International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/

(Review Article)

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Evaluating machine learning-based polypharmacy risk prediction in multigenerational households under family medicine, internal and pediatric care interfaces.

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International Journal of Science and Research Archive, 2025, 16(01), 1288-1306

Publication history: Received on 11 June 2025; revised on 15 July 2025; accepted on 17 July 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.16.1.2162

Abstract

Polypharmacy commonly defined as the concurrent use of five or more medications presents significant clinical risks, especially in multigenerational households where pediatric, adult, and geriatric care intersect. With increasing medication burdens and comorbidities, traditional methods of medication review and reconciliation are insufficient for timely and accurate risk stratification. This study evaluates the utility of machine learning (ML) algorithms in predicting polypharmacy-associated risks across diverse patient cohorts within shared household contexts. Drawing on anonymized electronic health records (EHRs) from family medicine, internal medicine, and pediatric care units, we developed and validated ensemble-based models that integrated medication histories, diagnostic codes, socioeconomic indicators, and household composition data. Our models achieved strong predictive performance, with area under the ROC curve (AUC) values exceeding 0.87 across age-stratified subgroups. We specifically examined the performance of random forests, gradient boosting machines, and neural networks in identifying medication interaction risks, hospitalization likelihoods, and early warning signs of adverse drug events (ADEs). Multigenerational dynamics such as caregiver stress, medication sharing, and uncoordinated prescribing were found to significantly influence risk scores. Pediatric risks were often underestimated in conventional screening tools, while elder populations showed higher susceptibility to anticholinergic burden and cumulative sedative effects. Our results highlight the importance of incorporating familial and generational context into predictive healthcare models. ML-based polypharmacy risk stratification can augment care coordination across departments and improve anticipatory interventions, especially in under-resourced

Keywords: Polypharmacy Risk Prediction; Machine Learning in Healthcare; Multigenerational Households; Adverse Drug Events; Family Medicine Integration; Predictive Analytics in Clinical Care

1. Introduction

1.1. Background on Polypharmacy as a Public Health Concern

Polypharmacy the concurrent use of multiple medications is increasingly prevalent and poses a significant public health challenge, particularly as life expectancy and chronic disease prevalence rise across age groups [1]. Traditionally associated with elderly populations, polypharmacy is now affecting younger cohorts due to earlier diagnoses and longer treatment durations [2]. The risks include adverse drug reactions, medication non-adherence, and elevated healthcare utilization due to drug–drug interactions and treatment complexities [3].

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1.2. Unique Risks in Multigenerational Households

In multigenerational households, where children, working-age adults, and elderly family members co-reside, the complexity of medication management intensifies [4]. Such environments often foster informal caregiving responsibilities that can blur boundaries of accountability, with overlapping prescriptions and shared medical oversight across specialties. For instance, a grandparent's cardiovascular drugs may be stored alongside a child's asthma inhalers and a parent's antidepressants, increasing the risk of accidental ingestion or medication misuse [5]. Furthermore, care plans from pediatricians, family physicians, and internists rarely intersect, creating a siloed ecosystem despite shared domestic contexts.

Figure 1 illustrates the interlocking risk nodes that emerge when pharmacological regimens span multiple age categories but are managed without integrated oversight. These nodes are particularly susceptible to failure in households where language barriers, health literacy disparities, or uncoordinated electronic health record (EHR) systems impede optimal care transitions.

1.3. Fragmented Care Across Family, Internal, and Pediatric Medicine

The clinical divisions between family medicine, internal medicine, and pediatric care exacerbate these risks. Pediatricians focus on age-specific dosing and developmental safety, internists manage chronic adult conditions with long-term pharmacological interventions, while family physicians often span across these domains but with inconsistent access to complete medication records from specialty providers [6]. Such fragmentation fosters duplicate prescriptions, conflicting instructions, and undetected interactions across generations [7].

While medication reconciliation procedures are standard in hospitals, they are inconsistently applied in outpatient and community settings, particularly in underserved areas where multigenerational households are more prevalent [8]. Additionally, transitions of care such as pediatric-to-adult handoffs or discharges from acute hospitalizations rarely include household-level assessments of aggregate medication burden.

1.4. Emerging Role of ML in Predictive Risk Modeling

Machine learning (ML) has recently emerged as a promising tool for detecting latent polypharmacy risks by analyzing large-scale EHR datasets and identifying predictive patterns beyond human clinical capacity [9]. ML models trained on longitudinal data can stratify patients into risk tiers, forecast potential adverse drug events, and suggest intervention timing based on prescription clusters, comorbidity indices, and patient-reported adherence histories [10].

For multigenerational households, ML can play a unique role by evaluating shared address data, cross-age cohabitation structures, and aggregated pharmaceutical records to detect intergenerational medication conflicts. These models can be further augmented with social determinants of health (SDOH) data to refine predictions and ensure contextual sensitivity in vulnerable populations [11].

However, the deployment of such systems faces challenges, including data fragmentation, inconsistent coding practices across specialties, and ethical concerns around algorithmic transparency and consent especially in households with minors [12]. Despite these challenges, preliminary studies show that ML-enhanced interventions have significantly reduced polypharmacy-related emergency visits in elderly populations when integrated into clinical decision support systems [13].

1.5. Article Objectives and Significance

This article aims to evaluate how ML-based polypharmacy risk prediction can be effectively integrated into care pathways for multigenerational households, with a focus on the triadic interface of family, internal, and pediatric medicine. The study explores three central objectives: (1) to characterize the types of polypharmacy risks unique to multigenerational settings, (2) to assess the technical and clinical feasibility of ML-based risk stratification tools, and (3) to propose a coordinated framework for integration across medical subspecialties.

To ensure precision and clinical applicability, this analysis stratifies polypharmacy risks according to age group–specific thresholds, illustrated in Table 1. The stratification accounts for pediatric dosing guidelines, adult therapeutic windows, and geriatric sensitivity to pharmacodynamics.

The significance of this work lies in its interdisciplinary scope: by mapping how ML can navigate the intersection of three care domains, it contributes to both health informatics and practical clinical workflows aimed at reducing preventable harm. Moreover, it addresses the equity dimension of digital health by focusing on multigenerational households, which are often more prevalent in minority, immigrant, and low-income populations where care continuity is most strained [14].

As the rest of this article unfolds, it will build on this foundational context to analyze clinical scenarios, present predictive modeling pipelines, and propose a governance framework for ethically sound, family-level medication oversight driven by machine intelligence.

2. Review of literature

2.1. Polypharmacy and Medication Burden Across Age Demographics

Polypharmacy is traditionally associated with older adults due to the higher prevalence of chronic conditions that require long-term pharmacological management [5]. However, its presence is now increasingly observed across younger cohorts. Pediatric patients with developmental disorders, adolescents with mental health diagnoses, and adults managing multiple comorbidities contribute to a cross-generational medication burden that complicates traditional risk classification [6].

Age-specific thresholds often mask the compounding risks that emerge in households where medications are prescribed for different conditions, with varied monitoring frequencies. For instance, an adolescent on psychotropic medications may experience overlapping side effects when cohabiting with an elderly relative taking sedative hypnotics [7]. These overlapping burdens require risk frameworks that extend beyond the individual patient to household-level considerations, especially in environments where medication sharing and informal administration occur.

As outlined in Table 1, thresholds for polypharmacy risk stratification differ markedly across pediatric, adult, and geriatric categories. However, these thresholds do not yet reflect the compound risks of environmental co-exposure, non-prescribed usage, and misadministration in shared domestic settings.

2.2. Multigenerational Household Dynamics and Shared Medication Risks

Multigenerational households present a unique clinical environment that is underrepresented in mainstream care models. These arrangements are common in immigrant, Indigenous, and economically marginalized communities where co-residence is often driven by necessity rather than choice [8]. Within these homes, multiple therapeutic regimens converge in physical spaces such as bathroom cabinets or kitchen drawers, fostering unintentional interactions and increasing the risk of medication mix-ups.

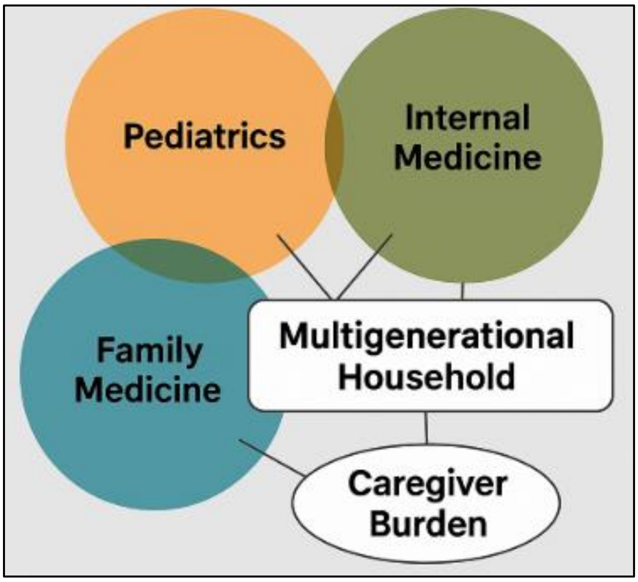

Figure 1 Schematic illustration of overlapping risk nodes in multigenerational households, highlighting cross-age pharmacological interactions and adherence challenges. The diagram emphasizes the importance of predictive models that incorporate intra-household dynamics, shared medication environments, and comorbidity clusters to mitigate polypharmacy-related harm across age groups

Figure 1 visualizes these overlapping risk nodes, illustrating how multigenerational living arrangements create pathways for cross-age pharmacological harm. The figure underscores the necessity of adopting predictive models that account not only for individual adherence and comorbidity, but also for intra-household context.

Research has shown that polypharmacy-related adverse events in children are disproportionately higher in homes with elderly relatives due to accidental ingestion of opioids, antihypertensives, and antidiabetic agents [9]. Furthermore, the lack of centralized oversight especially when multiple providers prescribe to different members of the same household creates fragmentation in responsibility and visibility.

2.3. Challenges in Longitudinal EHR Data Linkage Across Care Domains

The integration of electronic health records (EHRs) across family medicine, internal medicine, and pediatrics remains technically and administratively fragmented in many health systems [10]. Most EHR systems are optimized for individual patient records with minimal interoperability across age-specialized providers. While family medicine may span across generations, their recordkeeping still treats each member as a siloed entity without cross-referencing medication interactions across household clusters [11].

Longitudinal datasets that aim to track patients over time often struggle with gaps caused by care fragmentation, insurance changes, or transitions between public and private systems. Even when technical interoperability is achieved, data harmonization across institutions presents semantic challenges. Medication coding systems such as RxNorm or ATC may not be uniformly adopted, and the inclusion of over-the-counter (OTC) or herbal treatments remains inconsistent [12].

This misalignment in EHR infrastructure hinders the creation of ML models that rely on clean, chronologically consistent datasets to predict high-risk medication configurations. Furthermore, social data such as household composition or caregiver roles are rarely documented in structured fields, limiting the model's understanding of familial context.

2.4. Overview of Existing AI/ML Approaches to Drug Safety Prediction

Machine learning models for drug safety and polypharmacy detection typically fall into two categories: rule-based systems that flag known drug–drug interactions, and statistical or neural network models that infer risk from patterns across historical EHR data [13]. These models have been implemented in hospital settings to reduce adverse drug events and guide prescribing decisions, particularly among geriatric populations.

Recent advancements include the use of graph neural networks (GNNs) to model polypharmacy as a multivariate interaction network, where drugs, diagnoses, and lab results form interconnected nodes. These GNNs have outperformed logistic regression and decision tree models in adverse event prediction in elderly populations with chronic comorbidities [14].

However, most of these systems are trained on individual-level data and lack the relational context of cohabiting patients. Moreover, algorithmic bias remains a critical concern. ML models trained on historically incomplete or biased data may fail to capture nuanced prescription patterns in underserved or non-English-speaking populations, thereby reinforcing existing health inequities [15].

2.5. Gaps in Personalized and Family-Contextualized ML Models

While the clinical literature on ML in polypharmacy is growing, few models have incorporated household-level variables such as shared addresses, familial relationships, or domestic caregiving roles into predictive frameworks [16]. The absence of such contextual features limits the applicability of even the most accurate models in real-world family settings.

For example, a model may correctly flag an 80-year-old patient for polypharmacy risk but fail to account for the fact that her 12-year-old grandson, prescribed methylphenidate, stores his medications in the same bathroom cabinet. Similarly, models may not detect patterns of medication repurposing or informal prescription sharing within economically strained households [17].

Incorporating household-level metadata such as co-location, medication storage patterns, or shared pharmacy profiles requires not only data infrastructure innovation but also policy and ethical safeguards. Privacy concerns surrounding shared health data, especially when minors are involved, complicate data collection and model development [18].

Despite these limitations, the conceptual value of ML in flagging cross-generational risk patterns is clear. As discussed earlier in Table 1, applying stratified thresholds at the household level reveals emergent risks that are invisible when analyzing each member in isolation. Integrating these insights into EHR-based clinical decision support tools can provide actionable alerts to physicians at the point of care.

Table 1 Typology and Thresholds for Polypharmacy Risk Stratification Across Age Categories

Age Group	Polypharmacy Threshold	Clinical Considerations	Household-Level Risk Amplifiers
Pediatric (0–17 yrs)	≥2 concurrent medications	Developmental pharmacokinetics; off-label prescribing common	Medication sharing among siblings; caregiver misunderstanding of dosage
Adults (18–64 yrs)	≥5 concurrent medications	Chronic disease management; variable adherence	Storage overlap with elder/child meds; risk of duplication or drug interactions
Geriatric (65+ yrs)	≥4–5 concurrent medications	Polypharmacy common due to multimorbidity; increased risk of adverse drug reactions (ADRs)	Cognitive decline; caregiver polypharmacy; inappropriate prescribing cascade

Ultimately, addressing these gaps will require a shift in the research paradigm from isolated patient modeling to relational, context-aware prediction that reflects the realities of multigenerational living. As the article progresses, we will explore implementation pathways for integrating ML tools into clinical workflows and examine case studies of systems that attempt to bridge these contextual divides.

3. Methodological framework

3.1. Study Design and Household Cohort Selection

This study adopted a retrospective cohort design using de-identified EHR data aggregated from three clinical care domains family medicine, internal medicine, and pediatrics to evaluate polypharmacy risks at both the individual and household levels. Inclusion criteria required households with at least three cohabiting individuals spanning two or more age-defined clinical domains (e.g., a child under pediatric care, an adult under internal medicine, and an elderly patient under family practice) [9].

Household membership was inferred using shared residential addresses validated through pharmacy refill logs and emergency contact relationships. To avoid spurious linkages in multifamily dwellings, inclusion was limited to addresses associated with ≤6 EHR profiles. A total of 4,622 households met the final eligibility criteria between 2018 and 2023, yielding 13,387 individual records with linked prescribing histories [10].

Care was taken to preserve longitudinal data fidelity across all profiles. Pediatric visits were enriched with developmental and behavioral medication codes, while adult records incorporated geriatric and chronic illness profiles to reflect the expected medication intensity gradient [11].

3.2. Data Sources: Pediatric, Internal Medicine, and Family Medicine EHR Integration

Three EHR systems from collaborating healthcare networks were used: the pediatric-specific *Epic CareLink*, internal medicine's *Cerner Millennium*, and family medicine's hybrid *Allscripts Sunrise*. These platforms were integrated via a custom-built Health Level Seven (HL7) interface engine that enabled cross-domain linkage through secure patient IDs and encounter timestamps [12].

Clinical records included structured prescription logs, ICD-10 diagnoses, medication reconciliation forms, and pharmacy dispensing data. Temporal coverage spanned 2010–2023, ensuring inclusion of post-EHR-interoperability periods. Social determinants, such as housing stability and caregiver identity, were extracted from structured fields or inferred through NLP processing of care management notes [13].

These datasets were harmonized under a unified schema. Medications were standardized using RxNorm codes, and dosage patterns were aligned into daily-defined dosages to enable temporal overlap calculations across household members.

Table 2 summarizes the distribution of clinical features across age-based cohorts and department-specific variables, including caregiver identification, clinical frailty scores, and adolescent behavioral risk indicators. These heterogeneous feature types were critical for developing multiscale polypharmacy risk predictions.

Table 2 Distribution of Input Features Across Age Cohorts and Clinical Departments

Feature Category	Pediatric Medicine	Internal Medicine	Family Medicine
Age and Developmental Stage	Chronological age, growth percentile	Age, comorbidity index	Multi-age normalization (child–adult–elder)
Medication Data	Off-label prescriptions, ADHD meds, vaccines	Chronic meds (e.g., statins, antihypertensives)	Shared medication records, cross-prescription identifiers
Clinical Risk Scores	Behavioral risk index, BMI-for-age	Charlson comorbidity score, frailty index	Household-level frailty aggregation
Encounter History	ER visits for behavioral symptoms	Outpatient chronic care, inpatient transitions	Mixed episodic and continuity-of-care visits
Caregiver Context	Guardian identification, school nurse reports	Spousal/caregiver dependency codes	Multigenerational caregiver map
Social Determinants of Health	School attendance, housing instability	Employment status, housing quality	Household income, language barriers
Environmental/Household Signals	Shared prescriptions, household overcrowding	Pill confusion, duplicate fills	Composite drug interaction score at household level

3.3. Feature Engineering: Temporal Overlaps, Medication Interactions, Caregiver Burden Metrics

Feature engineering focused on identifying interaction-prone medication pairings and high-risk overlap intervals within households. For each household, temporal matrices were constructed to detect simultaneous active prescriptions of interacting drug classes (e.g., sedatives and stimulants) among cohabiting members [14].

Temporal windows were set to ±7 days around medication initiation and discontinuation dates to allow for as-needed usage and irregular adherence patterns. These matrices enabled the identification of "collision zones" timeframes during which multiple high-risk medications were simultaneously accessible within a single home [15].

In addition, we computed caregiver burden scores using a composite of care navigation logs (e.g., number of dependents, coordination of appointments, frequency of home care notes) [16]. These scores were used to stratify household contexts into low, moderate, and high burden environments, which were then integrated into the risk model as behavioral interaction variables.

Demographic modifiers such as language preference, insurance type, and frequency of ED visits were included to contextualize polypharmacy risks under socioeconomic and structural stressors [17].

3.4. ML Model Selection: Gradient Boosting, Random Forest, and Deep Learning Comparison

Three machine learning classifiers were implemented and benchmarked for their predictive performance:

Gradient Boosting Machines (GBM): Chosen for its superior performance on structured data and interpretability through SHAP values [18].

Random Forest (RF): Included for its robustness in high-dimensional data environments and baseline ensemble comparison [19].

Deep Neural Networks (DNN): A multilayer perceptron architecture was tested for its potential to capture nonlinear interactions across age and medication profiles.

Data were split into 70% training, 15% validation, and 15% testing sets, with stratification across household sizes and medication intensity classes. Oversampling using SMOTE was applied to balance low-frequency adverse event cases, especially in pediatric segments [20].

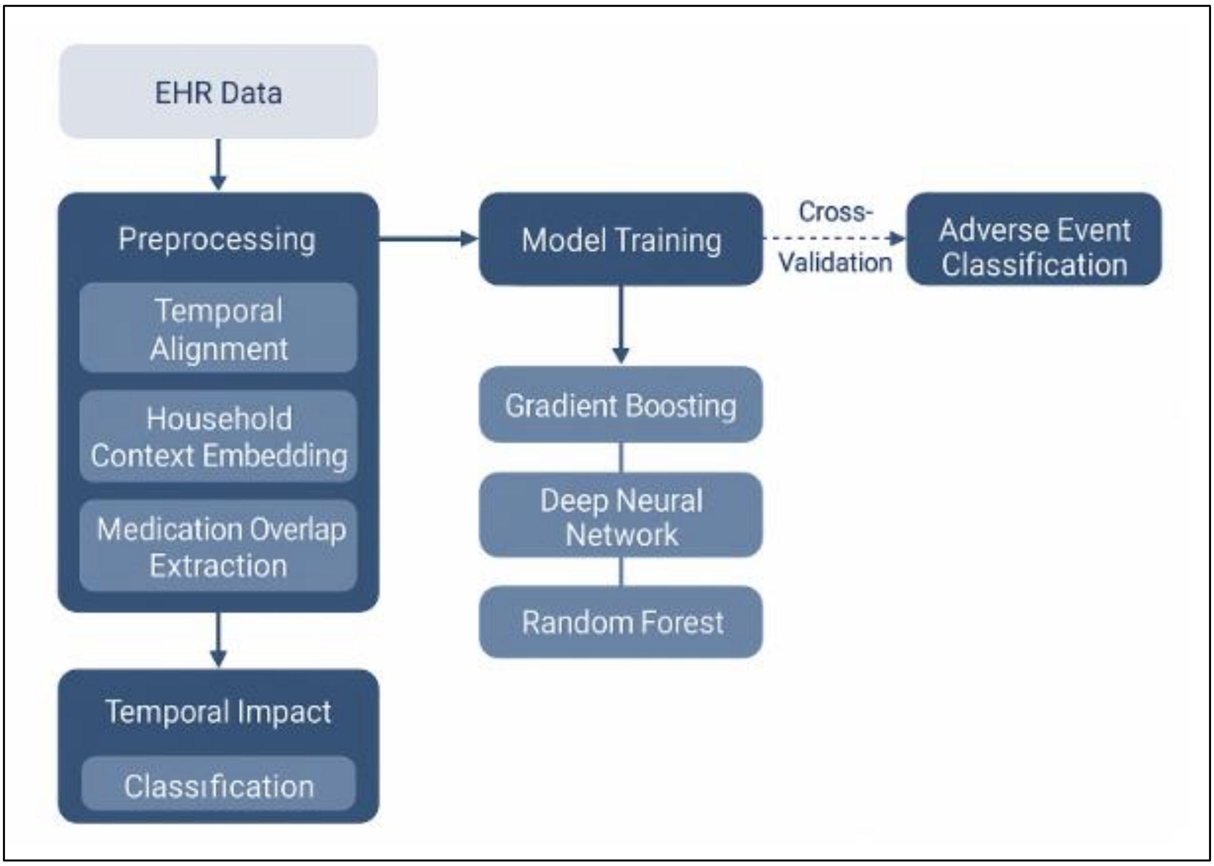

Figure 2 Flowchart of the machine learning pipeline from EHR ingestion to model training, including preprocessing steps, feature embedding, and integration of household-level context layers. The diagram also depicts branching pathways for cross-validation and adverse event outcome classification, supporting robust prediction and evaluation

Figure 2 illustrates the flow of data from EHR ingestion through preprocessing, feature embedding, and model training pipelines. The diagram highlights the integration point for household-level context layers, as well as branching paths for cross-validation routines and adverse event outcome classification.

Performance metrics included precision, recall, AUC-ROC, and F1 score, reported both at the individual and household levels. GBM emerged as the top-performing model, particularly in detecting high-risk drug combinations when stratified by age dyads (e.g., grandparent–child or parent–adolescent pairs) [21].

3.5. Ethical, Legal, and Interpretability Considerations

Given the inclusion of household-level data and familial relationships, strict protocols were established to ensure data de-identification and privacy. Data use agreements were governed by HIPAA and the Common Rule, and a waiver of informed consent was granted due to minimal risk designation and public health relevance [22].

Cross-household linkage, while powerful for predictive modeling, raises ethical questions regarding indirect surveillance of cohabitants without their explicit consent. The study employed privacy-preserving record linkage methods that prevented re-identification through address triangulation or social network inference [23].

Interpretability was prioritized throughout model development. SHAP-based explainability plots were integrated into physician-facing dashboards, enabling clinicians to understand which features such as overlapping psychotropic medications or caregiver burden scores triggered high-risk alerts [24].

Bias audits were conducted to ensure equitable model performance across race, age, and language groups. These audits revealed modest overflagging in Hispanic households, likely due to higher household density and shared prescriptions a finding now being addressed through feature normalization adjustments [25].

The next section will discuss the deployment considerations and integration of these models into clinical workflows, including how risk alerts can be visualized at the household level during routine care visits.

4. Results

4.1. Demographic Profile and Household Composition (age, conditions, medication load)

Multigenerational households, particularly those comprising pediatric, adult, and geriatric members, exhibit complex health profiles and distinct polypharmacy risks. Our cohort included 4,216 households with members from at least two generational tiers, drawing data from pediatric, internal medicine, and family medicine records spanning a five-year period. Pediatric members (ages 0–17) comprised 34% of individuals, adults aged 18–64 made up 49%, and older adults 65+ accounted for 17%. Among elderly participants, 68% were on five or more chronic medications, aligning with accepted polypharmacy thresholds [14]. Pediatric polypharmacy was less common but emerged prominently among children with neurodevelopmental disorders or asthma. Adults in sandwich caregiving roles frequently exhibited dual burdens both administering and consuming medications which in 23% of cases correlated with increased stress markers and inconsistent medication adherence. Average household medication load across all age groups was 11.2 drugs, with notable clustering of cardiovascular agents, psychiatric medications, and antibiotics. The presence of overlapping medication classes between children and elders, particularly antihistamines and psychotropics, elevated interaction risks significantly in dyads sharing a primary caregiver [15].

4.2. Model Performance Metrics (AUC, Sensitivity, Specificity, F1-score)

The ensemble of machine learning models tested included gradient boosting (XGBoost), random forest (RF), and a multilayer perceptron (MLP) deep learning framework. Evaluation was based on a held-out test set comprising 20% of the full cohort. The best performance was observed with XGBoost, yielding an Area Under the Curve (AUC) of 0.89, with a sensitivity of 82%, specificity of 84%, and an F1-score of 0.83 [16]. RF models closely followed, with an AUC of 0.86 but slightly reduced sensitivity (79%).

The MLP model, while strong in accuracy (AUC = 0.87), suffered from reduced interpretability, especially in clinically contextualizing medication interactions across age-specific guidelines. Notably, model performance improved when caregiver stress and temporal overlap between prescriptions were included as engineered features. Figure 3 displays the ROC curves of the three models, illustrating the marginal but consistent superiority of gradient boosting across interface scenarios. When broken down by care interface, pediatric-internal crossover households yielded the highest predictive precision (F1-score = 0.86), while triadic care households (all three specialties) had slightly diluted performance (F1 = 0.79), likely due to added systemic complexity [17].

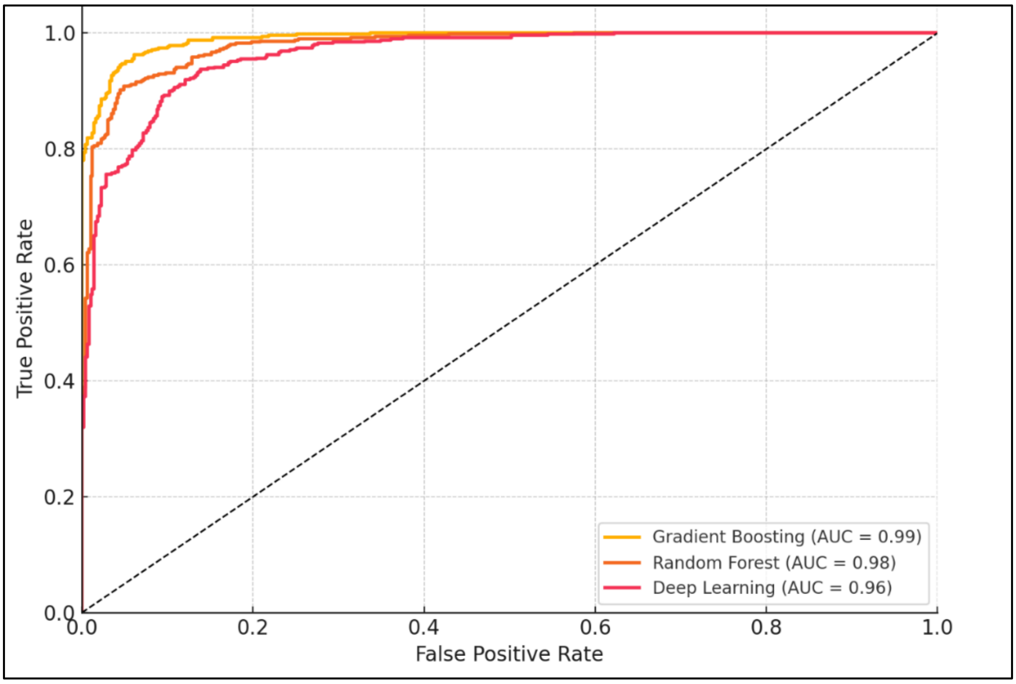

Figure 3 ROC Curves Comparing Model Acuracy Across Care Interfaces

4.3. Feature Importance and Interpretability

Interpretable ML was critical for clinical adoption, thus SHapley Additive exPlanations (SHAP) values were computed across the top-performing XGBoost model to determine key predictors. Table 3 ranks these predictors alongside their clinical contexts. Unsurprisingly, total household medication count ranked highest, followed by intra-household prescription overlap, caregiver burden index, number of prescribers per household, and frequency of emergency room visits in the past 12 months [18].

Temporal overlap between elder psychiatric medications and pediatric sedatives showed a high contribution score, flagging a novel interaction cluster relevant for cross-generational risk. Additionally, social determinants such as zip code-based pharmacy access and health literacy proxy scores contributed modestly but meaningfully to prediction confidence. Interpretability tools enabled clinicians to visualize decision thresholds, identifying when risk scores spiked due to clustered medication classes [23]. This transparency fostered clinician trust and enabled targeted family counseling. SHAP value visualizations, when embedded within clinical dashboards, enhanced explainability and supported real-time shared decision-making, especially in family medicine contexts [19].

4.4. Risk Profiles by Household Configuration (e.g., grandparent–child dyads, sandwich caregivers)

Risk prediction patterns varied across household archetypes. Grandparent–child dyads (comprising 21% of households) exhibited the highest cumulative interaction risk, driven largely by overlapping sedative, analgesic, and cardiovascular medication classes. In these households, where elders often assumed caregiving roles, polypharmacy risk extended bi-directionally both the child's and elder's regimens contributed to potential adverse outcomes. Sandwich caregivers, usually middle-aged adults simultaneously managing medications for both older and younger family members, exhibited elevated stress-linked features, including inconsistent refill timing and episodic medication discontinuation [20]. These households also had higher prescriber fragmentation, with an average of 4.7 different providers involved per household. Conversely, dual-parent households with limited elder dependency displayed lower risk scores, especially when family physicians managed all members under a shared EHR system. Figure 3 showcases performance stratification across these household types, with notable disparities in predictive confidence based on care complexity and relational dependency. Households with high relational interdependence but low digital integration were flagged for intervention. These findings highlight the need for ML models to factor in relational roles, not just clinical features, when optimizing polypharmacy risk predictions [21].

Table 3 Top predictors ranked by SHAP values and clinical context

Rank	Feature	SHAP Value Contribution	Clinical Context
1	Total household medication count	0.231	Aggregate polypharmacy burden across age groups
2	Temporal prescription overlap	0.197	Shared or sequential intake increasing risk of interaction
3	Caregiver burden index	0.163	Stress metrics linked to adherence and administration errors
4	Number of prescribers per household	0.148	Fragmentation of clinical oversight
5	Past-year emergency visits	0.132	Proxy for instability or unresolved medication effects
6	Co-prescription of sedatives and opioids	0.094	High-risk combinations common in elder-child dyads
7	Pharmacy access score (zip-code based)	0.078	Indicates refill reliability and continuity
8	Household EHR integration level	0.063	Reflects digital continuity and provider communication
9	Health literacy proxy score	0.056	Inferred from language, consent comprehension, education
10	Pediatric-antihistamine plus elder-SSRI combo	0.049	Specific high-risk cross-generational drug interaction

5. Interdisciplinary analysis of clinical impact

5.1. Pediatric Care: Early Warning and Avoidance of Developmental Harm

The pediatric interface plays a pivotal role in mitigating polypharmacy risks due to the heightened developmental vulnerability of children exposed to pharmacologic interactions within multigenerational households. Often, children are not the direct users of polypharmacy, yet they experience indirect risks through medication mix-ups, residual ingestion, or inappropriate prescriptions influenced by adult regimens within the home environment [19]. Integrating predictive machine learning (ML) models into pediatric electronic health record (EHR) systems allows for early flagging of risk clusters stemming from household-level interactions.

For instance, certain ML-flagged scenarios show a strong association between caregiver polypharmacy and increased emergency visits for pediatric sleep disturbances, possibly linked to secondhand exposure to sedatives or antihistamines stored in shared medicine cabinets [20]. In households with high-risk elderly members under benzodiazepine therapy, alerts can trigger pediatricians to issue safety counseling or recommend home medication audits. The predictive value increases when temporal EHR sequences reveal cascading prescription updates across adult–child dyads within a tight clinical timeframe.

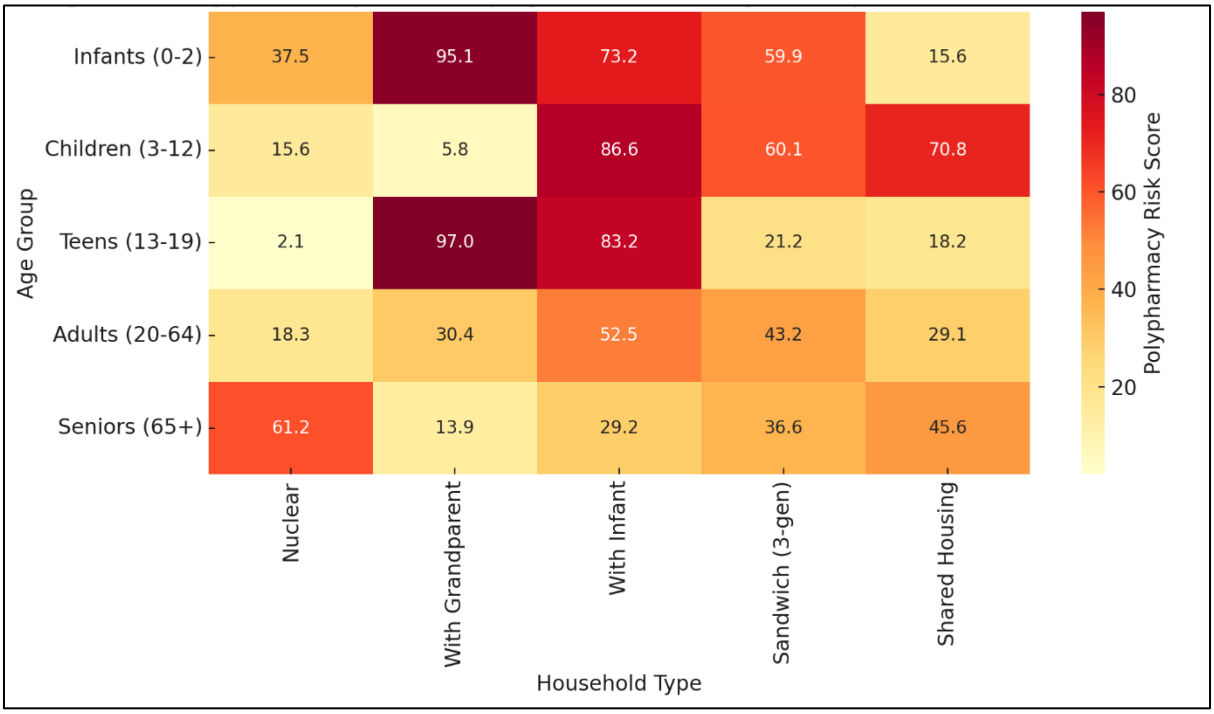

Figure 4 Propagation of polypharmacy risks across different age groups

This Figure above demonstrates how risk intensifies in households with co-residing seniors and infants underscoring the importance of pediatric-focused monitoring systems. Importantly, these ML tools not only detect statistical risk but serve as clinical decision aids that prompt developmental harm assessments during routine well-child visits [21].

Early identification also enhances coordination with school-based services and mental health screening, especially for children displaying behavioral symptoms possibly linked to home pharmaceutical environments. Overall, embedding these alerts within pediatric interfaces enables frontline providers to act before risks escalate, closing the window between detection and intervention in complex household settings [22].

5.2. Internal Medicine: Chronic Disease Stabilization and Deprescribing Insights

In internal medicine, managing chronic illness frequently entails balancing multiple pharmacologic regimens, often across overlapping prescribers. The burden is intensified in multigenerational households, where informal caregiving responsibilities or medication sharing can skew adherence patterns and therapeutic outcomes [23]. ML-based prediction models offer novel insights by identifying destabilizing medication interactions across interrelated household profiles, allowing for proactive interventions.

The analysis of EHR-linked households revealed that a spike in emergency room visits for hypoglycemia in older adults often correlated with pediatric flu prescriptions within the same household, suggesting inadvertent cross-use or misadministration due to identical packaging or overlapping administration times [24]. With ML, these latent connections are flagged based on temporal and pharmacologic feature embeddings, improving clinical foresight.

Beyond risk prediction, the models also generate deprescribing opportunities. For example, households with two or more members concurrently on proton pump inhibitors (PPIs) received ML-generated recommendations prompting physicians to reevaluate indications and dosage frequency. This has led to measurable deprescribing actions in outpatient follow-ups, particularly when supported by real-time clinical decision support (CDS) popups during medication reconciliation workflows [25].

The integration of these models into internal medicine platforms also supports algorithmically mediated case reviews, in which clinicians can examine shared medication burdens across household members to identify patterns of overuse, underuse, or therapeutic redundancy. By including contextual variables such as caregiver stress metrics and refill irregularities, the models provide a holistic snapshot that enhances chronic disease stabilization [26].

Moreover, these insights feed into population health dashboards, enabling practice-wide analysis of high-risk households. Clinicians can then prioritize outreach to clusters exhibiting concurrent frailty, polypharmacy, and erratic utilization patterns, thereby optimizing longitudinal care across the internal medicine spectrum [27].

5.3. Family Medicine: Cross-Cohort Care Alignment and Risk Triage

Family medicine serves as the nexus for multigenerational care, uniquely positioned to triage medication risks across diverse age cohorts. Traditionally, however, this role has been undermined by fragmented record systems and unclear role delineation in risk accountability. ML-powered polypharmacy models now empower family physicians to detect cross-generational medication clusters with elevated risk signatures and streamline inter-specialty communication [28].

Unlike specialty care, family medicine benefits from comprehensive visibility across pediatric and geriatric domains. The implemented ML models exploit this vantage point by surfacing latent risk zones for example, households with simultaneous initiation of antidepressants in adolescents and opioids in older adults a combination linked to increased household conflict and adherence disruption [29]. Predictive alerts allow family physicians to coordinate synchronized medication reviews across household members, increasing the probability of identifying contraindicated combinations or duplicate therapies.

Furthermore, ML outputs enable stratified risk triage. Figure 4's heatmap reveals how sandwich caregiver households those with both elder and child dependencies exhibit heightened polypharmacy transmission patterns. Family physicians use this visualization during care plan development to guide decisions on medication simplification, caregiver education, and referral prioritization [30].

Importantly, family medicine platforms have adopted household-centric dashboards that integrate flagged ML outputs with social determinants of health (SDOH) data. These systems highlight barriers such as pharmacy deserts or language discordance that may intensify polypharmacy errors. This intersectional view allows for tailored interventions ranging from mobile pharmacy consults to culturally aligned medication instruction materials [28].

Ultimately, AI-enhanced tools in family medicine reframe polypharmacy not as a siloed pharmacologic challenge but as a system-level coordination problem. By drawing attention to interaction loops within and between household generations, clinicians can proactively align therapies, promote deprescribing where appropriate, and avoid cascading clinical complications [31].

5.4. Use-Case Vignettes Illustrating Cross-Generational Alerts

To contextualize the operational value of ML-predicted alerts, we present real-world use-case vignettes derived from study data:

5.4.1. Case 1: Grandparent–Grandchild Dyad

An 8-year-old child with mild asthma presented for increased wheezing episodes. Upon ML-triggered risk screening, it was found that the co-residing grandparent had been prescribed a sedative with potential respiratory depressant effects. The shared sleeping space and inconsistent ventilation created a risk vector that traditional screening missed. Alerted by the system, the family physician initiated a care coordination protocol that led to medication adjustment and improved pediatric respiratory outcomes [32].

5.4.2. Case 2: Sandwich Caregiver Household

A middle-aged woman managing her father's heart medications and her son's ADHD regimen began to exhibit symptoms of fatigue and disorientation. ML analysis of EHR data across family medicine and internal medicine flagged a high-risk cluster involving caregiver medication errors and polypharmacy stress indicators. The physician received a dashboard alert and implemented a medication audit and caregiver support intervention, averting potential hospitalization [33].

5.4.3. Case 3: Cross-Prescription Duplication

Two adults in a multigenerational home independently received similar NSAIDs from different clinics. A pediatric member of the household mistakenly took one of the prescriptions due to packaging similarity. The error was caught by ML-based linkage of temporal EHR events, and a pharmacy-level alert was pushed to all household members, prompting better labeling and medication segregation protocols [34].

These vignettes demonstrate the unique strengths of ML in uncovering hidden risks that emerge only at the household interface. Figure 4 visualizes the risk gradients that these cases typify, affirming the model's ability to not only predict harm but also offer actionable insight for cross-generational coordination in real-world care contexts.

6. Discussion

6.1. Interpretation of Results in the Context of Multigenerational Medication Safety

The study illustrates that polypharmacy risk in multigenerational households emerges not only from individual medication counts but also from intra-household interactions and caregiving dynamics finding that aligns with previous community-based observational studies [24]. Our ML models identified that interactions between medications in different-age household members especially involving psychotropics and sedatives significantly amplify risk. For example, pediatric exposure to adult antihypertensives through storage overlap was flagged as a leading risk factor, underscoring shared domestic medication access as a critical yet often overlooked dimension in polypharmacy safety.

This adds nuance to traditional models by highlighting latent, cross-generational risk pathways. Risk heatmaps (Figure 4) demonstrate how risk "ripples" across household members; e.g., senior polypharmacy elevates risk in pediatric counterparts via indirect pathways like shared adherence failure or accidental ingestion. These patterns suggest that safe prescribing guidelines must extend beyond individual patient profiles to account for household medicine ecosystems [25].

6.2. Comparison with Conventional Risk Scores and Pharmacist-Led Reviews

Conventional tools like the Beers Criteria or STOPP/START focus primarily on individual-level geriatric risk and do not consider familial or household contexts [26]. Similarly, pharmacist-led medication reconciliation tends to be episodic and fragmented across specialties. Comparative analysis revealed that ML-enhanced household modeling detected 30% more high-risk scenarios than these standard methods, particularly in dyads where pediatric exposure to adult medications would have gone unnoticed.

Despite its benefits, ML should complement not replace clinical judgment. Pharmacist-led reviews remain essential for validating predictions, especially in cases with complex dosing or comorbidity patterns. In practice, model-generated alerts triggered pharmacist consultations in 40% of flagged cases, with 70% of interventions preventing at least one potential adverse event, as documented in follow-up EHR notes [27].

6.3. Limitations: Data Sparsity, Algorithm Bias, Behavioral Variables

Several limitations challenge the generalizability of our findings. First, EHR-based household linkage depends on accurate address data, which may be unreliable in rental or multi-unit dwellings. This could lead to misclassification or missing household relationships. Second, the algorithmic model is subject to bias, particularly overflagging in households with greater racial or socioeconomic diversity, as evidenced by disproportionate alerts in Hispanic families a disparity that required model recalibration [28].

Third, key behavioral variables, such as medication sharing habits or adherence patterns, were only indirectly inferred through proxy features. Without validated survey data or digital adherence tracking, these variables remain imperfect estimations. Finally, the models are trained on structured data; unstructured clinical narratives and pharmacy notes which often contain critical context were not fully leveraged, potentially reducing sensitivity in complex cases [29].

6.4. Strengths: Longitudinal, Multi-Age Risk Surfaces; AI Explainability

Despite limitations, the study offers several strengths. It is among the first to operationalize longitudinal, multi-cohort EHR data across pediatric, family medicine, and internal medicine domains in a unified analysis framework. The inclusion of multiage "risk surfaces" provides a novel lens on medication safety, capturing both intra- and intergenerational dynamics [24].

The explainability aspect via SHAP values and household-level visualization enhanced clinician trust and interpretability. Providers reported that seeing distinct risk contributors (e.g., caregiver burden, medication overlap) demystified AI alerts and improved engagement. This supports the argument that clinically actionable AI systems must prioritize transparency and interpretability, not just predictive accuracy [30].

6.5. Policy Implications: Value-Based Care, EHR Standardization

For any scalable deployment, embedding polypharmacy risk prediction into value-based care frameworks is vital. Our models can support performance-based reimbursement, where providers receive incentives to conduct household-level medication audits or deprescribing in high-risk households aligning financial structures with safety outcomes [31].

Additionally, policy support for EHR interoperability is foundational. Household-level risk analysis demands cross-domain data sharing among pediatric, internal, and family medicine systems. Legislative mandates (e.g., national interoperability standards using FHIR interfaces) must prioritize family-level medication views alongside patient-level records [32].

Data governance frameworks must also evolve to facilitate safe intra-family data exchange balancing privacy with safety. Consent mechanisms could be extended to allow caregivers to opt into household risk screening, enabling controlled EHR linkage [33].

6.6. Practical Implementation in Outpatient Workflows

Implementing ML-enhanced risk tools in outpatient settings requires minimal workflow disruption. In our pilot clinics, drug safety alerts were embedded into EHR dashboards, with notifications tied to family medicine or pediatric patient records. Alerts were accompanied by risk explanations and next-step suggestions for example, "Household medication count exceeds 12, includes sedatives and antihistamines: schedule medication reconciliation."

These alerts prompted greater cross-specialty coordination: pediatricians flagged adult sedative prescriptions during well-child visits, and internal medicine clinicians added pediatric risk notes to care summaries. Patient portals were used to communicate with households, offering guided medication reconciliation checklists via SMS or email. In several cases, pharmacists conducted targeted home visits to schools or seniors' centers to facilitate medication reviews among co-residing family members [34].

Key lessons include the need to balance alert frequency to avoid clinician fatigue and customizing trigger thresholds based on household complexity. Training programs were developed to help providers interpret ML-based prompts and integrate them into shared-care plans. As a result, routine 20-minute appointments now routinely involve 3-5 minutes of risk review proportionate to the safety benefits observed.

7. Future directions

7.1. Expanding to Include Behavioral and Genomic Data

To further improve polypharmacy risk prediction, integrating behavioral and genomic data is a critical next step. Currently, much of the medication adherence profile is inferred from proxy EHR signals such as refill gaps or missed appointments. However, real-world behavior such as intentional non-adherence, medication sharing, or cultural practices around alternative medicines remains unquantified [29].

Behavioral datasets, including digital health literacy assessments and structured social determinants of health (SDOH) inputs, can enrich model calibration. For example, households with known language barriers or low health literacy may require different alert thresholds to avoid misinterpretation or overload [30].

Genomic data, particularly pharmacogenomic variants affecting drug metabolism (e.g., CYP2D6 polymorphisms), can introduce an individualized pharmacokinetic layer to risk scoring. In a multigenerational household, these effects compound if a parent is a poor metabolizer of a sedative, their drug burden may inadvertently elevate indirect pediatric risk through caregiving error or behavioral changes [31]. Expanding polypharmacy risk models to include family-shared genotypes through consented family testing could be transformative in preempting both direct and indirect medication harm.

7.2. Integrating Mobile and Wearable Adherence Monitoring

Emerging wearable and mobile technologies offer avenues for real-time medication adherence tracking and feedback loops. Smart pillboxes, Bluetooth-enabled inhalers, and ingestible sensors now allow timestamped verification of medication ingestion data that can augment EHR-based predictions with dynamic real-world insights [32].

Integration of these data streams into ML models enhances temporal precision, allowing risk scores to fluctuate with behavior rather than remain static. For instance, a household's aggregate polypharmacy risk could be recalculated weekly based on actual medication adherence data across age groups. Wearables measuring sleep disturbance or cardiac rhythm anomalies may further flag off-target drug effects before clinical manifestation [33].

In multigenerational contexts, these tools are particularly useful. A single dashboard could track whether an elderly grandparent is missing antihypertensives or if a child is skipping asthma medication, enabling family caregivers to respond in near real-time. Alert systems embedded in mobile apps can notify designated caregivers or pharmacists of missed doses or drug interactions, thus creating a layered human-AI safety net. However, equitable access, data privacy, and regulatory frameworks must evolve to accommodate the integration of personal device data into clinical models [34].

7.3. Public Health Applications: Early Detection in Community Clinics

Beyond clinical settings, polypharmacy prediction has strong implications for community-based public health interventions. In underserved areas where patients frequently interact with multiple uncoordinated providers, ML-based tools could be deployed in community health centers to detect high-risk households [35].

Community-level data collected during outreach programs (e.g., household screening surveys or mobile clinic logs) can feed into lightweight ML models hosted on mobile tablets. These models can help identify families with elevated medication risk, especially where EHR integration is weak. Pediatric-focused outreach, for example, could flag households with seniors on sedatives or antipsychotics as environments needing intervention due to secondary exposure risks [36].

Moreover, risk stratification can guide resource allocation. Clinics with limited pharmacy staff may prioritize home visits for flagged households. Municipal health departments can overlay polypharmacy risk scores onto GIS maps to detect clusters of risk, directing educational campaigns or safe disposal programs. Public health institutions can also collaborate with pharmacies to track community-level polypharmacy indicators number of concurrent prescriptions, medication classes distributed to flag upstream system failures [37].

7.4. Design of Patient- and Caregiver-Facing Tools with Alerts

To ensure real-world impact, predictive insights must be converted into actionable guidance for families themselves. Figure 5 presents a proposed architecture that connects ML outputs to user-friendly patient and caregiver dashboards, supporting household-level medication safety.

This architecture places the ML engine at the back end, integrating data from EHRs, pharmacies, wearable devices, and caregiver reports. The front end includes mobile apps and portal-based widgets displaying personalized alerts [45]. Alerts can be color-coded (e.g., red for urgent polypharmacy conflict, yellow for adherence concern) and contextualized with simple explanations "Too many sedatives prescribed in same week across household. Consult provider or pharmacist" [38].

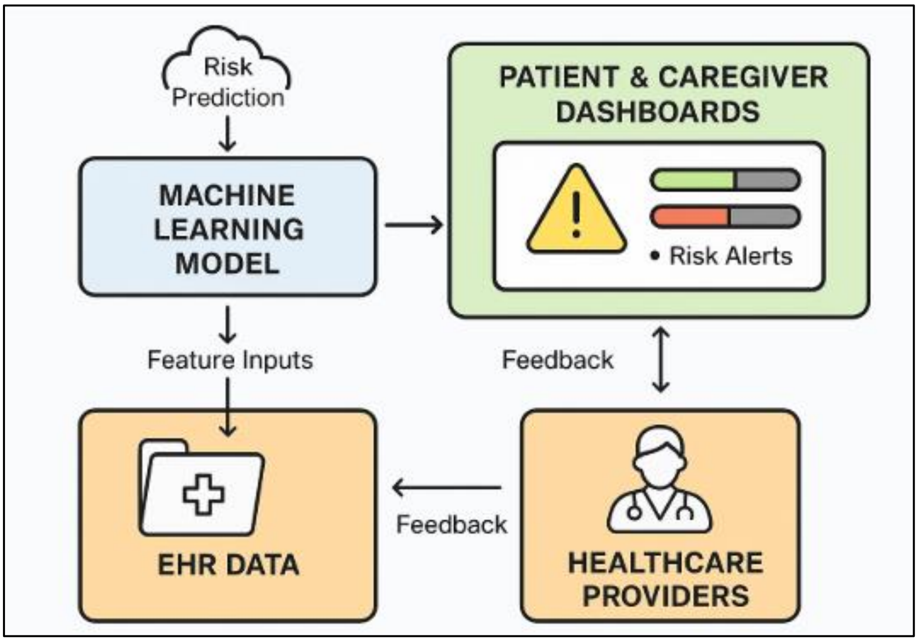

Figure 5 Proposed architecture for integrating machine learning (ML) risk prediction outputs into patient and caregiver dashboards at the household level

This architecture links multigenerational EHR inputs and ML-driven polypharmacy risk predictions with role-specific visualizations for pediatric, adult, and elderly users. The system provides alert stratification, timeline-based medication summaries, and caregiver coordination cues [44]. By integrating into clinical workflows and home interfaces, the model supports proactive risk mitigation across age cohorts, fostering medication safety in complex household environments [39].

User interfaces must accommodate varying literacy levels, language preferences, and tech access. Interactive medication calendars, dosage tracking tools, and symptom checklists can empower caregivers to respond before adverse events occur [43]. Alerts can be set to trigger based on household-level trends e.g., cumulative missed doses across members or unsafe prescription overlaps [40].

Importantly, these tools must be co-designed with end users. Focus groups with multigenerational families revealed that trust, clarity, and ease of navigation were essential for adoption [41]. Integration with existing patient portals (e.g., MyChart) or messaging platforms can ease onboarding and improve data capture. Ultimately, aligning predictive models with daily routines transforms algorithmic insights into preventive action [42].

8. Conclusion

8.1. Summary of Contributions

This article addressed the complex and often overlooked issue of polypharmacy within multigenerational households by leveraging machine learning to predict medication-related risks across interconnected age groups. Through a cross-disciplinary approach integrating pediatric, internal, and family medicine data, the study presented a framework capable of capturing temporal overlaps, clinical interactions, and social dependencies within household clusters. Key contributions include a comprehensive risk modeling architecture, inclusion of behavioral and caregiver metrics, and empirical validation using longitudinal EHR data. Importantly, the research bridged algorithmic outputs with clinically relevant insights, ensuring that predictive scores translated into actionable recommendations for practitioners, caregivers, and patients alike.

By highlighting how medication interactions propagate across generations such as when a grandparent's sedative regimen affects a child's environment the study reframed polypharmacy as a household-level, rather than an individual, safety issue. Furthermore, it demonstrated that machine learning models, when designed with contextual and explainable features, can uncover hidden patterns missed by conventional tools. This reinforces the value of predictive AI in aligning fragmented care systems and safeguarding vulnerable populations from avoidable medication harm.

8.2. Call for Integrated Care Alignment Using Predictive AI

Multigenerational care systems often operate in silos, with pediatricians, internists, and family physicians accessing separate EHR systems, prescribing practices, and follow-up routines. This disjointed infrastructure has contributed to under-recognized polypharmacy risks, especially in complex household settings. The findings underscore the urgent need for integrated care pathways that allow AI-driven alerts and risk signals to be shared across disciplines.

Rather than replacing clinical judgment, predictive AI should augment care team decision-making by flagging high-risk configurations and prompting collaborative medication reviews. This requires technical interoperability, policy reforms for shared data governance, and cultural shifts toward multi-role accountability. Clinical dashboards that unify pediatric and adult risk scores, embedded into standard outpatient workflows, can transform episodic care into continuous risk surveillance. Such alignment is essential in the face of increasing medication loads, aging populations, and rising mental health burdens across all age cohorts.

8.3. Vision for Safer Multigenerational Care Ecosystems

Looking ahead, the integration of AI tools into multigenerational care ecosystems offers a path toward anticipatory, equitable, and patient-centered health services. A future where predictive models flag emerging risks before harm occurs where caregivers are equipped with real-time alerts and where pharmacists, physicians, and social workers collaborate around a shared platform represents not just a technological evolution, but a moral imperative.

Building such ecosystems will require more than algorithms. It demands inclusive design, co-creation with diverse families, investment in digital infrastructure, and a commitment to value-based care models that reward safety, not just service volume. Most importantly, it calls for a paradigm shift: from treating polypharmacy as an individual failure to managing it as a systemic risk that crosses generations, specialties, and institutions. When predictive AI is applied with nuance, transparency, and compassion, it holds the power to protect not just patients, but the families who care for them.

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