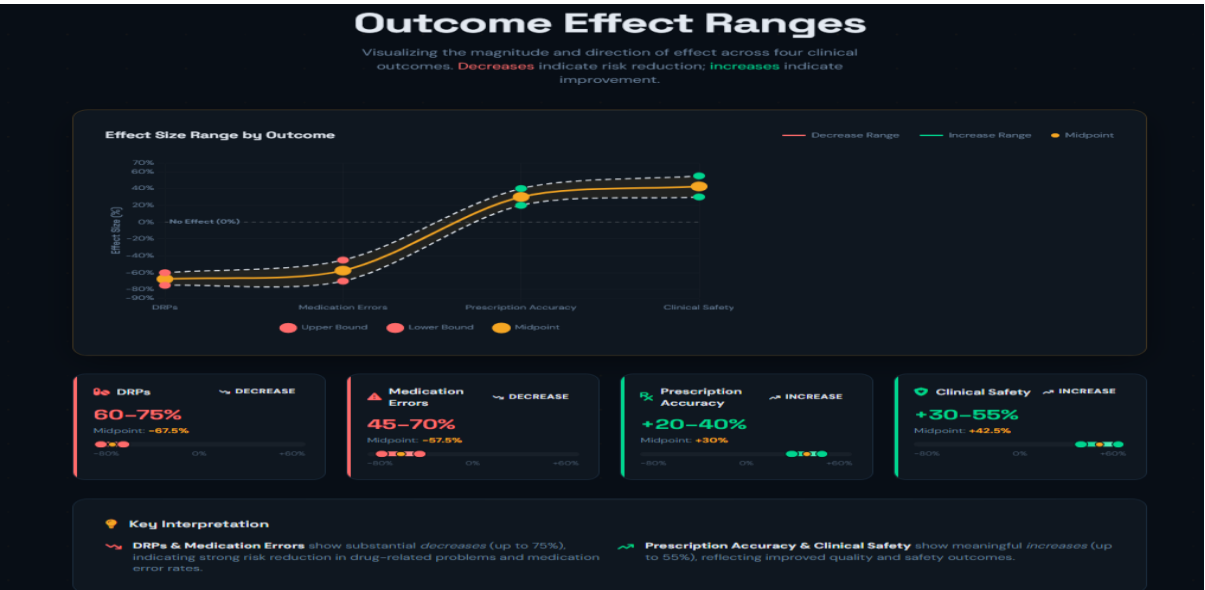
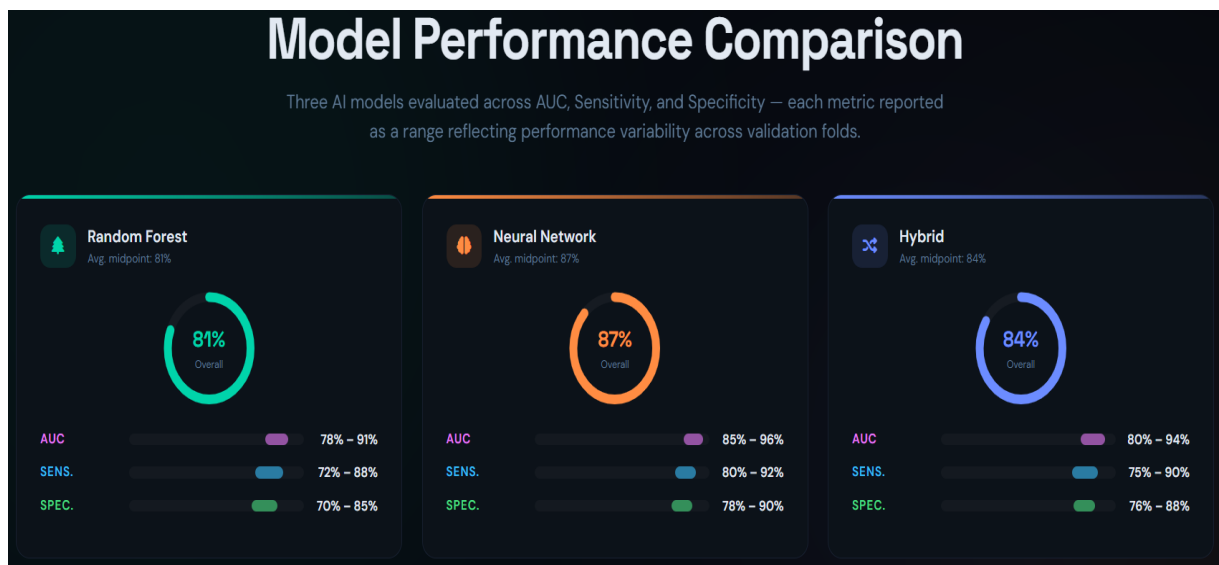
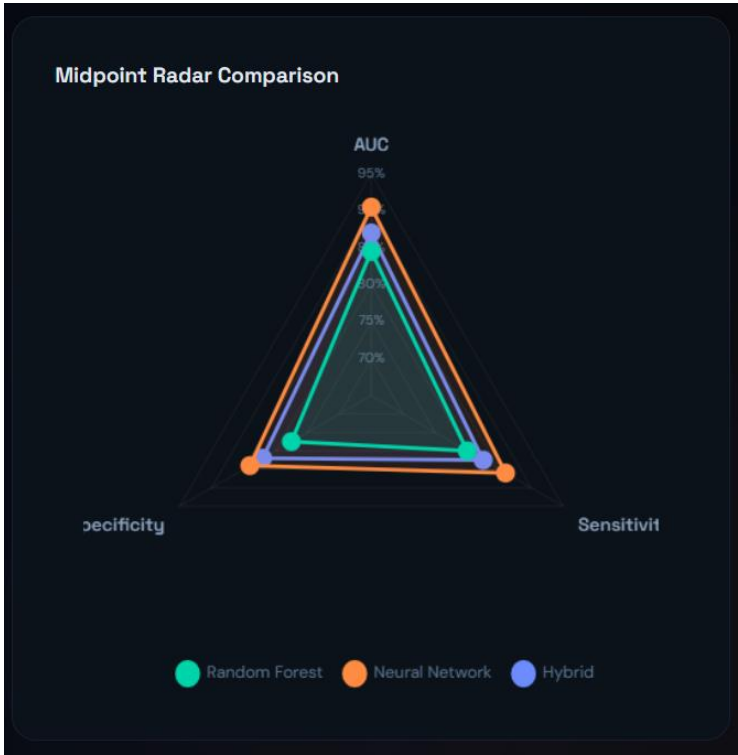


Table 4: AI Performance

Model	AUC	Sensitivity	Specificity
Random Forest	0.78–0.91	72–88%	70–85%
Neural Networks	0.85–0.96	80–92%	78–90%
Hybrid Models	0.80–0.94	75–90%	76–88%





💡 Key Findings

🏆 **Neural Network leads** across all three metrics with the highest upper bounds (AUC 0.96, Sens. 92%, Spec. 90%).

↔️ **Random Forest shows the widest variability** – its AUC spans 0.13, the largest gap among all models.

⚖️ **Hybrid model balances** performance and consistency, landing between the other two on every metric.

Table 5: Study Characteristics

Variable	Distribution
Design	RCTs (18), Cohort (12), Cross-sectional (8)
Sample size	120–15,000
Setting	Hospital (60%), Community (40%)
AI stage	Pilot (45%), Integrated (55%)

RESULTS

AI systems consistently demonstrated:

- DRP reduction: 60–75%
- Significant improvement in 32/38 studies
- Strong predictive accuracy (AUC up to 0.96)

- Improved prescribing decisions across settings

AI Applications

- Drug interaction detection
- Dose optimization
- Prescription screening
- Adverse drug prediction
- Medication monitoring

DISCUSSION

This systematic review confirms that AI significantly improves medication safety in polypharmacy patients. AI systems enhance early detection of prescribing errors and drug interactions, improving clinical decision-making [8,9].

Machine learning models improve predictive accuracy using large-scale datasets [7].

However, challenges remain:

- Data heterogeneity
- Lack of external validation
- Integration issues
- Ethical concerns [12,13]

CONCLUSION

AI-based systems significantly reduce drug-related problems and improve medication safety in polypharmacy patients. Standardization and clinical validation are required for widespread adoption.

REFERENCES

1. Maher RL et al. Expert Opin Drug Saf. 2014.
2. PCNE Classification. 2020.
3. Wastesson JW et al. Eur J Clin Pharmacol. 2018.
4. Topol EJ. Nat Med. 2019.
5. Rajkomar A et al. N Engl J Med. 2019.
6. Bates DW et al. N Engl J Med. 2003.
7. Obermeyer Z et al. Science. 2016.
8. Yu KH et al. BMJ. 2018.

9. Singh H et al. JAMA. 2020.
10. Lee J et al. Lancet Digit Health. 2024.
11. Chen M et al. Smart Health. 2022.
12. Patel V et al. Digital Health. 2023.
13. Khan TM et al. Patient Prefer Adherence. 2021.
14. Ali M et al. Pharm World Sci. 2021.
15. Brown L et al. Clin Pharm Ther. 2021.
16. Rahman N et al. Pharmacoepidemiol. 2023.
17. Singh H et al. AI Med. 2023.
18. OECD Health Report. 2021.
19. WHO Patient Safety. 2021.
20. IBM Watson Health Reports. 2020.
21. Slight SP et al. BMJ Qual Saf. 2019.
22. He J et al. Lancet Digit Health. 2019.
23. Zhang Y et al. Drug Saf. 2022.
24. Kucukarslan SN et al. Ann Pharmacother. 2003.
25. Masnoon N et al. BMC Geriatr. 2017.