PREDICTING PATIENT ENGAGEMENT TO ENHANCE PREVENTIVE CARE IN MEDICARE ADVANTAGE

Eighth Annual Humana-Mays Healthcare Analytics 2024 Case Competition

Humana®

TEXAS A&M UNIVERSITY
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Executive Summary

Introduction:

Humana is committed to improving the health and well-being of its members by enhancing their engagement in preventive care. By utilizing advanced data analytics, we will uncover key factors influencing member engagement and implement targeted interventions.

Objective:

The primary goal is to develop a predictive model to identify Local Preferred Provider Organization (LPPO) members at risk of not completing their annual preventive visits to Primary Care Physicians (PCPs).

Key Performance Indicators (KPIS):

The following key performance indicators (KPIs) are used to evaluate and select the best model by assessing its effectiveness, fairness, and predictive accuracy:

- ❖ **AUC (Area Under the Curve):** Measures the model's ability to distinguish between engaged and unengaged members, with higher values indicating better performance.
- ❖ **Receiver Operating Characteristic (ROC) Curve:** Visualizes the trade-off between true positive and false positive rates. An ideal curve approaches the top-left corner, indicating better model performance.
- ❖ **Confusion Matrix:** Summarizes model predictions by comparing true positives, false positives, true negatives, and false negatives, helping assess overall accuracy and error rates.
- ❖ **Disparity Score:** Evaluates fairness across demographic groups, such as race and gender, to detect and mitigate biases, ensuring equitable predictions.

Recommendations & Insights:

Based on the model's results, several strategies are recommended to improve engagement among high-risk groups and address healthcare disparities:

- ❖ **Veteran Care Enhancement Initiative –** Focuses on closing the care gap for veterans through personalized outreach and enhanced care protocols.
- ❖ **Health Support Program for Non-Group Members –** Promotes preventive care and chronic condition management for members with poorer health outcomes.
- ❖ **Incentive Programs for Members –** Provides health incentive rewards to encourage high-risk members to attend preventive visits, motivating greater participation
- ❖ **Automatic Medication Refill Reminders –** Notifies members with long prescription gaps, improving adherence and preventive care engagement.
- ❖ **ESRD Care Management Program –** Provides proactive care for members with end-stage renal disease (ESRD) to reduce hospitalizations and improve outcomes.
- ❖ **Tailored Campaigns for Minority Groups –** Implements targeted outreach for minority populations, addressing barriers and improving engagement.

Further details are provided in the full report starting on the next page

1. Business Understanding

1.1 Introduction

Humana, one of the largest health insurers in the U.S., focuses on providing "human care" by using technology, data, and active listening to address the needs of its members. The 2024 Humana-Mays Healthcare Analytics Case Competition aims to address challenges in preventive care, which is critical to Humana's mission to improve member health outcomes.

1.2 Background

Founded in 1961, Humana offers Medicare Advantage (MA) plans, including PPOs and LPPOs, providing comprehensive coverage with additional benefits. Humana's performance is evaluated through CMS Stars Ratings and Medicare Risk Adjustment (MRA), which impacts funding and the quality of care provided to its members.

1.3 Problem Statement

Annual preventive visits to Primary Care Physicians (PCPs) are essential for managing health. Members who miss these visits are considered "unengaged," affecting Humana’s CMS Stars Ratings and MRA scores, leading to reduced funding and poorer health outcomes. LPPO plans, with their flexibility, have a higher percentage of unengaged members compared to HMO plans, impacting the effectiveness of preventive care.

1.4 Objective

The goal is to create a predictive model identifying LPPO members unlikely to complete a preventive PCP visit. The model will guide targeted interventions to increase engagement, improve member outcomes, and boost Humana’s CMS ratings, while minimizing biases related to race, gender, and other demographics.

1.5 Success Criteria and Key Performance Indicators (KPIs)

Success will be measured by achieving a high AUC score and ensuring the model is fair and unbiased, particularly in terms of sex and gender. The model’s insights will inform outreach strategies to enhance member participation in preventive care services.

2. Data Understanding

2.1 Data Introduction/Sourcing

The dataset was compiled by combining data from 14 different Excel sheets using an outer join, ensuring all records from each sheet were retained. This resulted in a dataset with approximately 1.5 million rows and over 42 million missing values. The raw datasets for Quality Data, Member Claims, and Member Conditions were not initially at the individual member level. These datasets were aggregated by member ID, creating new columns such as HEDIS, Patient Experience, and Patient Safety for analysis at the member level.

2.2 Data Preparation

The dataset was compiled by merging data from 14 Excel sheets using an outer join, resulting in approximately 1.5 million rows and over 42 million missing values. Raw datasets, including Quality Data, Member Claims, and Member Conditions, were aggregated by member ID to create member-level columns like HEDIS, Patient Experience, and Patient Safety.

For data preprocessing, irrelevant columns were removed, and missing numerical values (e.g., age, income) were imputed with the mean, while missing categorical values were filled as 'Unknown.' A correlation analysis identified and removed redundant numerical features with a correlation above 0.7 or below -0.7. Variance analysis eliminated features with low variation, such as numerical features with variance below 0.003 and categorical features dominated by a single category (over 99.7%). Additionally, business-irrelevant columns, including certain health indicators and interaction count variables, were discarded, resulting in a refined dataset with only the most relevant information for modeling.

Target Variable for Prediction

The focus of this analysis is the binary target variable, ‘preventive_visit_gap_ind’, which indicates whether a member completed their annual preventive visit with a Primary Care Physician. A value of '0' represents an engaged member who attended their visit, while '1' designates an unengaged member who did not.

This analysis primarily targets the positive class, unengaged members, as they represent the key population of interest. The data shows an imbalance, with 840,844 eventful visits and 687,060 uneventful ones, meaning 18% fewer members missed their visits. The table below provides a clear summary of the target variable and the engagement gap between eventful and uneventful visits:

Table 1. *Breakdown of Preventive Visit Engagement Variable*

Target Variable	Description
Preventive_visit_gap_ind	Binary variable indicating if a member completed their annual preventive visit with a Primary Care Physician.
Value = 0 (Eventful)	Member is engaged, meaning they attended a preventive visit.
Value = 1 (Uneventful)	Member is unengaged, meaning they did not complete a preventive visit. (Primary focus)
Eventful Visits	840,844 members completed their preventive visits.
Uneventful Visits	687,060 members missed their preventive visits.
Engagement Gap	18% fewer members missed their visits (uneventful) compared to those who attended (eventful).

2.3 Data Exploratory Analysis / Data Visualization

Exploratory data analysis (EDA) and visualization were conducted using Python libraries like pandas, matplotlib, and seaborn to investigate the target variable. The visuals are shown in Appendix A, with the analysis divided into three sections: demographic analysis (Figure A1), provider attribution (Figure A2), and socioeconomic/disability factors, including seasonality and rural population trends (Figure A3).

Demographic Analysis: Race, Sex, Age

Demographic factors such as race, sex, and age were analyzed for their impact on preventive visit outcomes. Asian members had the highest attendance rate at 59.6% and White members at 56.5%. Black members showed a moderate engagement of 54.1% and Hispanic members 50.4%. Native American members had the lowest attendance at 22.6%. Female members were more likely to attend preventive visits with a rate of 59.8% compared to 51.3% for male members. Members aged 60-80 had the highest engagement in preventive visits, though this group also exhibited a higher rate of missed appointments. These trends are shown in Figure A1.

Provider Attribution, Socioeconomic, and Disability Analysis

Figure A2 highlights that having an attributed provider greatly increases attendance, with 59.9% of members with an attributed provider attending compared to 27.5% without one. Dual eligibility, disability status, and LIS status also impacted attendance rates. Non-dual-eligible members had a higher attendance rate of 57.0% compared to 48.2% for dual-eligible members. Non-disabled members had an attendance rate of 58.1%, while disabled members had 49.0%. Non-LIS members attended at a rate of 57.1%, compared to 49.3% for LIS recipients. These factors underline the role of social and structural influences on healthcare access.

Seasonality and Rural Population Trends Analysis

Seasonal trends influenced visit outcomes, with uneventful visits increasing during early 2022, and the gap widening in late 2022. Rural areas showed more missed visits, with a mean percentage of 34% for those missing visits compared to 30% for those attending, indicating potential access challenges. Figure A3 presents these findings, with the top graph showing monthly trends in preventive visits and the bottom graph comparing rural population percentages for eventful versus uneventful visits.

2.4 Feature Engineering

After exploring the data, new features were created to capture key relationships and improve the model's predictions, focusing on interactions between behavior, socioeconomic factors, and health risks. These newly engineered features, along with other selected variables, are now ready for modeling. Table B1 in the appendix displays the newly engineered features, offering additional context and insights that traditional variables alone may not provide.

2.5 Data Transformation

After feature engineering, data transformation was tailored to the model type to ensure effective processing and accurate predictions. Min-max normalization was applied to scale numerical features, such as age, to a range between 0 and 1. This prevents features with larger values from dominating the model and ensures all variables contribute equally. For categorical variables like 'sex_cd' and 'race,' one-hot encoding was used, converting them into binary columns to facilitate model processing.

3. Modeling and Evaluation

The modeling process was designed to build an effective classification model capable of predicting which members are unlikely to attend their preventive visits. To ensure reliable model performance, several key decisions were made regarding data partitioning, resampling, and handling of class imbalance. These choices were made to optimize the model's ability to learn from the data, avoid overfitting, and fairly represent both engaged and unengaged members.

3.1 Data Partitioning and Imbalance Handling

To evaluate model performance, the dataset was split into 80% training and 20% testing, with random seed 12345 applied for consistent model comparison. This 80/20 split ensures that the model is trained on a large portion of the data while reserving a separate subset to assess how well it generalizes to unseen data. The test set provides an unbiased estimate of the model's performance in real-world scenarios.

Due to the imbalance in the target variable, with 18% fewer members classified as unengaged compared to those who attended their preventive visits, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training data. SMOTE was selected to address this imbalance by generating synthetic examples of the minority class, unengaged members, which helped the model learn to better distinguish between engaged and unengaged members.

3.2 Model Selection

Several models, including Random Forest, Logistic Regression, Decision Tree, and XGBoost, were tested to predict member engagement. Due to the large dataset and diverse features, tree-based models were considered the most suitable for this case. Among these, XGBoost demonstrated the best performance and was selected for further optimization through hyperparameter tuning.

The performance of each model was evaluated using the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve, which measures the model's ability to distinguish between engaged and unengaged members. A higher AUC indicates better model performance. XGBoost achieved the highest AUC score of 0.76 and exhibited the fastest training time, enabling efficient hyperparameter tuning. Its superior performance and efficiency made XGBoost the preferred choice for this analysis.

3.3 Best Model Parameters

XGBoost was identified as the top-performing model based on its impressive AUC score of 0.76 and its efficient training capabilities. This algorithm, which leverages decision trees, is particularly adept at managing large datasets and capturing complex patterns within the data (XGBoost, 2024). It offers flexibility through a range of hyperparameters that control the learning process and model complexity. Hyperparameter tuning was done by using GridSearchCV, a tool in scikit-learn that automatically tests different combinations of settings to find the best ones for the model.

Along with selecting the best hyperparameters, cross fold-validation was used to ensure the model generalizes well across different data subsets and minimizes overfitting. This method provides a balance between bias and variance in performance estimates, leading to a more reliable assessment of the model's effectiveness. The performance metrics, including accuracy, precision, recall, and F1 score, will be discussed in the next section. Table B2 in the appendix shows the best parameters along with a summary of what they are and their values.

3.4 Best Model Evaluation

The XGBoost model is evaluated using the ROC Curve, which plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at different thresholds. The area under the curve (AUC) quantifies the model's ability to differentiate between the positive and negative classes, as shown in Figure 1.

An AUC of 0.5 indicates no discrimination ability, equivalent to random guessing, while 1.0 represents perfect classification. With an AUC of 0.76, the XGBoost model shows strong performance, effectively distinguishing between engaged and unengaged members. The confusion matrix in Figure 2 reveals that the model correctly identified 120,736 engaged members and 89,659 unengaged members but misclassified 47,279 engaged members as unengaged and 47,875 unengaged members as engaged. Despite these misclassifications, the model's overall performance remains strong.

Figure 1. *ROC Curve for XGBoost Model (Positive Class: Uneventful = 1)*

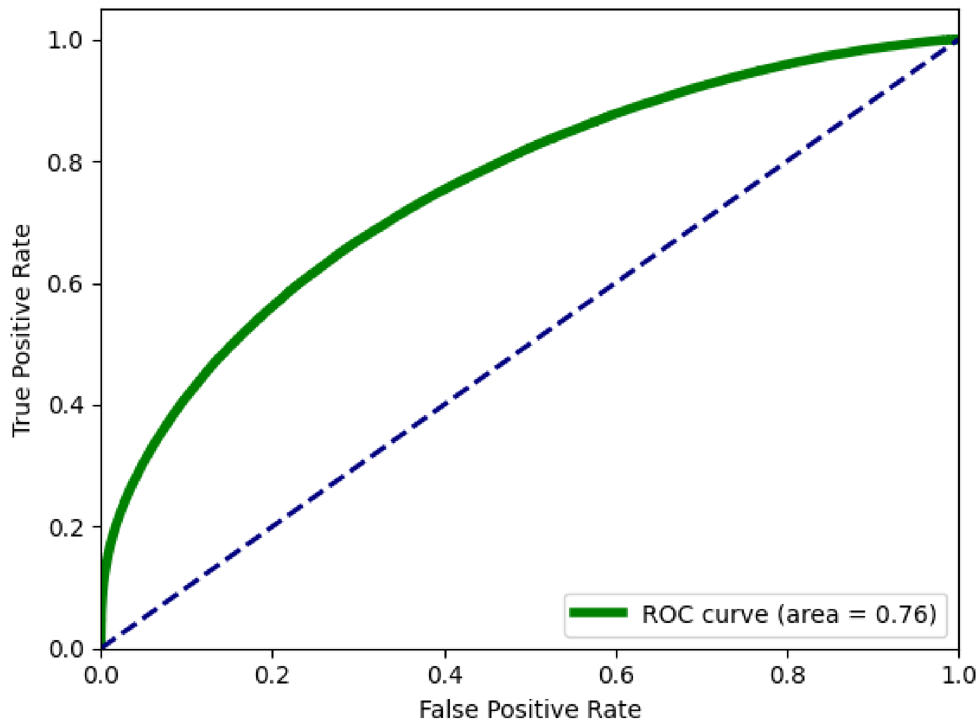
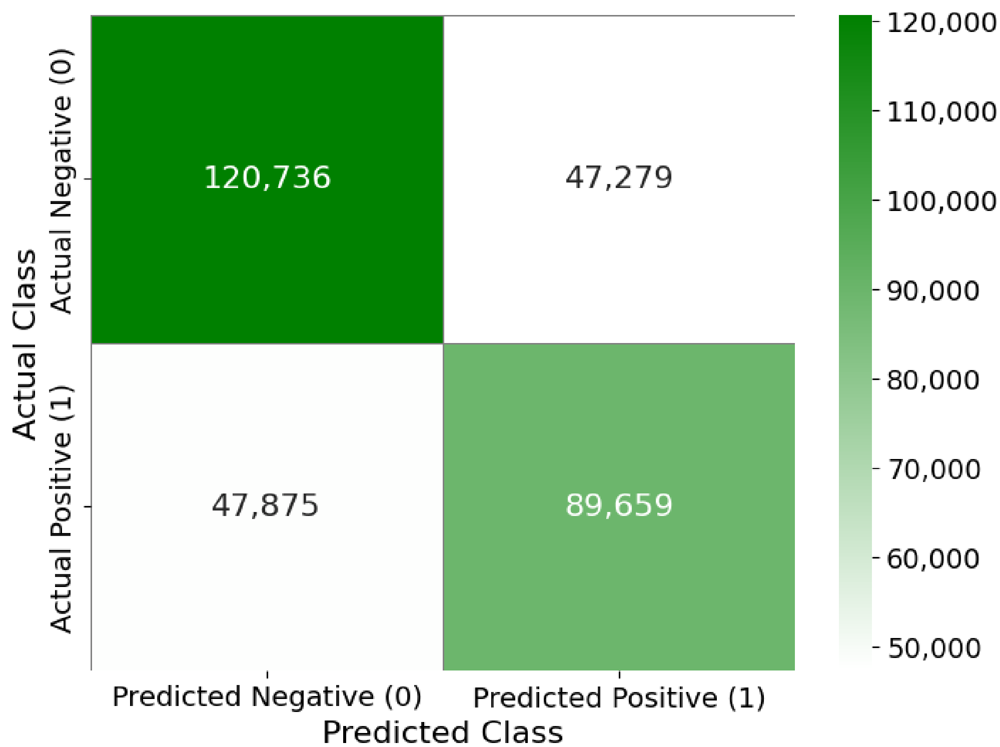


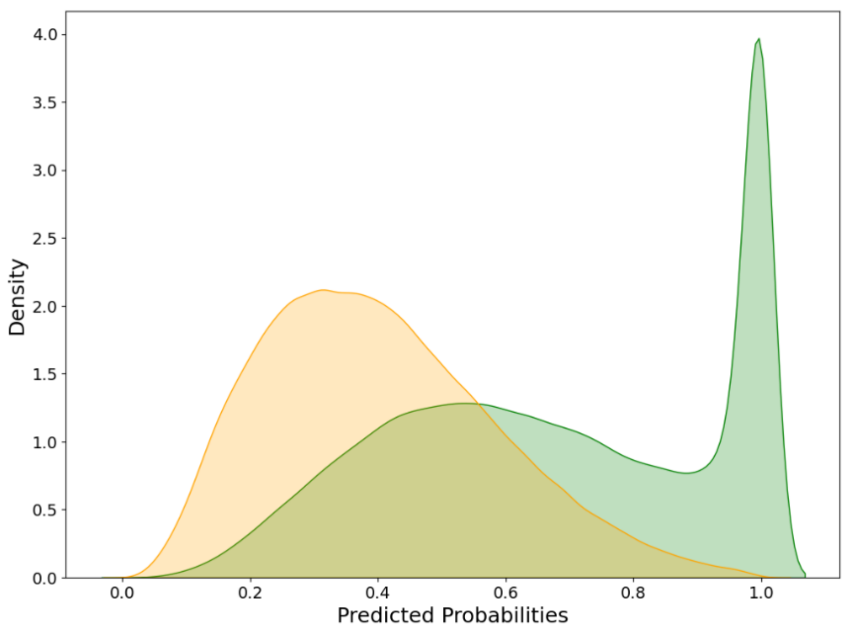
Figure 2. *Confusion Matrix for the XGBoost Model Predictions*



3.5 Model Probability Distribution Analysis

The XGBoost model's predicted probability distributions, shown in the Probability Density Function (PDF) plot in Figure 3 below, provide insights into its ability to distinguish between Uneventful Class 1 and Eventful Class 0 outcomes. The green curve represents uneventful cases, while the orange curve represents eventful ones. A higher concentration near 1 for uneventful cases indicates the model's confidence but overlap in the 0.2 to 0.6 range suggests challenges in differentiation, leading to potential misclassifications. Enhancements, such as incorporating additional data (e.g., socioeconomic or behavioral patterns) and adjusting the decision threshold, could further improve the model's predictive performance in healthcare contexts.

Figure 3 *Probability Density Function of Predicted Probabilities Outcomes*



3.5 Disparity Score Analysis for Evaluating Model Fairness

Fairness across demographic groups was a key evaluation metric for the XGBoost model, with a focus on disparity scores related to race and gender. Using White males as the reference group, disparity scores were calculated as percentages, comparing minority group performance to the reference group, as shown in Figure A4 in the appendix.

A minimum acceptable threshold of 90% was established, ensuring comparable performance across groups. The scores were: Female & Non-white (91.00%), Female & White (93.64%), Male & Non-white (93.51%), and Male & White (100%), all exceeding the fairness threshold. While the model demonstrates fairness overall, the Female & Non-white group had the lowest score, suggesting slight imbalance. Further enhancements, such as feature tuning or reweighting, and ongoing monitoring can ensure equitable performance across all demographics.

3.7 Key Drivers of Predictive Accuracy and Feature Importance

Feature importance analysis is crucial for understanding the factors driving model predictions and providing actionable insights. In the XGBoost model, feature importance is based on how frequently and effectively each feature contributes to predictions. As shown in Figure 4, Cost & Utilization is the most influential group at 27.30%, followed by Clinical Care at 14.78% and Health Behaviors at 12.55%. The prominence of Cost & Utilization highlights the impact of financial and utilization factors on member engagement. These insights help healthcare providers prioritize areas like clinical care, demographics, and pharmacy utilization to improve preventive care outcomes. Figure 4 visually represents these categories.

Figure 4. *Feature Importance for Healthcare Engagement by Category*

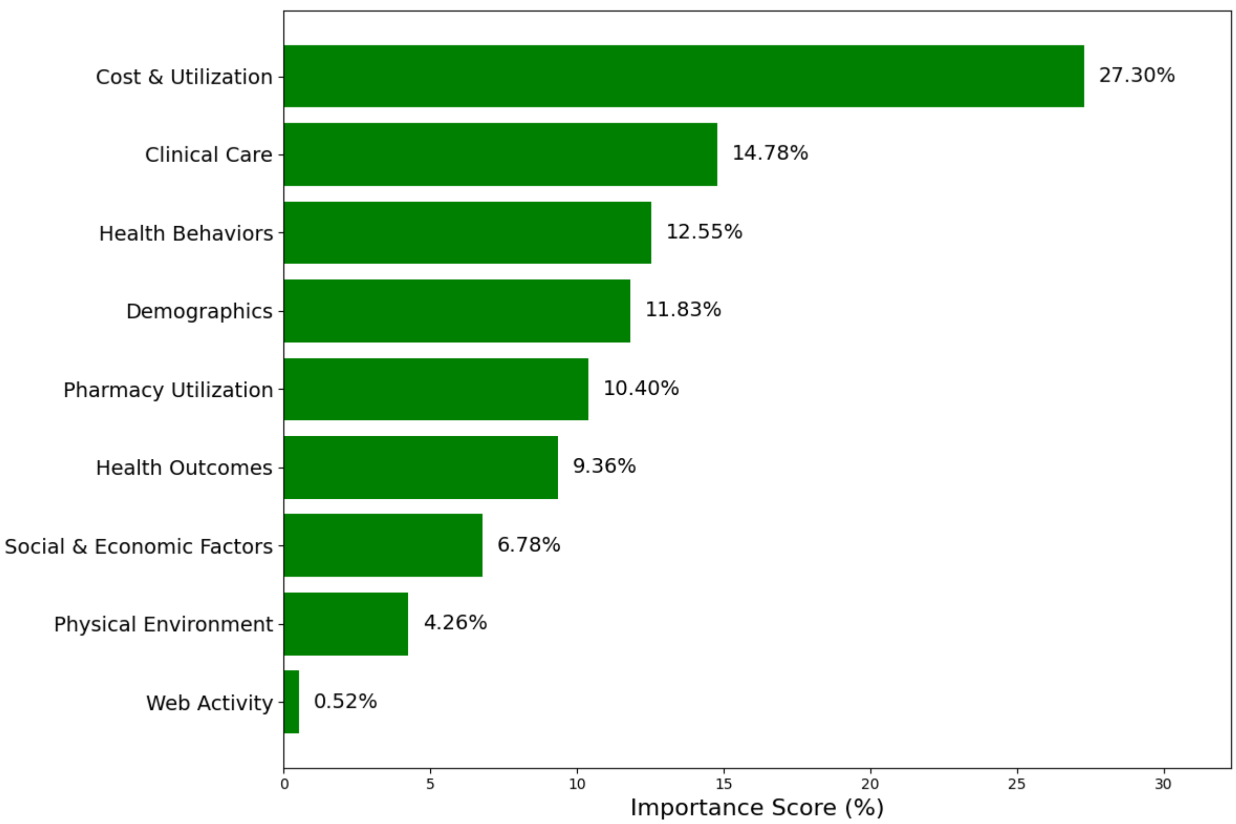


Table 2 below highlights the top 10 variables influencing member engagement in preventive care. Generic_grouper_Y (9.11%) leads, followed by Veteran_ind_Y (6.87%) and Unattributed_provider_Y (4.79%), reflecting healthcare challenges and continuity of care issues. ESRD_V24 (4.35%) and MEDICAL_V24 (2.64%) capture the impact of medical conditions, while demographic factors like Male (2.48%) and race categories offer insights into disparities.

Table 2. *Top 10 Most Influential Features in the Best Model*

Feature	Importance (%)	Description
Generic_grouper_Y	9.11	Categorizes members based on generic criteria.
Veteran_ind_Y	6.87	Indicates if the member is a veteran.
Unattributed_provider_Y	4.79	Flags cases with an unattributed provider.
ESRD_V24	4.35	Identifies members with end-stage renal disease.
MEDICAL_V24	2.64	Captures medical service usage.
Sex_cd_M	2.48	One-hot encoded variable indicating male gender.
Race_WHITE	2.11	One-hot encoded category for White members.
Race_BLACK	1.77	One-hot encoded category for Black members.
Rx_pharmacies_pmpm_ct	1.74	Number of pharmacies used per month in the past one year
Race_N AMERICAN NATIVE	1.74	One-hot encoded category for Native American members.

3.8 Model Deployment

Humana can integrate the XGBoost model into its healthcare systems to identify LPPO members at risk of missing preventive care visits, enabling targeted engagement that improves health outcomes, reduces disparities, and boosts CMS Stars ratings. The model will be hosted on a cloud platform, scalable for increasing demand, and integrated with Humana's patient management system via APIs for real-time predictions and batch processing. Patient data will be encrypted and managed under HIPAA standards, with restricted access to ensure compliance. Transparency in data use and regular audits will maintain trust, while continuous monitoring and retraining will ensure sustained model accuracy and improved engagement strategies.

4. Recommendations & Insights

Based on the insights derived from the XGBoost model, several targeted strategies can be implemented to improve preventive care engagement among Humana's LPPO members. These recommendations are designed to address key factors that contribute to member disengagement, with a particular focus on high-risk individuals and minority populations. Implementing these recommendations can significantly boost member engagement and improve healthcare outcomes.

Table 2 below outlines each recommendation, including the target audience, implementation plan, and its contribution to member engagement. The action plan section will detail specific steps and potential challenges for each proposal.

Table 2. *Recommendations for Enhancing Preventive Care Engagement*

Recommendation	Target	Proposed Plan	Improving Engagement for Humana
Veteran Care Enhancement Initiative	Veterans identified as high-risk, with low preventive visit attendance and safety ratings.	Provide personalized outreach and enhanced care protocols tailored to the needs of veterans.	Closes the care gap for veterans, boosting engagement through personalized outreach and enhanced care protocols.
Health Support Program for Non-Group Members	Members not classified under the generic grouper category, who have poorer health outcomes and higher health risk scores.	Launch a support program focused on regular check-ups	Improves health outcomes, reduces costs, and increases preventive care engagement, supporting Humana's member satisfaction goals.
Incentive Programs for Members	All members, with focus on high-risk groups identified by variables like rx_pharmacies_pmpm_ct, unattributed_provider_Y	Introduce health rewards (e.g., discounts or points) for completing preventive care visits, focusing on high-risk members.	Increases engagement by encouraging members to attend preventive care visits, particularly among high-risk groups, leading to improved health outcomes.
Automatic Medication Refill Reminders	Members with long gaps in prescription refills, identified by Rx_days_since_last_script	Implement an automated reminder system to notify members about overdue prescription.	Improves medication adherence, reduces care gaps, and encourages timely engagement in preventive care, enhancing overall healthcare outcomes.
ESRD Care Management Program	Members identified with ESRD, especially those with high medical service usage.	Deploy a care management program for ESRD members that includes telehealth and preventive services.	Reduces hospitalizations and healthcare costs by providing proactive care, improving outcomes, and supporting value-based care goals.
Tailored Campaigns for Minority Groups	Minority populations identified by variables such as race_BLACK and race_N AMERICAN NATIVE.	Develop outreach campaigns to address barriers to preventive care in these populations.	Increases engagement among minority groups by addressing their specific challenges, leading to more equitable access to preventive services.

5. Action Plans

This section outlines action plans to implement the strategies identified in 4. Recommendations & Insights. Building on the XGBoost model's predictions, the following action plans provide detailed steps for Humana to implement the recommendation strategies. These plans are designed to enhance member engagement, particularly among high-risk individuals and minority populations, while supporting improved health outcomes and member engagement.

5.1 Veteran Care Enhancement

The Veteran Care Enhancement Initiative seeks to improve care for veterans with low patient safety ratings. Our analysis identified segments at higher risk of missing preventive visits and disengaging from healthcare, highlighting the need for targeted interventions.

Humana monitors care quality through the Healthcare Effectiveness Data and Information Set, patient surveys, and safety indicators, but there is a significant disparity in safety ratings between veterans and non-veterans, likely due to unique health challenges such as chronic conditions and post-traumatic stress disorder (Moore, Shawler, Jordan, & Jackson, 2023). Humana serves over 6 million military members and holds a 53% market share in veteran-branded Medicare Advantage plans, yet veterans face barriers like homelessness, housing instability, and mental health issues that hinder access to care and increase healthcare costs (Guina, 2023).

Figure A5 in the appendix shows that 64.9% of veterans missed their preventive visit, compared to 42.5% of non-veterans, and veterans have a lower patient safety rating (0.376 vs. 0.629). To address these disparities, Humana should launch a Veteran Care Program focused on chronic conditions and post-traumatic stress disorder, supported by multidisciplinary care teams. Partnering with digital health companies like Digital Unity for Outreach Services could enhance care coordination through Medicare and veterans' benefits (Plescia, 2024).

Improved provider training and veteran-specific safety protocols, along with expanded partnerships with Veterans Affairs facilities, would further elevate care. Additionally, offering more in-person support and targeted communication methods, such as direct mail and community health fairs, will improve engagement, especially for older veterans.

5.2 Health Support Program for Non-Group Members

A key feature influencing our predictions is the generic grouper, which classifies a member's healthcare claims or conditions into a specific group. This binary indicator reflects a member's classification based on their healthcare history.

In our dataset, 58% of members are not classified under the generic grouper. Among them, 63% attended a preventive visit, compared to only 43% of those in the generic grouper category, showing a significant difference in healthcare engagement between the two groups.

Further analysis reveals that members outside the generic grouper category tend to have poorer health outcomes. The composite health risk score, which averages the Charlson Comorbidity Index, Diabetes Complications Severity Index, and Frailty Comorbidity Index, supports this. Members in the generic grouper category have a score of 2.66, while those outside it have a higher score of 3.00. A t-test confirmed a statistically significant difference, indicating that non-group members have more health issues.

Additionally, non-group members tend to fill more prescriptions, suggesting they may have chronic conditions that require regular monitoring. This could lead to more frequent check-ups and a higher likelihood of attending preventive visits.

Based on these insights, we recommend Humana launch the Health Support Program for Non-Group Members, targeting those with poorer health outcomes and higher health risk scores. By using data analytics to identify these members, Humana can implement tailored outreach, offering support through care coordinators and educational initiatives on managing chronic conditions. This program aims to boost preventive care engagement, improve health outcomes, and reduce healthcare costs, ultimately enhancing member satisfaction.

5.3 Incentive Programs for High-Risk Members

The Incentive Programs for Members action plan aims to motivate all members, particularly high-risk groups, to engage in preventive care. High-risk members are identified by factors such as high pharmacy usage and the absence of a designated healthcare provider. Figure A6 in the appendix shows that 65.5% of high-risk members missed their preventive care visits, while only 34.5% completed them. The 50% threshold is an important benchmark for measuring how well high-risk members are accessing preventive care. If less than half of these members are attending their preventive visits, it indicates a serious issue that needs to be addressed. Essentially, this threshold shows that many high-risk members are not receiving the care they need, which could lead to worsening health outcomes.

Humana should implement a rewards-based program for high-risk members, offering incentives like premium discounts, wellness service points, or gift cards for attending preventive visits. Personalized outreach, including tailored reminders via text, email, or phone, should encourage attendance. For members without a designated provider, assigning a primary care provider (PCP) should be prioritized, with added incentives for both the member and the PCP upon completing preventive visits. The program's success should be monitored by tracking visit completion rates and gathering member feedback for continuous improvement.

5.4 Automatic Medication Refill Reminders

Humana should implement an Automated Medication Refill Reminder Program for members with long gaps between prescription refills, focusing on those identified by the Rx_days_since_last_script feature. Timely automated reminders via text, email, or phone will help members avoid missing essential refills, improving their health management and engagement with preventive care visits. This initiative targets high-risk members with significant gaps in their medication history to reduce complications and enhance chronic disease management.

Figure A7 in the appendix shows the distribution of days since the last prescription refill for members who attended versus missed their preventive visits. Members who attended visits generally had shorter refill gaps, indicating a correlation between diligent prescription refills and preventive care engagement.

The red dashed line at 30 days marks a critical threshold, with members having gaps longer than 30 days at higher risk of complications and missed visits. Members in the uneventful group show longer refill gaps, particularly beyond 50 days, suggesting that longer refill gaps are linked to missed preventive visits. Outliers with refill gaps up to 500 days likely represent members who discontinued medication or face more complex healthcare challenges and should be prioritized for follow-up and care coordination.

5.5 Action Plan – ESRD Care Management Program

The ESRD Care Management Program aims to improve care for members with end-stage renal disease (ESRD), particularly those with high medical service usage. ESRD members often face frequent hospitalizations and treatments, driving up costs and reliance on reactive care (Centers for Medicare & Medicaid Services, n.d.). Humana can address these issues with telehealth, case management, and preventive services.

Telehealth will allow regular consultations without frequent in-person visits, benefiting members with mobility issues. Case management will coordinate dialysis, prescriptions, check-ups, and specialist consultations, reducing emergency interventions. Preventive services, including lab monitoring and health education, will help avoid severe health crises and hospitalizations. This integrated approach will improve outcomes and reduce healthcare costs for ESRD members.

5.6 Action Plan - Tailored Campaigns for Minority Groups

Minority populations, particularly Native Americans, face significant challenges in accessing preventive healthcare, especially in rural areas (National Academies, 2004; Kruse et al., 2016). Our analysis identified high rates of missed preventive visits in counties like San Juan, McKinley, and Apache in New Mexico, Arizona, and Oklahoma. Native American race is a key factor influencing preventive visit outcomes, with 77.4% of Native American members missing their visits, the highest among all racial groups (Figure A1).

Humana can target outreach campaigns in counties with large Native American populations, focusing on specific barriers like geographic isolation and limited healthcare infrastructure. For example, San Juan County had 98 missed visits among Native American males, and Apache County had 127 missed visits among females. Additionally, many Native Americans rely on underfunded healthcare services, so expanding access to Medicaid, Medicare Advantage, and affordable coverage options is crucial (Grow, 2024).

Collaborating with healthcare providers near Native American reservations, such as Cherokee Nation Health Services in Oklahoma, Banner Health in Arizona, and the University of New Mexico Health System, can improve access through mobile clinics, telehealth, and preventive care programs. These initiatives, focused on culturally competent care, will help reduce healthcare disparities and improve engagement in preventive care for Native American communities.

5.6 Generalization/Explanation of Recommendations and Action Plans

The action plans aim to enhance preventive care engagement for Humana's LPPO members, focusing on high-risk groups such as veterans, minority populations, and individuals with chronic conditions. For veterans, targeted outreach programs addressing health challenges like PTSD and chronic conditions, along with partnerships with veteran organizations, will improve attendance and ensure members receive necessary care.

For members with poorer health outcomes, particularly those without a designated healthcare provider, Humana can offer tailored support programs to promote chronic disease management. These programs would encourage regular check-ups and create personalized care plans to help members manage their health more effectively. Additionally, high-risk members—those with high pharmacy usage or no primary care provider—can be incentivized through reward-based programs, offering benefits such as premium discounts or wellness services. Automated medication refill reminders will also help members stay on top of prescriptions, reducing missed visits and improving overall health management.

Targeted outreach campaigns will address the specific needs of minority populations, particularly Native American communities, in regions with high rates of missed preventive visits. By understanding barriers such as limited healthcare access and cultural challenges, Humana can offer more effective interventions that improve health outcomes and reduce disparities. Collecting comprehensive data on health conditions and preventive care utilization will provide insights for refining outreach strategies, ensuring better member engagement, and supporting value-based care goals.

6. Future Scope

Looking ahead, Humana can build on the insights gained from this analysis and further refine its approach to preventive care engagement. By expanding the use of digital health tools, such as mobile apps and telehealth services, Humana can reach members in remote areas and those facing barriers to in-person care. As more data on members' health and care utilization becomes available, the company can identify emerging trends and adjust strategies accordingly. Partnerships with community organizations and healthcare providers can further enhance outreach efforts, making preventive care more accessible, particularly for underserved populations. By continuing to innovate and adapt, Humana can strengthen its commitment to providing comprehensive, equitable care that supports the well-being of all members.

6.1 Conclusion

The strategies outlined in this report are designed to improve preventive care engagement for Humana's LPPO members, particularly those in high-risk groups, such as veterans and minority populations. By addressing barriers to care and implementing targeted outreach programs, Humana can close care gaps, improve health outcomes, and foster more equitable healthcare experiences. The proposed initiatives, ranging from veteran-focused outreach to incentive programs for high-risk members, will drive higher engagement, reduce healthcare disparities, and align with Humana's value-based care goals.

As Humana progresses with these initiatives, continuous evaluation and refinement will be essential to ensure their success. The key to long-term effectiveness lies in leveraging data, gathering member feedback, and focusing on the unique needs of diverse populations. Through these efforts, Humana will enhance preventive care engagement and continue to lead the industry in delivering impactful healthcare solutions, improving member satisfaction, and supporting better health outcomes.

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Appendix A

Figure A1. *Percentage Distribution of Preventive Visit Outcomes by Race, Sex, and Age*

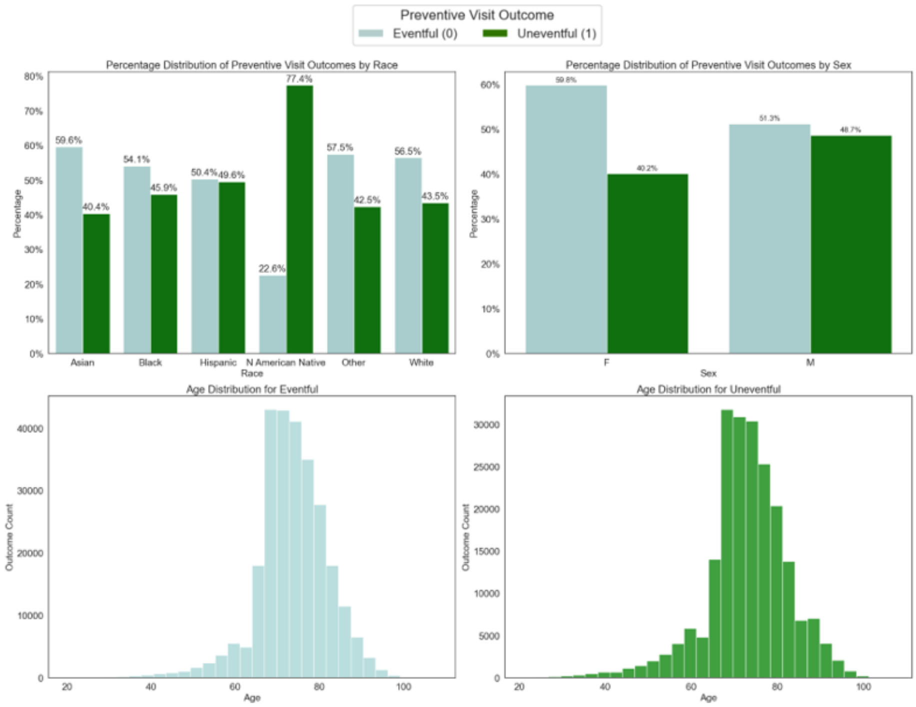


Figure A2. *Impact of Provider Attribution, Financial Status, and Disability on Target Variable*

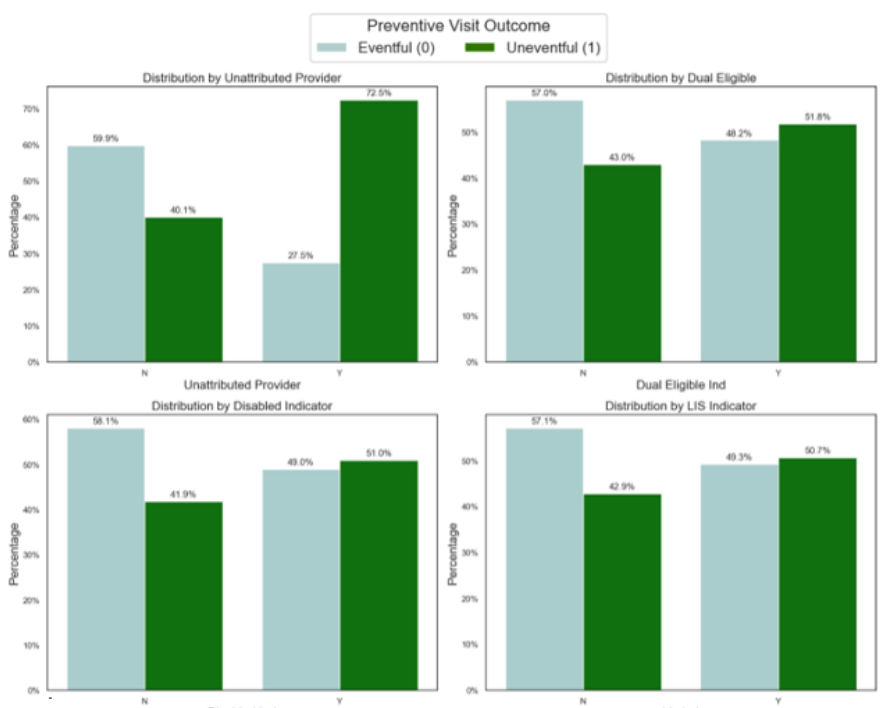


Figure A3. *Seasonality Trends and Rural Population Percentage by Preventive Visit Outcome*

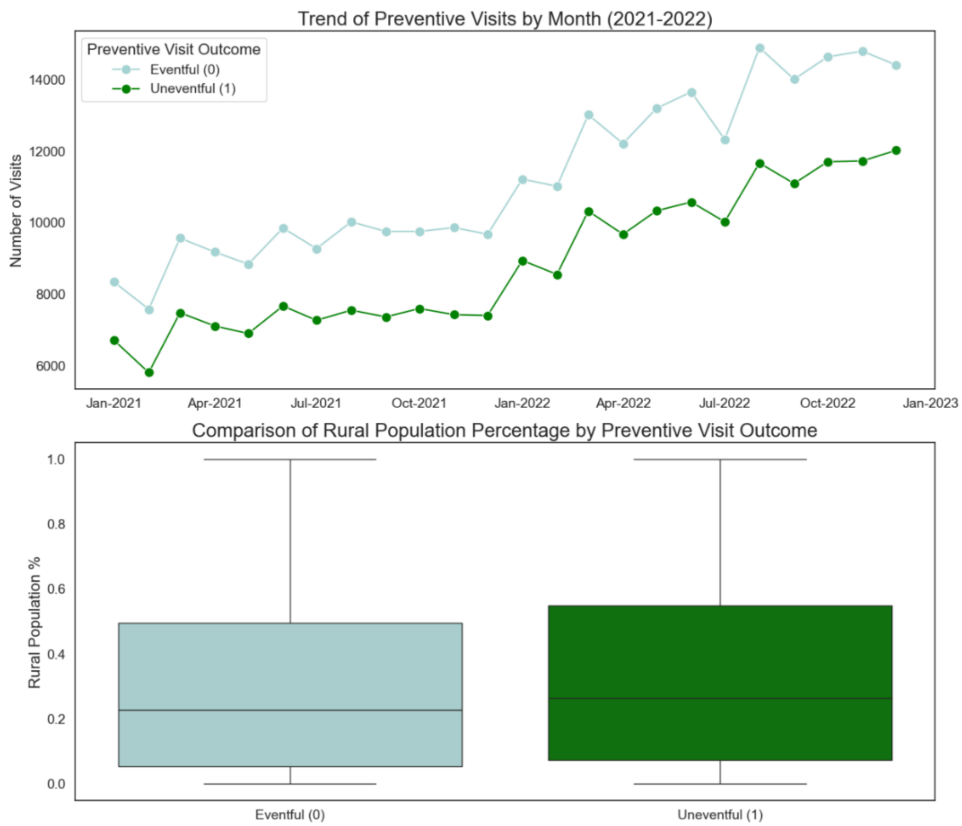


Figure A4. *Disparity Scores by Race and Gender Categories for XGBoost*

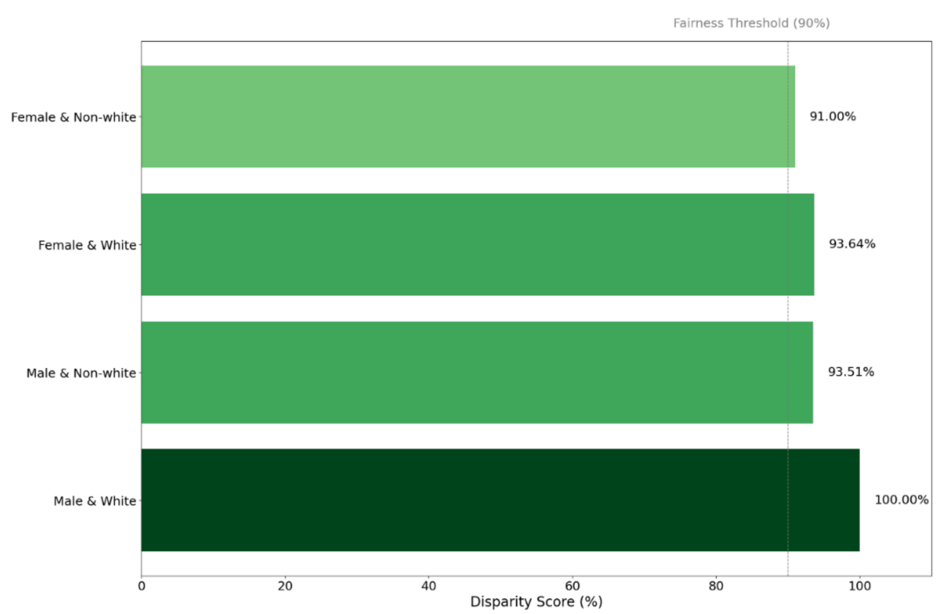


Figure A5. *Preventive Visit Outcomes and Patient Safety by Veteran Status*

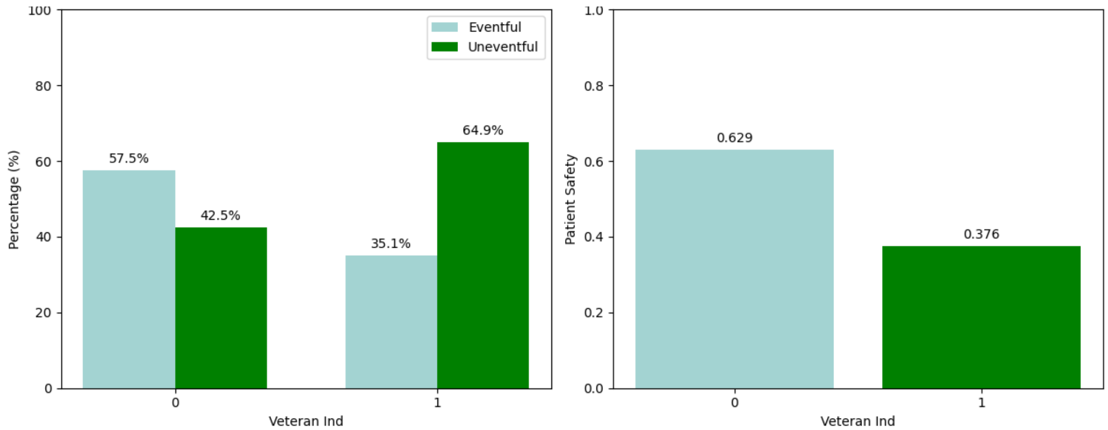


Figure A6. *Preventive Visit Completion Rates Among High-Risk Members*

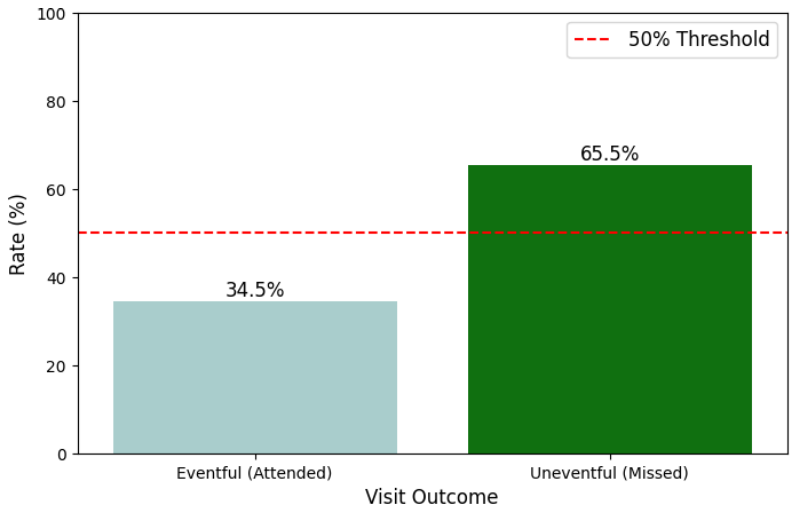
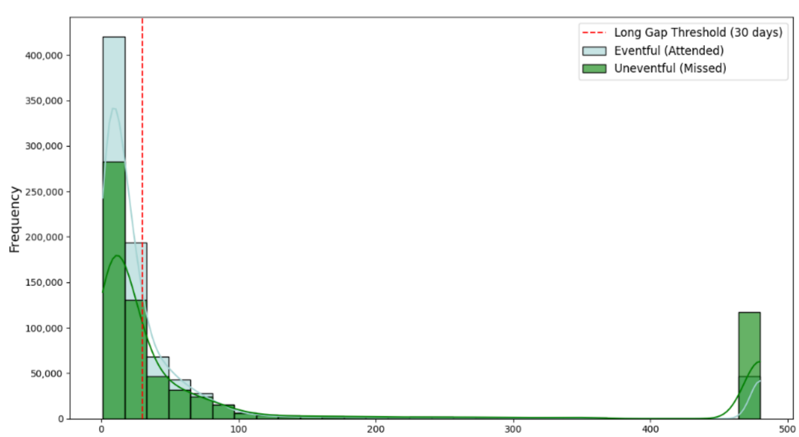


Figure A7. *Days Since Last Prescription Refill and Preventive Visit Outcomes*



Appendix B

Table B1. *Engineered Features and Their Definitions for Predictive Model Development*

Engineered Features	Definition
Channel Consumer Direct Score	Interaction between the Consumer Direct channel and the composite health risk score.
Channel DMS Telesales Score	Interaction between the DMS Telesales channel and the composite health risk score.
Channel Field Score	Interaction between the Field channel and the composite health risk score.
Channel Partner Call Center Score	Interaction between the Partner Call Center channel and the composite health risk score
Combined Health Index	A composite health index combining the composite health risk score, premature death rate, and diabetes percentage.
Composite Health Risk Score	This feature is the average of three health risk indicators—Charlson Comorbidity Index (CCI), Diabetes Complications Severity Index (DCSI), and Functional Comorbidity Index (FCI)
Economic Hardship Index	A composite economic hardship index combining median household income, unemployment rate, and child free lunch percentage.
High Tier Drug Ratio	Ratio of higher-tier drugs (tier 3 and 4) to lower-tier drugs (tier 1 and 2)
Interaction Health Term	Interaction term between composite health risk score and total interaction count
Region Frequency	Frequency-encoded values representing the relative frequency of residence by region.
Rucc Binary	A binary indicator for rural vs. metro residence, where metro (1, 2, 3) is coded as 1 and non-metro (4-9) is coded as 0.
Tenure Ratio	Ratio of consecutive tenure months to total tenure, indicating how consistently a member has stayed enrolled.
Total Interaction Count	Sum of interaction counts across multiple channels (email, print, VAT, web statements)
Total Out of Network Cost	Aggregated out-of-network costs, combining oontwk_allowed_pmpm_cost and nonpar_allowed_pmpm_cost.
Total Prescription Cost	The total cost of prescriptions, summing coinsurance, copay, deductible, and member responsibility costs.
Total Specialist Visits	Aggregated feature representing the total number of specialist visits.

Table B2 *Best XGBoost Model Hyperparameters and Their Functions*

Parameter	Value	Description
Number of Estimators	600	Controls the number of trees in the model. More trees can improve accuracy but increase training time.
Max Depth	10	Limits how deep each tree grows. Higher values capture complex patterns but can lead to overfitting.
Learning Rate	0.1	Adjusts how much to change weights at each step. Smaller values slow learning but improve accuracy.
Regularization Strength	2	Applies L2 regularization to reduce overfitting by penalizing large weights.
Subsample	0.8	Percentage of data used to train each tree. Lower values help reduce overfitting.
Scale Pos Weight	1.28	Adjusts the balance between classes in imbalanced datasets to focus more on the minority class.
Minimum Child Weight	3	Sets the minimum amount of data needed in a leaf to prevent overfitting on small data points.