ENHANCING ENGAGEMENT IN LPPO MEMBER'S PREVENTIVE ANNUAL PCP VISITS: PREDICTIVE ANALYSIS AND STRATEGIC IMPROVEMENT

HUMANA-MAYS HEALTHCARE ANALYTICS

CASE COMPETITION

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Contents

1. Executive Summary

Medicare is a federal health insurance program primarily designed for individuals aged 65 and older, but it also covers younger individuals with certain disabilities or chronic conditions. It is divided into several parts: Part A , Part B, Part C and Part D. Medicare Advantage (MA), also known as Part C, is offered by private insurers like Humana. MA plans must provide at least the same benefits as Original Medicare (Parts A and B) but often include extra benefits such as vision, dental, hearing, and wellness programs. MA plans come in different forms, including Health Maintenance Organizations (HMO) and Preferred Provider Organizations (PPO). HMO plans require members to choose a Primary Care Physician (PCP) and obtain referrals to see specialists, which ensures centralized care. On the other hand, PPO plans offer more flexibility, allowing members to see specialists directly. Humana's LPPO (Local Preferred Provider Organization) plans market share is growing.

Despite this growth, Humana faces a significant challenge with LPPO member engagement. Many LPPO members are not attending preventive visits with their PCPs, which is crucial for managing chronic conditions, performing health screenings, and updating their risk profiles. Without preventive care, Humana is missing key health condition related data necessary for Medicare Risk Adjustment (MRA), which determines CMS payments based on the member's health risk. Incomplete documentation can result in lower reimbursements from CMS which can cause Humana to bear the cost of care. Additionally, fewer preventive visits impact CMS Stars ratings which reduces bonus opportunities that Humana could reinvest in its plans. Improving engagement is essential to boost Stars scores, ensure accurate MRA payments, and maintain financial sustainability.

To address these challenges, we applied advanced modeling techniques. The data was cleaned by handling missing values, low-variance features, and class imbalance. After feature engineering and model building, we tested five machine learning models: Logistic Regression, XGBoost, CatBoost, LightGBM, and K-Nearest Neighbors (KNN). Among these, XGBoost emerged as the top performer with an adjusted AUC score of 0.7492, indicating strong predictive power for member engagement.

We recommend Humana implement several strategies to increase engagement of their LPPO members. Firstly, personalized outreach campaigns using data-driven messaging to remind members about preventive visits. Pharmacy partnerships can promote health engagement by encouraging screenings during prescription pick-ups. Expanding telehealth services will give members flexible options for care, particularly those who face barriers to in-person visits. Provider training on accurate risk documentation and introducing reduced-copay programs for specialist visit will help reduce financial barriers. We also advise addressing Social Determinants of Health (SDoH) by partnering with local organizations for mobile health clinics, and community outreach programs to remove obstacles to care. These strategies will ensure higher engagement, better Stars ratings, and optimized CMS reimbursements, securing financial sustainability for Humana.

2. Introduction

2.1 Case Background

Medicare is a federal health insurance program primarily for individuals aged 65 or older, but it also covers certain younger people with disabilities or specific health conditions. Medicare is divided into several parts:

- **Part A (Hospital Insurance):** Covers inpatient hospital stays, skilled nursing facility care, hospice care, and some home health care.
- **Part B (Medical Insurance):** Covers outpatient care, preventive services, medical supplies, and doctor visits.
- **Part D (Prescription Drug Coverage):** Provides coverage for prescription medications.

Medicare Advantage (MA): Medicare Advantage, or Part C, is a type of health plan offered by private insurance companies like Humana. These plans are required to offer at least the same coverage as Original Medicare (Parts A and B), but they often include additional benefits like vision, dental, hearing, and wellness programs. MA plans are structured into different types such as Health Maintenance Organizations (HMOs) and Preferred Provider Organizations (PPOs).

- **HMO (Health Maintenance Organization):** Requires members to choose a primary care physician (PCP) and get referrals for specialists, keeping healthcare more centralized.
- **PPO (Preferred Provider Organization):** Allows more flexibility by giving members direct access to specialists without needing a referral. However, out-of-network care generally comes with higher costs.

Over 30 million people are enrolled in Medicare Advantage plans, accounting for around 50% of the total Medicare population, with enrollment continuing to grow.[1]

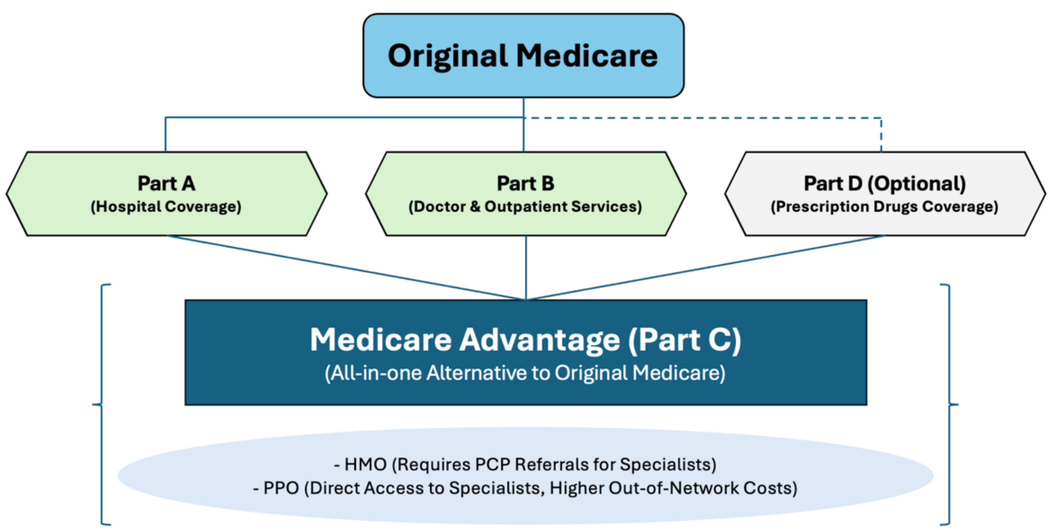


Figure 1: Medicare Advantage (MA) plan workflow

Despite having a growing market share in LPPO plans, Humana is experiencing lower engagement levels among members in terms of preventive visits with a PCP, which are crucial for Humana's success in key programs such as CMS Stars and Medicare Risk Adjustment (MRA). Addressing this issue is critical to maintaining high-quality care for members and ensuring financial sustainability for Humana.

2.2 The Business Issue

Humana is experiencing a growing challenge with its Local Preferred Provider Organizations (LPPO) plans, which have a significantly higher percentage of "unengaged" members compared to HMO plans. An unengaged member is defined as someone who has not had an annual preventive visit with their Primary Care Physician (PCP). This lack of engagement negatively impacts Humana's CMS Stars ratings and Medicare Risk Adjustment (MRA) programs.

The flexibility offered by LPPO plans allows members to see specialists directly without going through their PCP, making it easier for them to bypass annual preventive care visits. While this flexibility is appealing to members, it leads to fewer touchpoints with healthcare providers, especially primary care providers who play a crucial role in preventive care and chronic condition management. Additionally, LPPO members might seek care for acute issues or use emergency services without following up with their PCP for preventive care, further contributing to the unengaged member count.

The higher percentage of unengaged LPPO members has multiple negative implications for Humana. Preventive visits are crucial for scoring well in the CMS Stars program. Poor engagement leads to lower Stars ratings, which directly affects Humana's eligibility for bonuses. These bonuses are essential for reinvesting in member health plans and offering additional benefits. Medicare Risk Adjustment (MRA) relies on accurate documentation of member health conditions to determine funding. Fewer PCP visits mean fewer opportunities to capture and document chronic conditions, leading to underfunded care for these members. This incomplete documentation can result in lower payments from CMS, affecting the financial stability of Humana's LPPO plans. Again, fewer preventive visits and lower engagement can lead to unmanaged chronic conditions, increasing the likelihood of complications and more expensive emergency care. This not only impacts the health of members but also raises the cost of care for Humana.

2.3 Problem Statement

The central problem in this case is that Humana's Local Preferred Provider Organization (LPPO) plans exhibit a higher percentage of unengaged Medicare Advantage (MA) members compared to Health Maintenance Organization (HMO) plans. LPPO members, attracted by the flexibility of provider choice, often fail to engage in preventive visits with their Primary Care Physician (PCP), resulting in fewer critical touchpoints for health screenings and chronic condition management.

The goal of this case is to proactively and accurately identify members at risk of being unengaged in the calendar year and understand the key characteristics, activities, or events that increase this likelihood. Based on these insights, Humana needs actionable recommendations and strategies to enhance member engagement, ultimately improving Stars ratings and ensuring comprehensive risk documentation. Effective strategies may include targeted outreach, personalized reminders, and incentives for preventive care visits, thereby fostering better health outcomes and organizational performance.

2.4 Key Performance Indicators

Humana is dealing with the challenge of identifying and engaging Medicare Advantage (MA) members in LPPO plans who are considered "unengaged" due to their lack of preventive visits with a Primary Care Physician (PCP). To effectively manage and improve this engagement, machine learning models will be used to predict which members are likely to remain unengaged. Below are three key performance indicators (KPIs) used to evaluate the effectiveness of the model.

2.4.1 Receiver Operating Characteristic (ROC) Curve

The ROC Curve is a crucial tool in this case to assess how well the predictive model can distinguish between engaged and unengaged members. The Area Under the Curve (AUC) is the primary metric that summarizes this performance. A high AUC means that the model is effective in predicting which LPPO members are likely to remain unengaged (true positives) while also minimizing false positives (incorrectly predicting engagement) enabling Humana to target appropriate interventions for unengaged members. A lower AUC on the other hand would indicate the model is less effective, leading to missing opportunity to engage members who could benefit from preventive care. The AUC helps measure the quality of predictions, ensuring that Humana can deploy resources more efficiently to boost engagement, thus improving Stars ratings and ensuring more comprehensive risk documentation.

2.4.2 Confusion Matrix

The Confusion Matrix offers a deeper dive into the model's performance at a specific threshold. By breaking down the true positives, true negatives, false positives, and false negatives, it allows Humana to evaluate the sensitivity (ability to correctly identify unengaged members) and specificity (ability to avoid false positives). High sensitivity is crucial because identifying unengaged members accurately means the model can help guide outreach efforts toward those who have not had a preventive visit, thereby improving health outcomes. And high specificity on the other hand is equally important because it minimizes the number of false positives, preventing unnecessary interventions for members who are already engaged or who don't need additional follow-up. The Confusion Matrix also helps determine the overall accuracy of the model, ensuring that the recommendations for improving engagement are well-targeted and can positively affect Stars ratings and MRA documentation.

2.4.3 Disparity Score

The Disparity Score is essential for ensuring that the predictive model used in this case does not exacerbate biases based on sensitive features like race or gender. An unbiased model ensures that outreach and engagement strategies are fairly distributed among Humana's diverse LPPO membership.

If the Disparity Score for sensitive features (such as race or sex) is greater than 0.9, it indicates that the model is treating different demographic groups fairly. This is crucial because any disparity in outreach could mean that some populations are left further behind, potentially leading to negative health outcomes and lower Stars ratings in the long term. By ensuring fairness in the model's predictions, Humana can ensure that interventions designed to improve the engagement of the members are equitable across all demographics, further supporting their goals of improving member health, increasing provider touchpoints, and enhancing performance in the CMS Stars and MRA programs.

3. Understanding the Data

3.1 Data Overview

There were 14 different datasets for both training and holdout dataset to analyze and understand the behavior patterns of various individuals enrolled in the LPPO plan (1,527,904 unique members in the training dataset and 381,976 members in the holdout dataset) in order to predict whether or not they will make the yearly preventive visit indicated by the target variable: "*preventive_visit_gap_ind*". The following section describes briefly about the variables each file contained in Training and Holdout dataset:

- "Target members" file contains the information of the plan type, plan category and the year for which this study is to be conducted. This file contains the target variable "*preventive_visit_gap_ind*" It is a binary variable where 1 indicates that the member did not have a preventive visit and 0 indicates that they did have a preventive visit in calendar year 2023.
- The "Demographics" file covers information about the members attributed risk arrangement flags between insurer and provider such as upside, downside, reward and global agreements. It also contains the information about members geographic information and preferred language.
- The "Social Determinants of Health," discusses the data points which covers a wide array of factors that may influence a person's wellbeing. There are a total of 77 variables covered in this dataset and roughly categorized into the sections listed below:
  - **Clinical Care**: Social percentages with access to insurance and Medicare services including dental and mental health.
  - **Demographics**: General demographics of the neighborhood including age, language and race distribution.
  - **Health behaviors**: Social percentages that discuss unhealthy behavioral patterns such as smoking, drinking, drug abuse, insufficient sleep, car crashes, etc.
  - **Health Outcomes**: Discusses the outcomes of the unhealthy behaviors including mortality rates in children, HIV prevalence, etc.
  - **Physical Environment**: These are percentages that mostly discuss the conditions of physical environment including household and commute pattern such as household spending, housing problems, broadband connection, workforce that drives alone to work or how long they drive etc.
  - **Social and Economic Factors**: It discusses the socio-economic factors of the neighborhood such as household incomes, unemployment, violent crimes, and suicide rate etc.
- "Web Activity" dataset covers the login data in the past one year. It has multiple variables that discuss the count of logins via with a lag of 0 to 11 months from the score date in the past one year.
- "Pharmacy Utilization" dataset talks about the member' buying patterns at a pharmacy. This includes 16 variables including out-of-pocket cost for prescription, number of prescriptions, number of physicians used, number of pharmacies used, count of the prescriptions for each of the four tiers of drugs etc.
- "Cost and Utilization" dataset contains 35 variables that contains data about members' insurance claims and out-of-pocket cost for non-participating provider, out-of-network provider and in total.
- Marketing "Control Point" discusses the count of the interactions via various marketing mediums such as emails, live call, print, voice activated telephone call, and web statement.

- "Additional Features" covers additional information including CCI score, DCSI score, FCI score, payments for prescription drugs (part D) and Medicare Advantage (MA), grocery stores, fast food chain availability, restaurants, recreation facility of neighborhood and poverty rate.
- The "Member Claim" file talks about members' claims from PCP, preventive visits including different specialist visits such as endocrinology, oncology, urgent care, ER, etc. Most of the rows in this file is "Null" with a "Yes" for each line of visit. This data set contains 19,456,796 records of the different member claims. Not all members have claims given that unique member IDs are less than target IDs.
- "Member Conditions" data set talks about the different chronic conditions in the patients and different model classifications based on their conditions. This file contains a little over 4 million entries with information about the members having chronic diseases only.
- The "Member Details" talks about the basic personal information about each member including age, gender, race, state, country and region details.
- The "Member Data" file contains information about a member's tenure with Humana along with continuity of membership, also some additional information regarding membership facilities such as Part D subsidy and eligibility for Medicare and Medicaid etc.
- The "Quality Data" file contains results for 2020-2022 for HEDIS, Patient Safety, and Patient Experience quality measures.
- The "Sales Channel" contains a single variable that discusses the mode of sales such as Field, Brokerage, Consumer Direct, DMS Telesales, and Partner call center.

3.2 Data Exploration

For the initial impressions, we have put together a quick dashboard to visualize the data distribution at a glance. To avoid data privacy issues, instead of publishing online over the Tableau public forum, we have added snippets which can be found below.

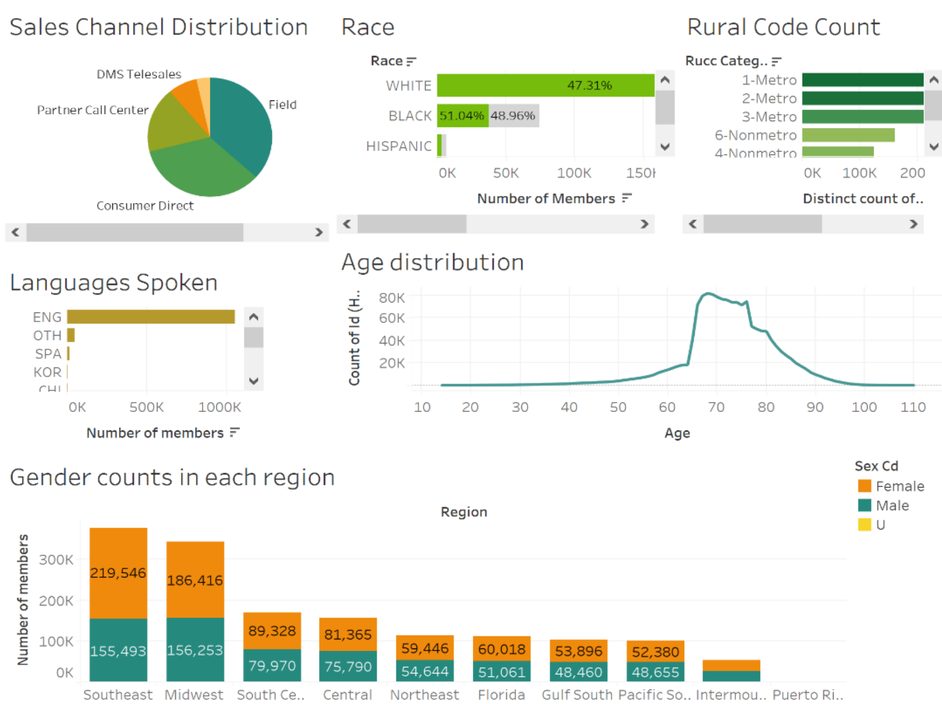


Figure 2: Static Dashboard for the variable distribution

If we look at the top languages that the members use to communicate, it is not surprising to see "ENG" at the top. A quick visual for the Rural code counts shows the distribution for the various categories in the Metro and Non-metro areas. The Sales Channel distribution chart shows that "Field" was the most common followed by "Consumer Direct" and "Partner Call Center" as the leading mediums for sales.

A quick glance at the "Race" data emphasizes the importance of handling missing values in this file as the graph captures them at the highest frequency. The column chart at the bottom shows us that the members are distributed near the Southeast and Midwest as they account for a huge percent of the dataset. The Male to Female ratio seems to be consistent throughout all regions. The graph highlights that the southeast and midwest regions hold most of our customers.

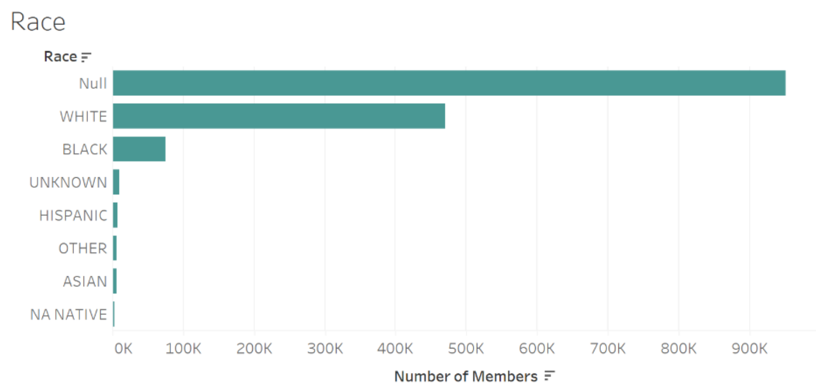


Figure 3: Bar Chart for Race Distribution in the Training Dataset

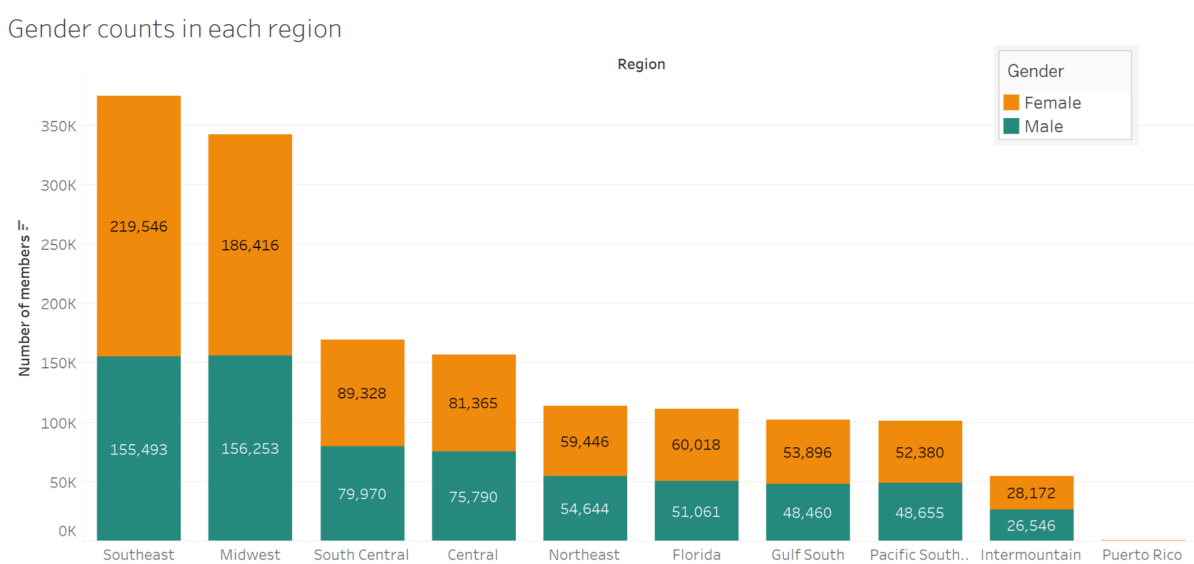


Figure 4: Count of members according to Gender per Region

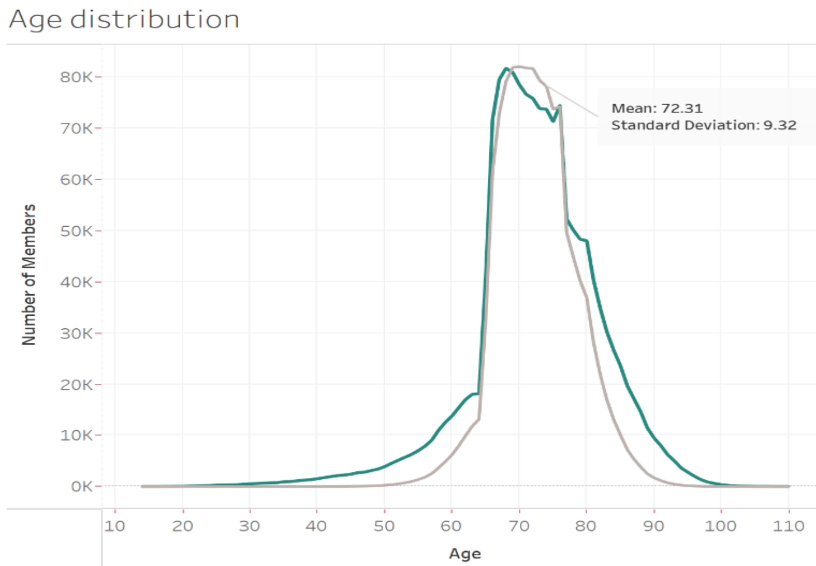


Figure 5: Age Distribution of Members with a superimposed normal distribution curve

Figure 5. indicates that the age range for the members under study is approximately from 50 to 95 years that is most of the members are senior citizens (> 65 years). A normal distribution curve for the standard deviation of 9.32 centered at the mean of 72.31 is super-imposed on the figure to the right to show an approximate normal behavior of the original data distribution.

This pie chart shows the percentages of engaged and unengaged where 0 represents individuals who are engaged and 1 represents those who are unengaged. Here, a little more than half of the members schedule an annual visit to their PCP appointments. The number:45% of unengaged members can be a little misleading as they could still be visiting a specialist doctor for their health condition(s). In other words, they could see a doctor and still be considered unengaged due to them not seeing a primary care provider for an annual physical meet.

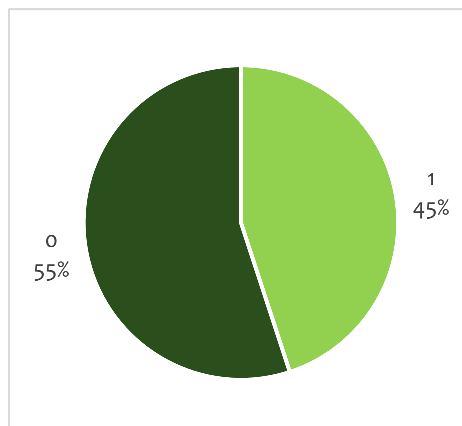


Figure 6: Distribution of Preventive Gap Indicator in Training Data Set

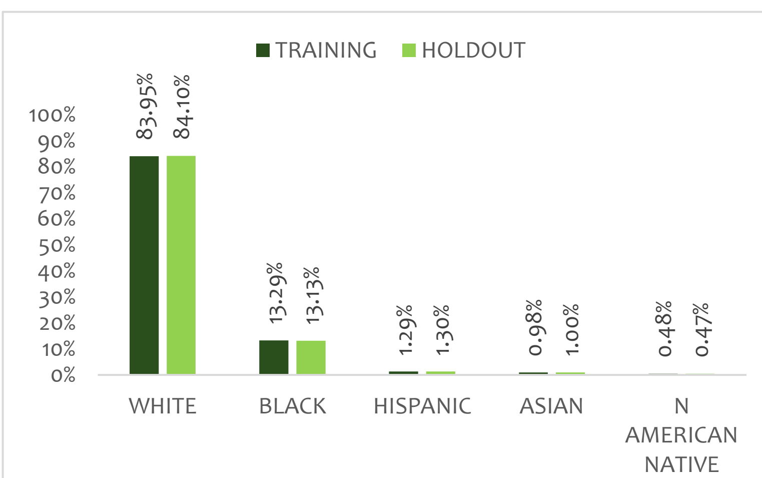


Figure 7: Race Distribution for Training and Holdout Data Sets

Figure 7. shows the distribution according to gender. There is not a large discrepancy between males and females with just under 10% difference. This distribution effectively minimizes the bias.

Noticeable in both gender and race graphs is the fact that both training and holdout have a similar distribution.

The bottom bar graph shows the distribution of race across the PPO in both the data sets: training and holdout. It shows that a vast majority of the members are white at just under 85%. Black is the next highest at just over 13% and the rest of the races combined account for under 3% of users.

This graph shows the distribution according to gender. There is not a large discrepancy between males and females with just under 10% difference. This distribution effectively minimizes the bias. Noticeable in both gender and race graphs is the fact that both training and holdout have a similar distribution.

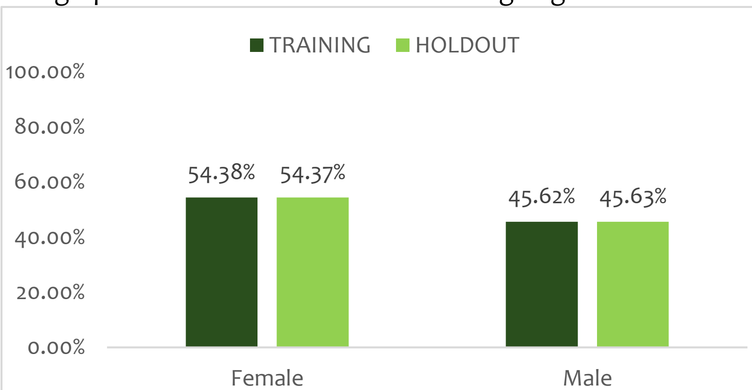


Figure 8: Gender Distribution in Training and Holdout

The Gender Influence chart breaks the distribution of preventive gap indicator into the different genders. You can see that females are more likely to be engaged. Nearly 60% of females are engaged while just under 50% of men are engaged.

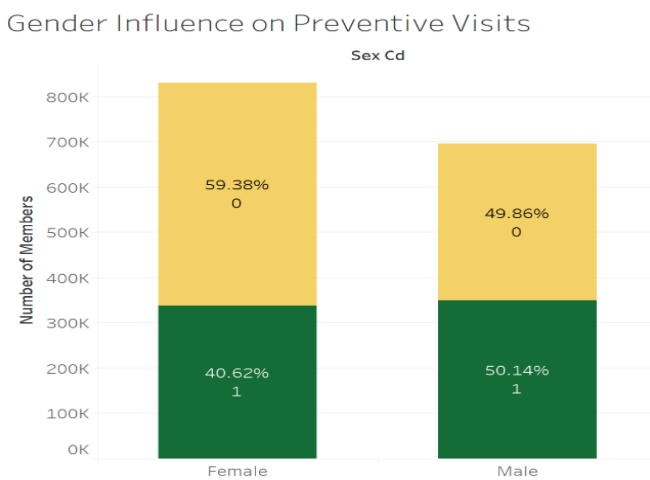


Figure 9: Gender Influence on Preventive Visits

Figure 10. also breaks the distribution of preventive gaps into smaller subsections, but this time according to the racial identity of the members. The distributions of engaged versus unengaged seem fairly similar across all races.

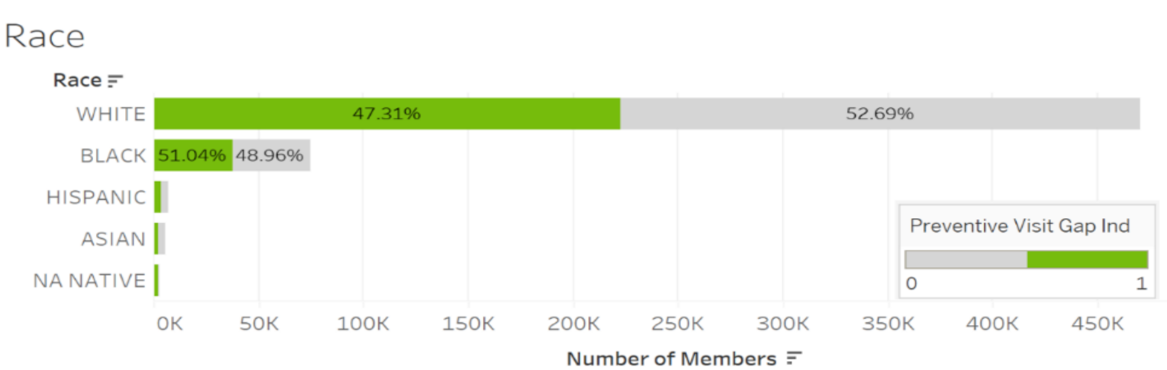


Figure 10: Race Distributions

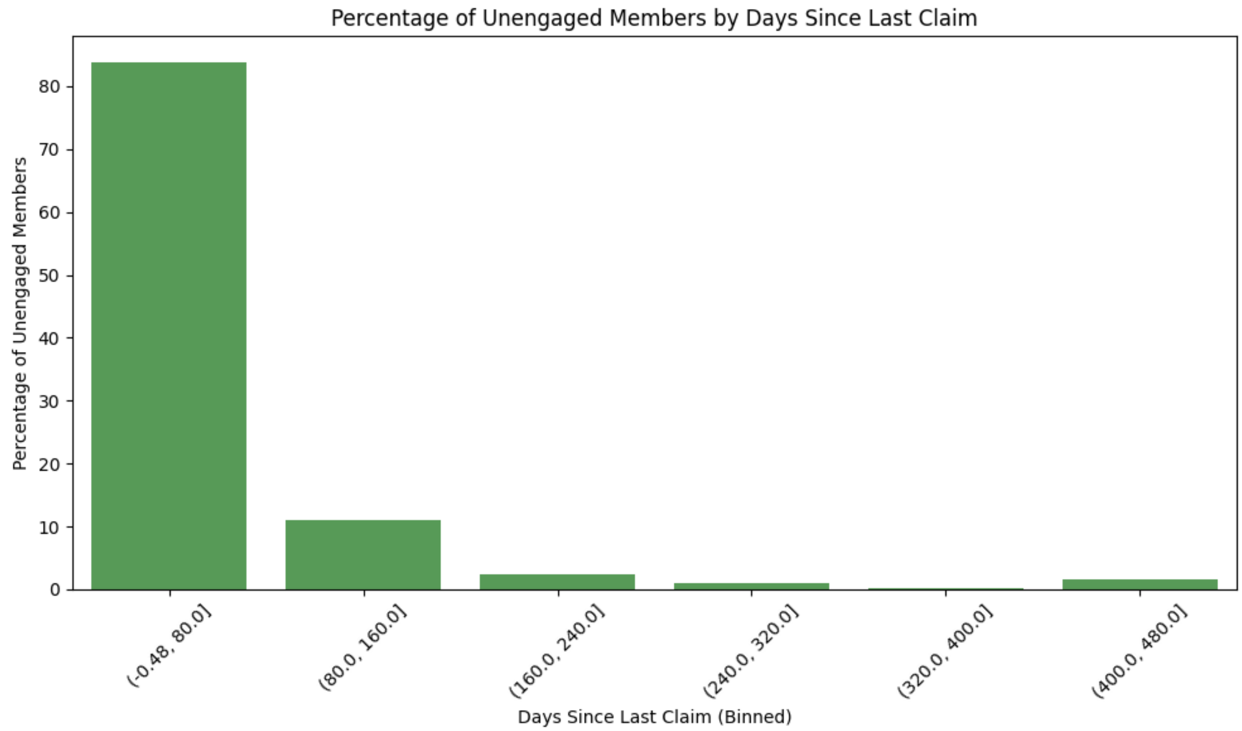


Figure 11: Percent of Unengaged Members by Days since last claimed

Most unengaged members have relatively recent claims, which provides a key opportunity for timely engagement efforts. By focusing on members who fall within the 0 – 80 days range, the insurance provider can potentially reduce unengagement and encourage these members to maintain regular preventive visits, leading to better health outcomes and improved customer retention.

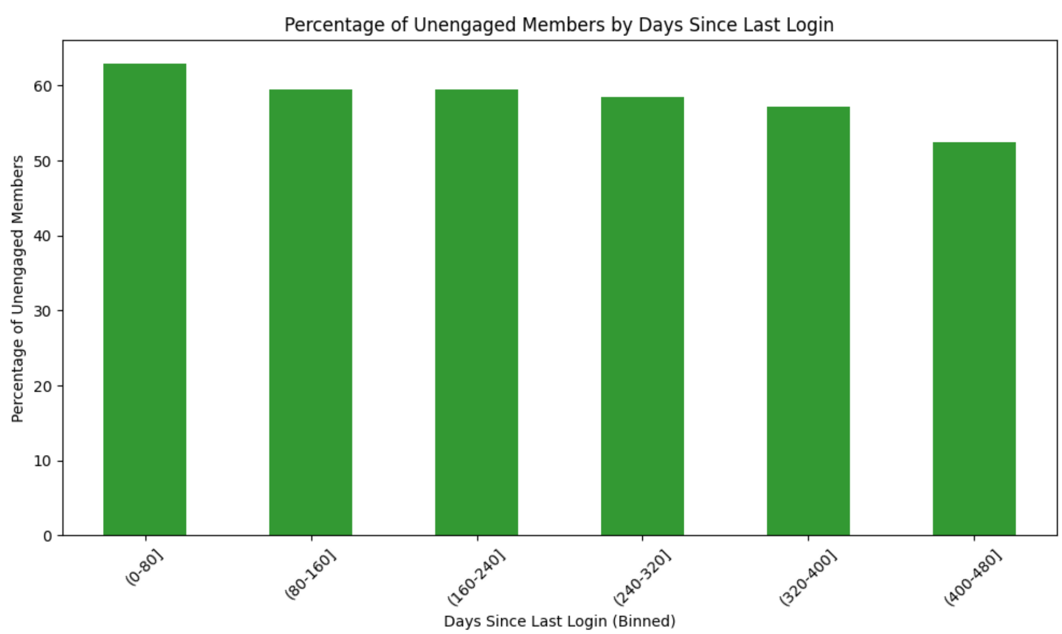


Figure 12: Percent of Unengaged Members by Days since last login

The graph illustrates the percentage of unengaged members across various time intervals, measured by "days since last login." The first key observation is that members who have not logged in for up to 80 days show the highest unengagement rates, with over 60% of them becoming unengaged. This suggests that many members lose interest or become inactive relatively quickly, making it crucial to focus on engagement strategies during this initial period. Beyond 80 days, the unengagement percentage gradually decreases, indicating that those who maintain some level of interaction early on are more likely to stay engaged over time. In the mid-range periods (160-400 days), the percentages remain relatively consistent, suggesting that members settle into a stable pattern of engagement or non-engagement. Finally, the long-term bin (400+ days) shows the lowest percentage of unengaged members, around 45%, possibly reflecting a smaller group of members who have either re-engaged after a long gap or have been classified as consistently unengaged. These insights point to the importance of early re-engagement efforts, sustained interaction strategies for mid-term members, and targeted approaches to reactivate long-term unengaged members.

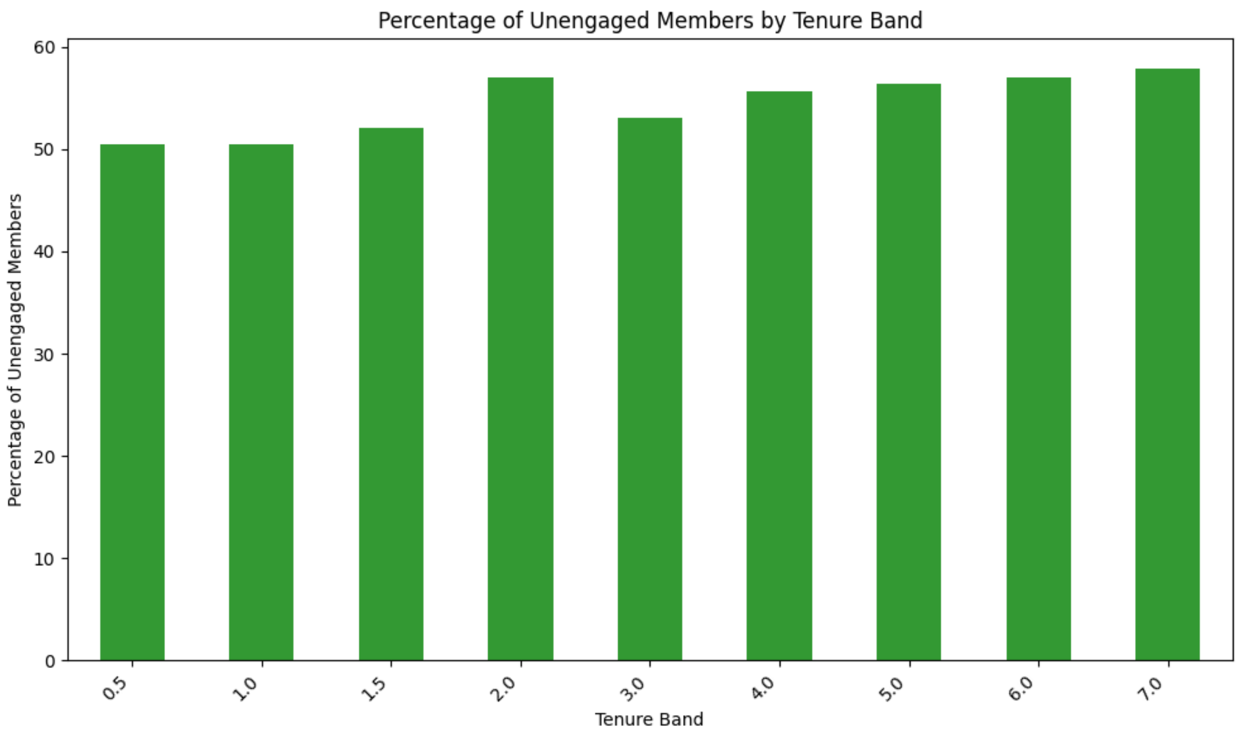


Figure 13: Percent of Unengaged Members by Tenure Band

The bar chart shows the percentage of unengaged members across different tenure bands, highlighting that unengagement remains consistently high—around 50% to 60%—regardless of membership duration. Notably, members with longer tenures (6.0 and 7.0) exhibit slightly higher unengagement rates, approaching 60%, suggesting that engagement in preventive visits may decline over time, possibly due to a sense of complacency or reduced motivation. This trend is evident across all stages of membership, indicating that engagement challenges are not limited to new or long-term members. These findings suggest a need for tailored strategies to address unengagement: early onboarding programs for newer members and re-engagement initiatives like personalized communication or loyalty rewards for long-term members could help improve preventive visit participation throughout the membership journey.

4. Data Preprocessing

4.1 Data Cleaning

After thoroughly analyzing the provided Training and Holdout datasets, we identified several key issues that needed to be addressed to ensure accurate and meaningful analysis. Firstly, we observed that some variables have low variance, which offer little to no useful information in differentiating between classes. These variables can introduce noise into the model and reduce its performance. Secondly, we found variables that were not aligned with the objectives of our analysis such as *calendar_year, product_type, plan_category, dos_year, clm_unique_key, serv_date_skey, chronicity, mco_contract_nbr measurement_year* etc. These variables potentially obscure important relationships in the data. In addition, we encountered variables with missing values, which, if left untreated, could lead to biases and inaccurate predictions. The dataset also included several categorical variables that required proper encoding techniques to be utilized effectively in machine learning models. Lastly, we noted a class imbalance in the target variable, where one class was overrepresented compared to the other, which can lead to biased predictions favoring the majority class. To deal with these challenges, we applied a range of techniques to ensure that our data is well-prepared for analysis and modeling, which are discussed in detail below,

4.1.1 Handling Null Values

There were multiple missing values in many variables. We dealt with each in their individual manner. In the "Demographics" filem the missing values in the *lang_spoken_cd* column were replaced by the value "ENG". The reasoning assumes that as Humana is located in the United States where English is the primary language, the members are likely to be comfortable communicating in English. Then, the top 2 languages were extracted, and the rest were categorized as "OTH" (Others). The missing values in the rest of the columns were filled with the mode of the respective columns.

The missing values in "Social Determinants of Health", "Web Activity", "Pharmacy Utilization", "Cost and Utilization" and "Control Point" files were coherently filled with the corresponding median for each variable with missing values. The "Additional Features" file includes multiple null values for different columns in the float form. For these, the blanks were filled with the median.

4.1.2 Handling Insignificant Variables and Variables with Low Variance

To ensure the dataset is optimized for analysis, we have dropped variables that did not contribute to the goals of our model, such as such as *calendar_year, product_type, plan_category, dos_year, clm_unique_key, serv_date_skey, chronicity, mco_contract_nbr measurement_year* etc. as they could potentially introduce noise and reduce predictive accuracy.

Additionally, we removed variables with low variance, which offered minimal discriminatory power between classes. By excluding these variables, we streamlined the dataset, focusing on features that provide meaningful insights and improve the model's performance. This step was crucial for reducing complexity and ensuring that only valuable data points are used for further analysis.

4.1.3 Handling Class Imbalance

To address the class imbalance in the target variable (*"preventive_visit_gap_ind"*), we evaluated various methods aimed at improving the model's ability to handle unequal class distributions. One of the methods was SMOTE (Synthetic Minority Over-sampling Technique), which synthetically generates new instances of the minority class to balance the dataset. We also explored ensemble models such as Random Forest, LightGBM and XGBoost, which are effective in handling class imbalances by aggregating multiple weak learners and giving more balanced performance across classes. Additionally, we considered undersampling the majority class and using class weighting in algorithms that allow the model to focus more on underrepresented classes.

After assessing these techniques, we ultimately selected ensemble models as our preferred approach. Ensemble models combine the strengths of multiple algorithms to create a more robust and generalized model, effectively addressing the challenges posed by the imbalanced class distribution while maintaining the integrity of both classes. This choice allows for better handling of complex relationships in the data, improving overall model performance and fairness.

4.1.4 Handling Categorical Variables and One-Hot Encoding

The null values in "Member Claim" file were first filled with N for the missing claims. Then the binary Y/N variables were converted to Y=1 and N=0 and merged based on id to remove multiple visits for the same id.

"Member Conditions" file contained multiple variables with different categories for each. For the *cond_key* column, the top 10 variables in number were identified and encoded. The rest of the condition keys were put into a separate column for "Others." The *hcc_model_type* was converted into a binary data type where the medical type was equal to 1 and the ERSD was 0. Same was done for *cms_model_vers_cd* where V28 entries were considered to be 1 and the V24 were 0. The rest of the columns were omitted to optimize the data frame. The whole dataset was then grouped by id to make sure that the multiple lines for a single id were combined.

The "Member Details" contained information about the target members in terms of race, religion, etc. For the missing values in the race column, the type "Unknown" was imputed to maintain the integrity of the data. The *sex_cd* column was converted into binary where M=1 and F=0. Similarly, the *veteran_ind* was also converted into binary where Y=1 and N=0. The column for age was converted into an integer format. The columns of residency were converted into upper case strings for coherency. The *race* column was divided into it's own categories like *race_WHITE, race_HISPANIC* where the null values were maintained under a new category "Unknown" to keep the data integrity intact. Similarly, the region column was divided into 10 new variables like *region_South Central* and *region_Southeast* along with one to incorporate the null values as *region_Unknown*.

The "Member Data" file contained multiple columns with Y/N type that were converted to binary were Y=1 and N=0. The *tenure_band* column was converted into a float variable. In the "Quality Data" file, we have encoded the *measure_type* variable into its types resulting in additional three variables which enabled us to combine lines for the same ID and multiple measures. By dropping a couple of columns like *measure_desc*, the final Quality data frame was reduced to 6 columns including id. The "Sales Channel" file contained multiple null values for the channel. Instead of filling it with a mode or a specific value, the blanks were considered as "Others" to preserve the data integrity and reducing bias.

Following new variables were generated to improve the model performance and avoid confusion in the models for categorical variables. This was done through the creation of the dummy variables through the process known as "One-Hot Encoding." One-Hot Encoding is a technique used to convert categorical variables into a format that can be provided to machine learning algorithms to perform better predictions. Categorical variables are often non-numeric, making them incompatible with most machine learning models, which require numerical input. One-hot encoding transforms each unique category value into a new binary variable, where "1" indicates the presence of the category and "0" indicates its absence.

We applied one-hot encoding to handle the categorical variables in the dataset, ensuring that these non-numeric variables could be effectively used in the machine learning models. By using this technique, we created 32 new binary variables from the original categorical features. Each new variable represents a unique category, allowing the model to interpret the categorical data without imposing any ordinal relationship between them. The following table gives a comprehensive list of the original and newly created variables.

Original Variable	New One-Hot Encoded Variables	Original Variable	New One-Hot Encoded Variables
lang_spoken_cd	*lang_spoken_cd_ENG* *lang_spoken_cd_SPA* *lang_spoken_cd_OTH*	*channel*	*channel_Consumer Direct* *channel_DMS Telesales* *channel_Field* *channel_Partner Call Center* *channel_others*
rucc_category	*rucc_1-Metro* *rucc_2-Metro* *rucc_2-Metro* *rucc_3-Nonmetro* *rucc_4-Nonmetro* *rucc_5-Nonmetro* *rucc_6-Nonmetro* *rucc_7-Nonmetro* *rucc_8-Nonmetro* *rucc_9-Nonmetro*	*cond_key*	*cond_key_23* *cond_key_37* *cond_key_38* *cond_key_48* *cond_key_59* *cond_key_108* *cond_key_226* *cond_key_238* *cond_key_280* *cond_key_329* *cond_key_Other*
measure_type	*measure_HEDIS* *measure_Patient Experience* *measure_Patient Safety*	*region*	*region_Southeast* *region_Midwest* *region_South Central* *region_Central* *region_Northeast* *region_Florida* *region_Gulf South* *region_Pacific Southwest* *region_Intermountain* *region_Puerto Rico* *region_Unknown*
race	*race_ASIAN* *race_BLACK* *race_HISPANIC* *race_N AMERICAN NATIVE* *race_OTHER* *race_UNKNOWN* *race_WHITE*		

Figure 14: Table for One-Hot Encoded Variables

4.2 Feature Engineering

To enhance the dataset for modeling, we introduced 12 new features based on our understanding of the problem statement and insights gathered from our exploratory analysis. To capture patterns more effectively related to this engagement problem, we created several derived metrics that better represent member behavior, healthcare usage, and preventive care engagement.

These derived metrics include variables that quantify members' history of drugs consumption pattern in different tiers, cost per physician or pharmacy, out-of-pocket payment ratio, tenure continuity ratio etc. By introducing these features, we aim to highlight patterns that can predict unengaged members, which is crucial for improving Stars ratings and ensuring proper risk documentation. The newly created dataset is now more aligned with the case objectives, ensuring the model has richer data to detect members at risk of becoming unengaged. These derived metrics are discussed in detail below.

File	Derived Features	Comments
Pharmacy Utilization	$drugs\_per\_pres = \frac{rx\_overall\_dist\_gpi6\_pmpm\_ct}{rx\_overall\_gpi\_pmpm\_ct}$	This variable gives us the average number of distinct drugs per prescription at GPI6 level.
	$rx\_tier\_1\_pres = \frac{rx\_tier\_1\_pmpm\_ct}{rx\_overall\_pmpm\_ct}$ $rx\_tier\_2\_pres = \frac{rx\_tier\_2\_pmpm\_ct}{rx\_overall\_pmpm\_ct}$ $rx\_tier\_3\_pres = \frac{rx\_tier\_3\_pmpm\_ct}{rx\_overall\_pmpm\_ct}$ $rx\_tier\_4\_pres = \frac{rx\_tier\_4\_pmpm\_ct}{rx\_overall\_pmpm\_ct}$	These variables give us the contribution of prescriptions related to Tier 1, 2, 3, and 4 drugs per month in the past year.
	$rx\_overall\_cost\_physican = \frac{rx\_overall\_pmpm\_cost}{rx\_perphy\_pmpm\_ct}$ $rx\_overall\_cost\_pharmacy = \frac{rx\_overall\_pmpm\_cost}{rx\_pharmacies\_pmpm\_ct}$	These variables calculate the average cost associated with each physician and pharmacy, respectively.
Cost and Utilization	$bh\_rtc\_admit\_ratio = \frac{bh\_rtc\_admit\_days\_pmpm}{bh\_rtc\_admit\_ct\_pmpm}$	This variable calculates average number of days per month a member was admitted at each time of their admission related to behavioral health claims
	$oontwk\_net\_paid\_allowed\_ratio = \frac{oontwk\_net\_paid\_pmpm\_cost}{oontwk\_allowed\_pmpm\_cost}$ $total\_net\_paid\_allowed\_ratio = \frac{total\_net\_paid\_pmpm\_cost}{total\_allowed\_pmpm\_cost}$	These variables calculate cost utilizations percentage for out-of-network claims and total claims in past one year
	$total\_ip\_admitted\_days = total\_ip\_acute\_admit\_days\_pmpm + total\_ip\_ltach\_admit\_days\_pmpm + total\_ip\_maternity\_admit\_days\_pmpm + total\_ip\_mhsa\_admit\_days\_pmpm + total\_ip\_rehab\_admit\_days\_pmpm + total\_ip\_snf\_admit\_days\_pmpm$	This variable calculates the total number of days the person was admitted in past one year taking all inpatient facilities into account.
Member Data	$tenure\_continuity\_ratio = \frac{consec\_tenure\_month}{all\_m\_tenure}$	This variable calculates loyalty of the member based on continuity ratio of the membership

Figure 15: Engineering Feature Calculations

5. Predictive Modeling

5.1 Model Selection

We started by building five models: Logistic Regression, CatBoost, K-Nearest Neighbors (KNN), XGBoost, and LightGBM. The data was split into training and test sets using a 70:30 ratio. Model performance was evaluated using the Area Under the Curve (AUC) for the Receiver Operating Characteristic (ROC) curve. The AUC values for each model are summarized in Table 3. Initially, all models used the same input data, but we then retrained them using the top 100 features based on feature importance. After tuning the hyperparameters, we compared the maximum AUC achieved by each model, with XGBoost emerging as the best performer in terms of adjusted AUC.

Model with hyperparameters	AUC	Disparity Score	Adjusted AUC
Logistic Regression penalty='l2', C=1.0, solver='lbfgs', class_weight='balanced', max_iter=1000, random_state=42	0.6856	0.9712	0.6658
LightGBM 'objective': 'binary', 'metric': 'binary_logloss', 'boosting_type': 'gbdt', 'num_leaves': 31, 'learning_rate': 0.1, 'feature_fraction': 0.8, 'bagging_fraction': 0.8, 'bagging_freq': 5, 'verbose': -1	0.7328	0.9807	0.7186
XGBoost 'objective': 'binary:logistic', 'learning_rate': 0.01, 'max_depth': 7, 'lambda': 5, 'alpha': 1, 'eval_metric': 'auc', 'subsample': 0.8, 'colsample_bytree': 1, 'n_estimators': 2000, 'min_child_weight': 1	0.7634	0.9815	0.7492
KNN n_neighbors=5, weights='distance', metric='minkowski', p=2	0.7127	0.9701	0.6913

CatBoost iterations=1000, learning_rate=0.05, depth=6, l2_leaf_reg=3, border_count=254, scale_pos_weight=2, auto_class_weights='Balanced', random_seed=42, verbose=100	0.7313	0.9813	0.7176

Figure 16: Evaluated Models with Hyperparameters

Following an in-depth comparison of performance metrics across multiple models, XGBoost stood out as the top choice. It achieved the highest AUC score of 0.76, surpassing other models with superior predictive performance for the variable '*preventive_visit_gap_ind*'. XGBoost's ability to manage large datasets, handle missing values efficiently, and leverage gradient boosting techniques reinforced its selection as the primary predictive model for the subsequent stages of this study.

For a dataset with feature set X and binary target variable Y ('*preventive_visit_gap_ind*''), the prediction at the m^{th} iteration can be expressed as:

$$E_m(X) = E_{m-1}(X) + \alpha_m \times h_m(X, r_{m-1})$$

Here, $E_{m-1}(X)$ is the predicted value up to the $(m-1)th$ iteration. The term $\alpha_m \times h_m(X,r_{m-1})$ represents the contribution of the m^{th} tree, with h_m being the function that predicts residuals r_{m-1} using features X, and α_m acting as a weight factor.

The learning process in XGBoost focuses on minimizing a loss function, which quantifies the difference between actual target values Y and the predicted values. The goal is to find parameters α_m and residuals r_{m-1} that minimize this loss, as expressed by:

$$\alpha_m, r_{m-1} = \arg\min \sum_{i=1}^{m} L(Y, E_{m-1}(X) + \alpha_m \times h_m(X, r_{m-1}))$$

Here, L is a differentiable loss function, and the optimization ensures that the model continuously refines predictions by reducing residuals at each step, ultimately boosting its predictive accuracy.

5.2 Model Results

The ROC curve can be a helpful tool to analyze the model performance. The AUC (Area under the curve) in the ROC graph shows a staggering value of 0.7582 quantifying the ability of the model to correctly predict the engagement outcome of the members under study.

According to the confusion matrix for the XGBoost model chosen, the model seems to be inclined to accurately predict the members who are engaged with their annual visits. The value is almost twice as much as the accurate prediction of the members who are unlikely to make their annual visits.

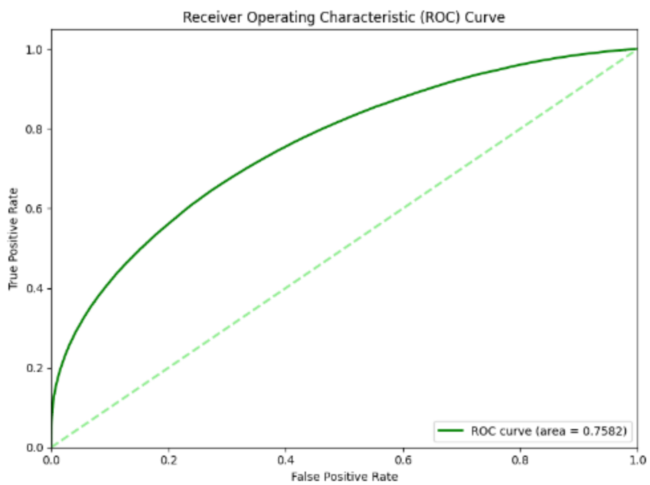


Figure 18: ROC Curve

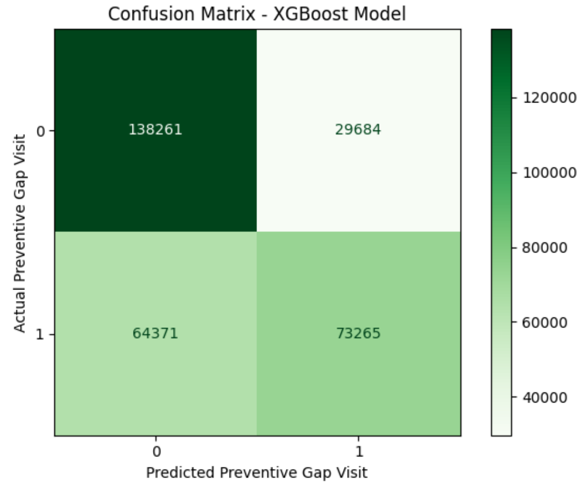


Figure 17: Confusion Matrix

5.3 Model Interpretation

The top 30 features were identified by the XGBoost model that is graphed below. The SHAP value analysis *also categorized top twenty of the most important features. Many of the features identified by the models overlap and 2 of the engineered features have made it at the top: race_OTHER and HCC_Medical.*

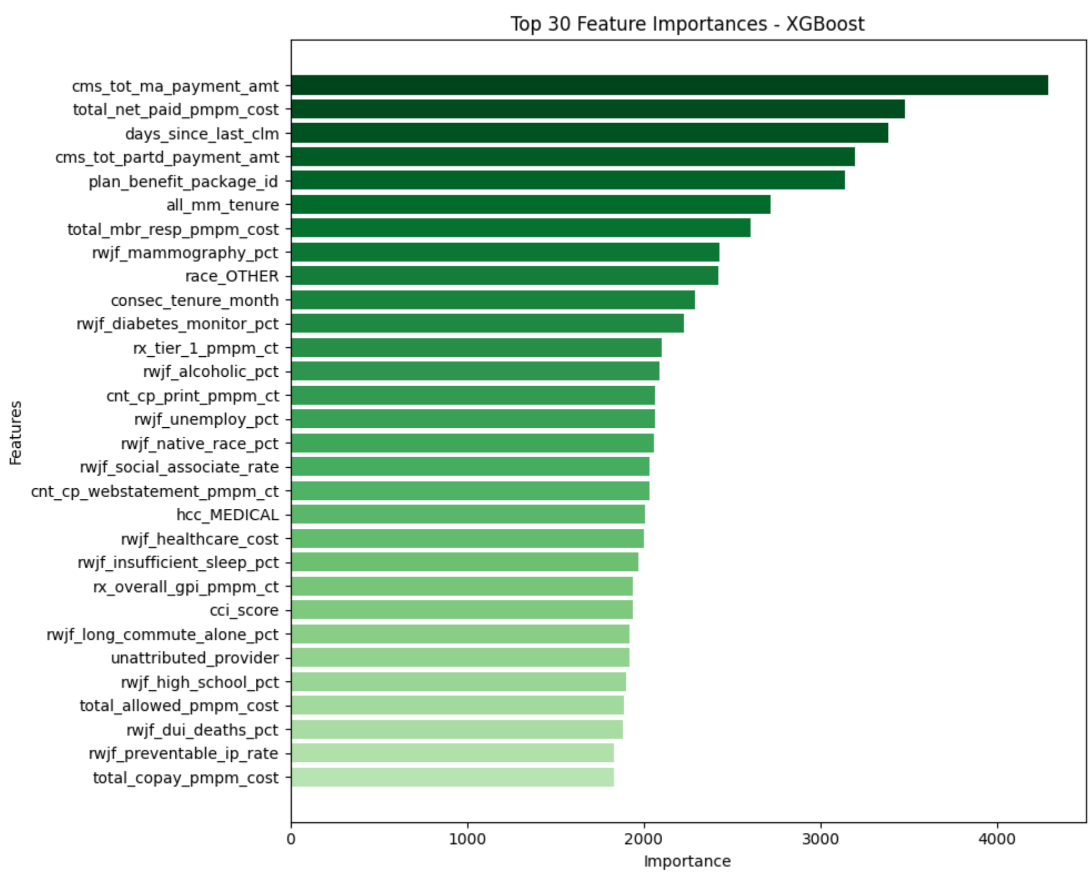


Figure 19: Top Features from XGBoost

According to conclusions derived by glancing at the charts, it looks like having a higher value of *total_net_paid_pmpm_cost* will actually encourage the members to make their annual visits. The blue color on the bar denotes that the lower values are more inclined to making it to the prediction value of "1" (right side of the zero line). This might be on the opposite spectrum which one might hypothesize regarding this variable. Having a higher net payment from Humana encourages the members to attend their annual visits.

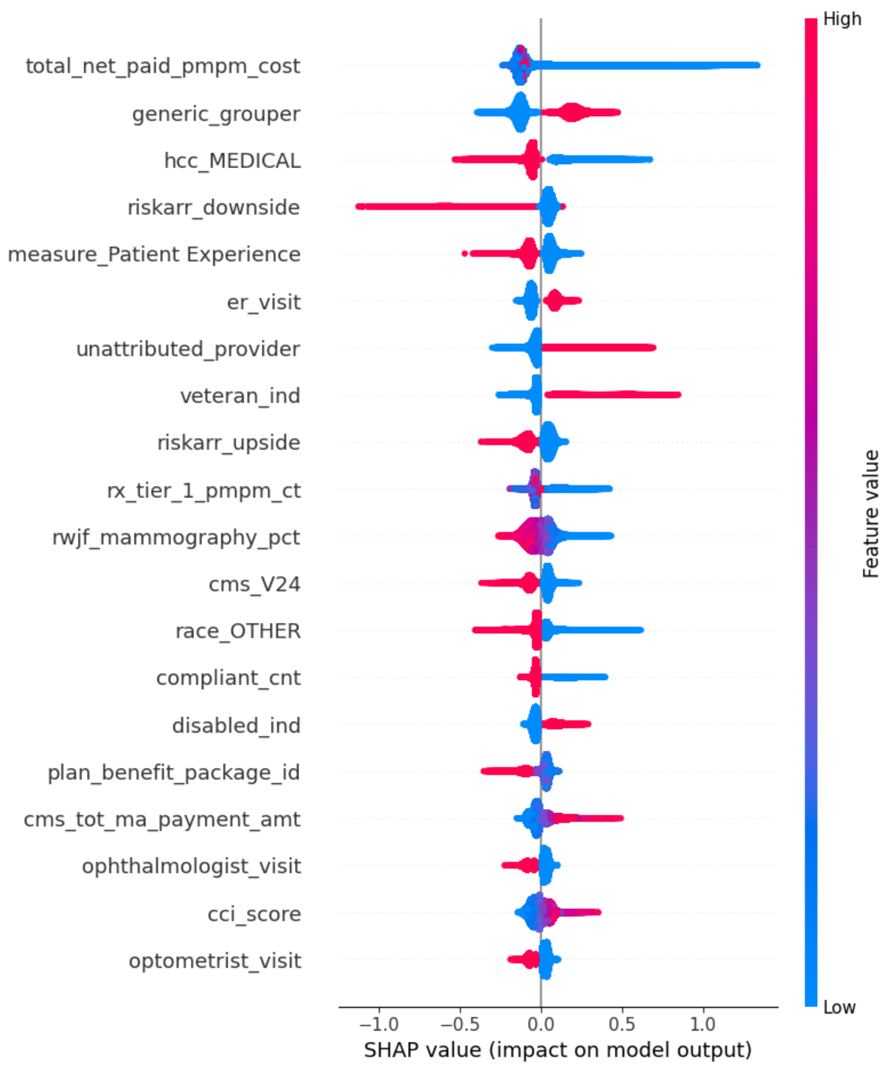


Figure 20: SHAP Value of Features

Another interesting feature that stood out was *race_OTHER.* Here, the bar is a little more blue to the right of the middle line. This shows that lower ranges (zero in this case as it is a binary variable) are more likely to be unengaged. This means that those who are not classified in the *race_OTHER* need to be a focus for the marketing team to boost engagement. Even though *race_WHITE* did not make it in the top variables list, as it contains the higher percentage of individuals, it could be an aspect to target the marketing towards that group for better results.

According to the SHAP value graph, the people who tend to visit the Emergency Rooms (*er_visit*) are more inclined towards non-engagement which is quite a surprising factor.

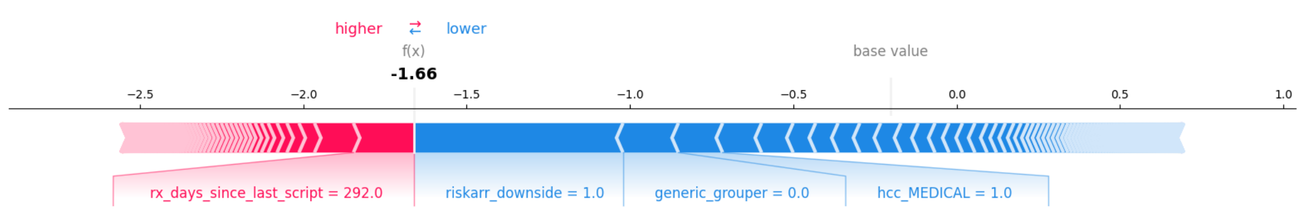


Figure 21: SHAP Feature Analysis

Decision Tree for Patient Journey - Preventive Visit Gap

The decision tree illustrates the journey of patients in terms of their engagement with preventive visits. The objective is to understand the factors that contribute to a "preventive visit gap" indicating whether a patient has missed or delayed a preventive care visit. These features and the decision model tree helped us identify the key features of the data set that had the most influential power over the prediction of the future engagement of the members.

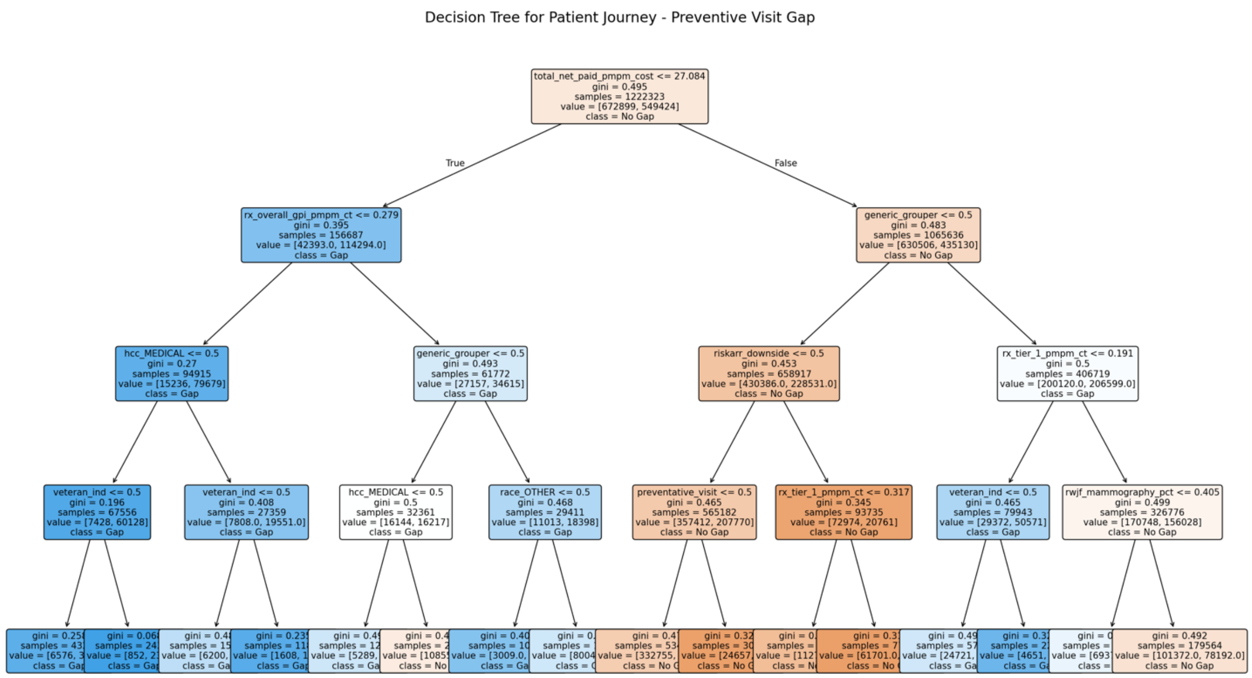


Figure 22: Decision Tree

Root Node:

- The journey begins with the root decision based on the variable rx_overall_gpi_pmpm_ct (a measure of prescription frequency). Patients with rx_overall_gpi_pmpm_ct <= 0.279 are more likely to have a "Gap" in their preventive visits, whereas those with higher values tend to have no gap.
- This variable's importance at the root highlights the significance of overall prescription use in influencing the likelihood of a patient attending preventive visits.

Left Subtree - Lower Prescription Users:

1. hcc_MEDICAL <= 0.5: Among patients with lower prescription use, the HCC medical score becomes a critical factor. Patients with hcc_MEDICAL <= 0.5 are split further:
    a. veteran_ind <= 0.5: The decision node focuses on whether a patient is a veteran or not. Veterans tend to show a gap, while non-veterans exhibit mixed behavior.

    b. Further Split on veteran_ind: Those who are non-veterans but with slightly higher HCC scores are evaluated for their veteran_ind status. This indicates that veterans have a different health-seeking behavior, impacting their preventive care.
2. generic_grouper <= 0.5: Patients with generic_grouper <= 0.5 (likely indicating generic prescription use) are further assessed:
    a. race_OTHER <= 0.5: Race becomes a determining factor, suggesting disparities in preventive visit adherence based on racial background.
    b. hcc_MEDICAL and race continue to play roles in this segment, identifying patients who might be more at risk of missing preventive visits.

Right Subtree - Higher Prescription Users:

1. total_net_paid_pmpm_cost <= 27.084: For patients with higher prescription use, the total net paid PMPM cost is a major determinant. Lower-cost patients are more likely to have a gap.
    a. riskarr_downside <= 0.5: For these lower-cost patients, the risk assessment downside measure helps in predicting gaps. Those with lower riskarr_downside are further divided based on their preventive visit history.
    b. preventative_visit <= 0.5: This variable directly measures whether a preventive visit has already been completed. Patients who haven't visited are identified as higher-risk for a gap.
2. rx_tier_1_pmpm_ct <= 0.191: Patients with higher prescription costs are further segmented by rx_tier_1_pmpm_ct (frequency of Tier 1 prescriptions). Lower tier prescription users tend to have gaps, and the decision tree considers veteran status among them.
    a. rwjf_mammography_pct <= 0.405: This node involves a regional or community-based measure of mammography rates, highlighting that community-level screening rates can impact individual-level preventive behavior.

The decision tree highlights a nuanced view of how various patient characteristics and behaviors influence their likelihood of a preventive visit gap. Patients with lower overall prescription use are more susceptible to gaps, particularly influenced by factors like their veteran status and racial background. On the other hand, higher prescription users are influenced more by their out-of-pocket costs and the type of prescriptions they use, such as Tier 1 medications. Community factors like mammography rates also play a role, reflecting how broader community behaviors can influence individual actions.

This tree provides valuable insights into different patient segments, allowing healthcare providers to target interventions effectively. For example, for patients identified as veterans or those with lower prescription use, tailored communication and engagement strategies could help reduce gaps. Understanding the factors at each node allows for a targeted approach to improve preventive care adherence and enhance overall patient outcomes.

6. Clustering

6.1 K Means Cluster

The Elbow Method is used to determine the optimal number of clusters by analyzing the relationship between the number of clusters (k) and the inertia, which measures the sum of squared distances between data points and their respective cluster centroids. As k increases, inertia naturally decreases because more clusters lead to tighter groupings. However, beyond a certain point, the reduction in inertia becomes less significant. This point, known as the "elbow," suggests the ideal number of clusters. In the provided plot, the elbow appears around k=3, where the drop in inertia begins to flatten. Choosing k=3 means that adding more clusters beyond this point yields minimal improvements in cluster tightness, thus balancing complexity and effectiveness. This selection allows for a simpler, more interpretable model while effectively capturing the major variance in the data. For example, with three clusters, we can categorize members into groups like "highly engaged," "moderately engaged," and "least engaged" in preventive care. This approach facilitates targeted strategies for each group, ensuring tailored interventions that could lead to improved engagement in preventive visits.

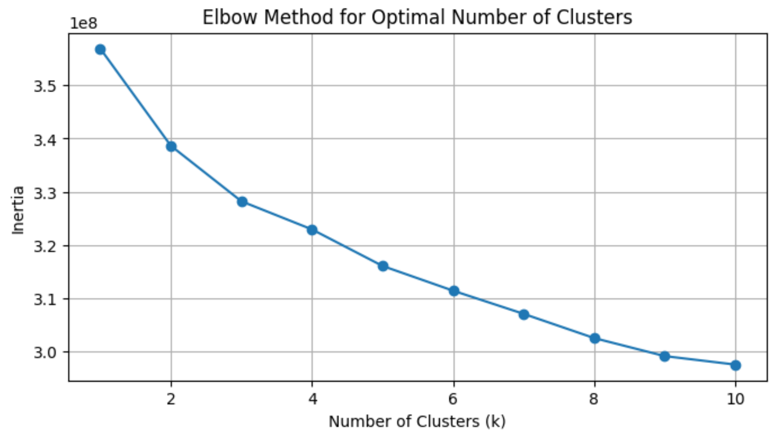
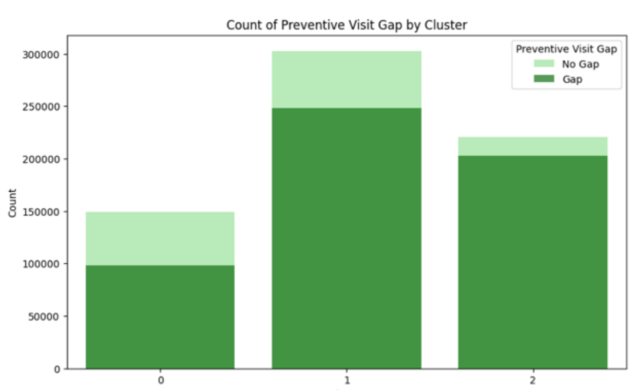


Figure 23: Number of Clusters

6.2 Clustering Results



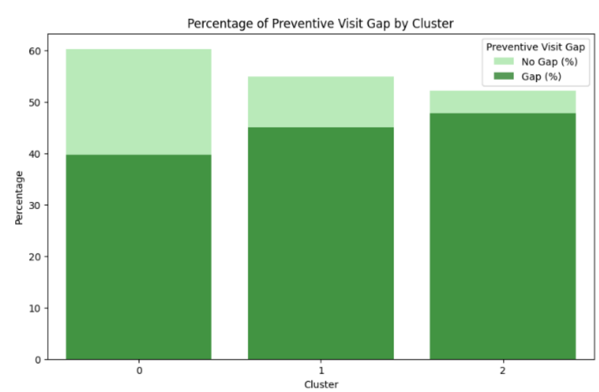


Figure 24: Count and Percent Preventive Visit Gap by Cluster

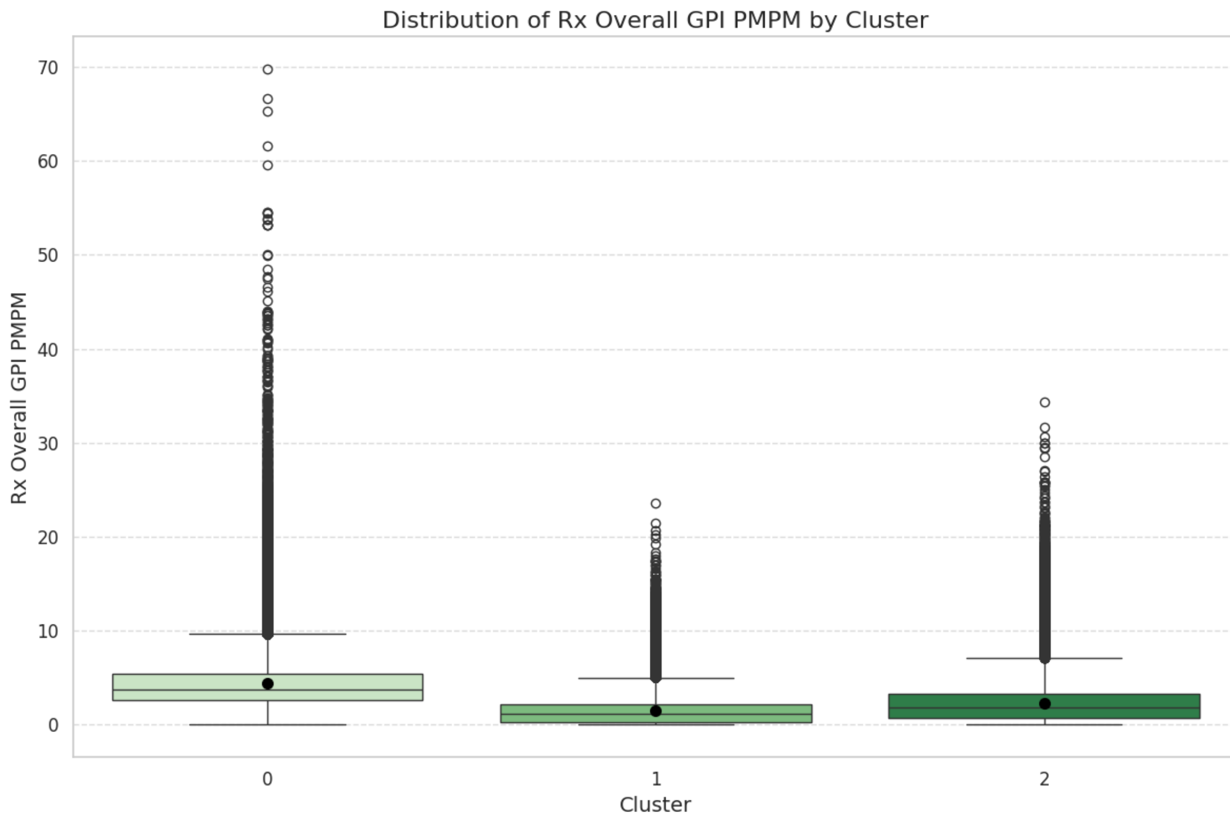


Figure 25: Visual of the distribution of Rx Overall GPI PMPM by Cluster

This box plot illustrates the distribution of "Rx Overall GPI PMPM" across three different clusters, each representing groups of members with varying engagement levels regarding their preventive visits. The variable "Rx Overall GPI PMPM" measures the monthly prescription costs per member, providing insights into the healthcare utilization patterns within each cluster.

Cluster 0 exhibits a higher median value for "Rx Overall GPI PMPM" compared to Clusters 1 and 2, indicating that members in this group tend to have higher prescription costs. The spread of values in Cluster 0 is also broader, with more outliers reaching up to 70. This suggests a diverse range of prescription needs among members in this group, potentially including high-cost individuals requiring specialized medications.

Clusters 1 and 2, on the other hand, show significantly lower median values and a tighter distribution, with fewer extreme outliers. This indicates that members in these clusters have more uniform and lower prescription costs. Such findings could suggest a relatively stable health status or lower dependency on prescriptions among members in these clusters.

The importance of this analysis lies in the ability to differentiate between clusters based on prescription costs. For instance, Cluster 0 may include members who are more at risk of high healthcare costs due to their prescription needs. This group could benefit from targeted interventions, such as medication management programs or personalized outreach to ensure they adhere to their prescriptions and maintain their health. Clusters 1 and 2, with their lower prescription costs, may require a different approach, focusing more on maintaining engagement and promoting preventive visits to avoid future health complications.

Understanding these nuances allows for more effective segmentation and tailored strategies to improve member engagement and optimize care delivery, ultimately helping to manage healthcare costs while ensuring that members receive the support they need.

b. Average total_net_paid_pmpm_cost per Cluster

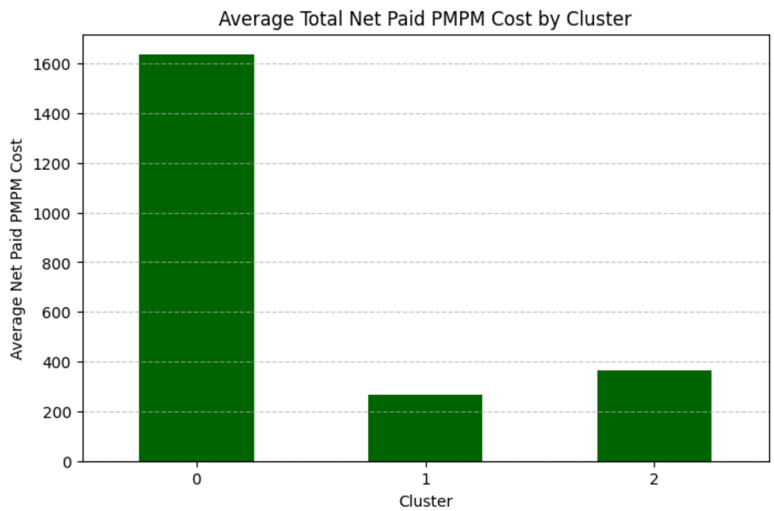


Figure 26: Average Total Net Paid PMPM Cost by Cluster

This bar chart represents the "Average Total Net Paid PMPM Cost" across three clusters, providing a clear comparison of the monthly average costs associated with each group. Cluster 0 stands out with a significantly higher average net paid PMPM cost, exceeding 1600, which suggests that members in this cluster incur considerably higher healthcare expenses compared to the other two groups. This could be due to a greater need for medical services, chronic conditions, or more frequent use of high-cost treatments among these members.

In contrast, Clusters 1 and 2 display much lower average costs, both under 400. The similarity between these two clusters in terms of their average costs might indicate that their members have more stable or lower healthcare needs, potentially with fewer chronic conditions or less intensive treatment requirements.

The key takeaway from this analysis is the significant variation in healthcare spending between Cluster 0 and the other two clusters. This insight is crucial for healthcare providers and payers as it highlights a group (Cluster 0) that may benefit from targeted cost-management strategies, such as care coordination, chronic disease management, or preventive interventions aimed at reducing the overall expenditure. Meanwhile, Clusters 1 and 2 might require a different focus, such as maintaining engagement with preventive care services to ensure that their lower-cost status is sustained over time. Understanding these distinctions enables a more tailored approach to member management, helping to balance care quality and cost efficiency.

c. Count of hcc_MEDICAL Across Clusters

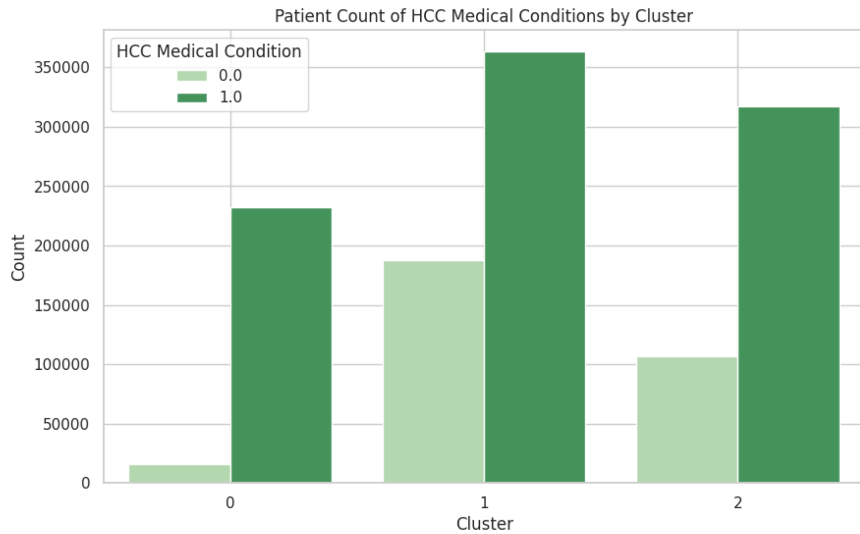


Figure 27: Patient Count of HCC Medical Conditions by Cluster

This chart visualizes the distribution of HCC Medical Conditions across three clusters. The analysis reveals significant variations in the prevalence of members with and without HCC medical conditions within each cluster.

- **Cluster 0** has a higher concentration of members with HCC conditions compared to those without. This suggests that this cluster might represent a group with more complex healthcare needs and potentially higher healthcare utilization.
- **Cluster 1** shows a more balanced distribution between members with and without HCC conditions. The proportion of members without HCC conditions is slightly lower than those with HCC, indicating a mix of healthcare needs within this cluster.
- **Cluster 2** has a similar distribution to Cluster 1 but with slightly fewer members without HCC conditions. This cluster might represent individuals who, despite having HCC conditions, are not as intensive in terms of healthcare interactions as those in Cluster 0.

These insights are valuable for segmenting populations based on healthcare needs. The understanding of such clusters can help tailor targeted interventions, such as providing specialized support to Cluster 0, which has a higher proportion of members with complex medical conditions. This segmentation approach supports more personalized and effective healthcare strategies.

2. Segment Analysis by Cluster

a. Segment Members by veteran_ind in each cluster

This chart illustrates the percentage of veterans across three distinct clusters, revealing the differences in veteran representation within each group:

- Cluster 0 has the smallest percentage of veterans, accounting for around 6% of its members. This indicates that this cluster has a lower concentration of veterans compared to the others.

- Cluster 1 stands out with the highest percentage of veterans, at approximately 12%. This suggests that this group has a significant representation of veterans, possibly indicating unique healthcare needs or behaviors related to their veteran status.
- Cluster 2 has a moderate percentage of veterans, around 10%, indicating that this group also has a notable veteran population, though slightly less than Cluster 1.

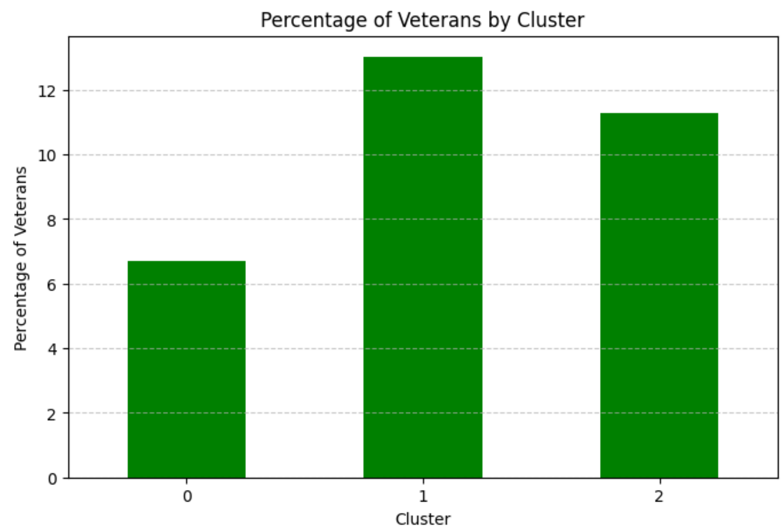


Figure 28: Percent of Veterans by Cluster

This analysis highlights the differences in veteran representation across the clusters, which can be valuable for tailoring healthcare outreach and interventions. For example, Cluster 1, with the highest veteran population, may benefit from targeted programs that address the specific needs of veterans.

b. Average days_since_last_clm Across Clusters

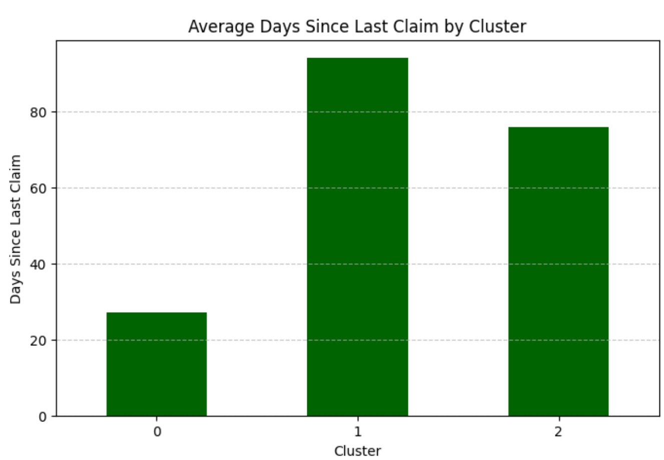


Figure 29: Average days since Last Claim across Clusters

This bar chart shows the average number of days since the last claim across three clusters, highlighting variations in recent engagement with healthcare services:

- Cluster 0 has the shortest average time since the last claim, around 20 days. This suggests that members in this cluster are more frequently engaged with their healthcare needs, making claims more recently.
- Cluster 1 shows a significantly higher average of over 80 days since the last claim. This may indicate that members in this group are less engaged or less reliant on their insurance benefits for recent healthcare needs.
- Cluster 2 has an average of around 60 days, positioning it between the other two clusters. Members in this cluster may be moderately engaged with their healthcare, not as frequent as Cluster 0 but more so than Cluster 1.

This distribution suggests different engagement levels among the clusters, which could be valuable for targeting interventions. For instance, Cluster 1, with the longest time since the last claim, might benefit from outreach efforts encouraging regular preventive care, while Cluster 0 may require a different approach given its members' more frequent interactions with healthcare services.

3. Heatmap of Feature Means by Cluster

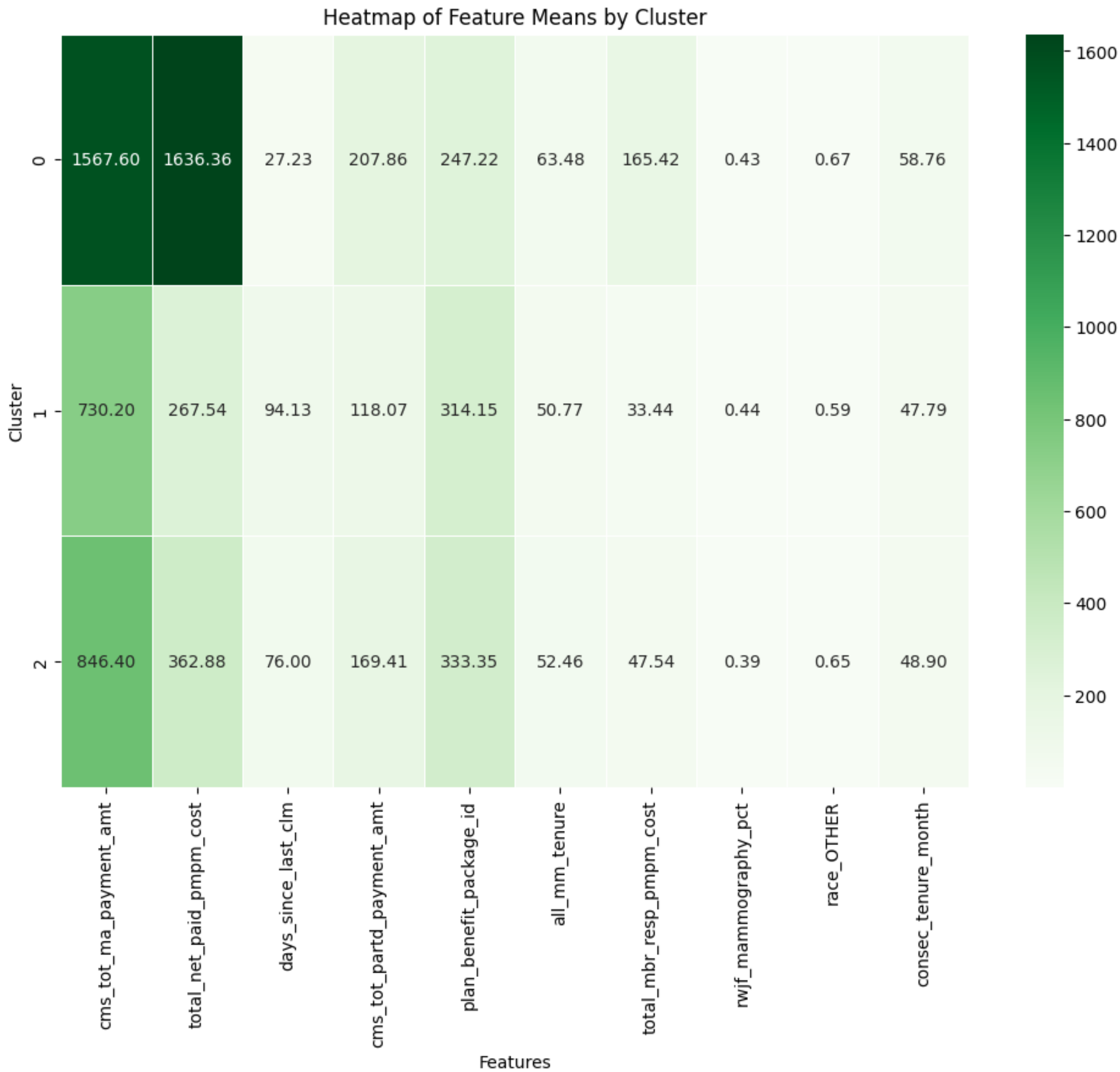


Figure 30: Heatmap of Feature Means by Cluster

This heatmap provides a detailed overview of the average values of key features across the three identified clusters, offering insights into the varying behaviors and characteristics of each cluster:

- Cluster 0:
  - Has the highest values for features like cms_tot_ma_payment_amt and total_net_paid_pmpm_cost, indicating a significant financial interaction with healthcare services.
  - The average days_since_last_clm is lower compared to other clusters, suggesting more frequent engagement with healthcare.
  - Higher values in plan_benefit_package_id and total_mbr_resp_pmpm_cost indicate a more comprehensive benefit package and member responsibility.
- Cluster 1:
  - Shows moderate average values across most features.
  - Higher days_since_last_clm indicates less frequent recent claims, suggesting a gap in engagement.
  - Relatively lower total_net_paid_pmpm_cost compared to Cluster 0 reflects a more conservative interaction with healthcare costs.
- Cluster 2:
  - Values are moderate to low for most features, with a balance between cost and engagement.
  - Higher tenure (all_mm_tenure) suggests longer membership duration.
  - Lower cms_tot_ma_payment_amt indicates lesser involvement in terms of managed payments.

The heatmap allows for a quick assessment of the differences in key features across clusters, aiding in identifying which clusters might require targeted strategies. For example, Cluster 1 might benefit from engagement campaigns to reduce gaps, while Cluster 0 might need optimized cost management due to higher expenses.

7. Recommendations and Business Implications

7.1 Proposed Solutions

Based on the insights from the XGBoost model and feature importance analysis, Humana can implement several strategies to increase engagement among LPPO members and motivate them to attend preventive care visits. We have come up with the following recommendations:

7.1.1 Recommendation 1: Engaging Members Through Targeted Communication

Personalized Messaging: We recommend Humana to implement personalized outreach campaigns using CRM systems that leverage member-specific data, such as health history, plan type, and recent claims activity etc. Personalized communication can include targeted SMS, emails, or phone calls reminding members about the importance of preventive care. For example, LPPO members with chronic conditions or members who haven't visited a doctor in over a year should receive customized reminders gently coaxing them to schedule preventive visits. Timely communication will not only promote preventive care but also help members avoid future complications by addressing chronic conditions at an early stage.

By adopting personalized messaging, Humana can significantly increase engagement by showing members that their health is actively monitored and supported. This approach will also improve patient-provider interactions, ensuring members are more likely to complete preventive visits, ultimately boosting Stars scores and increasing CMS bonuses.

Veteran-Centric Campaigns: Humana should create veteran-specific outreach campaigns by partnering with organizations such as the Veterans Health Administration (VA) or veteran-focused non-profits. Veterans may have unique healthcare needs that may require specialized communication techniques to encourage their overall participation in preventive visits. We recommend highlighting the additional benefits available to veterans under LPPO plans, such as free flu shots or waived copays for preventive services, etc.

This targeted campaign will create a stronger connection with veteran members and drive engagement by addressing their specific needs. Increased participation from veterans will improve chronic condition monitoring, better risk documentation, and enhance Humana's CMS reimbursement rates.

Leveraging Mobile Apps: We recommend Humana promote its mobile app to drive engagement by offering members a simple way to schedule preventive visits and receive health reminders. The app can also include wellness incentives, such as reward points or discounts on medications, for members who complete their annual check-ups. Push notifications through the app will serve as timely reminders to encourage scheduling annual visits. The app itself will be a great source for quick access to important health resources with just a swipe.

This app should not only be a resource for knowledge but also be used as an engaging tool for the members. With something like a small "pet" to take care of by making sure it is fed and taken care of in a timely manner, doctor's visits can be encouraged to score more points and keep the pet healthy. This symbolism will not only nudge the members to visit their PCP but also give them a cheerful reminder of the joy that "life" (in the form of this new pet) holds.

Digital tools will improve member engagement by making it easy to manage healthcare tasks and reduce barriers to access. Increased utilization of the mobile app will strengthen Humana's touchpoints with members, reduce unengaged members, and directly impact Stars scores by improving preventive care participation.

Pharmacy Partnerships: Pharmacies are often a key touchpoint for members, especially for those who regularly fill prescriptions for chronic conditions. We recommend Humana partner with pharmacy chains to promote preventive care at the point of prescription. Pharmacy staff can provide brochures or verbal reminders to members about the importance of annual preventive visits. Additionally, pharmacists could prompt members with chronic conditions to schedule appointments with their PCP.

Integrating these pharmacy touchpoints will help Humana to increase engagement of LPPO members, especially the elder population in the specturm. Pharmacists can also identify and flag members who fill multiple prescriptions but haven't completed preventive visits. This partnership will lead to improved Stars scores by boosting participation in wellness programs and will strengthen CMS reimbursements through better risk documentation.

7.1.2 Recommendation 2: Streamlining Provider Engagement and Incentives

Provider Attribution Optimization: Humana should optimize provider attribution processes to ensure that all LPPO members are assigned a provider and regularly engage with them. By using data analytics, Humana can identify unassigned members and proactively match them with nearby provider. These providers should then be notified and encouraged to reach out to their assigned members to schedule preventive visits. This process ensures members who are unaware of their assigned provider are actively engaged by the provider network.

If Humana can ensure accurate provider attribution, it will increase touchpoints between members and providers and it will directly improve participation in annual preventive visits. This will mitigate the risk of having unengaged members whose chronic conditions may go under-documented, potentially reducing reimbursement amounts and harming Stars performance.

Risk Adjustment Training: We recommend Humana provide risk adjustment training to providers and specialists to ensure accurate coding of chronic conditions. Accurate documentation is essential to reflect the true health status of members and secure appropriate CMS reimbursement. Providers must be trained to correctly submit diagnosis codes for chronic conditions and comorbidities during preventive visits, provider should ensure every condition is properly documented for risk adjustment purposes. Risk adjustment training will improve both engagement and financial outcomes. This will also encourage providers to prioritize preventive visits, knowing that accurate documentation benefits both patient health and financial performance.

Reduced-Copay Programs: Humana should consider implementing reduced-copay specialist programs as a reward if LPPO members do preventive visits. Offering reduced copay cost for specialist visit will incentivize LPPO members, who might otherwise avoid preventive care visits. This limited-time program can be marketed through personalized messaging, the mobile app, and pharmacy partners to encourage early engagement. Removing the copay barrier will increase participation in preventive care and reduce the number of unengaged members.

Member Rewards Program: We recommend Humana launch a Member Rewards Program that offers incentives to members who complete their annual preventive visits. Members could earn points for completing preventive visits. Humana can further align the program with its mobile app, making it easy for members to track their points and rewards.

This strategy will promote sustained member engagement by creating a positive association with preventive care. Incentivizing healthy behaviors will encourage LPPO members who tend to be unengaged. Furthermore, it ensures that Humana captures important risk adjustment data. This will reduce acute care events and enhance CMS reimbursements through better chronic condition management.

7.1.3 Recommendation 3: Building Sustainable Engagement through Partnerships

Telehealth Expansion: We recommend Humana expand its telehealth offerings to allow LPPO members to complete preventive care visits virtually. Many members prefer the flexibility that telehealth provides, especially for routine check-ups and chronic condition management. Humana can market telehealth as an alternative to in-person visits, ensuring members have no excuse to skip preventive care.

Telehealth will significantly increase engagement among LPPO members who might avoid traditional healthcare settings. Virtual visits will improve provider touchpoints and will ensure that members remain engaged even if they don't visit a clinic. This will improve Stars ratings by ensuring continuous care and prevent lapses in monitoring chronic conditions.

Community Health Partnerships: Humana should collaborate with community organizations to set up mobile clinics and health fairs in underserved areas. These clinics can provide free screenings, flu shots, and preventive care services, making healthcare more accessible to members with transportation challenges. Community health events can also be used to raise awareness about the importance of annual preventive visits. These efforts will ensure that more members receive preventive care, leading to better risk documentation and higher CMS reimbursements.

Behavioral Nudges: We recommend Humana implement behavioral nudges such as postcards, loyalty points, or small rewards to encourage preventive visits. Behavioral economics research shows that small, non-monetary incentives can have a significant impact on health behaviors. For instance, sending a postcard saying, "It's time for your annual check-up! Your health matters," can subtly encourage members to schedule appointments. These nudges will motivate members to take actions. The simplicity of behavioral nudges ensures a cost-effective way to increase engagement.

Addressing Social Determinants of Health: Social determinants of health such as income, education, transportation, and access to healthy food significantly affect healthcare outcomes. Humana should form strategic collaborations with community organizations to address these issues. For example, Humana could also partner with grocery stores to provide discounts on healthy foods for LPPO members. Partner with mental health and substance use organizations to provide counseling services, either virtually or in person. Collaborate with community centers and local non-profits to create programs that connect socially isolated members with community groups, such as fitness clubs, senior activities, and support groups. By addressing these social factors, Humana can encourage members to complete preventive visits and improve Stars ratings and CMS reimbursement accuracy.

7.2 Cost Benefit Analysis

Engaging Members Through Targeted Communication

Cost Center Name	Unit Cost ($)	Targeted Reach	Annual Cost
CRM systems cost			10,00,000
SMS Campaign	0.1	500000	50,000
Phone Call Campaign	2.0	1200000	24,00,000
Veteran-focused programs and community partnerships			5,00,000
Total Cost of the Program			**$39,50,000**

Improving Star Score	0.5 - 0.7
Increase in CMS Bonus	12% - 15%
Estimated Annual Savings	**$1,55,78,342**

Value Generated from the Program	**$1,16,28,342**

Streamlining Provider Engagement and Incentives

Cost Center Name	Unit Cost ($)	Targeted Reach	Annual Cost
Workshops, training materials, and analytics			30,00,000
Copay Reduction Cost	30.0	120000	36,00,000
Gift Cards	10.0	100000	10,00,000
Discounts	20.0	50000	5,00,000
Total Cost of the Program			**$81,00,000**

Improving Star Score	0.3 - 0.8
Increase in CMS Reimbursement	7% - 13%
Estimated Annual Savings	**$1,34,36,287**

Value Generated from the Program	**$53,36,287**

Building Sustainable Engagement through Partnerships

Cost Center Name	Unit Cost ($)	Targeted Reach	Annual Cost
Telehealth Platform & Provider Payments	50.0	120000	60,00,000
Mobile Clinic & Community Health Events	35000	35	12,25,000
Postcards, small gifts, and reward points	25.0	115000	28,75,000
Total Cost of the Program			**$1,01,00,000**

Savings from Hospitalization Cost	**$1,34,27,669**
Increase in CMS Bonus	**$1,24,63,786**
Estimated Annual Savings	**$2,58,91,455**

Value Generated from the Program	**$1,57,91,455**

7.3 Challenges and Mitigation

Engaging Members Through Targeted Communication

One significant challenge with outreach campaigns is the potential for low response rates. LPPO plan members who value flexibility, may ignore text messages, emails, or phone calls if they perceive them as spam or irrelevant. Additionally, privacy and compliance regulations, such as HIPAA, can limit how member data is used in personalized outreach. Pharmacy partnerships also introduce operational complexities, as coordinating across multiple pharmacy chains may lead to inconsistent messaging or delays in campaign rollouts.

To address these challenges, Humana should leverage A/B testing to determine the most effective message formats and optimal times to reach members, thereby maximizing engagement. To ensure compliance, Humana must use a HIPAA-compliant CRM platform and conduct regular audits to mitigate privacy risks. Additionally, Humana should streamline pharmacy partnerships by establishing centralized agreements with major chains and they should run regional pilot programs before expanding the initiative nationally to troubleshoot issues beforehand. This approach will help ensure smooth operations and consistent member experiences across different pharmacies.

Streamlining Provider Engagement and Incentives

Providers may resist participating in additional training programs due to time constraints or perceived administrative burden. Additionally, some members may find the rewards offered through incentive programs insufficient to motivate behavior change. There is also a financial sustainability challenge associated with reduced-copay programs since they could temporarily increase short-term costs for Humana, especially if utilization spikes rapidly without yielding immediate savings.

To overcome provider resistance, Humana should offer continuing medical education (CME) credits or performance bonuses as incentives for completing training. For members, the rewards program can be improved by implementing a tiered incentive structure, where members earn increasingly valuable rewards for completing multiple visits. This creates long-term behavior change. To manage the financial risk, Humana can launch limited-time waivers and monitor their effectiveness through metrics such as appointment volume and preventive care savings. This will allow Humana to refine the program before expanding it permanently.

Building Sustainable Engagement through Partnerships

Identifying which social determinants of health factors are most important to boost member engagement can be challenging, especially given the variability across regions. Tracking the direct impact of these interventions on health outcomes and CMS reimbursements can also be complex.

To address these challenges, Humana should use data analytics tools to analyze claims data and regional social determinants metrics in specific areas. Partnering with multiple organizations and service providers will ensure redundancy, mitigating the risk of capacity issues. To measure the effectiveness of interventions, Humana can develop KPIs such as reduction in ER visits or appointment adherence rates. This ensures interventions remain data-driven and cost-effective over time.

Telehealth Expansion and Virtual Care Options

A significant challenge with telehealth expansion is that some members, especially seniors, may lack the digital literacy or devices required for virtual visits. Additionally, reimbursement policies for telehealth services may vary by state or CMS guidelines which can potentially limit the financial viability of offering telehealth across all regions. Providers may also resist adopting telehealth due to concerns about maintaining quality of care, reimbursement rates, or the challenges of integrating telehealth systems into their existing workflows.

Humana can overcome technology barriers by offering educational programs and tech support for members, including simplified guides on using telehealth platforms and loaner devices for those without access to smartphones or tablets. To manage regulatory challenges, Humana should stay informed on CMS policy updates. This proactive approach ensures widespread adoption and sustained use of telehealth services.

Challenges	Mitigation Strategy
Low response rates to outreach	A/B testing for timing and message formats
HIPAA compliance issues	Use a HIPAA-compliant platform and conduct audits
Provider resistance to training	Offer CME credits and performance bonuses
Sustainability of reduced-copay programs	Implement limited time offers with evaluation metrics
Identifying key SDoH factors	Use claims and regional analytics for prioritization
Community partner capacity issues	Form redundant partnerships with multiple organizations
Technology barriers for telehealth	Provide tech support and loaner devices
Regulatory telehealth challenges	Monitor CMS policies and advocate for favorable rules
Budget constraints	Prioritize high-impact, low-cost initiatives
Cross-departmental coordination	Create interdisciplinary task forces
Member engagement fatigue	Use predictive analytics to optimize communication frequency

Figure 31: List of Challenges and Mitigation Strategy

8. Future Scope

8.1 Humana-Mays Index

In this section we will discuss an important aspect of the study with a basic framework of the approach. It will enable us to calculate the Humana-Mays Index to actively study different factors that influence the decision of the members to schedule annual doctor visits.

In this HMI (Humana Mays Index) -based methodology to predicting *preventive_visit_gap_ind*, we'll integrate the comprehensive analysis approach to recognize the factors that most influence the likelihood of gaps in preventive visits. Here's a detailed plan that takes us step-by-step through the process:

8.1.1: Data Normalization

By using the normalization technique, we can ensure that all features are on a comparable scale. No outliers or features should outweigh the others due to large values.

The *normalize( )* function will transform the data in each column to a scale between 0 and 1 resulting in a balanced dataset that is ready for correlation analysis and feature selection.

8.1.2: Correlation Calculations

By determining the correlations between variables, we can explore the complex interactions between the variables and identify those which introduce redundancy in the model. This method will explore both Bivariate and Trivariate correlations. By means of combining such variables, we will gain stronger insights into the features which have the strongest associations with the target variable.

8.1.3: Feature Weighting

This step will identify and prioritize features based on their influence on the target variable. By completing this step, we will set the weights to individual features that would rank from the most influential to the least. Higher weights imply a stronger influence on the target variable.
The methods used in this step will include SVM-based feature weighting (to identify key features using linear Support Vector Machines), Lasso Regression (to regularize coefficients), and PCA-based weighting (to reduce dimensionality and identify the most important features).
Moreover, the features can be classified into 4 categories as:

- ✓ **Behavioral**: Captures the behaviors and habits of members such as frequency of drinking alcohol, or adherence to medication and timely prescription refills.
- ✓ **Visual**: Visual trends and changes in the behavior such as change in frequency of visits or engagement with the providers.
- ✓ **KPIs**: Key Performance Indicators relevant to patient health and engagement like days since last visit.
- ✓ **Transactional**: Focuses on the interaction of the members in the transactional way like number of claims filed in a year and regularity in premium payments, etc.

By identifying the top features in each category, we can achieve a more granular understanding of the factors that influence engagement with their primary care providers.

8.1.4: HMI (Composite Score) Calculation

The combination of the weighted features in the four categories will result in the composite risk score known as the HMI (Humana-Mays Index). It will be an approximate reflection of the distribution and weight of the features that would impact the likelihood of annual PCP visits.

The HMI score is added as a new feature to the dataset, representing the overall risk of each patient having a gap in preventive care. Patients with higher HMI scores are more likely to have gaps in their preventive care.

This HMI Index can be studied under its various categories. For example, if a recommendation is being analyzed for the Southwest region where the HMI Index score calculations are fairly high due to the behavioral component of the score, relevant tailored communication strategies can be implemented. Similarly, if for another region there is a higher risk of no engagement due to the transactional features, the recommendations that improve "transactions" with Humana can be implemented.

Overall, this HMI is a very versatile and crucial score for data-driven decision making for improving engagement with the current plan members. By normalizing the data, evaluating various complex correlations, assigning feature weights, and creating a composite HMI score, Humana can segment patients more accurately and identify those at risk for of avoiding preventive visits. Including this index as an additional feature will not only improve the accuracy of existing predictive models but also guide strategic decisions for targeted communications, improving engagement outcomes, and optimizing resource allocation. By leveraging the power of HMI, a multi-faceted approach, and machine learning, Humana can guarantee that the members receive timely preventive care, ultimately making a long-term, life-changing impact on the member's overall health.

8.2 In-depth Feature Engineering

Due to the time constraints, it was nearly impossible to engineer the new features on a more granular and detailed level. One of the future scopes of the study is to make sure that the features receive the attention that they deserve in the model. One of the examples of additional computation is seen in the "Member Visit Claims" sheet where the members are noted to visit various specialty doctors for their persistent conditions. In this, each visit can be used as a numeric value instead of a binary one. The number will be derived from the difference between the visit date and the last day of the year under study. For example, if a member claimed from the Ophthalmology department on 1st Jan 2023 and we consider 31st December as the last day of the year, instead of "Y" in the Ophthalmology column, we add 365 (for the number of days since the last visit). This can be done to understand and pinpoint the departments and conditions that influence the member's engagement with their primary care providers.

Such in-depth feature engineering and calculations can improve the performance of the predictive model and provide a granular approach towards the features that are impacting the engagement.

9. Competitor Analysis

9.1 Plan Comparison

This section highlights two different plans. One is Humana's Full Access PPO and the other is United's AARP medical advantage from UHC. These plans are compared for a couple reasons. The first is that they are relatively similar in the fact that they have a $0 monthly premium and around a $4000 maximum monthly out of pocket expense. Another reason to compare the Humana plan with the United is that Humana is wanting to grab market share and United holds the most of it.

9.2 Pricing

The pricing of these plans is very similar. However, one thing to notice on the website is that United gives a much more detailed description that is much easier to follow as someone looking for a plan. While this is not directly related to the topic and the point this report is trying to prove, it is worth noting to potentially act on.

Covered Doctor Copays	In-Network	Out-of-Network
Primary care copay	$0 copay	$0 copay
Specialist copay	$40 copay	$40 copay
Provider network (estimated size)	35,000 participating providers	

Figure 32: Humana Coverage Cost (Humana, 2024)

Diving into the numbers, you can see that the numbers almost all point toward united being the better plan. There is a $500 for Humana while $0 for United, the max out of pocket is lower for United, copay is lower for United and based on the information provided in the "Doctor" section of the website, they offer more things for free. This puts Humana at a distinct disadvantage from the start. The only slight advantage that is apparent with Humana is they offer $10/3 months more on over-the-counter medications.

Costs	What you'll pay
Primary care provider (PCP)	$0 copay
Specialist	$30 copay
Virtual visits	$0 copay to talk with a telehealth provider online through live audio and video.
Annual routine physical	$0 copay, 1 per year
Preventive services (such as covered screenings, vaccinations, etc.)	$0 copay for covered services
Mental health (outpatient)	Group: $0 copay Individual: $0 copay
Opioid treatment services	$0 copay

Figure 33: United Plan Coverage (United Health, 2024)

9.3 Star Rating

It is probable that the biggest reason for this difference in plan benefits is the Star Rating that each plan has received. The paragraphs below go into the different benefits of the star ratings. The Humana plan is rated at 3.5 stars and the United plan is rated at 4.5 stars.

1. Bonus Payments Based on Star Ratings:

- **4 Stars and Above**: Plans that achieve a rating of 4 stars or higher receive a **5% bonus payment** from the federal government. This bonus is added to the monthly payment rate for each enrollee in the plan.
- **3.5 Stars or Below**: Plans with ratings below 4 stars do not receive a quality bonus payment. They are paid the base rate set by Medicare.

2. Rebate Percentages Based on Star Ratings:

Medicare Advantage plans also receive a rebate based on their star ratings. The rebate can be used to provide additional benefits, reduce premiums, or lower out-of-pocket costs for enrollees. The rebate percentage varies as follows:

- **5 Stars**: Plans with a 5-star rating receive a **70% rebate**. This means that 70% of the savings (the difference between the plan's bid and the benchmark set by Medicare) is returned to the plan.
- **4.5 Stars**: Plans rated 4.5 stars receive a **70% rebate** as well.
- **4 Stars**: Plans with a 4-star rating get a **65% rebate**.
- **3.5 Stars and Below**: Plans rated below 4 stars receive a **50% rebate**.

3. Impact on Payments and Competitive Positioning:

- Plans with higher star ratings (4 stars and above) can significantly increase their revenue through these bonus payments and rebates. The extra funding allows insurers to enhance benefits or reduce costs, making their plans more attractive to beneficiaries.
- Conversely, plans with lower ratings may struggle to compete because they do not receive bonus payments and have lower rebate percentages, limiting their ability to offer enhanced benefits.

As you can see, there is a huge difference in 3.5- and 4.5-star ratings. Firstly, 3.5 don’t receive the 5% bonus payment from the federal government. And the 3.5 only receives a 50% rebate instead of 70%. When we are looking at the 25% difference, it may not seem like a lot. However, with the number of individuals with plans, it adds up to millions of dollars that are not being received to enhance the 3.5-star plan. (Genzeon, 2024)

One interesting piece of information is that Humana has sued US health agencies because of star ratings. “The lawsuit argues that the US Medicare program was “arbitrary and capricious” in how it calculated the metrics for Humana’s health plans. The scores, known as star ratings, are linked to billions in bonus payments in future years.” (Tozzi, 2024)Humana hopes to have more clarity on how the stars scores are calculated.

9.4 Methods

One thing that is believed to help increase the star score is the percentage of people engaged in preventative health checks. There are many ways insurers try to encourage this. Many are done by all, such as no-cost visits, financial rewards, personalized reminders, telehealth visits and coverage, partnering with doctors to encourage, and other educational sources. However, their competitors are doing some things that are above and beyond these things. United offers more financial benefits for going annually, such as gift cards. Companies Kaiser and Molina do on site visits. Bringing doctors to workplaces and communities to do checkups there. Many companies are integrating fitness apps and wearable devices to get continuous information and tracking.

10. Conclusion

Engaging LPPO members in preventive healthcare is critical to Humana's success in a competitive Medicare Advantage market. Without adequate preventive visits, members' risk profiles may not be updated properly, leading to lower CMS MRA payments. This would force Humana to cover the additional costs of care, reducing profitability. Furthermore, a lack of touchpoints negatively impacts CMS Stars ratings, reducing bonus payments and limiting reinvestment in member benefits.

By adopting outreach campaigns, provider training, SDoH partnerships, and telehealth services, Humana can increase member engagement and improve documentation accuracy. This will lead to higher CMS reimbursements, lower healthcare costs, and better health outcomes for members. These strategies will position Humana to achieve sustainable growth, ensuring high-quality care and maintaining financial stability in the expanding MA market.

11. List of Figures

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