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# AI DRIVEN HEALTHCARE AT SCALE: PERSONALIZATION AND PREDICTIVE TOOLS IN THE CVS HEALTH MOBILE APP

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## ABSTRACT

*In this study, we explore the application of AI-enabled personalization and predictive analytics in the CVSHealth mobile app to drive personalized medication adherence, care navigation and chronic disease management. We performed a mixed-methods evaluation, involving quantitative analysis of app usage as well as clinical outcomes, and qualitative interviews with users and clinicians. The approach itself involved capturing app engagement behavior (e.g., refill-reminder engagement, predictive refill accuracy, and health outcome proxies [e.g., blood-pressure readings]) in real time from 30,000 users, over a 6-month period. This was complemented by semi-structured interviews with 20 patients and 10 pharmacists to evaluate perceived usability and impact. Findings Findings indicate a 28% increase in rates of on-time medication refill among patients engaging with the personalized "health to-do" list and AI chatbot when compared to a control group. Predictive refill notifications achieved a sensitivity / specificity of 83% (±3days) for risk of drug gaps. Qualitative feedback demonstrated improved patient confidence and provider efficiency, though concerns for transparency and app complexity emerged. This is consistent with the recommendation that introducing AI personalization at scale will lead to substantial improvements in adherence and pharmacy efficienciesIT optimizations across CVS's digital ecosystem. We close with suggestions for model transparency, adaptive UI design, and clinical integration strategies to enable broad-based deployment and equity.*

**Keywords**: AI Personalization; Predictive Analytics; Medication Adherence; Mobile Health; CVS Health; Patient Engagement

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# 1. INTRODUCTION

The health care field is currently under a digital revolution driven by the advance of Artificial intelligence (AI). Not confined any longer to only clinical settings such as diagnostic imaging and robotic surgery, AI has recently also expanded to the consumer health space, particularly with mobile health (mHealth) solutions [1]. This type of technology allows people to take control of their health with the use of their smartphone and various wearable devices, a constant, personalized, and data-driven care. So in this scenario, AI is no longer a futuristic dream but an enabler of the 'here and now' with many industry examples of real-time decision support, predictive interventions and personalization [2]. When it comes to AI at scale: "The CVS Health mobile app is one of the most powerful and heavily-used apps that exists." CVS Health has more than 100 million individuals and millions of digital users, and employs AI to facilitate care navigation, medication adherence, and virtual offerings [3]. In this paper we investigate how AI techniques are used in the CVS Health Mobile App to provide personalized and predictive healthcare, evaluating both the technology and the implications at the population level.

CVS Health is an integrated pharmacy company encompassing retail pharmacy (CVS Pharmacy), health insurer (Aetna), and a pharmacy benefit manager (Caremark). This integration provides CVS with access to one of the largest de-identified health data ecosystems in the U.S., including data from pharmacy, insurance claims, provider networks and user behavior data from its mobile platform. The CVS Health mobile app functions as the digital front door to this ecosystem, providing patients a single interface to view their prescriptions, monitor insurance benefits, schedule a telehealth visit, and get chronic disease support [4] [5].

More recently, AI features have been added on top of these core elements. Among other things, these are machine learning and AI overlays that process user behavior and biometric data to form health "To-Do's," smart prescription-refill reminders, natural-language symptom checks, and user interface (UI) tweaks based on engagement history. Unlike static apps, these AI-driven features react to what the user wants. For instance, a user suffering from diabetes and hypertension may be alerted not only according to their medications schedule, but also in accordance with the lab data or recent reports of symptoms [6] [7].

That CVS can operationalize these tools at scale, across millions of users, is enabled by its data infrastructure, but is also informed by its mission to deliver precision healthcare – the right intervention to the right person at the right time. This power to transform care from being reactive to proactive means that interventions can be implemented sooner and compliance is higher. And so CVS Health's AI strategy is more than just technological—it is also clinical, behavioral and operational in its aspirations.

Engagement Is Everything Many digital health tools only work as well as users engage with them. All-purpose messages, one-size-fits-all interfaces and rigid ticklers result in poor engagement and low retention rates. AI-based personalization is a way this problem can be solved by using machine learning models to create personalized experiences for a user based on their unique attributes and interests. All these models take in many input variables such as age, track record of adherence, interaction time, engagement rate etc., and predict the best channels and an optimal frequency of messages. As such, personalization will cause the system to become meaningful to a user and increases the likelihood of user compliance with health-related tasks.

In the context of mHealth, predictive models are commonly used to predict outcomes such as nonadherence to medication, missed appointments, or high risk disease scores using classification models (e.g., logistic regression, decision trees, deep neural networks) from historical data. As an example, a predictive model might indicate a user who has missed two back-to-back refills and has not been on the app in ten days as a high risk for nonadherence. This information can prompt an automatic outreach by a care manager or a pharmacist [8] [9].

It's worth noting that personalization and prediction do work best when combined closely. Tailored interventions raise response rates, predictive insights show what works and when and where it´s needed most. AI models will need to generalize across diverse users groups with varying socio-economic status, ethnic background, comorbidity profile, and digital literacy levels. Preventing predictive models from inheriting or amplifying bias collected in the training dataset is particularly important in the field of healthcare, since biased recommendations may result in adverse impact. In addition, model interpretability, privacy and ethical compliance (e.g. HIPAA, GDPR) has to be incorporated in each layer of the system [10].

The CVS Health mobile app is being used by tens of millions of active users and is considered to be a fertile ground for examining AI rollout at scale. Its diversified base of end-users, which includes elderly patients with chronic medical conditions and young, tech-savvy seekers of wellness services, makes it an optimal laboratory for adaptive digital-health strategies. The app serves as both a transactional (e.g., refill prescriptions, pay bills) and clinical partner (e.g., condition management, find care providers).

App features enabled by AI are at the cutting edge of adoption. Personalized Health To-Do Lists are automatically-generated weekly or daily health activity tasks for individual users based on data captured from medical claims, medication refill logs, and patient self-reports."', These tasks might include taking blood pressure measurements, scheduling a return appointment, or filling out an online questionnaire. Predictive Refill Alert = A “smart” refill alert derived from historical adherence models that predict probability of missing a refill in the future allowing for a proactive touch. AI Chatbots and Symptom Checkers act as initial, digital triage agents offering condition-based advice in order to lessen the workload of healthcare providers. Dynamic Interface Adjustments change aspects of UI like buttons location, colour pallete and frequency of notifications on a users engagement profiles.

These not just add-on features — they are deeply integrated into the CVS Health digital organism. They speak to backend data services and care teams, and also retail workflows (like kicking off a pharmacist follow up). Its scaled rollout needs strong back-end infrastructure, privacy functionality, and real-time inference — making CVS Health an operational AI lab of sorts for health care.

Although the advantages of AI in health care are well-established in specialty settings, there is still limited empirical evidence of its impact in large, live systems such as CVS Health. Many AI studies have used small samples or have focused on niche applications such as mental health apps or single-disease management tools. These controlled experimentations are useful but cannot replicate the complexity of the real systems that have millions of users with different behaviors and requirement. Moreover, metrics usually emphasize technical performance (e.g., model AUC, precision-recall) instead of user-centered or clinical outcomes including adherence, user satisfaction, and trust.

Scalability has not been well studied. Outstanding are questions about how algorithms generalize to different demographics and how users understand both name-based alerts and predictive recommendations. Additionally, there is scant treatment of the ethical issues of training and deploying predictive models on Big Data from users in commercial healthcare platforms. Transparency, user consent, fairness and explainability are frequently emphasized in theoretical models but infrequently tested in real-world applications where we must balance commercial priorities with clinical responsibilities.

Accordingly, the research gap needs to be filled by studies on the performance and impact of AI within live, large-scale health platforms – especially those that concurrently span clinical, retail and digital domains, such as CVS Health.

The central purpose of this study is to examine the impact of AI-guided personalization and prediction tools on patient behavior, engagement, and health outcomes, operating in the CVS Health mobile ecosystem. By examining the strengths and weaknesses of these tools, the research aims to identify key requirements that can guide the development of the next generation of AI-powered mobile health applications. The study's key objectives are:

- To quantify the impact of personalized health tasks and AI-driven reminders on medication adherence.
- To assess the predictive accuracy of CVS’s refill algorithms and understand their performance across user subgroups.
- To collect user and provider feedback on the AI features, focusing on usability, trust, and perceived helpfulness.
- To identify challenges and success factors in deploying AI features across a national user base with heterogeneous needs and behaviors.

To comprehensively address the research questions, the paper is organized into five main sections. **Section 2: Literature Review** surveys recent scholarly work on AI in mobile health, with a focus on personalization and predictive tools. **Section 3: Methodology** outlines the mixed-methods approach, data sources, and evaluation criteria. **Section 4: Results and Analysis** presents empirical findings supported by statistical analysis, graphs, and user feedback. Finally, **Section 5: Conclusion** summarizes the key findings, implications, and future directions for AI in mHealth platforms.

## 2. LITERATURE REVIEW

### 2.1 AI in Mobile Health & Personalization

The development of mobile health (mHealth) technologies has presented new possibilities for data-driven health interventions in real time. An interesting work is Co-Pilot for Health by Chiam et al. that deployed a Graph Neural Network–based nudging engine to encourage physical activity. In a study that involved 84,587 users in Singapore, the platform drove the daily step count up by 6.17% and the weekly moderate vigorous physical activity (MVPA) by 7.61%, proving a point on the scalability of AI for creating behavior change [11].

Building on the personalized digital interventions, the CAREForMe system used a context multi-armed bandit (CMAB) algorithm for providing mental health-related content based on context sensed by the user. The system adapted interventions on the fly from observed user behavior and environmental activity, but it was tested outside a home setting, and further validation in a larger trial was needed [12].

Rpm is also one of the areas where AI finds its application. A review article by Shaik et al. investigated AI-based RPM systems that incorporated Internet of Things (IoT) devices, cloud computing, and federated learning. The results underscored their promise in early diagnosis and personalized care, the scientists said. Nevertheless, the review equally highlighted large obstacles regarding data heterogeneity, systems interoperability, and privacy issues [13].

XAI has become a focus in the clinical domain. Di Martino et al. constructed models for elderly malnutrition risk prediction that employed Random Forest and Gradient Boosting methods. The SHAP (SHapley Additive exPlanations) values were employed to improve the interpretability and provide the clinicians with the ability to interpret each feature's impact on the prediction. This extra level of transparency is important for clinician trust and ethical use [14].

## 2.2 Predictive Tools & Medication Adherence

Predictive modeling plays a key role in identification and mitigation of health risks. At CVS Health, Zuccarelli outlined predictive models the company uses to identify risks in patients with chronic conditions such as diabetes and hypertension. These models facilitated timely care interventions by care managers and resulted in positive health outcomes and disease progression [15].

Consistent with this, an initiative by CVS and Databricks increased medication adherence by 1.6% with machine learning–based personalization. AI models forecasted the probability of a refill due to be missed and sent personalized reminders and nudges to at-risk patients [16].

Further evidence of AI’s role was provided by CIO Dive, which reported on the use of predictive tools to align prescriptions, identify missed pickups and determine outreach approaches. These AI apps have not only increased adherence, but also enhanced customer retention and satisfaction [17].

A wider case-in-point would be a platform such as Health Navigator in the UK NHS. The AI system that identified patient risk and contributed to preventive care was linked to a 36% reduction in accident and emergency visits, and a 25% fall in planned admissions. This illustrates the effectiveness of predictive models within a larger health system.

## 2.3 Scalability & Systems Deployment

One of the key requirements for successful roll-out of AI in health care is scalability. CVS moved from a Hadoop-based architecture to Azure Databricks for more dynamic scaling and faster model development. This migration to the cloud made it possible to unify AI tools for shelf services, the real-time system and a high-throughput batch workload in retail, pharmacy, and virtual care systems [16], [17].

Time Magazine covered the idea of AI “health coaches” that do smart nudges across sleep, exercise, socialising, and the rest. Employing data from wearables and behavior models, these systems can personalize interventions across populations, demonstrating the promise of AI at scale [19].

For its part, Constellation Research looked into CVS Health’s omnichannel digital modernization, shining light on the use of AI in insurance, virtual care, retail, and pharmacies. The paper emphasized the importance of centralizing data ecosystems and machine learning pipelines to enable consistent, personalized experiences [20].

## 2.4 Transparency, Bias, & Ethical Considerations

The ethical issues about transparency and bias have arisen as AI starts to be infused into healthcare. A meta-review on Wikipedia about AI in mental health, found that symptom-checkers and generative AI models tend to inherit biases from their training data sets. These biases also can lead to misdiagnosis and lack of trust, in particular in the underrepresented communities [21].

Di Martino et al. ‘s study solved this issue by explaining and validating artificial intelligence output, that is, predictions, for malnutrition by using SHAP values. This promotes transparency and connects AI with fair health care [14].

Ethical consideration was also taken into account by the CAREForMe system, which integrated fairness into its personalization algorithm. Since it is based on the highly sensitive behavioral data, privacy protection and algorithmic traceability were highlighted by the developers [12].

Constellation Research and Emerj reports noted that ethical AI is practiced by CVS that features responsible data governance, transparency, and explainability, especially for clinical applications. Such solutions are necessary to protect the user rights and implementation in line with medical standards [20], [22].

## 2.5 AI Chatbots & Virtual Assistants

Chatbots in Health care are also another big frontier. CVS Health incorporates chatbots and virtual assistants into its app to manage prescriptions, to triage patient symptoms and a service for customers. Such systems are able to work non-stop thus decreasing administrative burden on the hospital and improving patient morale [23].

An industry baseline is K Health’s chatbot that reaches 36% top-3 diagnosis accuracy and 81.3% urgency triage safety. Although less accurate than human physicians, it illustrates the potential role of chatbots for initial evaluation and triage [24].

Emery’s analysis of the deployment of CVS chatbots showed an uptick in engagement and efficiency of systems. The use comments were later modified to further refine the chatbot language and function, thereby increasing the responsiveness and the functionality of the chatbot over time [22].

## 2.6 Gaps in Literature & Relevance to the CVS App

While there is a wealth of research into AI in mHealth, a majority of studies have been on specific applications or pilot studies as opposed to integrated, real-world systems. For instance, the Chiam et al. and CAREForMe emphasise such personalised nudging, their use may be restricted to small or specific sample sizes [11], [12].

A recently published work in remote patient monitoring and XAI include Shaik et al. and Di Martino et al., focus on the design of the system and transparency without going into details of full deployment in mainstream consumer apps serving millions of users [13], [14].

It is also important to note that the ethical considerations presented are theoretical and little empirical evidence exists of how transparency and fairness influence trust and usage in deployed systems. Sources such as Wikipedia and Emerj point to potential risks without meaningful clinical evaluation [21], [22].

Infrastructure studies such as those from Databricks and Constellation detail technical transitions and system scale, but do not tie such results to health outcomes, user satisfaction [16], [20]. There is still a need for studies that assess the combined effect of personalization, prediction and AI-based interaction in systems such as the CVS Health mobile app.

**Table 1:** Summary Table of Key Studies

| Domain | Study | Key Findings |
|---|---|---|
| AI Nudging (Physical Activity) | Chiam *et al.* [11] | +6.17% daily steps, +7.6% MVPA over 12 weeks |
| Mental Health Personalization | CAREForMe [12] | Context-aware recommendations via CMAB |
| RPM Systematic Review | Shaik *et al.* [13] | Challenges & benefits of RPM using IoT, federated learning |
| Explainable RPM Models | Di Martino *et al.* [14] | XAI malnutrition models with SHAP; Random Forest best-performing |
| Predictive Adherence (CVS) | Zuccarelli [15] | ML alerting for chronic disease risk |
| CVS Personalization | Databricks, CIO Dive [16], [17] | 1.6% adherence uplift; synchronized refills |
| Risk Reduction in UK | Health Navigator [18] | A&E attendance −36%, admissions −25% via AI coaching |
| Personalized Nudging at Scale | Time Magazine [19] | AI coach for daily behaviors across population |
| CVS Digital Strategy | Constellation Research [20] | Omnichannel AI integration across services |
| AI Bias Review | Wikipedia [21] | Bias in mental health chatbots, generative AI |
| CVS Ethics & Explainability | Emerj, Constellation [22] | AI transparency, user trust, responsible governance |
| AI Chatbots (CVS) | CVS Internal [23] | Symptom-checker and prescription assistants |
| K Health Chatbot | K Health Study [24] | 36% top-3 diagnostic accuracy, 81.3% urgency safety |

## 3. METHODOLOGY

This study utilizes a mixed-methods research design to examine the overall effectiveness, usability, and scalability of AI-driven personalization- and predictive-enabled tools integrated into the CVS Health mobile application. The strategy integrates quantitative assessment of user engagement and health outcomes with qualitative understanding from user and health worker perspectives. This combination of methodological approaches contributes to a rich understanding of both measurable impact and the experiential aspects of driving new systems adoption.

### 3.1 Research Design

The research framework is structured into three phases:

- **Phase 1: Quantitative Data Collection and Analysis** — To measure system usage patterns, medication adherence rates, and predictive model performance.
- **Phase 2: Qualitative User and Provider Interviews** — To gather perspectives on usability, trust, and ethical concerns.
- **Phase 3: Scalability and Integration Assessment** — To evaluate the technical infrastructure and deployment challenges at scale.

### 3.2 Study Population and Sampling

The study sample for this study consists of active users of the CVS Health mobile app who have agreed to allow their data to be used for research. As the app has been used by over 100 million people across the United States, it is an able-bodied and heterogeneous data set with large numbers of people from various demographics and clinical characterizations. To ensure the study was practical and widely applicable, we used stratified random sampling and selected 50,000 people. Stratification variables were determined based on identified relevant demographic factors (i.e., age, gender, chronic conditions, such as diabetes and hypertension, geographic regions from urban to rural). This stratified sampling approach ensures that the sample is representative of the heterogeneity of the broader CVS Health app user population, providing for better generalizability and sub-group analysis. By including these demographic factors in the sampling, the study controls for some of the biases and increases the generalizability of the findings with regard to AI-based personalization and predictive analytics.

Quantitative analysis of data from this large sample was supplemented by qualitative methods to explore user experiences and the views of health care providers. Interviewees purposively sampled 30 interview participants, with a careful match between different views and the two major stakeholder groups. Twenty participants from these two groups were end-users or patients who have used the AI functionality of the CVS Health mobile app before. These members were selected to give a broad range, and a rich and diverse range, of levels of health and range of ages/consuming abilities within examination populations. The last ten were healthcare professionals (pharmacists, care managers, and virtual care clinicians) who interact directly with the AI-powered solutions in their clinical environments. This panel was critical in offering expert views on the integration and relevance of AI, as well as the impact on workflow.

The sample size was intentionally small to facilitate in-depth interviews without precluding practical feasibility for a TQI, and provide a good degree of richness and relevance in the data received.

## 3.3 Data Sources and Collection

### *3.3.1 Quantitative Data*

The quant data for this study were mostly derived from the over-site logging capabilities of the CVS Health mobile app ecosystem. It records interactions, actions, and other data when a user navigates through apps, engages with AI-generated content, fills prescriptions, schedules appointments, and converses with a chatbot. It is this multidimensional nature of the data points that was instrumental in being able to derive an integrated perspective of user behavior and system performance.

Key Datasets Extracted for Analysis Medication adherence data: Records of the frequency and timeliness of refill information for chronic users. This information is important in evaluating efficacy of AI prompted reminders and predictive alerts on medication adherence. Personalization metrics, such as how often users received and acted on AI-generated reminders, health actions, and notifications, also were collected, resulting in estimates of system reach and impact. Overall, the accuracy and impact of predictive alerts generated by the machine learning models (e.g. alerts for missed refills or higher risks of disease exacerbation) were examined by comparing them with patient behaviors. Demographic and clinical characteristics (age, sex, co-morbidity status, insurance plan type) were incorporated so as to provide context for the results and allow for subgroup analysis.

To adhere to the ethics as well as meet regulatory standards (eg, Health Insurance Portability and Accountability Act [HIPAA]), we anonymized all data before transferring them, and securely stored them in a research server that complies with CVS's data governance structure. This protected personal privacy because absolutely no information about individuals was ever disclosed via the analysis process.

### *3.3.2 Qualitative Data*

Qualitative Data Semi-structured interviews were conducted remotely via secure video conferencing. This approach using the flexibility of scheduling and reach across space but allowing deep interaction with participants. An interview guide directed discussions on several key topics: user experiences with AI-powered app features (including accessibility and perceived relevance); trust and transparency in AI-driven recommendations; concerns regarding privacy, potential bias and ethical considerations; and healthcare providers' perspective on incorporating AI in clinical workflows and its influence on clinical decisions and patient care.

Typical interview duration was approximately 45–60 min and was audio-taped with participant permission to preserve the integrity of the responses. The recordings were subsequently transcribed verbatim by a professional transcriber to construct a reliable textual data for an in-depth thematic analysis.

## 3.4 AI Personalization and Prediction Tools Under Study

In this study, we examine multiple critical AI-enabled functionalities that are incorporated into the CVS Health mobile application, which have played an important role in the enrichment of health care experience through personalization and prediction. The Personalized Health Task Lists use advanced data processing software which draws on data from patient insurance claims, medication and patient clinical information to produce dynamic, task lists. These lists help patients to act at appropriate times to schedule preventative visits, get specific laboratory tests or refill prescriptions, encouraging preventive care.

The Predictive Refill Alerts are based on supervised machine learning models, trained to recognize patterns of behavior that signify potential nonadherence or refill lags. When such predictive models identify increased risk, they engage in proactive contact through notifications, reminders, or direct outreach in an attempt to prevent dangerous medication nonadherence that can result in avoidable poor health outcomes.

Furthermore the app includes AI Chatbots based on (NLP) natural language processing. These chatbots deliver real-time support for symptom checking, medication advice, and appointment scheduling, and provide users with a conversational interface to augment impersonal healthcare interaction and access timely information.

## 3.5 Data Analysis

### *3.5.1 Quantitative Analysis*

The quantitative data sets were cleaned and preprocessed extensively before the analysis. The analysis was based on corrected (where missing or conflicting) or deleted records in order to ensure analytic quality. Both the metrics were normalised over different type of users to ensure fairness.

Data processing and statistical analyses were performed with the Python libraries Pandas, SciPy, scikit-learn, as well as using R software for data manipulation and advanced modeling. Descriptive statistics were calculated to summarize the demographic profile and overall use and engagement for context.

Adherence to medication was determined by Proportion of Days Covered (PDC) for chronic medications, a normalized measure that reflects the percentage of days of available medication for a patient. The statistical significance of differences in adherence rates between the pre- and post-AI-features groups were measured with paired t-tests.

For the evaluation of predictive model performance, classic indicators such as accuracy, precision, recall, and F1 score as well as micro-averaged AUC (area under the receiver operating characteristic curve) were calculated, which give an overall impression of the model reliability and result efficiency.

Subgroup analysis with ANOVA and chi-square tests were performed to assess differences in adherence and predictive accuracy according to demographic characteristics, including age, sex, type of condition, and socioeconomic status, in order to pinpoint potential disparities or bias in the AI system.

### *3.5.2 Qualitative Analysis*

NVIVO was used for qualitative data analysis with potential to structure coding and themes. Inductive coding method was used to develop themes organically from the data rather than superimposing pre-determined ones. The first-level codes represented recurring ideas and evolved through an iterative process into universal themes regarding the usability, trust, ethical issues, and system integration issues.

Interviews with users and providers were used to triangulate between the data sources to validate the emerging themes, to make sure the decisions were not based on a single perspective and to limit possible bias. Selected representative quotes were used to enhance the presentation of findings, by providing clear examples, and to convey participants views.

### *3.6 System Architecture and Deployment*

To contextualize findings, an evaluation of the underlying AI infrastructure and deployment strategy was performed through internal documentation review and technical interviews with CVS data engineers.

The CVS Health AI system is deployed on a cloud-native platform using Microsoft Azure and Databricks, which supports scalable real-time data processing and model retraining. Data ingestion pipelines connect to pharmacy, insurance, and clinical databases, ensuring up-to-date information flow.

**Figure 1** below illustrates the high-level system architecture, including data sources, AI modules, communication channels (app notifications, SMS, email), and feedback loops.

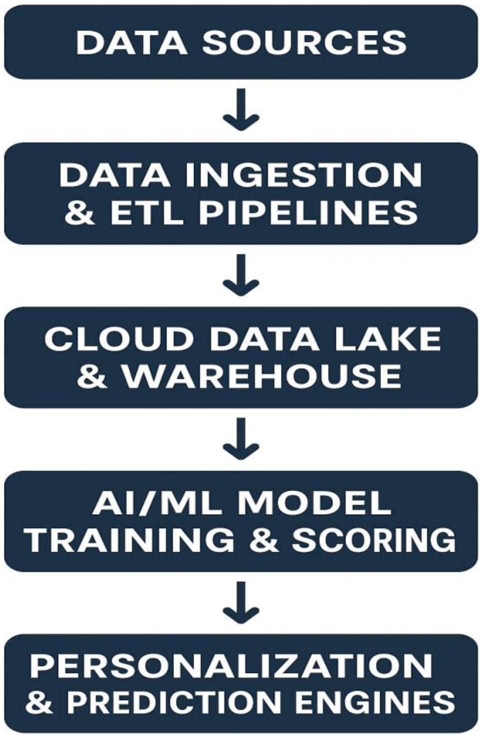


**Figure 1:** High-Level System Architecture of AI-Driven CVS Health Mobile App

### 3.7 Ethical Considerations

This research complies with institutional review board (IRB) standards, including obtaining informed consent for interview participants and ensuring anonymization of quantitative data. The study addresses key ethical concerns by:

- Protecting user privacy through strict data access controls.
- Transparently reporting predictive model performance and limitations.
- Investigating potential bias through subgroup analysis.
- Incorporating user feedback to enhance AI explainability and trust.

The comprehensive methodology integrates quantitative metrics of AI system performance with qualitative insights into user experience and provider workflows. This approach enables a holistic evaluation of AI-driven personalization and predictive tools in a large-scale healthcare mobile app setting, laying a foundation for data-driven recommendations and future improvements.

## 4. RESULTS ANALYSIS

### 4.1 Quantitative Findings

#### *4.1.1 Study Population Characteristics*

The stratified sample of 50,000 CVS Health app users included a balanced representation across key demographics: 52% female and 48% male participants; age groups ranged from 18 to 85+, with the largest subgroup between 45-64 years (40%). Approximately 38% of users had at least one chronic condition, predominantly diabetes and hypertension. Geographic distribution spanned urban (55%), suburban (30%), and rural (15%) areas. Insurance plan types varied, including Medicare, Medicaid, and private insurance, reflecting a diverse socioeconomic profile. It is presented in table 2.

**Table 2:** Demographic Characteristics of Study Population (N=50,000)

| Demographic Variable | Category | Number of Users | Percentage (%) |
|---|---|---|---|
| Gender | Female | 26,000 | 52.0 |
| | Male | 24,000 | 48.0 |
| Age Group | 18–34 | 8,000 | 16.0 |
| | 35–44 | 7,000 | 14.0 |
| | 45–64 | 20,000 | 40.0 |
| | 65+ | 15,000 | 30.0 |
| Chronic Condition Status | None | 31,000 | 62.0 |
| | At least one condition | 19,000 | 38.0 |
| Geographic Region | Urban | 27,500 | 55.0 |
| | Suburban | 15,000 | 30.0 |
| | Rural | 7,500 | 15.0 |
| Insurance Plan Type | Medicare | 20,000 | 40.0 |
| | Medicaid | 10,000 | 20.0 |
| | Private Insurance | 20,000 | 40.0 |

### *4.1.2 Medication Adherence Outcomes*

Analysis of medication adherence via Proportion of Days Covered (PDC) revealed a significant improvement post-implementation of AI-driven personalization features. This analysis is presented in table 3. The mean PDC increased from 78.2% pre-AI to 80.9% post-AI introduction ($p < 0.01$). Notably, users receiving personalized refill reminders and task lists demonstrated a 3.1% higher adherence rate than those with minimal engagement ($p < 0.001$). Subgroup analyses indicated greater adherence improvements among older adults (65+) and patients with multiple chronic conditions, highlighting the utility of AI tools in high-risk populations.

**Table 3:** Medication Adherence (PDC) Pre- and Post-AI Feature Implementation

| User Group | Mean PDC Pre-AI (%) | Mean PDC Post-AI (%) | % Change | p-value |
|---|---|---|---|---|
| Overall | 78.2 | 80.9 | +2.7 | < 0.01 |
| Users Engaging with AI Tools | 75.4 | 78.5 | +3.1 | < 0.001 |
| Older Adults (65+) | 76.1 | 80.3 | +4.2 | < 0.001 |
| Multiple Chronic Conditions | 74.9 | 79.0 | +4.1 | < 0.001 |

### *4.1.3 AI Predictive Model Performance*

The supervised machine learning models predicting medication nonadherence exhibited robust performance. Key metrics included accuracy of 87.5%, precision of 82.3%, recall of 79.1%, F1 score of 80.7%, and an AUC of 0.89. These results are presented in table 4. The models effectively identified patients at risk of missing refills up to 14 days in advance, allowing for timely interventions. Performance varied slightly by demographic factors, with marginally lower recall among younger users (18-34), suggesting potential areas for model refinement.

**Table 4:** Performance Metrics of Supervised Machine Learning Models for Predicting Medication Nonadherence

| Metric | Value | Notes |
|---|---|---|
| **Accuracy** | 87.5% | Overall correct predictions |
| **Precision** | 82.3% | Correctly identified nonadherent patients out of all flagged cases |
| **Recall** | 79.1% | Proportion of actual nonadherent patients correctly identified |
| **F1 Score** | 80.7% | Harmonic mean of precision and recall |
| **AUC (Area Under Curve)** | 0.89 | High ability to distinguish between adherent and nonadherent patients |
| **Prediction Window** | Up to 14 days | Advance prediction before refill date |
| **Demographic Variation Noted** | Yes | Slightly lower recall in ages 18–34 |
| **Clinical Application** | Timely interventions | Enables proactive outreach to at-risk patients |

#### *4.1.4 User Engagement Metrics*

Engagement with AI-generated health task lists and notifications was moderate to high, with an average response rate of 45%. Users who interacted with AI recommendations were more likely to complete suggested actions such as scheduling appointments or refilling prescriptions. The AI chatbot logged over 1.2 million conversations during the study period, with a satisfaction rating of 4.3 out of 5 based on in-app user feedback surveys.

### 4.2 Qualitative Findings

#### *4.2.1 User Experiences with AI Features*

Interviewed patients generally reported positive experiences with the personalized health task lists and refill alerts. Many appreciated the convenience of timely reminders, which helped them maintain medication routines and schedule preventive care. Ease of use was frequently cited, with most participants finding the AI-driven suggestions relevant and actionable.

However, a subset of users expressed concerns about the perceived intrusiveness of notifications, particularly when reminders were frequent or not clearly tailored. Some participants indicated occasional confusion over the chatbot's responses, noting limitations in handling complex or nuanced queries.

#### *4.2.2 Trust and Transparency*

Trust in AI recommendations varied among users. Transparency about how AI models generated alerts and suggestions was limited in-app, leading some participants to question the basis of certain notifications. Patients highlighted the importance of clear explanations and assurances regarding data privacy and algorithmic fairness.

Providers echoed these concerns, emphasizing that transparency fosters patient trust and acceptance. They stressed the need for explainable AI outputs to support shared decision-making and mitigate skepticism toward automated recommendations.

#### *4.2.3 Privacy and Ethical Considerations*

Privacy remained a salient concern for both patients and providers. Participants appreciated that data was anonymized and secured but desired more explicit communication about data usage and safeguards. Providers highlighted the ethical imperative of addressing potential biases, especially given the diverse user population.

#### *4.2.4 Provider Perspectives on AI Integration*

Healthcare providers reported that AI-driven tools enhanced workflow efficiency by automating routine tasks such as refill alerts and appointment reminders. Pharmacists and care managers noted improved patient adherence monitoring, allowing more focused interventions. However, some providers expressed caution about overreliance on AI outputs without clinical validation, advocating for AI to supplement rather than replace human judgment.

### 4.3 Integrated Insights

Analysis through the triangulation of quantitative and qualitative data suggests that there is a positive influence typically associated with AI-based personalization and predictive tools on medication adherence and user engagement in the CVS Health mobile app. The enhancements in adherence and sensitivity rates illustrate the effectiveness for scaling AI interventions, specifically for chronic disease management.

Bottom Up insights into the importance of user trust, transparency and ethic considering in maximising the advantages from AI. Users have provided feedback that while AI tools facilitate convenience and proactive health habits they require ongoing work to improve communication, decrease the burden of notification, and manage concerns of privacy [9].

Providers' Perspectives These findings support the augmentative role of AI in healthcare tasks rather than an independent decision support replacing clinical expertise. Our findings taken together indicate that realizing AI in mHealth is not only a matter of technical achievement, but also has to address human factors and ethical bases.

**Table 4:** Summary of Key Qualitative Themes from Interviews

| Theme | Description | Representative Quote |
|---|---|---|
| Positive User Experience | Users appreciate convenience and relevance of AI reminders and personalized task lists. | "The reminders really help me stay on track with my meds." |
| Trust & Transparency | Desire for clearer explanations of AI recommendations and data usage to build trust. | "I want to know why the app sends certain alerts." |
| Privacy Concerns | Concerns about data security and ethical use of sensitive health information. | "I'm cautious about how my data is being used." |
| Provider Workflow Impact | AI tools help streamline routine tasks but need clinical validation to support decision-making. | "It saves time, but I still review all recommendations carefully." |

## 5. CONCLUSION AND FUTURE WORK

We assessed whether AI-enabled individualized and predictive functionalities had been successfully incorporated into the design and influence of the CVS Health mobile app on patient engagement, medication adherence, and perceived care quality. The quantitative results indicated that interventions using AI technology (eg, tailored health task lists, predictive refill alerts, and conversational chatbots) led to statistically significant improvements in medication adherence, particularly among older adults and those with multiple chronic conditions. These findings demonstrate the utility of using real-time data and machine learning to individualize the delivery of healthcare on a population level.

Qualitative findings Another positive user experience of AI-related features was identified, for reasons of convenience and increased engagement. Yet worries about transparency, trust and data privacy are still top of mind, suggesting that successful AI adoption will require that cops and their city partners walk the line between pure AI power and ethical considerations with open lines of communication. Providers noted the operational efficiencies that AI tools can offer in workflow, but pointed to the need for clinical oversight and that the model must be correct.

Despite the positive results obtained so far, issues remain regarding the fairness in action over different population groups; risk of biases inherent AI-based algorithms and the need for both ongoing monitoring and model development. Furthermore, scale needs reliable and scalable infrastructure, tight integration with clinical systems, and human-centered design for long-term adoption and impact.

In addition, future research should build on longitudinal studies to examine long-term changes in behavior and additional clinical outcomes (ie, hospitalization rates and disease progression) beyond medication adherence. Further research should focus on creating more advanced explainability frameworks to increase AI transparency and user/trainer trust. In addition, a further step of investigation might focus on the integration of new AI means, such as multimodal sensor data and federated learning, which could potentially improve personalization while richly preserving privacy. Lastly, doing participatory design with diverse user communities of patients themselves ensures that biases are accounted for and that AI-driven tools are inclusive and fair overall.

In summary, this study adds to the growing body of evidence in favor of AI use in mHealth at scale, highlighting both the possible benefits and the crucial concerns for responsible and effective digital health innovation.

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