Predicting Factors Influencing Insurance Members' Non-Adherence to Preventive Visits

Humana-Mays 2024 Case Competition

Humana

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1 Executive Summary

The objective of this report is to analyze the preventive care behavior among Medicare Advantage (MA) members, specifically focusing on members enrolled in Humana's Local Preferred Provider Organization (LPPO) plans. Preventive visits to Primary Care Physicians (PCPs) are vital for managing chronic conditions, detecting health risks, and maintaining the health of elderly populations. However, approximately 45% of LPPO members are not engaging in these preventive visits, which significantly affects Humana's performance in programs like CMS Stars and Medicare Risk Adjustment (MRA).

This report outlines a comprehensive analysis using both exploratory data analysis (EDA) and predictive modeling to understand the factors driving non-engagement. The dataset includes demographic, behavioral, and healthcare utilization data, with key features influencing member behavior. Leveraging tools such as Excel, Power BI, and Python, including the advanced Light GBM model, we have developed a predictive solution to identify members who are at risk of not attending preventive visits.

The findings from this study provide actionable business recommendations to help Humana target unengaged members more effectively, improve preventive care participation, and ultimately enhance the quality of care. Key recommendations include outreach strategies tailored to low-income populations, veterans, and demographic groups with lower engagement rates. Implementing these recommendations could significantly improve member outcomes, reduce healthcare costs, and improve Humana's CMS Star ratings.

2 Case Background

2.1 Context

Humana Inc. is a major provider of Medicare Advantage (MA) plans, offering a wide range of healthcare services to millions of Americans, including families, veterans, and individuals enrolled in Medicare and Medicaid. As part of its MA offerings, Humana provides Local Preferred Provider Organization (LPPO) plans, which allow members more freedom in selecting healthcare providers but also present challenges in ensuring consistent healthcare engagement, especially in preventive care.

Medicare Advantage plans are critical for the well-being of elderly and vulnerable populations, offering services that range from hospital visits (Part A) to outpatient and doctor visits (Part B) and prescription drug coverage (Part D). The importance of preventive visits, specifically, cannot be overstated—these visits allow healthcare providers to identify potential health risks, monitor chronic conditions, and guide patients toward healthier outcomes. Moreover, engaging in preventive care improves overall health outcomes and plays a critical role in Humana's CMS Stars ratings, which directly influence financial reimbursements and bonuses that Humana reinvests into member benefits.

Despite the benefits, approximately 45% of LPPO members do not engage in these preventive visits, leading to adverse health outcomes and financial implications for Humana. The LPPO plans, while offering flexibility, tend to have lower engagement rates compared to Health Maintenance Organization (HMO) plans. This disengagement limits provider touchpoints with members, reducing the opportunity for healthcare professionals to conduct necessary screenings, manage medications, and address health risks.

2.2 Problem Statement

The primary challenge Humana faces is the low rate of preventive visit participation among LPPO members, with 45% of members skipping these essential healthcare appointments. This lack of engagement not only threatens members' health but also has broader business implications, including reduced CMS Star ratings and incomplete risk documentation, which directly affect reimbursement levels under the Medicare Risk Adjustment (MRA) program.

The goal of this report is to explore why such a high percentage of LPPO members are not attending preventive visits and to build predictive models that can help Humana target unengaged members through more effective outreach programs. By understanding the underlying barriers, this analysis will provide actionable recommendations to increase engagement rates and improve health outcomes for MA member.

3 Preliminary Data Analysis

3.1 Data Overview

In this analysis, both the training and holdout datasets are composed of **14 data tables**, providing a wide range of demographic, behavioral, healthcare utilization, and pharmacy-related information about target members.

- **Training Dataset**: This dataset consists of the same 14 tables as the holdout dataset, with a total of **1,527,904 rows** for 11 of the tables. The remaining three tables contain significantly more data:
    - **humana_mays_target_member_visit_claims.csv**: 19,456,796 rows and 27 columns
    - **humana_mays_target_member_conditions.csv**: 4,009,342 rows and 7 columns
    - **QUALITY_DATA.csv**: 33,572,241 rows and 8 columns

Across all 14 tables, the number of columns ranges from **7 to 78**, resulting in a total of **295 columns**. A key feature in the training dataset is a column indicating whether a member participated in a preventive visit (1 for non-participation, 0 for participation). This serves as the target variable for training models to understand factors influencing preventive visit behavior.

- **Holdout Dataset**: The holdout dataset has the same structure as the training dataset, with the same 14 tables. However, it **does not include the preventive visit column**, which is the target variable that the model needs to predict based on the other features in the dataset.

Key files in both datasets include:

- **humana_mays_target_members.csv**: Contains core member information for both datasets.
- **Additional Features.csv, Control Point.csv, Cost & Utilization.csv**: Provide supplemental data on healthcare usage, medical costs, and other relevant aspects.
- **Demographics.csv, Social Determinants of Health.csv**: Provide essential background information about the members' socioeconomic and health conditions.
- **Web Activity.csv, Pharmacy Utilization.csv**: Offer insights into digital interactions and pharmacy claims data.
- **Member and Quality Data**: Provide further information on member health status and quality of care received.

The key challenge is to leverage these features to accurately predict the likelihood of preventive visits in the holdout dataset.

3.2 Tools Used

We primarily utilized Excel, Power BI, and Python for our analysis and recommendations. During the exploratory data analysis (EDA) phase, we leveraged Excel and Power BI to explore the general structure of the data and the relationships among various datasets, while also visualizing the distributions of key demographic information. In the preprocessing and modeling phases, our main tool was Python, employing essential libraries such as NumPy, Pandas, Matplotlib, Scikit-learn, and specially, Optuna for hyperparameter tuning. This setup enabled us to clean the data effectively and derive aggregated variables, followed by fitting and tuning different models to enhance our analysis.

3.3 Exploratory Data Analysis

3.3.1 General Data Overview

This section presents a visual analysis of the dataset, providing a comprehensive overview of key aspects related to demographic factors and preventive visit rates.

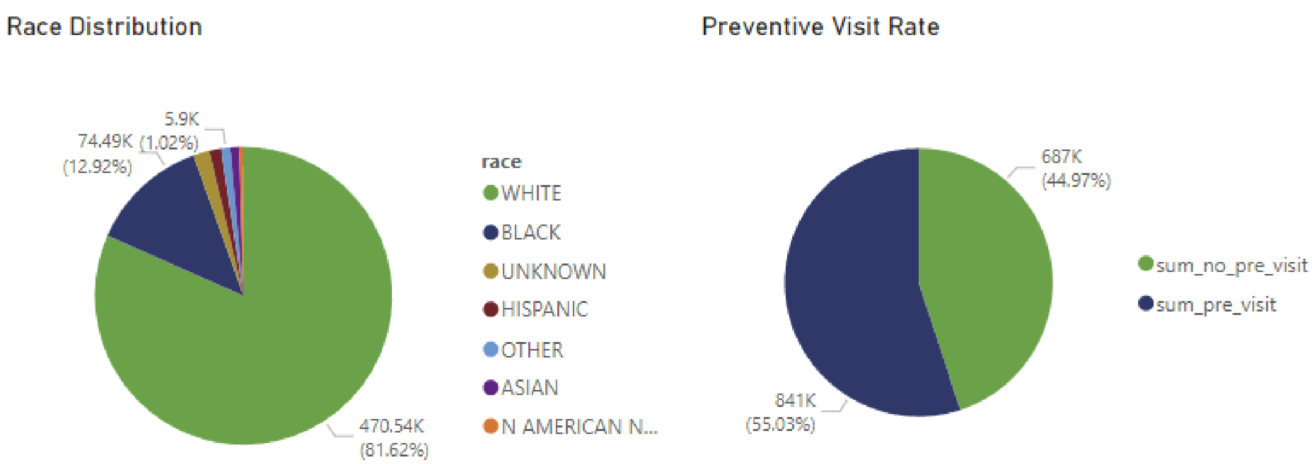

Figure 3.2.1.1 Race Distribution and Preventive Visit Rate

● Race Distribution: The pie chart on the left illustrates the distribution of races in the dataset. It reveals that:

- White individuals constitute the overwhelming majority at 81.62%
- Black individuals form the second largest group at 12.92%
- Hispanic, Other, Asian, and Native American groups make up smaller percentages of the population

This distribution allows us to identify the predominant racial groups in the dataset, with White individuals forming a clear majority.

It's important to note that approximately 60% of the overall data lacks race information. However, given the large sample size of the remaining 40% (which amounts to hundreds of thousands of individuals), we can reasonably assume that this subset is statistically representative of the entire population. The large volume of data, even at 40%, provides a robust basis for identifying general distribution trends across racial groups.

● Preventive Visit Rate: The pie chart on the right displays the rate of preventive visits among the population:

- 55.03% (841K individuals) have had preventive visits (sum_no_pre_visit)
- 44.97% (687K individuals) have had no preventive visits (sum_pre_visit)

This chart indicates that slightly over half of the individuals in the dataset have not had preventive visits, while a substantial minority has engaged in preventive care.

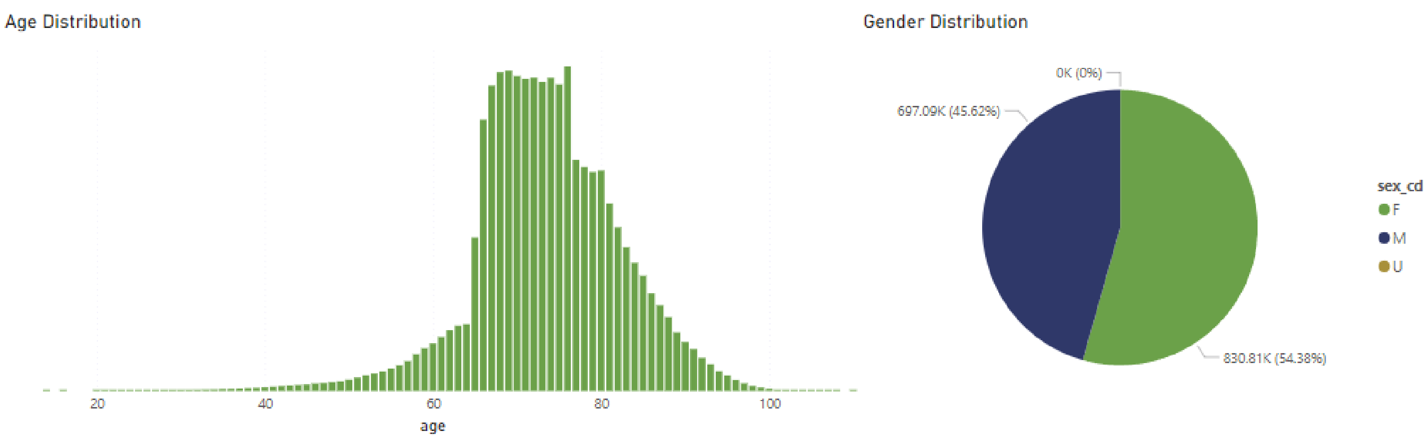

Figure 3.2.1.2 Age Distribution and Gender Distribution

● Age Distribution: This histogram illustrates the age distribution of individuals receiving preventive visits. The distribution is right-skewed, with the majority falling within the age range of 60 to 85 years. This indicates a higher likelihood of engaging in preventive care among older and elderly individuals. There's a noticeable peak around 65-75 years, suggesting that this age group is particularly active in seeking preventive healthcare services.

● Gender Distribution: This pie chart displays the gender breakdown of target members. Females comprise 54.38% of the population, while males make up 45.62%. The slight female majority aligns with general population trends, especially considering the focus on an older demographic where women tend to have longer life expectancies. This gender distribution provides insights into potential differences in preventive care utilization between men and women in the studied population.

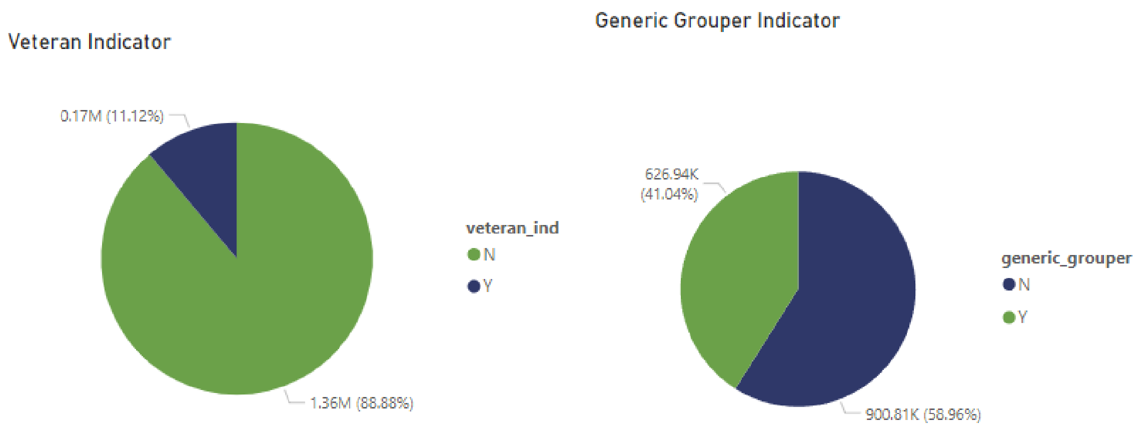

Figure 3.2.1.3 Veteran Indicator and Generic Grouper Indicator

● Veteran Indicator: This pie chart illustrates the proportion of veterans in the dataset. The vast majority, 88.88% (1.36M individuals), are non-veterans (N), while veterans (Y) comprise 11.12% (0.17M individuals) of the population. This significant presence of veterans, though a minority, suggests that military service history could be an important factor in analyzing preventive care patterns.

The veteran status of individuals may influence their engagement with preventive healthcare services. Veterans often have unique healthcare needs and experiences that can affect their approach to preventive care. Factors such as access to VA healthcare, service-related health conditions, and differences in health-seeking behaviors could potentially impact their preventive visit rates[i]. In subsequent analyses, it would be valuable to examine whether there are notable differences in preventive care utilization between veterans and non-veterans, and to explore any specific barriers or facilitators to preventive care that may be unique to the veteran population.

● Generic Grouper Indicator: This pie chart illustrates the distribution of individuals with and without chronic conditions in the dataset. 41.04% (626.94K individuals), are marked as 'Y', indicating the presence of chronic conditions. The majority, 58.96% (900.81K individuals), are labeled as 'N', representing those without identified chronic conditions.

This distribution of chronic condition status may have important implications for preventive healthcare engagement, as it will be discussed in later section.

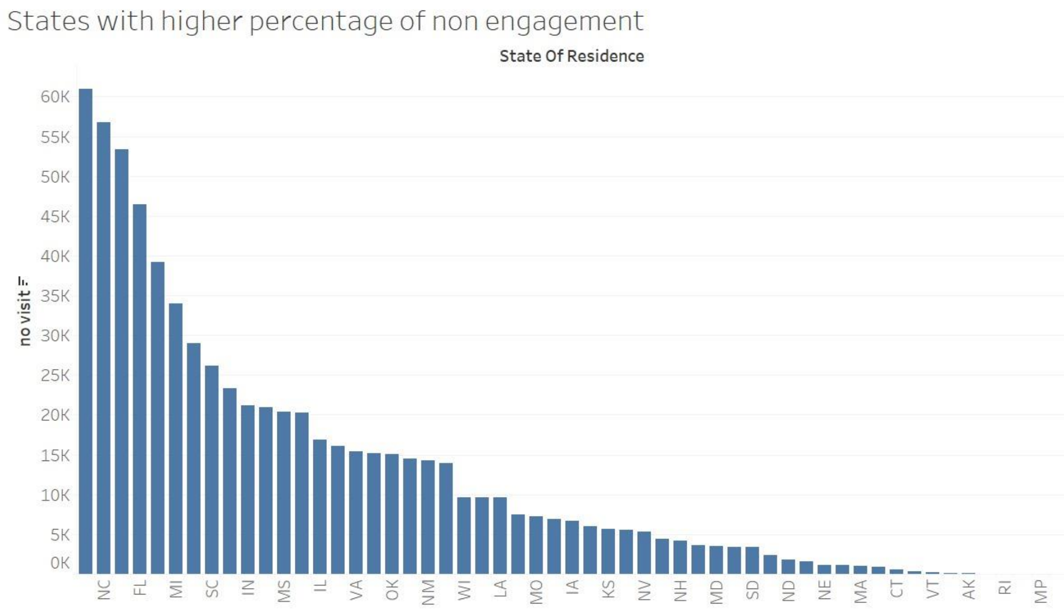

Figure 3.2.1.4 States with Higher Percentage of Non-Engagement

In addition to the insights gained from demographic status, the dataset also exhibits notable regional differences. These geographic disparities are critical when formulating business recommendations, as they enable us to narrow down key features and target the most relevant areas with tailored, region-specific strategies. Understanding these regional variations allows us to provide more accurate and localized advice, which is essential for addressing the unique healthcare needs of different areas.

3.3.2 Preventive Visit Rate per Race

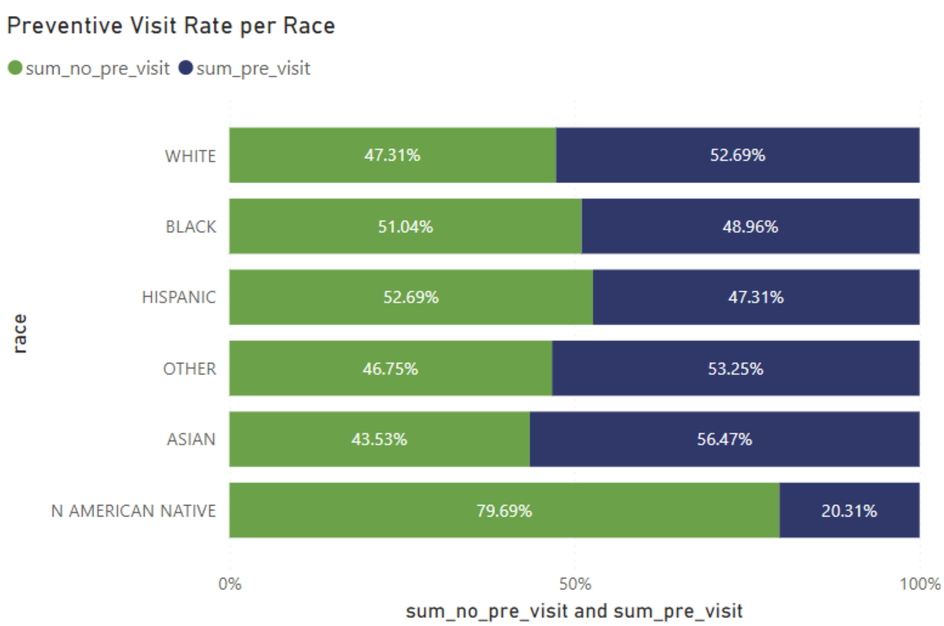

Figure 3.2.2.1 Preventive Visit Rate per Race

This analysis reveals significant disparities in preventive care utilization across racial groups. Asian individuals have the highest rate of preventive visits, while Native American individuals have the lowest. White and Other racial categories show above-average rates of preventive care, while Hispanic and Black individuals have below-average rates.

3.3.3 Preventive Visit Rate per Sex

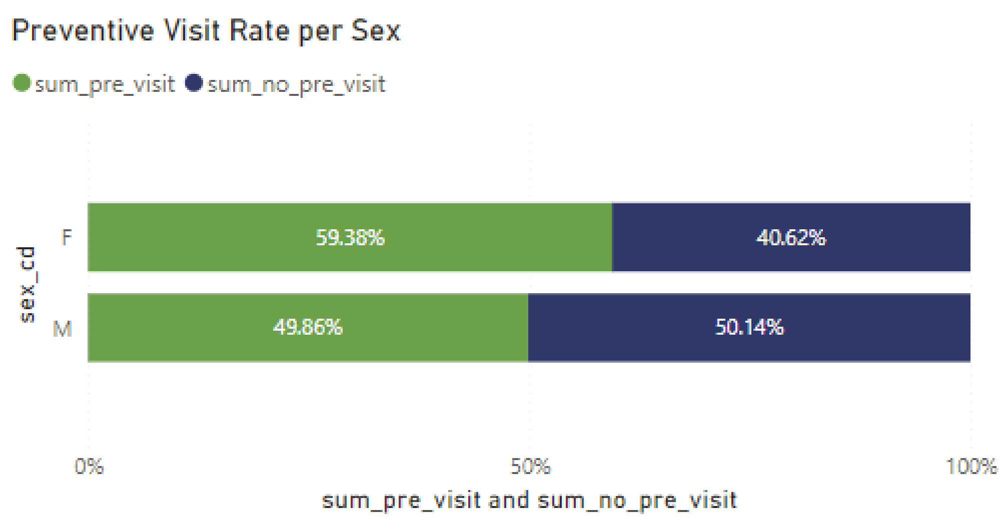

Figure 3.2.2.1 Preventive Visit Rate per Race

Females show a significantly higher rate of preventive visits compared to males, with nearly 60% of females engaging in preventive care versus just under 50% of males. The almost 10 percentage point gap (59.38% vs 49.86%) in preventive visit rates between females and males is substantial. This disparity could be attributed to various factors, such as:

1. Different health-seeking behaviors between genders
2. Variations in health awareness or education
3. Potential differences in access to or utilization of healthcare services
4. Specific health needs or recommended screenings that may differ between sexes

These findings suggest that targeted efforts to increase male engagement in preventive care might be beneficial. Additionally, further investigation into the reasons behind this gender disparity could provide valuable insights for improving overall preventive care utilization across the population.

3.3.4 Veteran Status on Preventive Visit Rate

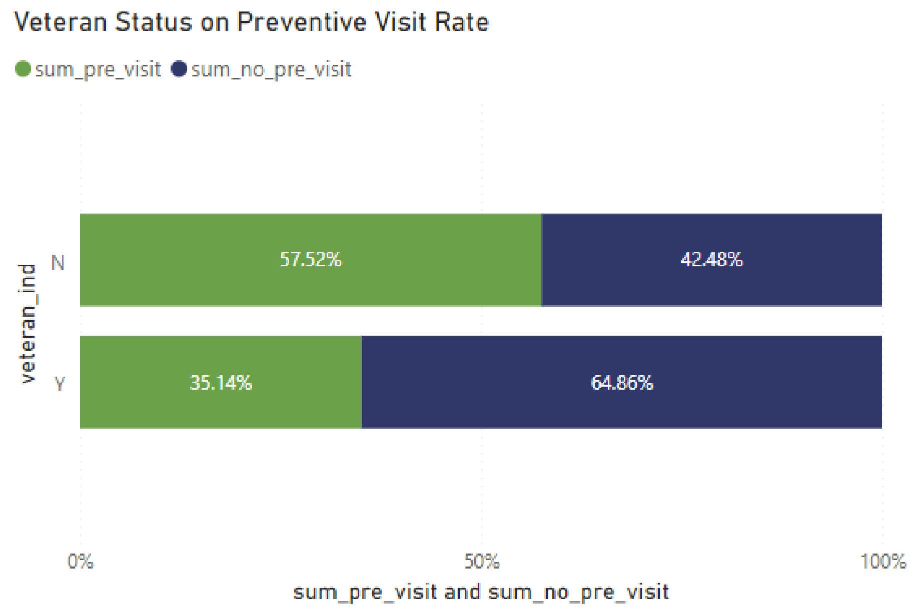

Figure 3.2.2.1 Veteran Status on Preventive Visit Rate

Veterans have a much lower rate of preventive visits, with only about a third (35.14%) utilizing these services. There's a 22.38 percentage point gap between non-veterans and veterans in terms of preventive visit rates.

This stark contrast raises important questions about factors affecting veterans' healthcare utilization:

1. It could indicate potential barriers to access for veterans, despite the existence of VA healthcare.
2. There might be differences in health-seeking behaviors or attitudes towards preventive care among veterans.
3. The veteran population may have unique healthcare needs or priorities that aren't being fully addressed by current preventive care services.
4. There could be systemic issues within veteran healthcare services that discourage or hinder preventive care visits.

These findings suggest a critical need for targeted interventions to improve preventive care utilization among veterans.

4 Modeling

4.1 Pre processing

The preprocessing steps, including index conversion, feature engineering, handling missing values, and removing irrelevant features, finalized a dataset consisting of **1,527,904 rows** and **277 columns**, ready for further analysis and modeling.

4.1.1 Index Conversion

The key preprocessing step was converting claim-level data to member-level data. This allowed for all datasets to be unified using a common index, such as id, across the various tables. Here's how this was done for each relevant dataset:

- **Visit Claims Data (humana_mays_target_member_visit_claims.csv)**:
  The original dataset contained claim-level data, where each row represented a different clinic visit. Most columns recorded the number of visits to specific types of clinics (e.g., cardiologists, radiologists). To align this data with member-level information, the number of visits was aggregated by summing the total number of visits for each clinic type for every member (using id as the grouping key).
- **Conditions Data (humana_mays_target_member_conditions.csv)**:
  This dataset included records of chronic diseases for each claim. To preprocess it, the data was aggregated by calculating the most frequently occurring chronic condition (the mode) for each member. Additionally, four new columns were generated:
  - **ESRD**, **MEDICAL**, **V24**, and **V28**: These columns were used to count the occurrences of certain conditions under the **HCC model type** and **SMC model type** for each member.
- **Quality Data (QUALITY_DATA.csv)**:
  Most columns in this dataset were categorical, representing different types of quality measures (e.g., quality performance indicators). To transform this into member-level data, the most frequently occurring measure type for each member (grouped by id) was calculated. This allowed us to capture a summary measure of each individual's quality data.

4.1.2 New Features Generation

During this process, new features were generated to enhance the predictive power of the data:

- **Visit Counts**: Total number of visits to different clinic types for each individual was computed from the visit claims data.
- **Chronic Condition Mode**: For the conditions data, the mode of chronic conditions was calculated to represent the most common health issue each member faced.

- **HCC and SMC Model Type Counts**: As mentioned in index conversion, for conditions, additional features were created to count occurrences of specific condition types (ESRD, MEDICAL, V24, V28), relevant to predicting healthcare utilization patterns.
- **Quality Measure Mode**: The most frequently occurring quality measure for each member was calculated from the quality dataset.

These preprocessing approaches above ensure that all datasets are now aligned at the member level, allowing for easier integration of various feature tables in modeling preventive visit participation.

4.1.3 Handling Features with Null Values

The newly generated three tables based on id calculations have 1,329,101 rows (claims), 1,152,178 rows (conditions), and 1,350,479 rows (quality), which leads to missing value rates of 15.0%, 32.6%, and 13.1% respectively. For other features in the dataset, the majority had missing value rates not exceeding 7%.

We addressed null values as follows:

1. Continuous variables (e.g., total MA payment, age, CCI score): Median imputation.
2. Categorical variables (e.g., measure type, sex, region): Mode imputation.

For categorical variables with an "unknown" category, null values were assigned to this group. This approach maximizes usable data while maintaining overall data characteristics.

4.1.4 Removing Unnecessary Features

Two types of features were removed:

1. **Constant value features**: These are features with only one value across all records, providing no variability and therefore no useful information for predictive modeling.
2. **High-cardinality categorical features**: Features such as various types of keys (e.g., claim keys or prescription IDs) that had over 1,000 unique categories were excluded, as they would add little value to the model. Only the necessary identifiers like id were retained.

This ensured that only the most relevant and interpretable features were kept for modeling.

4.1.5 Summary

In summary, after completing the preprocessing steps, including index conversion, feature engineering, handling missing values, and removing irrelevant features, we finalized a dataset consisting of **1,527,904 rows** and **277 columns**, ready for further analysis and modeling.

4.2 Model Selection: Comparing Models

We compared four models: Logistic Regression, Random Forest, XGBoost, and LightGBM. Given the large dataset, tree-based models were particularly suitable because of their ability to effectively handle high-dimensional data and capture complex patterns through feature interactions. The data was split into training and test sets with a 70:30 ratio, and the models were evaluated using the Area Under the ROC Curve (AUC). After tuning each model, we selected the model with the highest AUC for further analysis.

LightGBM performed the best, followed by Random Forest and XGBoost. One key advantage of LightGBM is its faster training speed, especially for large datasets, due to its use of a leaf-wise tree growth strategy, which can reduce overfitting and increase efficiency. Tree models, in general, are also robust with missing data and are better suited for datasets with a large number of features, making them a strong choice for our scenario. As a result, we proceeded with LightGBM as the final model for deployment.

Table 1. AUC achieved using each model and the advantages and disadvantages of each model.

	Logistic Regression	**Random Forest**	**XGBoost**	**LightGBM**
Test Set AUC	0.722	0.756	0.727	0.769
Advantages	Easily interpretable, fast, low computational costs	Good performance, can handle complex relationships, resistant to overfitting	Fast, considerable tuning capabilities, resistant to overfitting	Highest AUC, fastest, considerable tuning capabilities
Disadvantages	Lowest AUC, limited in capturing non-linear relationships	May require more memory for large datasets	More difficult to interpret, requires tuning of hyperparameters	More difficult to interpret, requires tuning of hyperparameters

4.3 Model Tuning of LightGBM Model

For tuning the LightGBM model, we used **Optuna**, a modern and efficient hyperparameter optimization framework. Optuna follows a **Bayesian optimization approach**, which allows it to intelligently explore the parameter space by trying values that are likely to improve model performance based on previous trials .[1] This method is generally more efficient than traditional grid search, where all possible combinations of parameters are exhaustively evaluated, or random search, where parameters are selected randomly without considering prior results.

Here's how we applied it:

- **Optuna setup**: We created an optimization study that aimed to maximize AUC, the evaluation metric for our model.

  In each trial, Optuna proposed a new set of hyperparameters, which were evaluated using five-fold cross-validation on the training data. This allowed us to search more efficiently compared to grid search, which would have been computationally expensive given the large dataset and the complexity of the model.

- **Hyperparameter details**: Below are some of the key hyperparameters tuned with Optuna:

Model	Tuned Hyperparameters	Average AUC Score on Test Set
Final LightGBM	objective = 'binary' metric = 'auc' boosting_type = 'gbdt' max_depth=8 subsample=0.6 n_estimators=900 learning_rate=0.05 num_leaves=128 colsample_bytree=0.6	0.769

Table 2. Tuned hyperparameters and AUC scores for the final model.

This approach was beneficial for fine-tuning the LightGBM model, allowing us to find the optimal parameter configuration with fewer trials and reduced computational resources.

4.4 Final Model

The tuned LightGBM model was evaluated against the test set, and an AUC score of 0.769 was obtained. This AUC value suggests that the model has relatively strong predictive power in identifying individuals likely to not participate in preventive visits.

[1] https://github.com/optuna/optuna

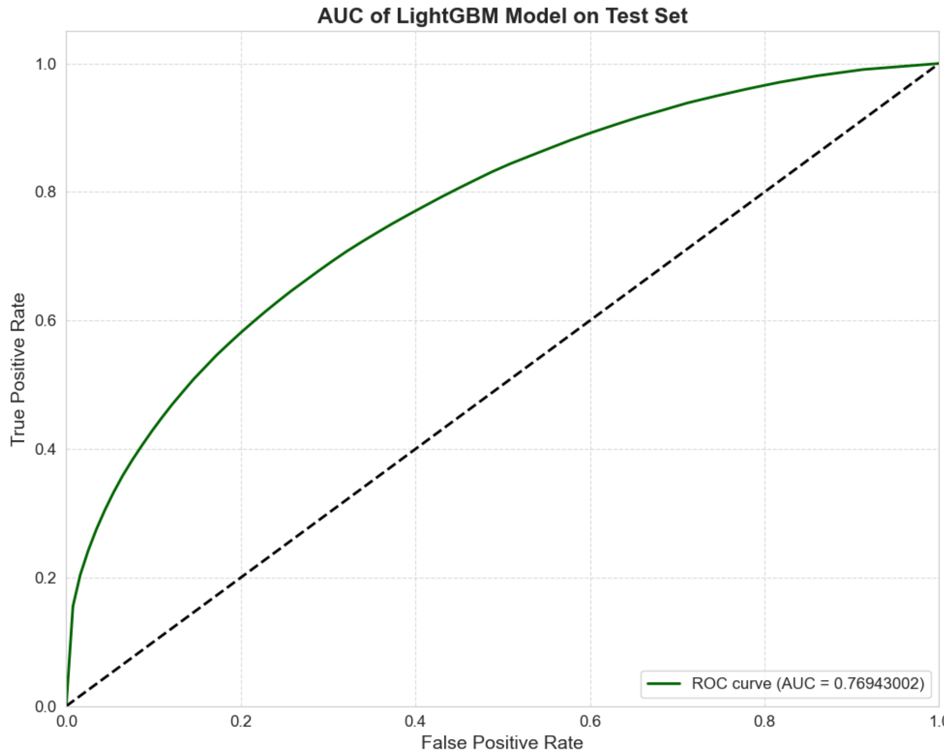

Figure 4.4.1 Receiver operating characteristic (ROC) curve of the model predictions of the test set.

The confusion matrix analysis yielded the following key metrics for the model's performance:

- **Sensitivity (True Positive Rate):** 57.02%
  The model correctly identifies 117,684 out of 206,385 actual positive cases, highlighting its effectiveness in recognizing positive cases.
- **Specificity (True Negative Rate):** 80.86%
  The model successfully identifies 203,753 out of 251,987 actual negative cases, demonstrating strong performance in distinguishing negative cases.
- **Overall Accuracy:** 70.13%
  The model correctly classifies 321,437 out of 458,372 total cases, achieving an overall accuracy of 70.13%.

These results indicate that the model performs well in identifying both positive and negative cases, with a better performance on negative cases. The probability threshold was set at **0.4** to optimize for the highest possible accuracy, as this value balanced sensitivity and specificity, maximizing overall accuracy at 70.13%.

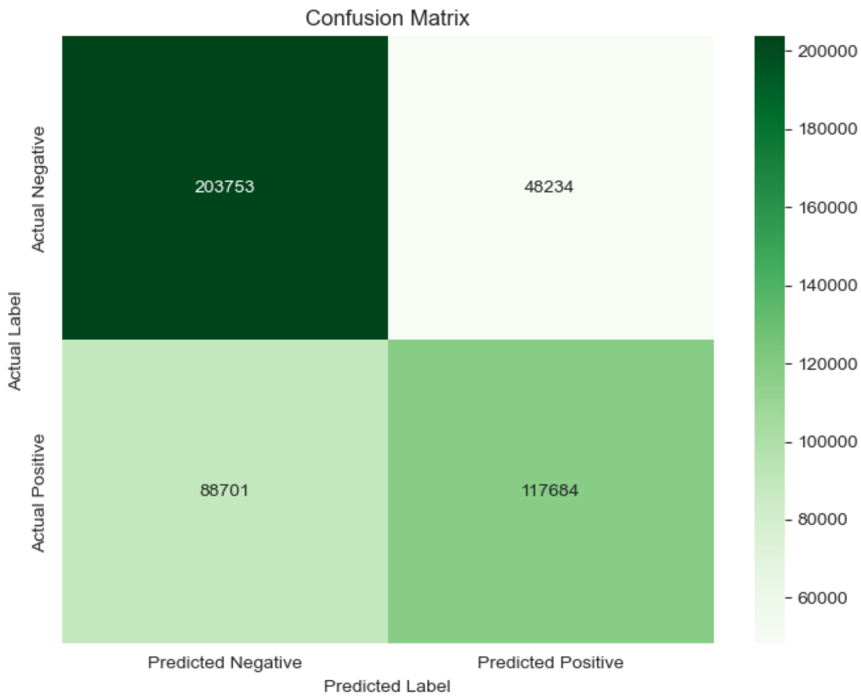

Figure 4.4.2 Confusion matrix for predictions of the test set with threshold of 0.4.

We also assessed the model for fairness by calculating the disparity score, evaluating the AUC for different subgroups of sensitive variables (race and sex). The disparity score is determined by dividing the AUC of each minority group by the AUC of the reference group, which in our case is white males.

An acceptable threshold for fairness is set at a disparity score greater than **0.9**, ensuring the model is not significantly biased towards the reference group. Our model achieved a disparity score of **0.9816**, indicating a fair treatment of all groups and minimal bias towards the reference group. This result suggests that the model maintains equity across different demographic categories while delivering accurate predictions.

4.5 Feature Importance

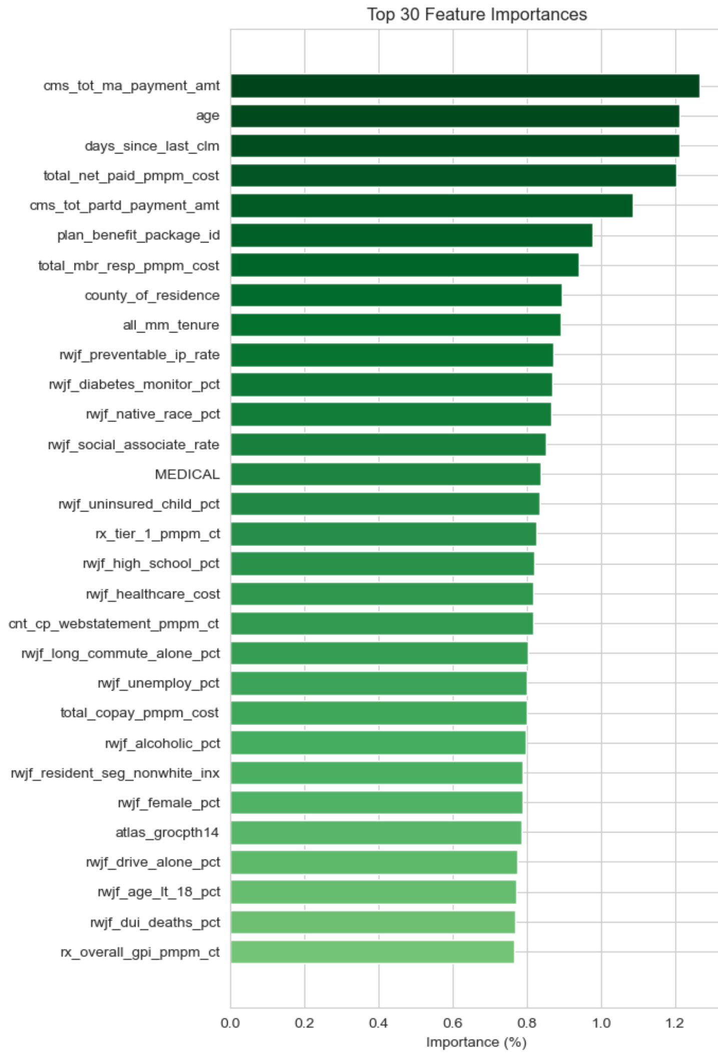

Figure 4.5.1 Percent Importance of Top30 Features

Based on our analysis, the twenty most important factors influencing preventive visits are summarized below and presented in Figure 8. Unlike some models where a single feature may dominate, our findings indicate that the importance of the top features is relatively evenly distributed, with each feature having an importance score around 1%. This suggests that a range of factors contributes to the likelihood of preventive visits, indicating a complex and diverse interplay.

We categorized the top features into five distinct categories: **Socioeconomic**, **Health Status**, **Payments**, **Visits/Days**, and **Other**. This classification allows for a more structured analysis of the factors influencing preventive visits.

1. **Socioeconomic**:
   - **atlas_povertyallagespct**: Reflects the poverty rate across different age groups, which may impact individuals' health management capabilities.
   - **atlas_fsrpth14**: Indicates household income levels, directly affecting access to healthcare services.
   - **rwjf_population**: Involves population density and structure, influencing the distribution of health resources.
2. **Health Status**:
   - **er_visit**: Reflects the number of emergency room visits, indicating the urgency of overall health issues.
   - **cardiologist_visit**: Records visits to cardiologists, signaling cardiovascular health status.
   - **radiologist_visit**: Records visits to radiologists, reflecting checks for potential health problems.
3. **Payments**:
   - **cms_tot_ma_payment_amt**: Reflects total payments under Medicare Advantage, influencing individual healthcare costs.
   - **cms_tot_partd_payment_amt**: Indicates payments related to prescription drugs, affecting medication access.
   - **rx_overall_copay_pmpm_cost**: Monthly out-of-pocket costs for prescription drugs, influencing patients' medication adherence.
4. **Frequencies/Days**:
   - **days_since_last_clm**: Days since the last claim, indicating patients' visit frequency.
   - **cnt_cp_webstatement_4**: Number of times patients viewed their online statements, reflecting interaction frequency with healthcare services.
   - **rx_days_since_last_script**: Days since the last prescription, affecting patients' willingness to adhere to treatment.
5. **Other**:
   - **rx_overall_dist_gpi6_pmpm_ct**: Monthly distribution of prescriptions, reflecting patients' medication management practices.

By leveraging insights gained from feature importance analysis, our subsequent business strategies will focus on the factors identified within these categories. This structured approach aims to enhance participation in preventive visits and ultimately improve health outcomes for members.

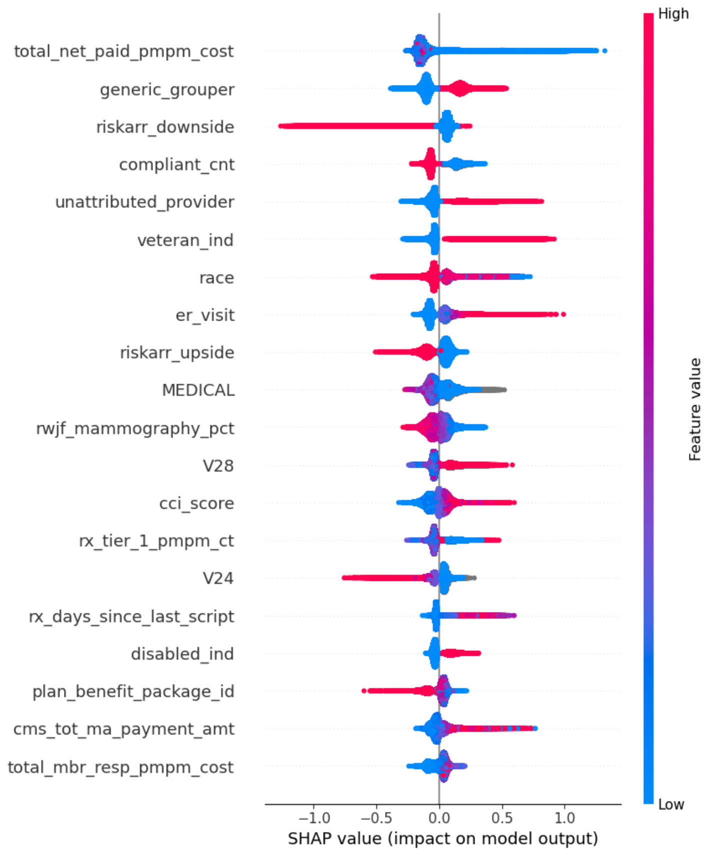

Figure 4.5.2 SHAP Value of Features

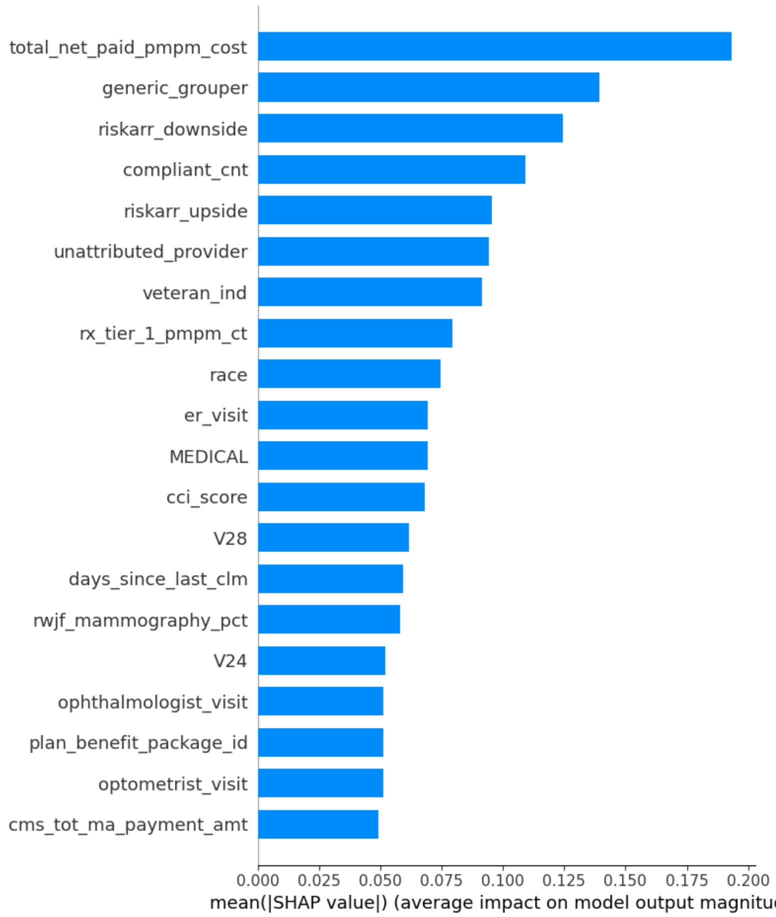

Figure 4.5.3 SHAP Bar Plot

The SHAP value graph illustrates the influence of the top 20 features on the model's predictions, enhancing the transparency of its decision-making process. Unlike traditional feature importance measures, SHAP values provide a clearer picture of each feature's absolute impact on the final prediction, while also indicating both positive and negative effects on the outcome.

From the SHAP bar chart, we can observe that seven features have an impact on the model's final output exceeding 0.1, with the ‘total net paid’ feature demonstrating an even greater influence, exceeding 0.2. This indicates that SHAP values offer greater differentiation in feature selection compared to conventional importance metrics.

● Features that Stand Out in their Influence:

Among the myriad features, a few distinctly stand out at the top of the plot: 'total_net_paid_pmpm_cost', 'generic_grouper', 'riskarr_downside', 'compliant_cnt', and 'unattributed_provider'. These features, with their wider SHAP value distributions and positioning at the top of the plot, play a central role in the model's predictive outcomes.

'total_net_paid_pmpm_cost' is particularly noteworthy, showing a strong positive impact when its value is high (red dots extending far to the right), indicating that individuals with higher claim amounts are less likely to seek preventive care.

● Features with Complex Relationships: Several features demonstrate intriguing patterns. For instance, displays a unique pattern where high values can have significant but two opposing impacts.

● Features with Categorical Impacts: Certain features like 'veteran_ind' and 'disabled_ind' show distinct clusters of SHAP values, indicative of their categorical nature. For 'veteran_ind', there's a clear positive impact for one category (likely indicating veteran status), while 'disabled_ind' shows a more nuanced effect across its categories.

5 Business Implications & Solutions

5.1 Business Implications

5.1.1 Preventive Visit and its implication on chronic diseases

Preventive visits play a crucial role in early disease detection and prevention. Regular check-ups allow healthcare providers to identify potential health issues before they become severe. Through screenings, tests, and physical examinations, doctors can detect abnormalities or risk factors that may indicate a developing disease. Early diagnosis enables timely intervention, often leading to more effective treatment options and improved outcomes. By catching diseases in their early stages, preventive visits can help prevent serious complications, reduce the need for invasive procedures, and ultimately improve overall health and quality of life. According to the latest find from the CDC, a sheer drop in preventive visit during the COVID-19 period increased the number of chronic diseases amongst Americans during the period after.

5.1.2. Targeting Socioeconomic Barriers and Low-Engagement Regions

Our analysis shows a clear link between poverty levels and low engagement in preventive care, particularly in regions like TX and NC, where socioeconomic barriers are more prominent. For example, the SHAP analysis identified factors such as total_net_paid_pmpm_cost and generic_grouper as key predictors of low engagement. Members in lower-income areas often face challenges like transportation issues and healthcare access limitations. To address this, Humana could implement mobile clinics or telehealth services in under-engaged regions, reducing access barriers and providing essential care.

Kaiser Permanente's[2] mobile health clinics have been successful in underprivileged communities, offering a model Humana could replicate. Mobile clinics, combined with partnerships for subsidized transportation, can ensure low-income individuals reach the necessary healthcare services. In areas where public transport is unreliable, or car ownership is not feasible due to costs, discounted transport services can be a critical intervention.

Addressing these socioeconomic challenges requires collaboration with social service agencies. By partnering with these organizations, Humana can offer more comprehensive support to patients, helping to schedule appointments, manage transportation, and alleviate financial concerns. Social workers can educate patients about the benefits of preventive care and build stronger community connections, fostering trust.

Humana's efforts to remove socioeconomic barriers would also enhance its standing in terms of ESG (Environmental, Social, and Governance) standards, a key point for long-term financial and social sustainability. While these initiatives may require initial investment, long-term gains in health outcomes, reduced disparities, and improved

[2] https://communityhealth-midatlantic.kaiserpermanente.org/health-care-access/mobile-health-vehicle/

patient engagement will ultimately benefit both the company and the communities it serves.

In summary, by investing in mobile clinics, transportation solutions, and partnerships with social services, Humana can empower low-income individuals to prioritize preventive care and improve overall health outcomes.

5.1.3 Business Implications of Veteran Status on Preventive Visits

We have seen from the initial preliminary data analysis **Figure 3.2.1.3** that veterans tend to not go to preventive visits despite their qualifications. Hence simply, by making them go to preventive visits more, we can achieve a higher percentage of preventive visits amongst insurance policyholders. Our desk research indicates that veterans may face specific obstacles in accessing preventive care.

Veterans often experience mental health conditions such as PTSD or depression, which can significantly interfere with preventive care. These conditions may lead to feelings of anxiety, avoidance, or a lack of motivation to seek healthcare. Additionally, veterans may face challenges in navigating the healthcare system, including finding providers who specialize in veteran health issues. This can result in delays in obtaining appointments, receiving appropriate care, and addressing specific concerns related to their military service. [3]

Furthermore, veterans may not be fully aware of the importance of preventive care or the specific benefits they are eligible for. This lack of knowledge can hinder their ability to make informed decisions about their health and take proactive steps to prevent future problems.

Improving Preventive Care Access for Veteran

To address these challenges and improve preventive care access for veterans, Humana can implement the following strategies:

Humana can launch specialized campaigns specifically targeting veterans, emphasizing the importance of preventive care and highlighting the benefits they can receive. These campaigns can include financial incentives such as free lunches or reductions in annual insurance premium increases to encourage participation.

Providing comprehensive mental health services is essential to address underlying issues that may be impacting veterans' health and well-being. Ensuring that healthcare teams include mental health professionals who are trained to work with veterans can help address these concerns effectively.

Expanding access to preventive care services, including telehealth options and extended hours, can accommodate the schedules and preferences of veterans. Additionally,

[3] Factors Associated With Use of the Preventive Health Inventory in US Veterans | Public Health | JAMA Network Open | JAMA Network

partnering with healthcare providers who have experience working with veterans and are equipped to address their specific health concerns can further improve accessibility.

By understanding the unique challenges faced by veterans, Humana can implement targeted strategies to improve preventive visit rates and enhance the overall health and well-being of this population.

5.1.4 Addressing Preventive Visit Gaps Across Racial and Gender Groups

From our analysis, we observed that Native American individuals had the lowest preventive visit rate at 20.31%, while Asian individuals had the highest at 56.47%. Additionally, there is a 10-percentage point gap between females (59.38%) and males (49.86%) in preventive visit participation. These gaps reveal that specific racial and gender groups are not engaging with preventive healthcare at expected levels. Targeted outreach campaigns can help bridge this disparity.

Humana can implement targeted outreach for under-engaged groups. For Native Americans, partnerships with tribal health organizations or culturally tailored communication can be key. For men, a campaign addressing common barriers to healthcare, like work schedules or social stigma, could drive engagement.

The "Man Up[4]" campaign in Australia increased preventive care engagement among men through targeted marketing. Similarly, Humana can create campaigns that speak directly to these disengaged groups, promoting free first visits, or wellness programs specific to their needs.

5.2 Business Solutions

5.2.1 Awareness Campaign with Local Resources and Free Lunch Offering

Solution Overview: Humana can initiate awareness campaigns in under-engaged regions, identified through the demographic analysis of the data. These campaigns would target communities with higher rates of non-engagement (e.g., Native American communities with a 79.69% non-engagement rate, as indicated in your analysis) and racial groups like Black and Hispanic populations who show below-average preventive visit rates (e.g., Black at 51.04%, Hispanic at 52.69%). To further enhance engagement, offering a free lunch during these events would serve as an incentive to attract a wider audience.

Implementation Strategy:

1. Localized Approach: The campaign should be tailored to each under-engaged region's specific socio-cultural and economic conditions. Leveraging local resources such as community leaders, local clinics, and non-profit organizations can ensure that the message is delivered in a culturally relevant manner. For example, in regions with lower income or healthcare access, the campaign can emphasize how preventive visits can reduce long-term healthcare costs and lead to early detection of illnesses.

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[4] https://manup.org.au/

2. Awareness Through Education: During the campaigns, key healthcare benefits, including preventive care, should be explained in simple, relatable terms. Members could be educated about the specific services covered under Humana's plan, such as $0 copay for primary care and the importance of preventive visits for long-term health, especially for the older age group which dominates the member population (e.g., those aged 65-75).
3. Free Lunch Offering: A free meal can serve as an attractive incentive for community members to attend. This strategy has been proven effective in several outreach efforts. For instance, food drives and free meal events have been used successfully by non-profits and healthcare providers to draw participants for vaccination drives or health screening campaigns. It helps break down barriers such as financial burden or skepticism, encouraging participation in a comfortable and welcoming environment.

This strategy has been successfully implemented in various public health campaigns[5] [6]. For instance, food-based incentives have been used effectively in school settings, where healthy lunch programs were designed not only to provide nutritious meals but also to promote health awareness and behavioral changes in students. The USDA's[7] Healthy Food Financing Initiative, for example, has aimed to increase access to fresh, healthy food in underserved areas through community partnerships, demonstrating the impact of combining incentives with education to improve health outcomes.

In terms of estimated effectiveness, campaigns that include incentives have been reported to increase participation by 30-50%, depending on the local engagement and the effectiveness of the outreach strategy. This approach can be especially beneficial in reaching marginalized or underserved populations, where barriers to healthcare access are higher.

5.2.2 Proactive Digital Outreach and Telehealth Integration

Based on Humana's existing outreach efforts and digital platforms, another practical solution is to expand **proactive digital outreach and telehealth integration** for preventive care. This solution targets unengaged members, identified from the data analysis, by leveraging **personalized digital reminders** and **telehealth services** to lower barriers to preventive care.

1. **Personalized Outreach via Digital Channels**: Humana can implement data-driven digital campaigns to deliver personalized messages through SMS, email, or mobile app notifications. These messages could include:
    - **Preventive Care Reminders**: Automated notifications when a member is due for a preventive visit, tailored to the individual's age, risk profile, and

[5] https://www.sdgaccountability.org/working-with-informal-processes/raising-awareness-through-public-outreach-campaigns/
[6] https://placebased.media/blog/health-promotion-strategies
[7] https://www.rd.usda.gov/about-rd/initiatives/healthy-food-financing-initiative

medical history (e.g., flu shots, wellness check-ups, or screenings based on their demographic group).

  - **Appointment Scheduling Assistance**: Simplified scheduling links integrated within the message, allowing members to easily book appointments through Humana's mobile app or website.

2. **Example**: Humana already offers features like **MyHumana**[8], which members use to access healthcare information and manage appointments. Expanding its use for preventive visit scheduling and reminders could streamline the process for unengaged members, reducing friction that may contribute to low participation[9].

3. **Telehealth Solutions**: **Telehealth consultations** can be offered for routine preventive screenings, such as wellness check-ups or initial consultations before in-person visits. For members in rural or under-served areas, this lowers the barrier of having to travel long distances, a factor that often contributes to low engagement in preventive services.
During the COVID-19 pandemic, Humana expanded telehealth services to improve access to care. Telehealth has been proven to be effective in maintaining continuity of care and improving preventive healthcare utilization by reaching members who may have difficulty accessing physical healthcare facilities.

Humana has already seen success with its **Preventive Care Outreach Program**, which utilizes **data-driven outreach** to encourage members to complete screenings and preventive services, including flu shots, cancer screenings, and wellness exams. By integrating telehealth services into these reminders, the initiative could be expanded to reach a wider audience with minimal disruption to daily routines.

Studies have shown that personalized reminders can increase healthcare engagement by **15-25%**. When combined with telehealth services, which have been shown to improve engagement among rural and underserved populations by reducing access barriers, Humana could see a substantial increase in preventive care utilization.

5.2.3 Innovative and Reliable Solutions Based on Real-Time Successes

Humana can draw inspiration from successful industry practices that have proven effective in improving member engagement, preventive care participation, and overall health outcomes. By integrating these real-world strategies into their outreach efforts, Humana can enhance the effectiveness of its health initiatives and ensure better engagement from members, particularly in under-engaged regions or populations. Below are some innovative solutions successfully implemented by other major healthcare providers, which demonstrate how proactive engagement, technology integration, and behavioral science can improve member participation in preventive health.

1. **Kaiser Permanente's Thrive Campaign**:

[8] https://docushare-web.apps.external.pioneer.humana.com/Marketing/docushare-app?file=4565899
[9] https://healthequity.humana.com/

- **Overview**: Kaiser's "Thrive" campaign is a great example of engaging members through preventive care by emphasizing wellness and active lifestyles. The campaign utilized predictive analytics to identify members needing interventions and connected them with care providers.
- **Application**: Humana could implement a similar proactive health program, focusing on outreach to members with long gaps between visits or in high-risk categories based on your model. Offering digital tools like wellness apps can further engage members.

2. **UnitedHealth Group's Use of Wearables**:
   - **Overview**: UnitedHealth uses wearables to track member activity levels and offers rewards for healthy behaviors, such as completing a certain number of steps or engaging in preventive care visits.
   - **Application**: Humana could integrate wearable technology to engage members and track health status in real-time. Offering reduced premiums or incentives for maintaining healthy habits and attending regular health checkups could enhance member engagement.
3. **Aetna's Telemedicine Expansion**:
   - **Overview**: Aetna successfully expanded its telemedicine services to reach unengaged members, particularly in underserved areas. This made it easier for members to connect with providers and reduced barriers to healthcare access.
   - **Application**: Humana could implement or expand telemedicine services, particularly for LPPO members in regions with lower healthcare engagement. Providing easy access to virtual care for wellness visits and check-ins can increase engagement, especially for members who are hesitant to visit physical locations.
4. **Cigna's Behavioral Engagement Model**:
   - **Overview**: Cigna uses behavioral science to design targeted interventions for members, focusing on nudges that encourage preventive care and health screenings.
   - **Application**: Humana can adopt a similar behavioral approach by sending personalized nudges via SMS, email, or app notifications to remind members to schedule wellness visits, fill prescriptions, or follow up on care recommendations. Personalized engagement could be timed around high-risk periods (e.g., before benefits renewal deadlines or during seasonal flu outbreaks).
5. **Oscar Health's Concierge Teams**:
   - **Overview**: Oscar Health uses concierge teams to guide members through the healthcare system, providing personalized advice on doctors, treatment options, and preventive care.

    - **Application:** Humana could introduce dedicated concierge teams to assist unengaged LPPO members. These teams would provide tailored recommendations, scheduling assistance, and follow-up support to improve engagement and enhance the overall member experience.

5.3 Cost Analysis

This cost-benefit analysis (CBA) evaluates the potential financial implications of implementing preventive care initiatives based on the findings from the previous analysis. It examines the costs associated with these initiatives and the potential benefits in terms of improved health outcomes, reduced healthcare expenditures, and enhanced member satisfaction.

For this analysis, we've made several assumptions. First, we believe that by implementing these preventive care initiatives, Humana can increase the percentage of subscribers who receive preventive visits by 10% in the long run. While this might be optimistic, it doesn't significantly impact our cost analysis.

Additionally, we focused on two major chronic diseases: cancer and dementia. These conditions were chosen because they have significant healthcare costs and can be influenced by preventive care.

Finally, we made general assumptions about the effectiveness of preventive visits in reducing chronic diseases. For cancer, we referenced a Harvard Public Health Magazine article suggesting a reduction rate between 30% and 70%. To be conservative, we adopted a 30% reduction rate.

Regarding dementia, a Johns Hopkins study indicated that one-third of dementia cases could potentially be prevented through cautious measures. We estimated that annual preventive visits could address at least half of this preventable portion, leading to a 18% reduction rate in our analysis.

Here is our Cost-Benefit Analysis:

Costs

- Direct Costs:
    - Extra Insurance Cost: Increased preventive visits will lead to higher insurance payouts for these visits (estimated at $171 per visit).
    - Program Development and Implementation: This includes costs for outreach programs (e.g., free lunch campaign), mobile clinics, telehealth services, and digital platforms (estimated at $300 per member for targeted groups like low-income and veterans).

Benefits

- Improved Health Outcomes:
    - Reduced Chronic Disease Incidence: Early detection through preventive care can lower the number of new cases of chronic diseases like dementia and cancer.
- Reduced Healthcare Expenditures:
    - Lower Treatment Costs: Early intervention can prevent the need for expensive treatments and hospitalizations for chronic diseases.
    - Decreased Emergency Room Visits: Preventive care can address potential health concerns before they require emergency room visits.

Basic Numbers	
US Population[10]	333,290,000
Humana's Subscriber[11]	16,900,000
Humana Member's to US Population Ratio	5.07%
Annual New Cases of Dementia (USA) [12]	500,000
Annual New Cases of Cancers (USA)[13]	1,900,000
New Annual Patients for Two Chronic Diseases to US Population Ratio	0.72%
Expected new annual Chronic Disease patients among Humana's Subscribers	121,680

Cost & Benefit		
Cost	Program Development and Implementation (Cost of Recommended Solution Aggregated)	Poverty 16,900,000*15%*$300 Veterans 16,900,000*11.12%* $300
	Extra Insurance Cost (Preventive Visit)	16,900,000*10%*$171[14]
	Subtotal	$ 1,324,284,000

[10] Population Clock (census.gov)
[11] Medical membership of Humana 2023 | Statista
[12] Alzheimer's Facts & Statistics | Alzheimer's San Diego (alzsd.org)
[13] Cancer Facts & Figures 2022 | American Cancer Society
[14] How Much Does a Primary Care Visit Cost in 2022? - K Health

Benefit	Reduced Cancer Medical Expenditure	$59,822 * 121,680*80% *30%[15]
	Reduced Dementia Medical Expenditure	$81,000[16]* 121,680*20% *18%[17]
	Subtotal	$ 2,101,812,710

Humana Savings

Benefit Subtotal – Cost Subtotal = Annual Expected Humana Profit
$ 2,101,812,710 - $ 1,324,284,000 = $ 777,528,710

Cancer type	Initial Care	Continuing Care	End of life Care
Breast cancer	$43,516	$5,518	$109,727
Cervical cancer	$58,716	$3,956	$97,026
Colorectal cancer	$66,523	$56,246	$110,144
Leukemia	$47,264	$12,701	$169,588
Lung cancer	$68,293	$12,389	$110,248
Prostate cancer	$28,109	$2,603	$74,227
Subtotal	$52,070	$15,569	$111,827
Average of Subtotal	$59,822 [18]		

This cost-benefit analysis (CBA) suggests that implementing preventive care initiatives could be a financially sound decision for Humana. While there are upfront costs associated with program development and increased insurance payouts for preventive visits, these are projected to be outweighed by the long-term benefits.

The analysis estimates a potential net profit of $777 million due to reduced chronic disease incidence and the associated decrease in healthcare expenditures. Additionally, improved member experience and stronger member relationships could contribute to increased loyalty and subscriber retention.

It's important to acknowledge the limitations of this analysis. The effectiveness of preventive care programs can vary, and the assumptions used here may need further

[15] The Cancer Miracle Isn't a Cure. It's Prevention. | Harvard Public Health Magazine | Harvard T.H. Chan School of Public Health
[16] Economic Costs of Dementia - Reducing the Impact of Dementia in America - NCBI Bookshelf (nih.gov)
[17] Dementia Prevention: Reduce Your Risk, Starting Now | Johns Hopkins Medicine
[18] https://www.cancercenter.com/community/blog/2023/07/managing-cancer-treatment-cost#Q1

refinement. However, this CBA provides a strong starting point for Humana to consider the potential return on investment associated with prioritizing preventive care initiatives.

6 Conclusion

Our analysis has highlighted key socioeconomic and geographic factors contributing to low engagement in preventive healthcare among Humana's members, particularly in underserved regions. Through advanced data analysis and predictive modeling, we identified significant drivers of this issue. To address these challenges, we recommend targeted business solutions, including mobile clinics, telehealth expansion, transportation partnerships, and awareness campaigns. These campaigns would focus on educating communities about the importance of preventive care and how to access available services, ensuring that more individuals take advantage of healthcare opportunities.

The cost-benefit analysis supports these interventions, showing substantial long-term savings despite initial investments. The financial projections demonstrate cost reductions through increased preventive care participation and decreased chronic disease management expenses. The financial analysis shows a projected net annual profit of $777 million, driven by reduced chronic disease costs and improved preventive care engagement. This demonstrates that the proposed solutions not only enhance health outcomes but also provide significant financial returns for Humana.