

Smart Medication Safety: Real-Time Drug Interaction Alerts via EHR Integration

Rongrong Wang, Jinying Xing, Shengji Jin, Shujun Jiang

Abstract

This paper proposes an AI-powered medication interaction monitoring platform that addresses the growing challenges of polypharmacy through seamless integration with Electronic Health Record (EHR) systems and a patient-facing mobile application. The platform provides real-time, context-aware medication safety alerts to both healthcare providers and patients. By leveraging Fast Healthcare Interoperability Resources (FHIR) standards, advanced natural language processing, and a comprehensive knowledge graph, the system delivers personalized interaction warnings, educational content, and safer alternative suggestions. This integrated approach aims to reduce adverse drug events, improve medication adherence, and enhance health literacy across clinical and home settings. The paper outlines the technical architecture, development methodology, clinical applications, and sustainable business model for implementation.

1. Problem & Background

Polypharmacy, defined as the concurrent use of multiple medications, has become increasingly prevalent among older adults and individuals with chronic or complex health conditions. Recent evidence indicates that nearly 45% of individuals aged 65 and older are prescribed five or more medications, a rate that has steadily increased over the past two decades (Delara et al., 2022; Moriarty et al., 2015). While polypharmacy is often clinically necessary, it significantly raises the risk of drug–drug interactions (DDIs) and drug–food interactions (DFIs), which may alter drug absorption, metabolism, or efficacy (Peng et al., 2021; Koziolk et al., 2019). These pharmacokinetic and pharmacodynamic interactions can lead to treatment failure, increased toxicity, or unexpected adverse drug events (ADEs). Notably, a recent umbrella review found that polypharmacy in older adults is consistently associated with elevated rates of hospitalizations, inappropriate prescribing, and preventable ADEs (Davies et al., 2020).

Despite the seriousness of these risks, many patients lack adequate knowledge about potential interactions between their prescribed medications and common foods or supplements. On the clinical side, existing electronic health record (EHR) systems often provide limited or non-specific interaction alerts, which are typically static, generic, and not tailored to the patient's full context. This can lead to alert fatigue among providers or, worse, overlooked warnings.

Moreover, current systems generally lack intelligent, real-time mechanisms that can dynamically analyze a patient's updated medication list and deliver personalized, timely warnings. There is also a gap in tools that can actively engage patients outside of clinical settings—for example, by notifying them about high-risk interactions or updated guidelines through mobile push notifications or other patient-facing channels.

In this context, there is a clear need for an intelligent platform that:

- Integrates seamlessly with EHR systems to extract and analyze medication records in real time;
- Provides accurate, context-aware interaction warnings to support clinical decision-making and patient self-management;
- Delivers personalized safety alerts and educational messages to patients, thereby enhancing awareness and reducing preventable adverse events.

2. Proposed Solution and Key Features

To address the increasing risks of polypharmacy and the limitations of current systems, we propose an AI-based medication interaction monitoring platform that bridges clinical and home settings through three interconnected components: EHR integration, a patient mobile application, and an intelligent knowledge engine.

2.1 EHR Integration via FHIR Standards

The platform features seamless integration with major Electronic Health Record systems through Fast Healthcare Interoperability Resources (FHIR) standards, enabling real-time clinical decision support. This integration automatically screens for potential drug-drug and drug-food interactions during the prescribing process. When a clinician prescribes a new medication, the system analyzes the patient's current medication regimen, health conditions, and personal factors to identify potential interaction risks. The context-aware alert system considers patient-specific factors such as age, comorbidities, and organ function to minimize alert fatigue while maximizing clinical relevance (Slight et al., 2019). For identified risks, the system provides clear warnings and may suggest safer therapeutic alternatives based on current clinical guidelines.

2.2 Comprehensive Patient Mobile Application

For patients, a comprehensive mobile application serves as their personal medication safety companion outside clinical settings. This user-friendly interface includes medication scanning capabilities to identify potential interactions with current regimens, a customizable food database screening tool that warns about specific dietary considerations, and voice-enabled reminders that improve accessibility for older adults or visually impaired users. Patients receive timely notifications about foods to avoid, potentially dangerous drug combinations, or dosage reminders based on their medication profiles. The application supports multiple languages, initially English and Chinese, with an architecture designed to accommodate additional languages as needed. Through this mobile interface, patients can transition from passive medication recipients to informed self-managers with greater confidence in their medication regimens.

2.3 Knowledge Graph and Intelligence Engine

Powering these interfaces is a sophisticated knowledge graph and intelligence engine containing comprehensive medication-food interaction data built from authoritative sources including DrugBank, FDA databases, and peer-reviewed literature. Natural language processing capabilities translate complex medical warnings into patient-friendly language, while a risk stratification algorithm categorizes interactions by severity and provides appropriate recommendations. The system combines three main functions: interaction risk detection, educational content delivery, and alternative therapy suggestions. Machine learning components continuously improve detection accuracy based on clinical feedback and emerging evidence (Chen et al., 2022).

2.4 Expandable Architecture for Future Integration

The platform's expandable architecture supports future integration with additional data sources such as genomic information for pharmacogenomic-guided therapy, interoperability with wearable health devices to incorporate real-time physiological data, and secure data sharing capabilities with healthcare providers, caregivers, and family members when authorized by patients. This forward-looking design ensures the system can evolve alongside advances in personalized medicine and digital health technology.

3. Clinical Impact & Users

The proposed AI-based platform is designed to improve medication safety and efficiency across the care continuum for three key stakeholder groups: patients, clinicians, and healthcare institutions.

3.1 Patient Benefits

For patients with complex medication regimens, particularly older adults and those with chronic conditions, this platform provides contextual support and timely guidance. Through real-time alerts, dietary advice, and accessible educational content, patients can adhere more effectively to their medication schedules and develop greater understanding of proper administration protocols. The system helps patients avoid potentially dangerous drug-drug or drug-food combinations through clear, timely warnings delivered in user-friendly language. These features collectively reduce the risk of serious medication-related adverse events, including side effects requiring emergency department visits or hospitalization. This approach transforms patients from passive medication consumers to informed participants in their care management.

3.2 Clinician Advantages

Physicians and pharmacists often operate under significant time constraints while attempting to evaluate potential interaction risks during brief clinical encounters. This platform enhances clinical workflow by providing automated interaction screening during the prescription process with immediate alert generation for identified risks. The system suggests evidence-based alternative medications tailored to the patient's specific clinical profile and aligned with current therapeutic guidelines. Furthermore, clinicians can leverage the system's educational content to enhance patient consultations about medication risks and safety precautions. These features support more efficient, safer, and confident clinical decision-making in routine practice.

3.3 Healthcare Institution Value

At the organizational level, hospitals and healthcare systems face challenges including rising costs, patient safety concerns, and digital transformation imperatives. This platform delivers system-level value by reducing preventable medication-related adverse events and subsequent readmissions, thereby improving both financial outcomes and quality metrics. It advances digital health integration by connecting AI-powered tools with existing EHR systems and patient-facing applications through standardized interfaces. The system helps institutions meet regulatory and accreditation requirements related to medication management and safety. Additionally, it optimizes staff time utilization by automating routine interaction checks, allowing clinical teams to focus their expertise on more complex cases requiring human judgment.

4. Technical Plan

The proposed platform comprises three primary interconnected components designed to function as an integrated ecosystem, supported by a comprehensive development and implementation strategy.

4.1 System Architecture

The core knowledge engine forms the foundation of the platform, featuring a medication-food interaction database compiled from multiple validated sources including DrugBank, FDA databases, PubMed, and

SUPP.ai. This component employs a graph database architecture that enables complex relationship modeling between medications, food items, and patient factors. A natural language processing pipeline translates technical pharmacological information into appropriate language for different user types, while a RESTful API layer provides secure, standardized access to interaction data.

The clinical integration module consists of FHIR-compliant integration adapters for major EHR systems such as Epic, Cerner, and Allscripts. This component includes a clinical decision support service that evaluates medication lists against established interaction rules, an alert generation system with configurable severity thresholds to reduce alert fatigue, and comprehensive audit logging and reporting capabilities to track system usage and clinical impact.

The patient-facing mobile application is developed using cross-platform (iOS/Android) technology via React Native to ensure a consistent user experience. This component features a local medication database synchronized with clinical records through secure API connections, camera-based medication identification utilizing optical character recognition technology, a push notification system for timely interaction alerts and medication reminders, and encrypted local storage of sensitive health information.

4.2 Development Methodology

The development approach follows an agile methodology spanning 18 months from initial research to pilot deployment. The first three months focus on knowledge graph schema development, user interface prototyping, technical architecture finalization, and regulatory framework assessment. Core development occupies months 4-9, encompassing knowledge base construction, backend services implementation, EHR integration, and mobile application development.

Months 10-12 are dedicated to comprehensive testing, including laboratory validation with synthetic data, controlled clinical environment testing, performance optimization, and security penetration testing. The final six months involve limited rollout in partner healthcare institutions, user feedback collection, performance monitoring, and feature refinement based on real-world usage patterns.

4.3 Implementation Requirements

This implementation requires a multidisciplinary team including full-stack developers, machine learning engineers, and medical informatics specialists, supported by clinical subject matter experts including pharmacists, physicians, and nutritionists. Infrastructure needs encompass cloud hosting, database services, and development environments, while external partnerships with EHR vendors, pharmaceutical database providers, and healthcare institutions will be critical for successful deployment and validation.

5. Business Model

Our business model emphasizes multi-stakeholder value creation, balancing social impact with long-term financial sustainability.

Social Business Model Canvas: Medication Interaction Monitoring Platform

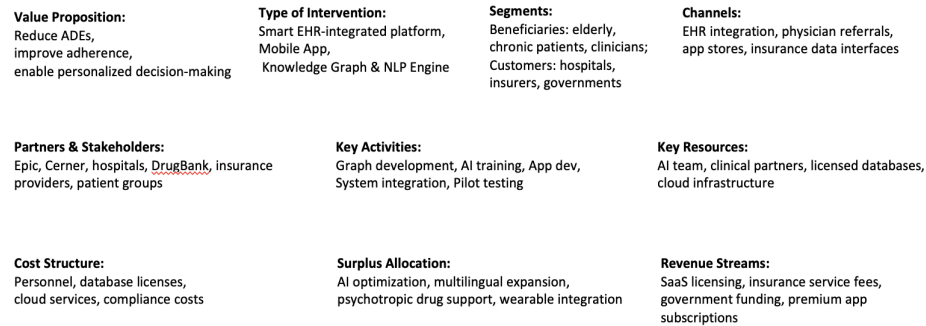


Figure. Social Business Model

5.1 Value Proposition

The platform creates social value through reduction in adverse drug events by proactively identifying potential drug-drug and drug-food interactions, improved medication adherence and health literacy by empowering patients through accessible educational content, and support for precision medicine through context-aware clinical decision-making. For customers, hospitals and clinics benefit from reduced preventable readmissions and improved patient satisfaction metrics. Healthcare providers save clinical time and cognitive load through immediate, context-specific alerts at the point of care. Patients receive clear, timely, and personalized instructions to support independent, informed medication use.

5.2 Market Segments and Distribution

Primary beneficiaries include older adults subject to polypharmacy, patients with chronic conditions, and healthcare professionals seeking intelligent support tools. Key customer segments comprise medical institutions responsible for prescribing and pharmacovigilance, health insurance providers managing pharmaceutical expenditures, and government agencies aiming to improve medication safety outcomes.

Distribution channels include healthcare systems integration via FHIR-compliant APIs with leading EHR systems, patient access through app marketplaces and point-of-care physician recommendations, insurance and risk management partner integration, and initial adoption via pilot hospitals and healthcare networks.

5.3 Key Partners and Resources

Essential partnerships include EHR system vendors and interoperability solution providers, hospitals and clinical trial networks, drug interaction database licensors, health insurance companies, and patient advocacy groups. The platform requires a cross-functional AI and software development team with expertise in medical informatics, clinical partners providing access to real-world prescribing data, licensed access to drug safety databases, and secure cloud infrastructure for deployment.

5.4 Financial Sustainability

Revenue streams include licensing fees and SaaS subscriptions paid by healthcare institutions, risk mitigation service fees from insurance providers, government grants for medication safety initiatives, and premium mobile app subscriptions for advanced features. The cost structure encompasses personnel-related expenses, database licensing fees, system hosting and maintenance, and regulatory compliance activities. As a mission-driven social enterprise, surplus will be reinvested into ongoing AI model optimization, expanded application to additional drug categories, and integration with wearable devices for personalized monitoring.

6. Implementation and Feasibility Statement

The software is available in two different versions mainly for doctors and patients, and they will be significantly different in terms of front-end UI and functionality.

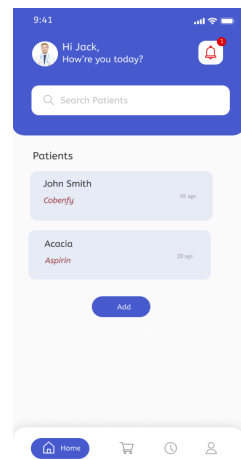


Figure. Clinicians' UI

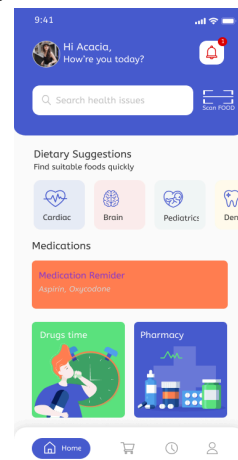


Figure. Patients' UI

This system implements a barcode-based scanning feature designed to assist patients in identifying basic information about common food and drug items, particularly those currently in use. The primary objective is to enhance patient safety and autonomy by enabling real-time detection of potential interactions between scanned items and the patient's existing medications.

The system includes a built-in risk detection and alert mechanism. If a scanned food or drug item poses a serious interaction risk with the patient's current medications, the system issues a high-risk warning and provides appropriate alternative recommendations. Additionally, if an item has been blacklisted by a healthcare provider, the system advises the patient to use it with caution. The user interface allows patients to view their scan history and access detailed interaction descriptions. For example, grapefruit juice, which can significantly increase simvastatin levels in the body, is flagged as high risk, with orange juice suggested as a safer alternative. This feature demonstrates both feasibility and practical value in supporting informed decision-making in daily patient care.

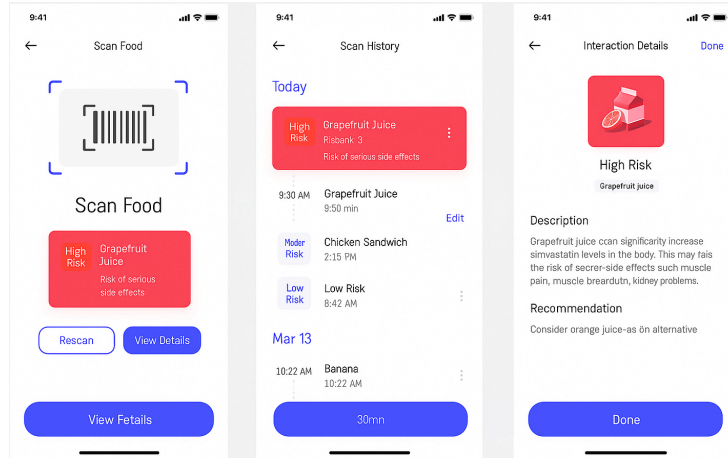


Figure. Scanning Function Demonstration

In addition, the drug management system has features for physician notification and intervention mechanisms. When a potential interaction risk is detected (e.g., between a prescription drug and a food), the system automatically notifies the physician. This allows the healthcare provider to assess the severity of the interaction and determine if medical intervention or prescription adjustments are needed.

For example, if a patient is prescribed oxycodone and also consumes broccoli, the system detects that broccoli may reduce the drug's efficacy. It issues a high-risk warning, displays the interaction details, and provides alternative recommendations (e.g., suggesting green beans as a substitute). The interface supports timely alerts, personalized drug schedules, and clear risk visualization, enabling both patients and doctors to make informed decisions in a safe and efficient manner. This feature demonstrates practical feasibility for integration into clinical workflows, enhancing patient safety through proactive risk management.

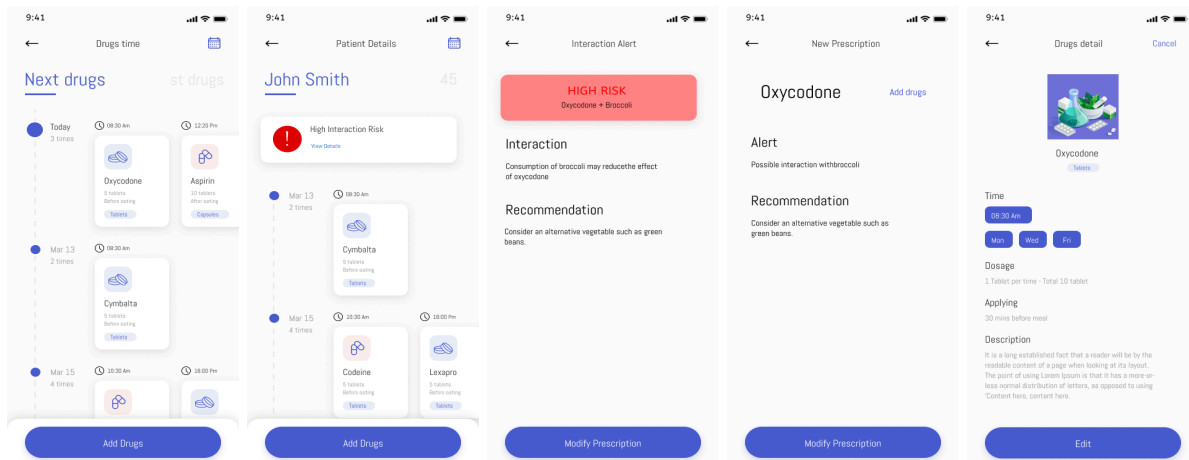


Figure. Drug-Food Interaction Alert and Physician Notification Process

The below figure illustrates a proposed knowledge graph developed using Neo4j, designed to support personalized food-drug interaction management. Each node represents a specific biomedical entity, such as drugs, food items, conditions, genetic factors, lab tests, prescriptions, and physician advice. The relationships (edges) capture clinically relevant interactions including drug-gene associations, prescription details, dietary guidance, and lab test outcomes.

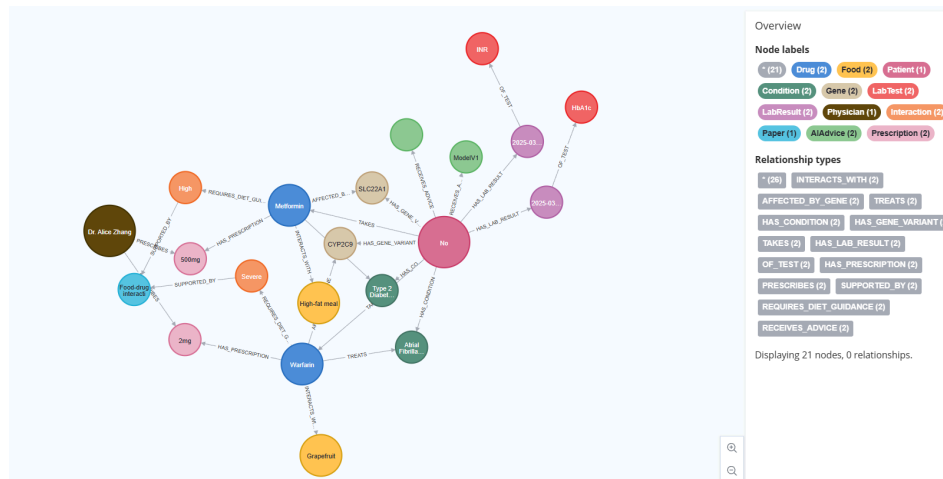


Figure. Neo4j Drug Interaction Graph Database

This semantic structure enables the system to reason over complex relationships—for instance, how metformin's effect is influenced by gene *SLC22A1*, or how warfarin interacts with grapefruit or high-fat meals. The graph also captures dosage-specific interactions and contextual factors such as severity and dietary requirements. On the right, node labels summarize the ontology design, covering 21 node types and multiple relationship types. This knowledge graph framework forms the backbone of AI-powered clinical decision support, enabling explainable, patient-specific recommendations.

For example, by querying the Neo4j-based knowledge graph, we can retrieve patient-specific drug-gene-lab interactions and corresponding clinical recommendations. In the left query, for a given patient (e.g., patient ID "P1001"), the system identifies drugs taken, their associated gene variants (such as *CYP2C9* or *SLC22A1*), relevant lab tests (e.g., INR, HbA1c), and AI-generated advice (e.g., "Consider lowering dose due to *CYP2C9* variant"). This allows for individualized monitoring and optimization of drug therapy based on genetic and laboratory data.

```
MATCH (p:Patient
{patient_id:"P1001"})-[:TAKES]->(d:Drug)-[:AFFECTED_BY_GENE]->(g:Gene),
(p)-[:HAS_GENE_VARIANT]->(g),
(p)-[:HAS_LAB_RESULT]->(lr)-[:OF_TEST]->(t:LabTest),
(p)-[:RECEIVES_ADVICE]->(advice:AIAdvice)
RETURN d.name AS Drug, g.name AS Gene, t.name AS LabTest, lr.value AS
LabValue, advice.text AS Advice
```

Drug	Gene	LabTest	LabValue	Advice
Warfarin	CYP2C9	HbA1c	8.2	Avoid high-fat meals with Metformin
Warfarin	CYP2C9	HbA1c	8.2	Consider lowering dose due to CYP2C9 variant
Metformin	SLC22A1	HbA1c	8.2	Avoid high-fat meals with Metformin
Metformin	SLC22A1	HbA1c	8.2	Consider lowering dose due to CYP2C9 variant
Warfarin	CYP2C9	INR	3.4	Avoid high-fat meals with Metformin
Warfarin	CYP2C9	INR	3.4	Consider lowering dose due to CYP2C9 variant

```
MATCH
(doc:Physician)-[:PRESCRIBES]->(rx:Prescription)-[:HAS_PRESCRIPT
ION]->(d:Drug)-[:INTERACTS_WITH]->(f:Food),
(d)-[:REQUIRES_DIET_GUIDANCE]->(i:Interaction)-[:SUPPORTED_BY
]->(paper:Paper)
RETURN doc.name AS Doctor, d.name AS Drug, f.name AS Food,
i.advice AS Recommendation, paper.title AS Reference
```

Doctor	Drug	Food	Recommendation	Reference
Dr. Alice Zhang	Metformin	High-fat meal	Take before meal	Food-drug interaction of grapefruit with Warfarin
Dr. Alice Zhang	Warfarin	Grapefruit	Avoid grapefruit with Warfarin	Food-drug interaction of grapefruit with Warfarin

Figure. Examples of Using Graph Database

In the right panel, another query enables physicians to explore food-drug interactions based on prescribed medications. For instance, when Warfarin is prescribed, the system suggests avoiding grapefruit or taking the drug before meals if a high-fat meal is involved, along with supporting references

from scientific literature. These examples illustrate how the graph structure enables precise and explainable decision support across multiple clinical dimensions.

7. Limitation and Future Direction

Despite the promising design of our AI-powered medication interaction platform, several limitations remain. First, the platform relies heavily on the accuracy and completeness of EHR data, which may vary across institutions due to differences in documentation practices and data standardization. Incomplete medication histories or missing genomic and dietary information could reduce the precision of context-aware alerts. Furthermore, while the integration of machine learning and knowledge graphs enhances personalization, model performance is contingent upon the quality and diversity of training data; limited exposure to rare drug interactions may affect predictive accuracy. Lastly, user engagement, especially on the patient side, remains a potential barrier—elderly users or those with low digital literacy may not fully utilize mobile features without sufficient onboarding and support.

To address these limitations, future work will prioritize expanding the platform's interoperability with diverse EHR systems using standardized protocols such as HL7 FHIR, and incorporating real-world patient data through broader clinical collaborations. Additional features like wearable device integration and pharmacogenomic data inclusion can enhance personalized risk detection. Moreover, adaptive user interfaces and voice-enabled features tailored for older adults or non-native speakers will be refined to increase accessibility and patient engagement. On the clinical side, continuous model training using federated learning techniques may help mitigate data privacy concerns while improving algorithm generalizability. A pilot deployment with longitudinal monitoring will also be necessary to evaluate the platform's long-term clinical effectiveness and cost impact.

8. Conclusion

This project presents a novel AI-driven medication safety platform that addresses critical gaps in current drug interaction monitoring systems. By integrating real-time alerts with EHR data, leveraging knowledge graphs, and incorporating patient-centric mobile technologies, the solution enhances both clinical decision-making and patient self-management. It not only improves the detection of drug–drug and drug–food interactions, but also promotes proactive engagement through personalized, context-aware notifications. With its scalable architecture and cross-platform design, the system holds significant potential to reduce adverse drug events, improve treatment adherence, and contribute to the broader goals of precision medicine and digital health transformation. Continued development and clinical validation will be key to realizing its full impact across diverse healthcare settings.

References:

1. Chen, Y., Zhang, L., & Huang, J. (2022). Machine learning approaches for drug-drug interaction prediction: A review of current status and future prospects. *Briefings in Bioinformatics*, 23(1), bbab301. <https://doi.org/10.1093/bib/bbab301>
2. Slight, S. P., Beeler, P. E., Seger, D. L., Amato, M. G., Her, Q. L., Swerdloff, M., Dalleur, O., Nanji, K. C., Cho, I., Maniam, N., Eguale, T., Fiskio, J. M., Dykes, P. C., & Bates, D. W. (2019). A cross-sectional observational study of high override rates of drug allergy alerts in inpatient and outpatient settings, and opportunities for improvement. *BMJ Quality & Safety*, 28(3), 217-225. <https://doi.org/10.1136/bmjqs-2018-008306>
3. Davies, L. E., Spiers, G., Kingston, A., Todd, A., Hanratty, B., & Robinson, L. (2020). Adverse outcomes of polypharmacy in older people: systematic review of reviews. *Journal of the American Medical Directors Association*, 21(2), 181–187.e6. <https://pubmed.ncbi.nlm.nih.gov/31926797/>

4. Delara, M., Murray, L., Jafari, M., & Woodman, R. J. (2022). Prevalence and factors associated with polypharmacy: a systematic review and meta-analysis. *BMC Geriatrics*, <https://pubmed.ncbi.nlm.nih.gov/35854209/>
5. Moriarty, F., Hardy, C., Bennett, K., Smith, S. M., & Fahey, T. (2015). Trends and interaction of polypharmacy and potentially inappropriate prescribing in primary care over 15 years in Ireland: A repeated cross-sectional study. *BMJ Open*, 5(9), e008656. <https://bmjopen.bmj.com/content/5/9/e008656>
6. Peng, L., He, Z., & Chen, W. (2021). Mechanisms and risk factors of drug–drug interactions: A pharmacokinetic perspective. *Pharmacological Research*, 170, 105694. <https://pmc.ncbi.nlm.nih.gov/articles/PMC7912632/>
7. Koziolk, M., Grimm, M., Becker, D., Iordanov, V., Zou, H., Shimizu, J., & Weitschies, W. (2019). Investigation of pH and motility in the gastrointestinal tract of fasted human subjects using telemetric capsules. *European Journal of Pharmaceutical Sciences*, 134, 31–59. <https://pubmed.ncbi.nlm.nih.gov/25411065/>
8. Schmidt, L. E., & Dalhoff, K. (2002). Food-drug interactions. *Drugs*, 62, 1481-1502.
9. Bushra, R., Aslam, N., & Khan, A. Y. (2011). Food-drug interactions. *Oman medical journal*, 26(2), 77.
10. Wang, L. L., Tafjord, O., Cohan, A., Jain, S., Skjonsberg, S., Schoenick, C., ... & Ammar, W. (2019). SUPP. AI: finding evidence for supplement-drug interactions. *arXiv preprint arXiv:1909.08135*.
11. Schäfer, J., Tang, M., Luu, D., Bergmann, A. K., & Wiese, L. (2022). Graph4Med: a web application and a graph database for visualizing and analyzing medical databases. *BMC bioinformatics*, 23(1), 537.