

Humana-Mays Healthcare Analytics

2022 Case Competition

**Prediction of Housing Insecurity for
Humana members**

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1. Executive Summary

Housing insecurity is the lack of access to quality and safe housing. It is a crucial factor in human health, resulting in health problems ranging from allergies to neurological to heart damage. Humana strives to support whole-person health, including physical, mental, and social health, and ultimately, helps people achieve their best health. To achieve this goal, we analyze the data with Humana members to identify people who are most likely to be experiencing housing insecurity issues.

First, we cleaned the data and did the data processing, selecting the critical feature to provide helpful information for our prediction model. Then, we built a predictive LightGBM model with an AUC score of 0.745 to identify members experiencing housing insecurity issues. Finally, based on the features most related to housing insecurity, we analyzed the needs of Humana MAPD housing insecure members. We provide three recommendations to help these members achieve their best health, including launching the Housing Care Program that explicitly addresses housing-insecure members' needs, developing affordable housing communities, and deploying MLOps.

2. Context

2.1 Case Background

According to the American Public Health Association, before the pandemic started in 2020, 3.6 million evictions occurred annually across the United States, and by the end of 2020, around 40 million renters were at risk for eviction (Versey, 2021). The impacts of COVID-19 have been especially brutal on low-income households and people with disabilities/chronic diseases. Ever since the pandemic had cooled down in 2021, the demand and price in the rental housing market has been growing rapidly, with an increase of around 870,000 renter households from the start of 2020 to the third quarter of 2021 and around 14 percent increase in rents(America's rental housing 2022, 2022). The low-income households are either left with low-quality housing or no housing at all.

While housing insecurity has always been a problem in the past few years, it has been exacerbated by the recent record-breaking housing shortages and rent price increases. As of this year, there are approximately 4 million people experiencing housing insecurity and roughly 600,000 people experiencing homelessness(America's rental housing 2022). If this problem is left untreated, people that are experiencing housing insecurity will have great difficulties finding affordable and accessible sources of care and medication, causing a great decline in both physical and mental health.

2.2 Business Problem

The purpose of this analysis is to help Humana better identify groups that are more prone to housing insecurity by creating a classification predictive model with data provided by Humana and provide business recommendations. As one of the world's largest health insurance companies dedicated to improving individuals' health and wellbeing, Humana is highly motivated to provide tailored solutions for its most vulnerable and underserved populations that are experiencing housing insecurity.

In a research published by American Health and Drug Benefits, the study shows that 33% of ER visits are made by patients experiencing homelessness, and those patients visit the ER five times annually and accumulate annual costs of \$18,500(Versey, 2021). Tackling the problem of housing insecurity will not only help improve the health and wellbeing of Humana members but also allow Humana to spare extra capital for other SDOH causes, increase hospital resources for the general population, and many more benefits.

3. Data Preparation

3.1 Data Overview

Training Data Set: 48300 records by 880 variables columns, plus one 'hi_flag' target column.

Holdout data: 12220 records by 880 variables.

This dataset includes a one year look back at Humana MAPD members' data prior to the data that the member responded to the screening. The target variable is the housing insecurity indicator which is a binary flag to indicate each member's housing insecurity status. Members do not have

housing insecurity when the `hi_flag` value is '0'; otherwise, they will have housing insecurity when the `hi_flag` value is '1'.

The dataset consists of four kinds of features. The first kind of data is about medical claims and the condition, including the claim count and the cost of different treatment places like inpatient and outpatient, CMS diagnosis, and behavioral health conditions. The second kind of feature is about pharmacy claim count and cost classification by drug's attributions like the brand or generic, mailed or non-mailed, and so on. The third feature concerns age, gender, race, and disability demographics. The last feature is the remaining information in this dataset, like revenue, rural atlas SDOH, and credit data which are not directly related to Humana products.

The data types of variables in this dataset include scalar, integer, float, double, binary categorical, and multi-class categorical. The dataset is imbalanced in the housing insecurity indicator, with only 2,118(4%) records shown as '1', and 46,182(96%) records are '0'. Just a few members show that they have housing insecurity.

3.2 Data Cleaning

3.2.1 Data Type Handling

Most of the column's data type is consistent. However, there is one column called "`cms_race_cd`", which not only has a mixed-data type problem, but also contains several meaningless values (like "**"). To handle this, we first drop those meaningless values, then use the `pd.to_string()` function in Python to convert the data type into string (we can also use `pd.to_numeric()` here, just to make sure

the data type is consistent). By data dictionary, we know this feature represents the code indicating a member's race, so it should be categorical data. We then used one-hot encoding to handle this kind of feature (See 3.3.1).

3.2.2 Missing Value Handling

Most of the columns in the dataset are complete in terms of missing values. While there are still columns that have more than 8300 null values (less than 40000 non-null values). Since these columns will influence the quality of our final predictive model, we decided to drop them all. For other numerical features with less than 8300 null values, we used the median to replace the null values. For other categorical features with less than 8300 null values, we decided to import unknown as a new category to replace the null values.

For instance, the categorical feature “cms_orig_reas_entitle_cd” has four categories: 0 - Old Age Survivors Insurance (OASI), 1 - Disable, 2 - End Stage Renal Disease (ESRD), 3 - Both. There are also 1867 missing values in this column. We defined a new category: 4 - Unknown, and used this category to replace all missing values.

3.2.3 Outlier Handling

We have tried two methods to handle outliers for numerical data. For the first method, we defined outliers as those data whose percentile is smaller than 1 or larger than 99. For the second method, we defined outliers as those data which are smaller than $QL - 1.5IQR$ or larger than $QU + 1.5IQR$.

(QL: Lower Quartile, 25th percentile data. QU: Upper Quartile, 75th percentile data. IQR: Interquartile range, the difference between the 75th and 25th percentiles of the data.)

The results show that the second method performed better in terms of handling outliers.

3.3 Feature Engineering

3.3.1 One-hot Encoding

One-hot encoding is a good method to convert categorical data into a numerical one. For a categorical feature that has m categories, after the one-hot encoding, it will become m binary features, with value '1' representing belong to that category, and value '0' representing not belong to that category. We need to drop the original categorical feature. Also, we need to drop one binary feature that has the least '1' values to prevent the collinearity problem.

3.3.2 Feature Selection

After data cleaning and one-hot encoding, we noticed that there are still more than 800 features. So, we try to find the more important feature to use in our final model because too many features cannot bring more information and much noise into the model. We decided to use the XGBoost model first to calculate the feature importance of each column, then select the more valuable feature to build the final model.

According to XGBoost's feature importance, we select the first 100 features as the cumulative contribution of these features has already arrived at 85%. Then, we did further research on each feature to understand the logic between these features and housing insecurity. Based on these

features and our research, we split these features into three main categories: claims or costs related to mental, behavioral, and neurodevelopmental disorders, claims or costs related to physical diseases, and population demographics.

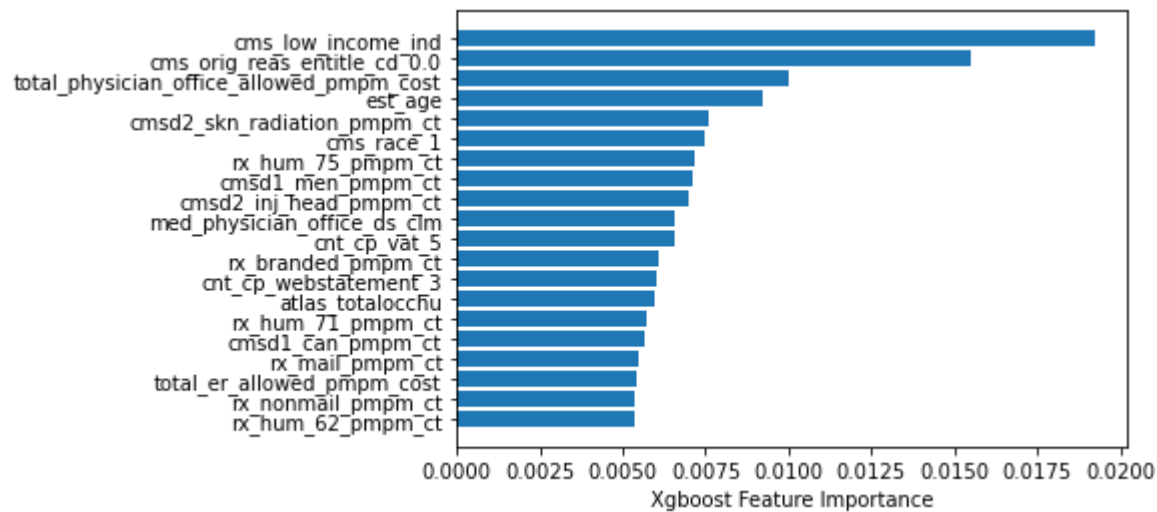


Figure 1 Xgboost Feature Importance (first 20 features)

Claims or costs related to mental health

Claims or cost related to mental health means members' claims count and their monthly cost related to several mental, behavioral, and neurodevelopmental disorders, including features like behavioral syndromes associated with physiological disturbances, intellectual disabilities, and mood disorders in the past year.

The feature 'cmsd1_men_pmpm_ct', which means the total number of claims per month related to all mental health, ranks sixth in the feature importance ranking. Therefore, mental health is a significant factor in housing insecurity.

Claims or costs related to physician diseases

Claims or costs related to physician diseases mean members' claims count and monthly costs. This feature set is related to several body diseases like eye disease, musculoskeletal system and connective tissue disease, and circulatory system disease.

According to the feature importance, 'cmsd2_skn_radiation_pmpm_ct' is the most crucial factor in the feature set of physician diseases. This feature is about claims per month related to diseases of the skin and subcutaneous tissue, especially for radiation-related disorders of the skin and subcutaneous tissue in the past year.

Population demographics

Population demographics information contains some of the most critical factors influencing housing insecurity. Features include age, health status, income, and race. Some features in this group will give multiple information such as 'cms_orig_reas_entitle_cd,' a classification variable indicating the original reason for entry into Medicare, including Old Age Survivors Insurance (OASI), disabled, End Stage Renal Disease (ESRD), or Both.

4. Modeling and Analysis

4.1 Model Selection

We chose Xgboost and LightGBM as our final model candidates.

For Xgboost, it has many powerful built-in functions. This includes:

1. Built-in L1 (Lasso Regression) and L2 (Ridge Regression) regularization to prevent the model from overfitting.
2. Built-in capability to handle missing values. Even though we have already tried several ways to handle missing values, this function can still be a reference.

3. Built-in capability to handle unbalanced dataset.

For LightGBM, it will produce more complex trees. Compared to other tree-based method, LightGBM follows leaf wise split approach instead of traditional level wise split approach, so that it can achieve a better performance. It also uses a histogram-based algorithm, making it training faster than other models (including Xgboost).

4.2 Parameter Tuning

4.2.1 Parameter Tuning for Xgboost

There are 6 hyperparameters that we need to tune in Xgboost:

1. **N_estimators:** The number of trees in the model. The more the better initially, but it will increase the training time. The performance of the model will not improve significantly after a certain number.
2. **Learning_rate:** Step size shrinkage used in update to prevents overfitting.
3. **Max_depth:** The maximum depth of the tree. The larger the value, the more complex the tree. This can be used to control overfitting, typical values are 3-10.
4. **Gamma:** This specifies the size of the minimum loss function reduction required when a node is partitioned.
5. **Subsample:** Subsample ratio of the training instances.
6. **Min_child_weight:** defines the minimum sum of weights for all observations in a subset.

This can be used to reduce overfitting, but too high a value can also lead to underfitting.

Using grid search method and cross validation, the final best hyperparameter set is: {'N_estimators': 95, 'Learning_rate': 0.1, 'Max_depth': 3, 'Gamma': 0, 'Subsample': 1, 'Min_child_weight': 1}.

4.2.2 Parameter Tuning for LightGBM

There are 5 hyperparameters that we need to tune in LightGBM:

1. **Boosting_type:** The type of boosting trees. We have tried three boosting types: 'gbdt', which stands for traditional Gradient Boosting Decision Tree; 'dart', which stands for Dropouts meet Multiple Additive Regression Trees; 'goss', which stands for Gradient-based One-Side Sampling.
2. **N_estimators:** The number of boosting trees in the model.
3. **Num_leaves:** Maximum tree leaves for base trees.
4. **Max_depth:** The maximum depth of the tree. Negative values indicates no limit.
5. **Learning_rate:** Boosting learning rate.

Using grid search method and cross validation, the final best hyperparameter set is: {'Boosting_type': 'dart', 'N_estimators': 25, 'Num_leaves': 31, 'Learning_rate': 0.11, 'Max_depth': -1}.

4.3 Feature Importance

The following picture shows the first 20 features. It includes all three category features, Claims or costs related to mental health, claims or costs related to physical diseases, and population demographics.

The most important feature is the original reason for entry into Medicare. We put this feature in our population demographics feature set. For people with housing insecurity, the number of people who enter Medicare is old age survivors insurance, and those whose reason is disabled are basically the same. However, for the people who do not have housing insecurity, the number of people whose reason is old age survivors insurance is almost third times the number of people whose reason is disabled. That means the disabled may influence housing insecurity.

Table 1

Housing insecurity

Classification	Count	%
0 - Old Age Survivors		
Insurance (OASI)	999	52%
1 - Disable	910	48%
Total	1,914	100%

Non-Housing insecurity

Classification	Count	%
0 - Old Age Survivors		
Insurance (OASI)	32,360	73%
1 - Disable	12,120	27%
Total	44,480	100%

The first important feature in variables related to physical diseases is the total allowed cost per month for overall claims related to the physician's office in the past year. As the following table shows, the cost per month related to a physician's office for people who are not in housing insecurity is higher than the cost for those who are housing insecure. Therefore, the cost of a physician may not influence the probability of people getting housing insecurity.

Table 2

	Count of id	Sum of cost	Per_id
Non-Housing insecurity	46,182	2,562,488.62	55.49
Housing insecurity	2,118	101,579.40	47.96

4.4 Model Evaluation

Since the dataset is extremely unbalanced, even if we predict all labels to be 0, we can still get more than 95% of accuracy. So in this case, it is meaningless to calculate the accuracy score. We used AUC score instead to evaluate the model performance

.

The following graph shows the AUC-ROC Curve for Xgboost and LightGBM respectively.

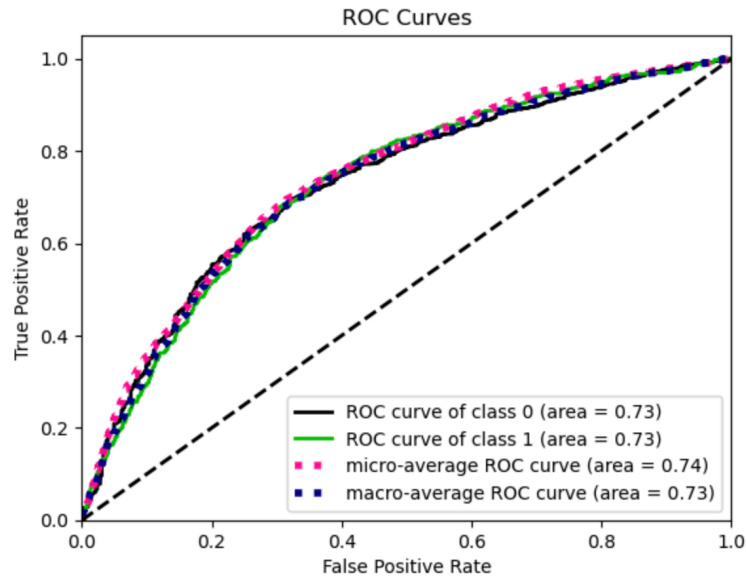


Figure 2 ROC Curve for Xgboost

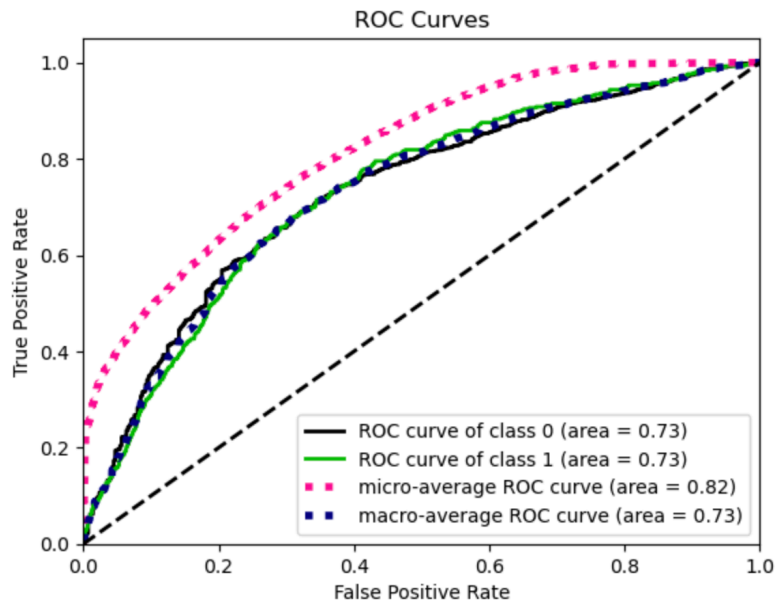


Figure 3 ROC Curve for LightGBM

We finally chose LightGBM as our final model because its average AUC score is a little higher than Xgboost.

5. Business Analysis and Recommendations

5.1 Rationale Behind Recommendations

Housing Insecurity is detrimental not only to the affected individuals' health but also the overall economic health of the country. The goal of this project is to help Humana provide customized solutions for the groups of people that are most affected by housing insecurity. When developing solutions to help the community members fight housing insecurity, we have carefully considered the practicality and overall alignment to Humana's existing business operations, goals, and members in the Humana community.

In our most important features, using feature importance score generated by XGBOOST, some of the significant findings that we have found among the most important features are:

Members with disability and End-stage renal disease (ESRD) as their original reason for entry into Medicare have the largest proportion of members that are experiencing housing insecurity, at approximately 7% and 13%, respectively. Members that are receiving subsidies from Humana had the largest proportion of members experiencing housing insecurity, at approximately 8%, and that members receive. Compared to members that are not experiencing housing insecurity, members that were experiencing housing insecurity also received lesser amount of allowed cost to physician office in the past year, longer days since last claim for non-behavioral health issues, less visits per month for claims relating to physician office, more claims related to mental, behavioral and neurodevelopmental disorders, and lastly, Hispanic and Black population have the highest proportion of housing insecurity, at approximately 9% and 6% respectively.

Through our analysis, we have identified and found that the members that are most likely experiencing housing insecurity are people with disabilities, End-stage renal disease, mental and behavioral disorders, and people with low income. We speculate that members with End-stage renal disease and disabilities are more likely to experience housing insecurity due to the physical constraints that the disabilities and disease pose, and members receiving subsidies are more likely to experience housing insecurity because of lack of employment opportunities with adequate pay. As we have mentioned before, according to our research, the lingering financial impacts of COVID-19 have caused demand for affordable housing and rental prices to skyrocket. Through our analytics results and research, we have concluded that housing affordability is an important problem that our solutions must tackle and that housing affordability is most likely to have been caused by either, physical, behavioral, mental chronic health problems, or/and lingering impacts of COVID-19 on employment and housing market.

5.2 A New Housing Care Program

While medical conditions can aggravate housing insecurity, housing insecurity can adversely affect personal well-being. (Qinjin Fan, Danya E Keene, Matthew P Banegas, Sarah Gehlert, Laura M Gottlieb, K Robin Yabroff, Craig E Pollack. 2021.) Therefore, the best way to help Humana members achieve their best health is to tackle both the issues – their original medical conditions and housing insecurity. Bearing this goal in mind, we suggest that Humana launch a new program that specifically addresses the needs of those prone to housing insecurity. We'd like to name this program the Housing Care Program for now. Like many other Humana programs, the Housing Care Program will be an additional insurance plan to complement basic Medicare plans but with a series

of customized services that best fit into addressing housing insecurity related issues. Because our analyses suggest that physical and mental conditions and low income might play a major role in housing insecurity for Humana MAPD members, we therefore designed the Housing Care Program in a way that focuses on reducing the harmful effects of these disadvantages, including approaches to relieve our members' economic pressure, expand access to helpful resources and strengthen physical and mental health. The following features show how this new program is designed.

Housing Care Program Features:

- 1) Specially designed insurance coverage
- 2) Referrals to external resources that help improve housing affordability
- 3) Group-based support and management
- 4) Monthly quota for in-home medical care and communication
- 5) Activities enhancing enrolled members' mental health and fulfilling their social needs
- 6) Benefits and rewards when an enrolled member referred their family member to the program

The six bullet points listed above briefly summarize the characteristics of the program. The following section will give more detailed clarifications on the behind-the-scene mechanism of each feature and how exactly this program will serve to assist housing-insecure Humana members.

Feature 1: Specially designed insurance coverage

We want to ensure that every penny spent on the Housing Care Program membership is worthy and not wasted so enrolled members can save some extra money on their rent and efforts that help improve their housing experience. Therefore, the Housing Care Program is designed to cover more medical events with a strong correlation to housing insecurity cases and cut off other events less

related to housing insecurity. For instance, we found that members with housing insecurity tend to have significantly more claims related to mental, behavioral, and neurodevelopmental disorders and significantly fewer claims for radiation-related disorders of the skin and subcutaneous tissue. Accordingly, the Housing Care Program will include the former in its insurance coverage and exclude the latter. Moreover, the coverage can be dynamic and changeable over future years as underlying patterns of housing insecurity are better studied and familiarized.

Feature 2: Referrals to external resources that help improve housing affordability

As indicated by our analyses, a large portion of Humana members with housing insecurity suffer from disabilities, mental or behavioral disorders, or renal diseases. These disadvantages may bring extra challenges for them to search for resources that may improve their housing quality, leading to exacerbation of their housing insecurity as well as their health conditions. This is where referrals to external resources can be beneficial. By seeking meaningful resources for them, Humana can be a reliable friend willing to give a hand and share the burden of all the members struggling with housing issues.

Based on what is already offered in the Humana Cancer Program and Humana telephonic case and care management programs ([Humana Cancer Program](#), [Chronic Care Programs - Humana](#)), referrals can be further tailored to meet the unique needs of housing-insecure members. Besides organizations that offer certain financial support, Humana can associate with housing agents, who have substantial housing resources and are well familiar with the housing marketplace. An ideal situation would be that the association housing agent gives priority to Housing Care Program members when the agent gets nice and cheap housing resources, which is a plausible situation if

Humana's large number of members constitute an attraction to the housing agent. The reputation of helping the needy may also be attractive to them.

In addition, information on eligibility and the application process for subsidies and personal funds can be collected and used to refer enrolled members. As policies and relevant procedures are constantly changing, it might be difficult for housing-insecure Humana members with disabilities and other health conditions to do this job themselves.

Referrals and resource sharing can be done via group-based support and management, which will be elaborated on in the following section.

Feature 3: Group-based support and management

When an individual experiences housing insecurity, it might be considered personal feelings, but when a large group of people faces this same misery, it is more likely to draw some societal attention and constitute a powerful voice for social awareness. That is why we expect all our Housing Care Program members to join online Humana groups (e.g., Whatsapp groups) where they can connect with others experiencing the same difficulty. Each group is expected to have a Humana staff member as the group manager, who will share helpful resources and respond to group members' questions. This group-based management is widely employed by many businesses and has been proven effective in creating a deeper relationship between customers and the company. In Humana's case, it not only can strengthen the link between Humana and Humana members, helping Humana employees provide their services more efficiently, but also reduce the communication barriers between Humana and housing-insecure members who, as indicated from analyses, might

have trouble in connecting with Humana services due to their physical, mental, or financial constraints.

Housing insecurity can result from systemic inequities and discrimination. (Carli Friedman. 2022.)

This might explain why a higher proportion of black members is found with housing insecurity than white members in the dataset. As a medical insurer, Humana's ability to help out the housing-insecure has limitations inherently. However, Humana can still facilitate improvements in the housing situation for its needy members via group-based support. As groups are formed and growing larger, Humana can provide information on advocacy pathways to addressing housing insecurity, such as video recording to let more people know about this group. The group manager can also launch online donations for enrolled members. Most of the donation money received can be used to help those members in serious need of quality housing. The rest of the funds can be used to develop the Housing Care Program and pay the Humana group manager in charge of the donation as an incentive. In general, the events mentioned in this section aim to develop the power of the housing-insecure people by bonding them together so they can help each other and make their voices heard, which may give them access to more resources from philanthropists and external organizations.

Feature 4: Monthly quota for in-home visits

All the Housing Care Program members will be allocated a monthly quota for in-home visits, which will be particularly meaningful to enrolled members. As stated earlier, Humana MAPD members who are prone to housing insecurity are identified as being more likely to have disabilities, end-stage renal disease, low income, or mental health conditions. In-home visits can well save them

both the trouble and cost of traveling to pharmacies or Humana centers to get services. An enrolled member can make an appointment at a physical Humana center, online, or over the phone on a range of services including but not limited to mental health guidance, behavioral assessment, educational advice on general well-being, insight into the scope of their Humana medical benefits ([Humana Cancer Program](#)), and general communication and assistance depending on the member's specific needs. Furthermore, because most MAPD members are the elderly, to whom electronic devices and online communication might be less friendly and comfortable, in-home visiting staff can even instruct them on how to use the Humana app, website, online groups, online appointment-making, and online resources searching so as to better benefit them from the Housing Care Program. In a more extreme case, an enrolled member may not even have a phone due to financial stress; the visiting staff member can help them find an affordable device. The in-home visits feature will require visiting staff to receive professional training since they will probably need to be extra flexible in dealing with enrolled members' issues, given the nature of this service. Still, it will distinguish Humana from other medical insurers that do not offer such humanized and customized services.

Feature 5: Activities enhancing enrolled members' mental health and fulfilling their social needs

Physical and online activities will be held to consolidate the above-mentioned efforts further in bettering Housing Care Program participants' health. They can include lectures on ways to improve housing quality, such as house-cleaning tips, healthy and affordable culinary science, approaches to getting along with neighbors, access to coupons and promotions in daily shopping, etc. Lightweight sporting activities such as bike riding, excursions, yoga, and slow walking along

the river can also be covered. The Housing Care Program members can relax their nerves, network with others, and acquire knowledge to keep them in good health through these activities.

Feature 6: Benefits and rewards when an enrolled member referred their family member to the program

Usually, when an individual is housing-insecure, their family members are likely to suffer the same problem considering they probably live in the same house. Benefits and rewards will be given to members enrolled in the Housing Care Program when they refer their family members to this program. This feature serves the purpose of building up the program and informing more people with housing insecurity about this program.

In general, the features of the Housing Care Program are designed to comprehensively address different pathways of housing insecurity that Humana MAPD members most likely suffer from. On top of that, a series of health-enhancing efforts are made in various forms that are friendly and easily accessible to the housing-insecure group in need. First, methods to improve housing affordability are provided. Features 1 and 4 offer straightforward money-saving approaches to cut down enrolled members' financial costs of getting medical care and drugs. Feature 2 links enrolled members with resources that potentially improve their financial situation. Second, Features 2 to 5 are meant to accommodate housing insecure members' needs in getting medical care, obtaining relevant information, networking, and achieving better health. Lastly, Features 2, 3, and 6 coordinate all the efforts mentioned above in an organized and efficient way, which benefits Humana in terms of reputation, service quality, and profitability. To add a cherry on top, these features can be adjustable

and integrated into a machine learning operations process for further optimization, which is the focus of our recommendation in Section 5.4.

5.3 Affordable Housing Communities

Over the past few years, Humana has made around 50 million investments in affordable housing to increase the supply of affordable housing across the whole country and it has proven successful, improving health outcomes of members, and decreasing housing insecurity. To maximize the benefits that these affordable housing communities bring, our recommendation is to provide easily accessible medical resources customized for its members and employment assistance to the members within the affordable housing communities. This solution could increase Humana members' housing affordability and lower their potential chance for housing insecurity.

Accessibility to medical resources

The first dimension of this recommendation is aimed to provide a suitable living environment tailored to fit the needs of the members that are eligible to live in these communities. As indicated in our analysis, we have discovered that members that have disabilities, radiation-related disorders of the skin and subcutaneous tissue, chronic disorders related to mental, behavioral, and neurodevelopmental were the most affected groups within Humana members. Since health outcomes and housing insecurity affect one another, we think it is vital for the affordable housing communities to provide easily accessible medical resources and a suitable environment for these members.

Within the affordable housing communities, we propose to implement handicap features in the housing community to provide a comfortable living space for members that have disabilities. For instance, features such as slope ramps, automatic doors, handicapped restrooms, and elevators etc... This could relieve them of the hazards that would often happen in low-quality rental housing, and it could also reduce medical

expenses for Humana. Since the most affected groups of members have disabilities and/or disorders that will limit their mobility, it is also important to improve the accessibility for this group of members within the housing community.

By implementing medical care facilities and teams within the community and customized to treat for the members based on the health problems they possess, it could prevent members to wait until their health conditions worsen and get timely help, prevent disease progression in a timely manner, and help improve members' overall quality of life etc. The medical expenses should be covered by the members' original health insurance plans and additional accumulated costs should be adjusted reasonably based on the average income of members within the community. The benefits mentioned would help reduce costs for Humana and its members.

Employment resources

The second dimension of this recommendation is aimed to provide job resources specialized for the members living in the community. Since a large proportion of Humana members are people with disabilities, disorders, and mental/behavioral health conditions, these constraints can often pose a great challenge for them to search for employment opportunities. The skills that are needed in the normal job market are sometimes impossible for this group of people to acquire.

We believe that by providing suitable and easily accessible job resources for the members within the community, Humana can lower their members' future risk of facing housing insecurity.

To implement this strategy into the affordable housing communities, Humana can partner up with various non-profit organizations in the United States whose goals include helping previously unemployed people and people with physical and mental health constraints find suitable jobs. For instance, MassHire Career

center is a non-profit organization that provides workshops for workers with disabilities, and some of these workshops include resume-writing, career counseling and interview techniques etc. By partnering up with non-profit organizations that can provide these types of workshops, Humana could be benefited indirectly by reducing the members' future change of facing housing insecurity while incurring no cost.

5.4 MLOps Deployment

Machine learning operations (MLOps) can be pretty powerful to an organization like Humana, which possesses enormous amounts of data. It is a core function of Machine Learning engineering, focused on streamlining the process of taking machine learning models to production and then maintaining and monitoring them. (Databricks glossary: [MLOps – Databricks](#)) Banks use this technique to automatically decide whether to approve a customer's credit card application through artificial intelligent analysis of the customer's features. It helps lower operating costs and reduces data management challenges. (Daniel Martin. 2021.) Likewise, Humana can implement MLOps to make recommendations automatically on the best suitable program for the members. This is an effective and efficient way to detect housing-insecure members among all MAPD members. Instead of expecting housing-insecure people who might be financially or physically strained to find the Housing Care Program, Humana can proactively find them using MLOps. MLOps can also be employed to assess the effectiveness of the Housing Care Program and optimize the methodology to provide better care for the housing insecure. Additionally, MLOps can be applied to a larger scope. Not only can members from other Humana programs benefit from MLOps on treatment assessment, but also, the machine learning algorithm in MLOps can be modified to fit into other scenarios in the future. Lastly, MLOps can be adapted to select suitable members for Humana's affordable housing communities and help them further by identifying their needs.

Although deploying a complete MLOps pipeline can be a challenge to an organization new to this practice, MLOps vendors are all around the Internet ready to help organizations start this compromising investment, and we consider MLOps an advanced system that can raise Humana's service and capacity to a whole new level.

6.Conclusion

The goal of this case study is to identify Humana MAPD members experiencing housing insecurity, gain insights from our analysis and provide practical and possible solutions for Humana. We have chosen to build XGBoost and LightGBM models for this case study and decided the LightGBM model as the final model. It had the best performance out of the two with an AUC score of 0.745 . The recommendations that we have made are based on analytic results that we have found within the most important features.

Reference

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