2021

HUMANA-MAYS HEALTHCARE ANALYTICS

OVERCOMING BARRIERS TO VACCINE ADOPTION

Executive Summary

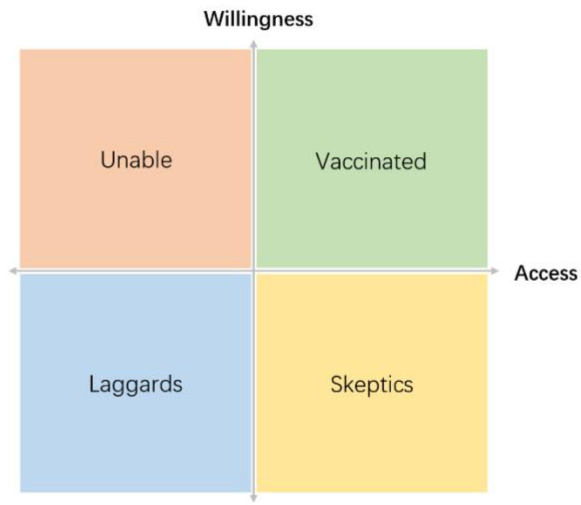
Since its first observed case on December 31, 2019, COVID-19 has developed into a worldwide pandemic. In the face of such crisis, Humana strives to combat this ongoing global health crisis, improve public health, and utilize the effort to better understand its customer group.

This study leverages machine learning methods to supplement Humana's current efforts to better protect its members by identifying members hesitant to COVID vaccination and designing targeted outreaches for them. We developed a classification model to predict the probability of a member being vaccinated in the 3rd week of March 2021. We analyzed the important features based on models, putting forward corresponding strategies targeting at different segments of members. This report is divided into three major sections: data exploration and cleaning, model building and interpretation, deployment, and risks.

The first part of our project is exploring available datasets provided by Humana to identify patterns between variables. The data suggest that vaccine hesitancy varies across race and age subgroups. We then prepared the data for modeling through data cleaning, feature engineering, one-hot encoding, and feature selection. The resulting dataset contains 503 features.

The second part of our project is developing a classification model to predict members' vaccination status. Using AUC as a performance evaluation indicator, we tested and tuned models including Support Vector Machine, Random Forests, Extreme Gradient Boosting, and Light Gradient Boosting. The optimal model (XGBoost) resulted in an in-sample AUC of 0.672. Based on this result, we performed feature importance analysis, concluding factors like age, awareness and accessibility, financial status, political affiliation have significant influences on members' vaccination status.

In the last part, we provided actionable insights and recommendations based on data analysis findings, model results, and secondary research. We developed a quadrant framework to break down the identified issues into willingness/access. Our five strategies aim to migrate members from other quadrants to the vaccinated quadrant.



Employer Driven Compliance: A campaign based on the recent mandate published by President Biden. The initiative aims to provide members with adequate support to get vaccinated in the form of PTO by offering incentives to employers.

“Close the Distance”: A campaign based on recent BCBS’s partnership with rideshare companies to provide free transportation to vaccination sites. The initiative supports Humana’s members by lowing their access barrier to receive the vaccine.

Online Search Advertising Campaign: A campaign based on ELM (Elaboration Likelihood Model) to increase the population’s likelihood to search vaccine-related terms. The campaign leverages on congruence effect and priming effect to promote attitude change among vaccine hesitant members and vaccine apathy members,

“Kiss the Air”: A peripheral persuasion campaign featuring vaccinated Republican leaders, leveraging on mere exposure effect to shift the attitudes of anti-vaccine Republicans. The campaign consists of a website highlighting endorser anecdotes and a set of outdoor ads to increase awareness of the campaign.

Community Outreach: A campaign leveraging local clinics, which are uniquely positioned to promote the vaccine. Targeting local communities, this initiative aims to change the social norm within the community from no-vaccine to vaccine.

Our team estimated the potential financial outcomes for adopting our recommendations. With our recommendations we believe that Humana would be able to convert 9% of the currently unvaccinated and have conducted scenario analysis to measure financial implications of our recommendations. In the expected scenario, we would attain a profit margin of 16%, retaining profits equal to 7.11% of Humana's 2020 total profits. In the best case where we convert 10% and the worst case where we convert 8%, we would achieve a profit margin of 24% and 5%, representing 12.15% and 2.07% of Humana's 2020 total profits, respectively. In all three scenarios, our recommendations have achieved higher profit margins than Humana's 2020 profit margin (4.36%), as recorded on December 31, 2020.

By adopting our recommendations, Humana will be able to increase the vaccination rate among people who were previously identified as not likely to get the COVID vaccine by 9% within the first year of deployment.

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1 Business Understanding

1.1 Case Background

1.1.1 COVID Disease and Vaccine

Coronavirus disease 2019, hereinafter referred to as COVID, is the contagious disease caused by the new coronavirus called SARS-CoV-2. Since its first observed case on December 31, 2019, COVID has developed into a worldwide yet ongoing pandemic.

The COVID vaccine, intended to provide acquired immunity against the SARS-CoV-2, has been rapidly developed and approved by nations across the world to stop the spread of COVID. In the United States, Pfizer-BioNTech, Moderna, and the Janssen COVID vaccine have been approved by the U.S. Food & Drug Administration for emergency use. This article will refer to these vaccines collectively as "COVID vaccine". Although ample research has shown some variation in levels of protection offered by the mentioned three vaccines, all "provide substantial protection against COVID-19 hospitalization" (Self, et al., 2021)

1.1.2 Humana

Humana Inc, (Humana) leader in the U.S. health insurance industry, is interested in the barriers to getting COVID vaccine among its members. The company's priority has been increasing the COVID vaccination rates among its members, especially focusing on providing vaccination opportunities for the most vulnerable and underserved populations.

1.1.3 Vaccine Hesitation

Vaccine Hesitancy, as defined by the SAGE Working Group[1], refers to the "delay in acceptance or refusal of vaccination despite the availability of vaccination services." (SAGE Working Group on Vaccine Hesitancy, 2015) Development of such sentiment has been long established but is becoming increasingly alarming in the face of the recent COVID outbreak, and the reason for it is "multifaceted, culture-specific, and often not completely understood." (Nossier, 2021) This paper will serve to identify, review, and address vaccine hesitancy among Humana health

[1] The Strategic Advisory Group of Experts on Immunization (SAGE) is charged with advising WHO on overall global policies and strategies, ranging from vaccines and technology, research and development, to delivery of immunization and its linkages with other health interventions.

insurance subscribers in the United States. Note that vaccine hesitation is different from vaccine apathy, which is explained in the next point.

1.1.4 Vaccine Apathy

While vaccine hesitancy describes a weak attitude, vaccine apathy is an outright disinterest in the topic. It is "characterized by weak attitudes and little time spent considering vaccination." (Wood & Schulman, 2021) People categorized as vaccine apathy cannot be described as hesitant, as they are yet to make any psychological investment.

1.1.5 Health Literacy

Health Literacy can be defined as "the degree to which individuals have the capacity to obtain, process, and understand basic health information needed to make appropriate health decisions." (Health Resource & Service Administration, 2019). It is believed that higher health literacy is correlated with higher vaccine acceptance, as shown by a recent study, quoting "the risk of being in "hesitant", rather than "pro-vaccination" was higher among individuals having a bad health literacy score." The same study further suggested that increasing "individuals' ability to detect fake news and health literacy through education and communication programs" would "promote acceptance of a vaccine against SARS-CoV-2." (Montagni, et al., 2021)

1.2 Business Problem

Increasing the vaccine rate can be beneficial for Humana, its customers, their family, and friends, as well as the general public. As discussed above, FDA approved vaccines available to Humana subscribers are clinically proven to be effective against the COVID disease and its hospitalization. We drew the inference that raising the vaccination rate will be beneficial for:

A. reducing the risk of an individual member contacting or getting severally ill by COVID
B. improving public health to reduce the risk of an individual member contacting COVID

This will, in turn, reduce the cost for Humana by limiting potential medical claims related to COVID disease. These costs commonly include hospitalization, prescription, and diagnostic fees.

To effectively raise the vaccination rate among its subscribers, Humana should target insurance members who are reluctant to get the COVID vaccine due to a myriad of reasons, including misinformation, lack of trust, inequality, etc. These members "will require personalized outreaches involving clinical conversations to build trust in the vaccine." (Humana Inc., 2021)

This paper demonstrates our process to build a model that predicts the probability of vaccination for such a member and to unveil the rationale behind their behaviors. The model would help identify reasons for hesitancy and generate insights that help increase the vaccination rate and the health of the public, thus ultimately increasing Humana's profitability by reducing unseen cost.

1.3 Data Science Problem Definition

Specifically, we want to predict for each member, whether column "COVID_vaccination" would be "no_vacc" or "vacc", using all the relevant features given in the dataset. By building a model, we rank each individual subscriber by their probability of being hesitant to the vaccine.

2 Data Understanding

Two datasets are given to us to perform further analyses. The first dataset is for training with 974,842 records and 368 columns, and the second one is the holdout dataset with 525,158 records and 367 columns. In this chapter, we will mainly explore the training dataset to understand it for classification modeling.

2.1 Exploratory Data Analysis

The training dataset contains Humana MAPD members' information of eight feature groups, including *Medical Claims Features, Pharmacy Claims Features, Lab Claims Features, Demographics/Customer Data, Credit Data, Condition Related Features, CMS Features, and Other Features*.

Each record in the training dataset represents the information of one member. Each record has a binary flag named *COVID_vaccination,* which indicates the member's vaccination status as of the 3rd week of March 2021. This target feature is imbalanced with 83% records of 0, i.e members who hadn't been vaccinated at that time point.

Two major features that probably cause bias inherent in the data are *race_cd* and *sex_cd*. The binary variable *sex_cd* is relatively balanced with 54% female and 46% male, while the categorical variable *race_cd* is highly imbalanced with Caucasian accounting for 83%, Black accounting for 9%, and the other races accounting for 0%~2% each. Considering the imbalanced class problem, we would use sampling methods and set certain parameters to minimize the bias caused by this feature when modeling.

3 Data Preparation

3.1 Data Cleaning

The original dataset has a series of problems such as missing values, imbalanced class, etc. To make machine learning algorithms perform better, we clean the raw data in the following steps:

- We went through all the features one by one and dropped features that are obviously anomalous.
- A great number of features in the training dataset contained null values. Given the negative effects of null values, we removed features that contained 60% or more null values.
- We dropped imbalanced columns with the highest proportion larger than 98% and columns that have a variance of zero.
- Numerical variables have different ranges, so we apply normalization to them to achieve a common scale.

After the cleaning steps above, there are 267 features remaining in the training dataset.

3.2 Feature Engineering

3.2.1 Synthesized Features

Researchers from Carnegie Mellon University and the University of Pittsburgh recently published a report showing that vaccine hesitancy varies across race and age subgroups. For example, young Black people are more hesitant than young Caucasian people, while the reverse is true in older populations. (King, Rubinstein, Reinhart, & Mejia, 2021) To fully explore the interaction effects of age and race, we create a new variable race_age. We set three age cutoffs based on the age structure and interacted with age and race to create 28 subgroups. Below is the distribution of twenty-eight subgroups.

		Race						
		0 Unknown	1 White	2 Black	3 Other	4 Asian	5 Hispanic	6 American Native
Age Group	1 (≤35)	01:482	11:9354	21:2226	31:144	41:187	51:475	61:77
	2 (35-65)	02:5826	12:133655	22:25330	32:2177	42:1892	52:4532	62:586
	3 (65-80)	03:16567	13:675488	23:63940	33:1009	43:8510	53:10475	63:1207
	4 (80≤)	2548	160361	11551	2455	2150	2021	178

Table 1 Age Group and Race Distribution

3.2.2 One-hot Encoding

We have 66 categorical variables remaining in the training dataset after data cleaning and apply one-hot encoding to convert them into numerical variables. Compared to other encoding methods, one-hot encoding results in binary rather than ordinal variables that are computable by machine learning algorithms.

Some categorical features reflect the trend of certain indicators, and these features have twelve different values, Inc_1x-2x, Inc_2x-4x, Inc_4x-8x, Inc_over_8x, Dec_1x-2x, Dec_2x-4x, Dec_4x-8x, Dec_over_8x, Resolved, No_Change, No Activity, New. To avoid generating too many variables which could have a negative influence on model performances, we merged values of these features into five categories, Increase, Decrease, Resolved, No_Change, No Activity. Additionally, we processed *MABH_SEG, CONS_HHCOMP*, *hum_region* in a similar way.

553 columns remain in the datasets after one-hot encoding and downsizing the categorical features.

3.3 Feature Selection

To avoid including features that are highly correlated, we removed the feature pairs whose absolute correlation is higher than 0.9 and kept only one feature from the pair.

The final dataset for modeling contains 503 features.

4 Modeling

4.1 Model Building

We examined four classification algorithms: Support Vector Machine, Random Forests, Extreme Gradient Boosting (XGBoost), Light Gradient Boosting.

4.1.1 Support Vector Machine

Support vector machine (commonly referred to as SVM) is a well-known classifier for its optimization solution. It is also well known for its computational complexity, as it needs to solve the quadratic programming problem in order to find a separation hyperplane. With the training data set having more than 900,000 records, it would take too long for the SVM to compute. There has been plenty of research on how to apply a SVM to larger data sets, generally, there are two approaches:

A. Improve the SVM algorithm so that it can be applied to large datasets, or
B. Select representative training data from the dataset so that normal SVM can handle them (Cervantes, Li, Yu, & Li, 2008)

However, given the scope of this case and the known availability of other powerful machine learning algorithms, we chose to subsample the data set randomly and ran SVM based on the subsampled set.

The SVM resulted in an AUC of 0.619, which was not a good result compared to the other models we built.

4.1.2 Random Forest

Random Forest is an ensemble model combining multiple decision trees. Each tree fits on a sub-sample of the dataset and averaging the prediction to improve accuracy and avoid overfitting. However, it is found to be potentially biased when training on the dataset with a substantial number of categorical variables. It resulted in an AUC of 0.645. The most important feature selected by the model with both significant MDI and SHAP values is age (*est_age*). Considering *est_age* is an imbalanced feature, this estimation result may reveal some training bias.

4.1.3 Extreme Gradient Boosting

Extreme Gradient Boosting is an optimized distributed gradient boosting model with high prediction performance on classification and regression problems. The model is comparatively faster than other ensemble tree models and has a variety of internal parameters for cross-validation tuning. Parameters are designed to control the learning depth to avoid overfitting. The model also addresses the imbalance class issue that is likely to occur in our training dataset. The average AUC for this model is 0.672, while it has the best OOS AUC compared to other models.

4.1.4 Light Boosting Gradient Machine

Light Boosting Gradient Machine is a gradient boosting model based on decision tree algorithms, with a better computation power compared to XGB. It splits the tree leaf-wise other than level-wise for achieving higher accuracy, and meanwhile takes less memory space and performs faster training on a large dataset. The model has the best overall in sample AUC (0.685); however, a potential overfitting issue has also been noticed.

We compared these four models with a 5-fold cross-validation. Based on the model results, Random Forest, XGB and LGB had better average AUC score and were selected for hyperparameter tuning.

Model	*Average AUC Score*
Support Vector Machine	0.619
Random Forest	0.645
Extreme Gradient Boosting	0.672
Light Gradient Boosting	0.685

Table 2 Model Performance: AUC Score

4.2 Hyperparameter Tuning

A randomized search across a wide range of parameters was performed on selected models with Optuna, an automatic hyperparameter optimization software framework. According to the tuning results, Random Forest was deserted due to the low performance of AUC and its potential training bias, as the imbalanced feature *est_age* was chosen as an important feature; LGB had higher average in-sample AUC than XGB, but its out-of-sample AUC tested based on holdout set was lower than XGB. Therefore, we chose XGB as our final model, and the optimized hyperparameters and AUC scores are listed in Table 3.

Model	*Tuned hyperparameters*	*Average AUC Score*
XGB	learning_rate = 0.0657281142012396 max_depth = 3 colsample_bytree = 0.6 n_estimators = 669 scale_pos_weight = 4.4361232303441795	*0.673*

Table 3 Tuned Hyperparameters

4.3 Final Model

The XGBoosting model was identified as the optimal one and was thus selected for predicting the holdout data. This final model led to an optimal ROC curve with an in-sample AUC score of 0.673.

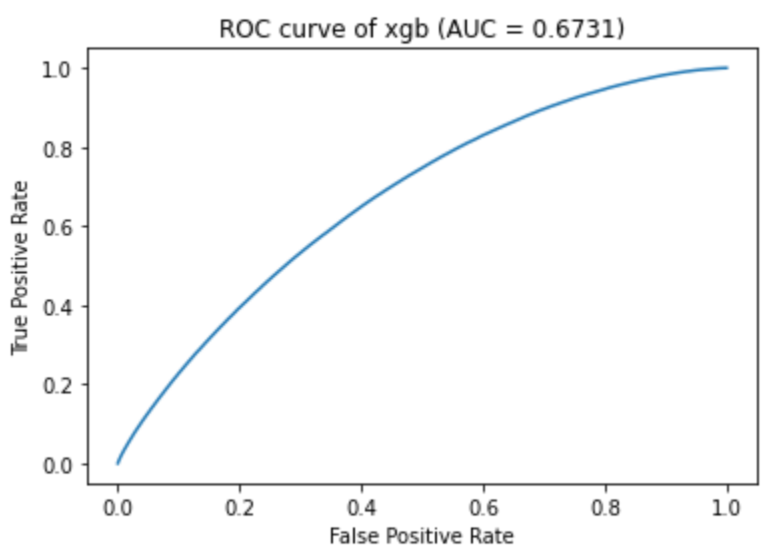


Figure 1 ROC curve of XGBosoting Model

4.4 Feature Importance

To fully understand which of the features have the greatest impact on the target variable and develop actionable insights from the model output, we plotted the top 20 most important features. As to the type of feature importance plot, we chose "Gain" which implies the relative contribution of the corresponding feature to the model.

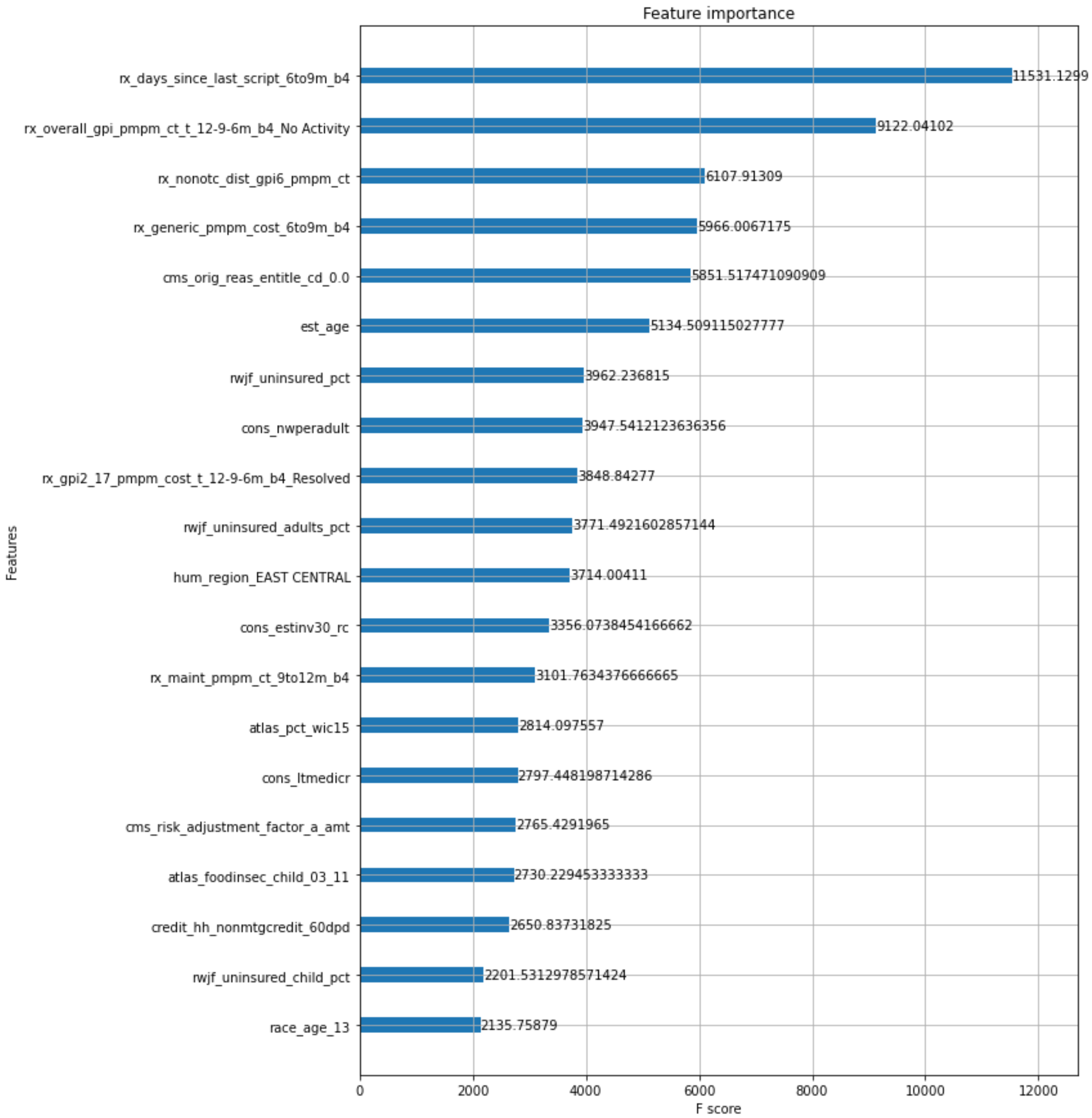


Figure 2 Feature Importance

In addition to the gain plot, SHapley Additive exPlanations (SHAP) is applied to interpret the effects of the given features by computing its contribution in comparison to the prediction. Important features selected based on SHAP values are as shown in Figure 3.

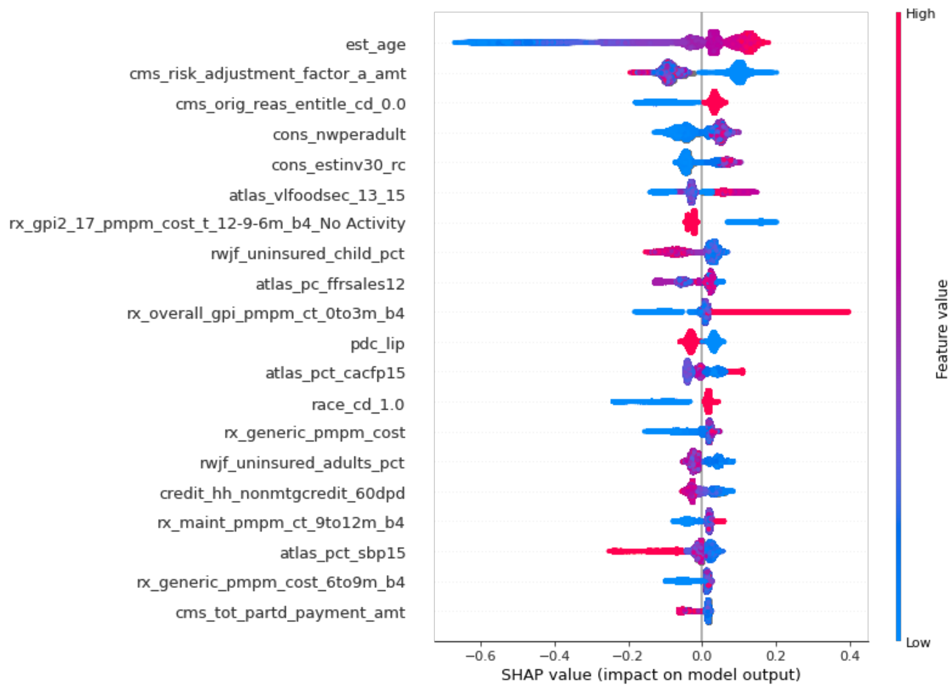


Figure 3 SHAP Plot for important Features

4.4.1 Individual Dependency Analysis on Important Features

<u>Age:</u>

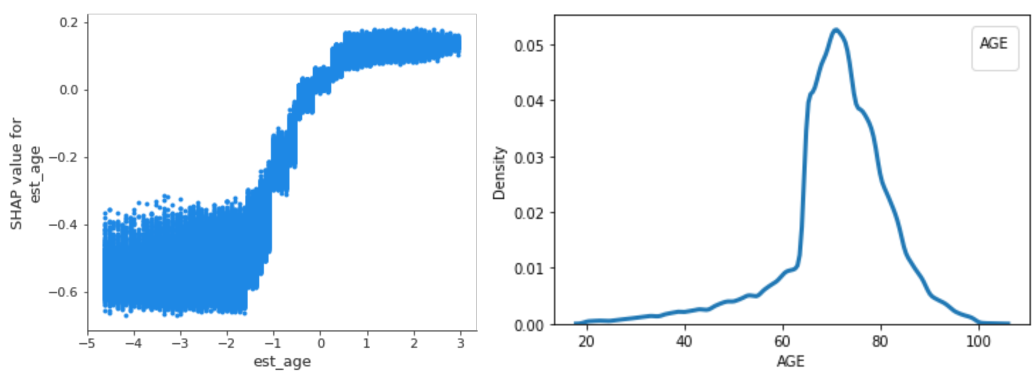


Figure 4 SHAP values for est_age and age distribution

The SHAP values of est_age are positive when the feature values roughly fall into the range of 65-100, indicating a positive correlation between vaccination status and the age of a member when his/her age is above 65. For customers under 65, the SHAP values disperse and thus, there are other features that will impact their vaccination status.

<u>Awareness and Accessibility:</u>

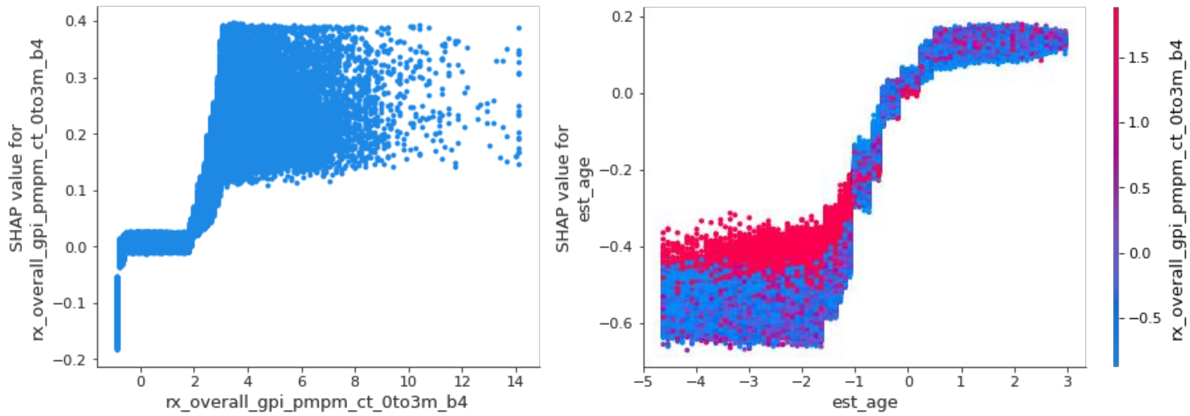


Figure 5 SHAP Value for rx_overall_gpi_pmpm_ct_0to3m_b4

To further explore the customers with younger age, we make another dependence plot (Figure 5) for feature *rx_overall_gpi_pmpm_ct_0to3m_b4*, which is also an important feature given in the SHAP plot. We assume the number of prescriptions per month can be used as an evaluation on people's health awareness and the accessibility to clinics/medical center. For customers aged below 65, if customers have higher health awareness and sufficient access to medical resources, they are more likely to get vaccinated. By investigating this feature independently, it generally has a greater effect on vaccination status when it has a higher value.

<u>Financial Status:</u>

We have selected several important features that disclose customers' financial status. The positive correlation between financial status and vaccination status is validated through the SHAP plot of these features.

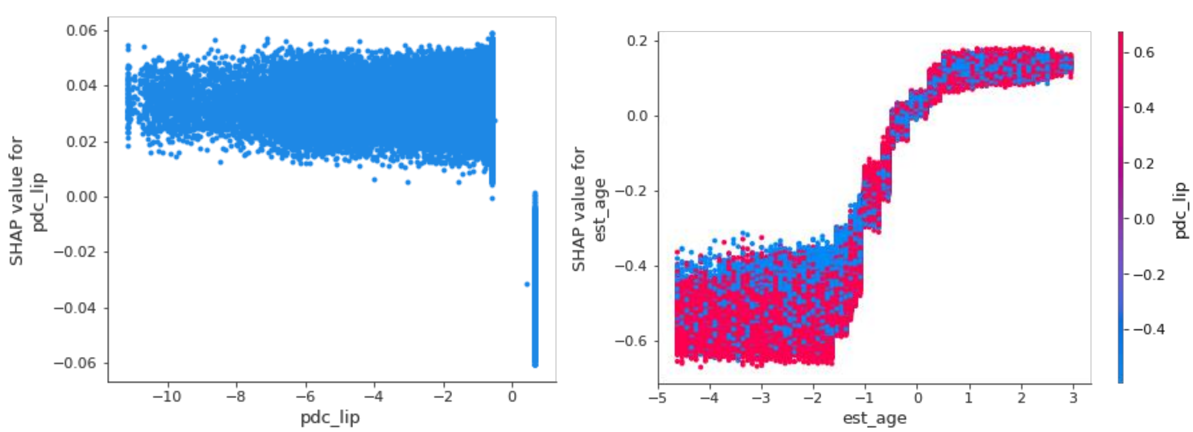


Figure 6 SHAP value for pdc_lip

pdc_lip means the proportion of days covered for prescriptions related to hyperlipidemia in the past year. Some studies have revealed the association between the increasing risk of dyslipidemia and lower socioeconomic status, so we interpret customers with higher *pdc_lip* tend to have worse financial status. (Clark, DesMeules, Luo, Duncan, & Wielgosz, 2009) The first graph above shows a negative correlation between the feature and vaccination status, and in the second graph, customers aged under 65 with a higher *pdc_lip* rate are less likely to get vaccinated compared to those of the same age but with a lower *pdc_lip* rate.

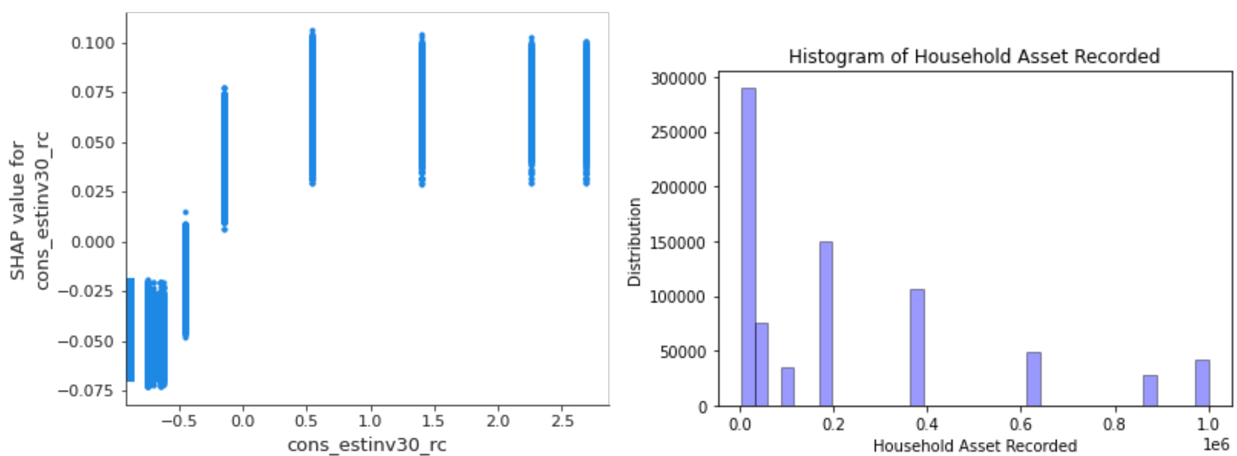


Figure 7 SHAP Value for cons_estinv30_rc

cons_estinv30_rc is an important feature identified by both “Gain” and “SHAP” methods. Presumably, a customer with more estimated household investable assets recoded usually has better financial status. Thus, Figure 7 indicates that a higher SHAP score is associated with a record of a better financial status.

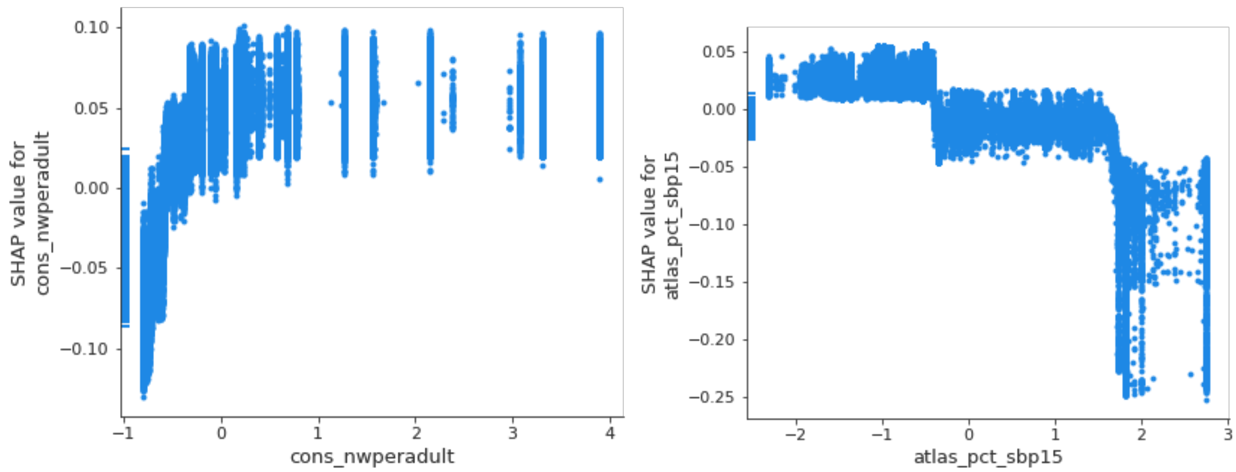


Figure 8 SHAP value for cons_nwperadult & atlas_pct_sbp15

Features *cons_nwperadult* and *atlas_pct_sbp15* are 2 possible important features that reveal one's financial status. Customers with higher net worth value tend to have better income, and we assume the families with more student breakfast plans subscribed will have lower household income. Figure 8 above detail a positive correlation between one's financial status and vaccination status.

<u>Political Affiliation:</u>

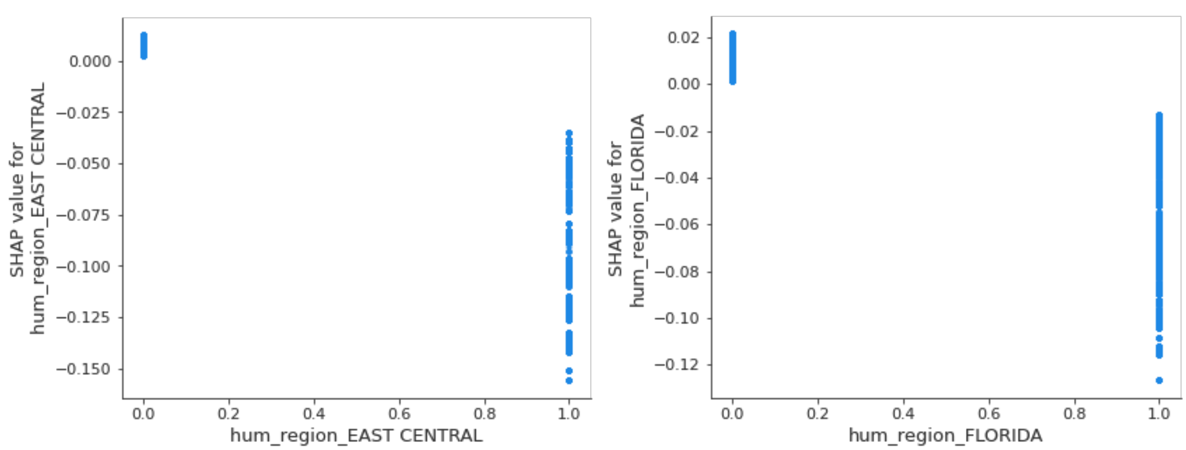


Figure 9 SHAP value for hum_region_EAST CENTRAL & hum_region_FLORIDA

hum_region_EAST CENTRAL is an encoded region feature ranked significant by feature importance plot. The customers not living in east central region have higher SHAP scores. One possible reason we have identified is political affiliation. By comparing the SHAP values distribution of another republican state *hum_region_FLORIDA*, we interpret that republicans may have conservative views towards COVID vaccination. Meanwhile, we analyze the SHAP values of the interactions between *hum_region_EAST CENTRAL* and two noticeable features with class imbalance problem, *est_age*/*race_cd_1.0*. Figure 10 shows that the SHAP values of age/race sparse evenly within each customer group, so we can assume the trend reflected in Figure 9 is not due to the effects brought by age and race features.

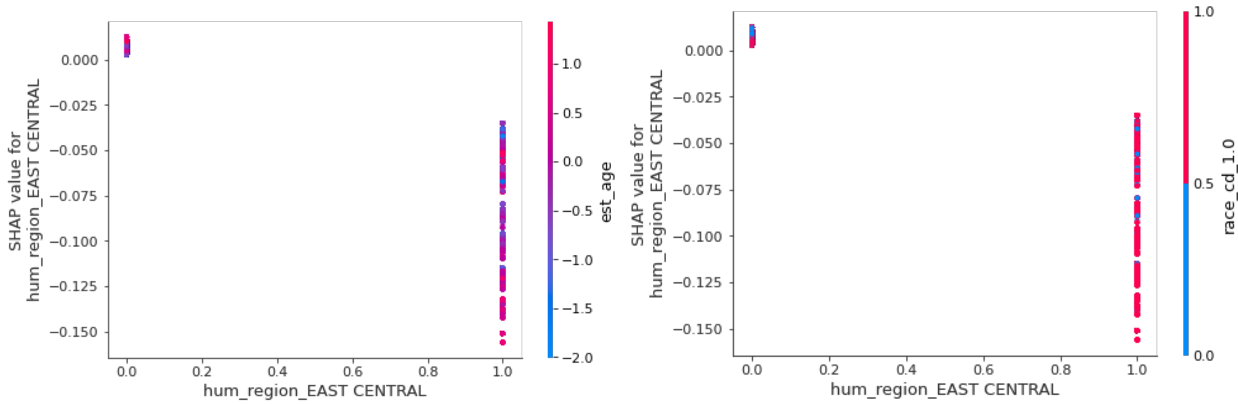


Figure 10 hum_region_EAST CENTRAL with race/age

5 Deployment

5.1 The goal of Model Deployment

The model we've built identifies the probability of an individual member being hesitant to the COVID vaccine. It is recommended that Humana use this predicted probability to identify members to target while further studying their subgroup to adopt a strategy.

The goal of such strategy should be that, within the members that was previously identified as not likely to get COVID vaccine, increase the percentage of people in such group by 9% within the first year of deployment.

We believe that the potential cost-saving of successfully targeting a reluctant member for vaccination would be around $4540. This figure is derived from the following calculations:

Cost Saving = (Hospitalization Rate – Hospitalization Rate with Vaccine) * Cost of Hospitalization + (Critical Care Rate – Critical Care Rate with Vaccine) * Cost of Critical Care

$$C = (R_i \times R_h - R_{iv} \times R_{hv}) \times C_h + (R_i \times R_h \times R_c - R_{iv} \times R_{hv} \times R_{cv}) \times C_c$$

Please note that this figure is calculated by taking the average of a best-case scenario and worst-case scenario. Refer to: Estimate for the source of each figure and detailed calculation.

5.2 Recommendation Framework

The prevalent framework is one developed by SAGE Working Group: "Vaccine hesitancy … is influenced by factors such as complacency, convenience, and confidence." (SAGE Working Group on Vaccine Hesitancy, 2015)

- Confidence: distrust in the safety and effectiveness of COVID vaccine and the agencies involved in the development/dispersion/issuance of the COVID vaccine.
- Complacency: belief that severity of the COVID doesn't warrant the need for a vaccine.
- Convenience: include location, time, comfort, and other factors affecting accessibility

Our quadrant framework is an alternation of the SAGE framework that is tailored to best capture our recommendations.

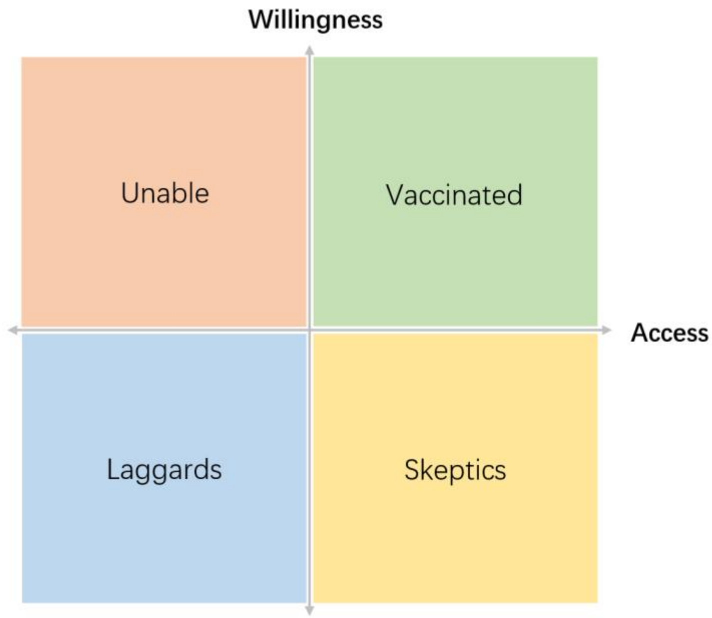


Figure 11 Quadrant Framework

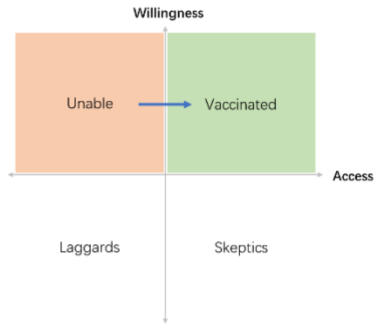
Whereas, the horizontal axis on the above chart represents access: the right end of the axis showing high access to the vaccine, and the left end limited access. This access address "convenience" in the SAGE framework. It includes economic, educational, and informational power to obtain the COVID vaccine. For example, low access can mean the person hasn't got the time, or is too far away, or cannot acquire the adequate information to get vaccinated.

The vertical axis shows willingness, with the upper end meaning high willingness and the lower meaning unwilling. This willingness spectrum addresses "confidence" and "complacency" in the SAGE framework. For someone on the lower end of the willingness spectrum, the person might believe that vaccine is harmful or don't think the COVID symptom is severe enough to warrant the need for vaccination.

5.3 Recommendations

Our recommendations are based on feature importance derived from the model and secondary research. Each recommendation and its effects can be projected onto the graph as a vector, with the direction representing a combined effect on access and willingness.

5.3.1 Employer Driven Compliance



In September of 2021, President Biden announced a rule that required all employers with 100 or more employees to ensure their workforces are fully vaccinated or conduct COVID testing at least once a week. The magnitude of effect for this emergency rule is huge, covering over 80 million workers. According to KFF, 49.6% of the U.S. population purchases insurance through its employer. (Kaiser Family Foundation, 2019) Signaling that there is a huge opportunity to increase vaccine coverage through employers.

According to this new emergency rule, large employers have the option to either enforce mandatory vaccination or conduct weekly COVID tests. We suggest that Humana offer incentives to employers and award them for a vaccination rate above 95%. McKinsey & Company conducted research with more than 400 US-based companies across a broad range of industries and analyzed the results. The graph in Appendix C: Supplementary Graphs and Charts highlights the most effective initiative measured by % of employees showing a significant increase in the likelihood of receiving COVID vaccine (Azimi & Cordina, 2021).

Based on this report, offering PTO (Paid Time Off) appears to be the most effective initiative among all mentioned, yet only 34% of the employers are pursuing this initiative. Humana can accelerate the initiative by taking on some of the cost of PTO. Humana can sell the partnership idea to these large employers by highlighting what's in it for them, in essence, cost savings and discounted premiums.

$$T_e = c_{tk} * \frac{1-(1+i)^{-nt}}{\mathrm{i}}$$

Where T_e depicts the per person cost for implementing weekly testing, c_{tk} represents the cost of a testing toolkit, *n* represents the number of employees in the company, *i* represents the weekly interest rate, and *nt* represents the number of payments.

Appendix A. Estimated cost for weekly COVID tests outlines a potential pitch for the employers.

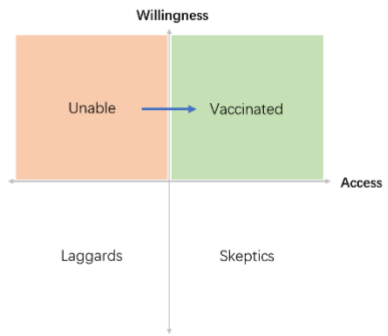
It is clear that implementing testing toolkits for the assumed 1-year period would be way more costly ($918.2 - $39,026) compared to pushing forward vaccination coverage for employers by offering PTO ($285.3). Theoretically, if all employers acted rationally, all employers would choose to enforce vaccines among employees. However, the low implementation rate of this strategy has revealed that there might be more to the equation. For example, they might not have conducted analysis and intuitively deemed that providing PTO for employees seems more costly. It is up to Humana to show them that this is a great chance to engage in a socially responsible and cost saving initiative.

We believe that popularizing this initiative would be very effective and would be the biggest contributor to increased vaccination coverage amongst our recommendations.

Target wise, this approach would work specifically well towards the younger members. A recent global survey highlighted that although young people are less likely to accept the vaccine, their acceptance is higher compared to the older group when a vaccine is required by the employer. “People aged 65+ were more likely to accept the vaccine than those who were younger…The opposite trend was observed in regard to acceptance of the vaccine if one’s employer required it.” (Lazarus, et al., 2020) This finding is congruent with our model result – younger members are less likely to get vaccinated compared to 65+, as shown in Figure 4 SHAP values for est_age. By adopting this strategy, we can effectively target the younger generation that is observed to have a lower vaccination acceptance.

On the other hand, this campaign addresses the accessibility issue by guaranteeing employees PTO, thus ensuring their time constraint is met. This can result in a three-way win. From the employee’s perspective, their PTO is spent on vaccination, including potential post-vaccine rest days. From the employer’s perspective, they now have even bigger savings compared to having to conduct test every week. From insurance provider's perspective, vaccine hesitancy among the young workforce is addressed.

5.3.2 "Close the Distance" Campaign



In addition to the direct financial impact, another barrier to vaccine adoption was access. Low access was one of our most important features in predicting vaccination status.

We believe that it is also important to provide solutions to low access problems. BCBS has invested in the partnership of Ride United NC and Lyft to provide access to COVID vaccination spots all over North Carolina. The initiative was not only successful in terms of increasing vaccination rates, but it also generated a lot of earned media for BCBS. We recommend Humana partner with ride share apps and provide Humana customers with free rides to vaccination spots to increase vaccinations rates among customers with low access. Humana would open a channel in the user portal for customers to submit their proof of vaccination and their travel itinerary to receive travel cost reimbursement capped at $100 per trip ($400 per person for 2 doses). We believe that this would be an extremely effective way to help low access members overcome barriers and receive full vaccination.

Our team has created an estimated cost for rolling out the program:

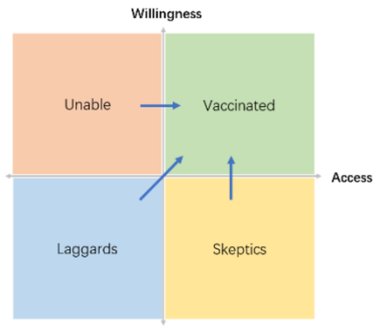
$$C_t = \sum_{k=1}^{n} 4 \times C_k$$

$$C_t = \bar{c} \times 4 \times n$$

Where C_t depicts the total cost of the program, k represents an individual customer, n represents the total number of people enrolled in Humana's program, C_k represents the cost of the individual customer. The second equation demonstrates another approach to where $\bar{c}$ is the average cost of a rideshare ride to the vaccination spot and n represents the total number of people enrolled in Humana's program.

With the effort to increase access to vaccination spots, we believe that Humana would be able to convert "Unable" into "Vaccinated".

5.3.3 Online Search Advertising Campaign



Since the launch of the vaccine, there have been multiple advertisement campaigns aimed to increase vaccination adoption rate. However, the number of COVID campaigns gradually decreased. (Christensen, 2021) Advertising experts believe that it is because the campaigns are no longer persuading the unvaccinated due to their nature of hard selling.

During early stages of vaccine launch, advertisements focused on awareness of the vaccine accompanied with strong pro-vaccination messages. Our group has identified multiple barriers to vaccine adoption, including political stance and confidence in the vaccine. Republicans are more likely to hold their anti-vaccination ground, and many of them are inoculated to vaccine advertisements, blocking these messages as soon as they realize this is a vaccine ad. Thus, traditional vaccination advertisement would have minimal impact, if not negative impact due to the boomerang effect.

Even then, advertisement is still proven to be one of the more effective ways to increase awareness and promote vaccination. Now, unlike mass marketing done in the early stages, we can identify specific segments and tailor our marketing messages utilizing our model. Since strong messages would likely be counter, we would target these segments through soft sells.

One proven effective way to nudge people with hesitation to the other end of the vaccine adoption spectrum is Online Search Advertising Campaigns (OSAC). (Krupenkin, Yom-Tov, & Rothschild, 2021) Such a campaign can raise the awareness and interest of COVID vaccine by improving member Health Literacy. Higher health literacy correlates to higher acceptance rate to the COVID vaccine.

To further break this down, we suggest conducting the following test to optimize resource allocation when investing in online marketing activities (search keyword that leads to vaccine ads). OSAC is shown to have both

- Congruence Effect: increasing likelihood of future vaccine searches by showing the target advertisements when search keywords are related (health, cough, etc)

- Priming Effect: increasing likelihood of future vaccine searches by showing the target advertisements when search keywords are unrelated. (Prime is related to Amazon, etc)

However, the congruence effect is shown to be stronger on targets who have positive attitudes on the topic. The priming effect, on the other hand, shows similar effectiveness across attitudes. With our given target segment in mind, our initial hypothesis would be to focus more on the priming effect – invest more in the unrelated keywords.

5.3.3.1 Strategy Deployment: Congruence Effect and Priming Effect

An A/B test could be conducted to measure the effectiveness for each part of OSAC. The effectiveness of the campaign could be measured by the following equation:

$$E_c + E_p$$

$$E_c = P\ (V|R= 1, A = 1) – P\ (V|R=1, A = 0)$$

$$E_p = P\ (V|R= 0, A = 1) – P\ (V|R= 0, A = 0)$$

Ec depicts the effectiveness of congruence effect measured in change of probability to search for vaccination, which is P(V|R= 1, A = 1) - P(V|R= 1, A = 0), the probability (P) that the target searched vaccine (V) given that the target previously searched on related keywords (R=1) and an advertisement was present (A=1) subtracted the probability (P) that the target searched vaccine (V) given that the target previously searched on related keywords (R=1) and an advertisement was not present (A = 0).

Ep depicts the effectiveness of Priming effect also measured in change of probability to search for vaccination, which is P(V|R= 0, A = 1) - P(V|R= 0, A = 0), the probability (P) that the target searched vaccine (V) given that the target previously searched on unrelated keywords (R=0) and an advertisement was present (A=1) subtracted the probability(P) that the target searched vaccine (V) given that the target previously searched on unrelated keywords (R=0) and an advertisement was not present (A = 0).

We suggest Humana test run OSAC for a month, collect data on results and optimize their advertising based on the following function.

$$\max\ [E_c \times B + E_p \times (1\text{-}B)]$$

Where the total marketing budget allocated to the campaign is depicted by B.

Assuming the cost of keywords are the same, if Ec > Ep, maximum effectiveness could be achieved by prioritizing all relevant keywords and bidding for irrelevant keywords with the remaining budget. If Ec < Ep, maximum effectiveness could be achieved by prioritizing irrelevant keywords and bidding for relevant keywords with the remaining budget.

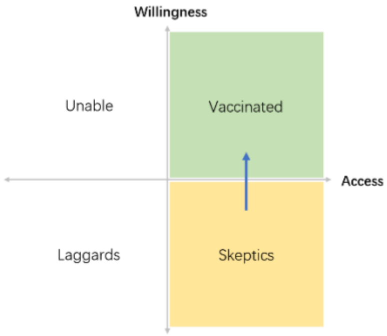
Realistically, the cost of keywords would be different, and we would optimize G_t to achieve maximum gain:

$$G_t = \frac{E_c \times B}{C_c} + \frac{E_p \times (1 - B)}{C_p}$$

Where G_t represents the total change in probability of searching for vaccine, C_c depicts the average cost of relevant keywords and C_p depicts the average cost of irrelevant keywords.

The online search advertising campaign addresses multiple quadrants at the same time. It increases willingness for the skeptics quadrant by applying the Congruence Effect and Priming Effect. People who belong to this quadrant are best predicted by their political affiliation and financial status, as outlined in Figure 9 SHAP value for *hum_region_EAST CENTRAL* & *hum_region_FLORIDA*. Meanwhile, this campaign can also target the unable quadrant by providing information to people with low health literacy. This provides some degree of accessibility to the group. Benefits of such a campaign include the high reach, allowing it to target a wide range of members, and large amounts of data generated for further analysis. The campaign is especially prominent in the case of Humana as the barriers to vaccine adoption differ greatly among customers, and OSAC is an efficient and effective way to accommodate these differences. Its shortcomings lie in the time needed to observe the effectiveness and potentially high campaign deployment cost.

5.3.4 Endorsement: "Kiss the Air" Campaign



From our exploratory analysis and feature importance, we can observe the difference in vaccination rate across states in Figure 9 SHAP value for *hum_region_EAST CENTRAL* & *hum_region_FLORIDA* and Figure 10 *hum_region_EAST CENTRAL*.

As shown from the above figures, one of the more important features our model identified was the region of the state. These regions are all ones that have more republican states than Democratic states. Research has shown that in addition to demographic and ideological factors, vaccine attitudes are also driven by political ideology. (Kohlhammer, Schnoor, Schwartz, Raspe, & Schafer, 2007) Compared to Democrats, Republicans are twice as likely to believe the widely debunked myth that vaccines cause autism (Fridman, Gershon, & Gneezy, 2021). In addition, the anti-vaccination tweets made by President Trump have led to increased concern about vaccines among his supporters (Hornsey, Finlayson, Chatwood, & Begeny, 2020).

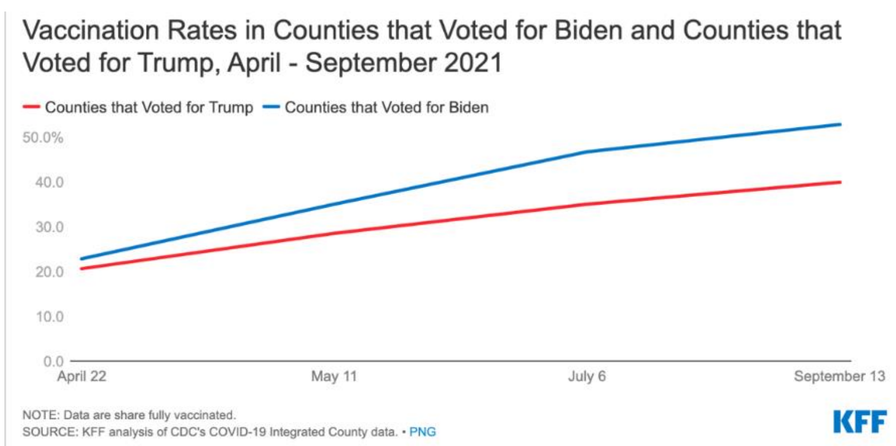


Figure 12 Vaccination Rates in Counties that Voted for Biden and Counties that Voted for Trump, April - September 2021

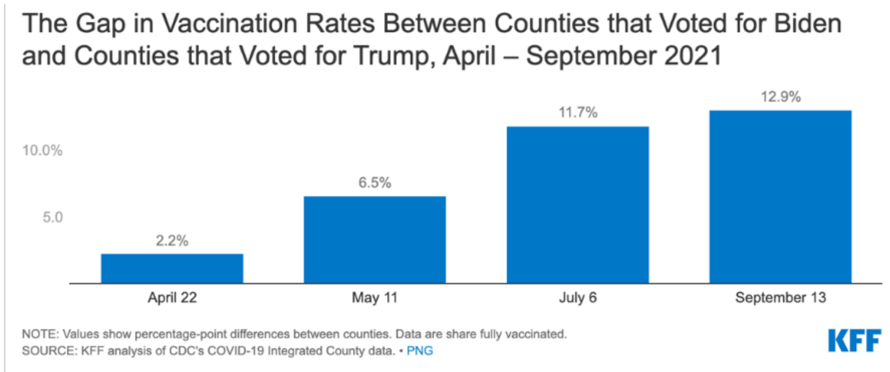


Figure 13 The Gap in Vaccination Rates Between Counties the Voted for Biden and Counties that Voted for Trump, April - September 2021

Many of his supporters can be classified as, rather than hesitant, outright apathy. How to tackle such rejection has been under discussion for a long time. A recent study on persuasion methods for vaccine apathy using ELM (Elaboration likelihood model) revealed that people who are disinterested in vaccination are better persuaded by messages that are processed through the peripheral route, which relies on argument cues rather than strong messages. (Wood & Schulman, 2021)

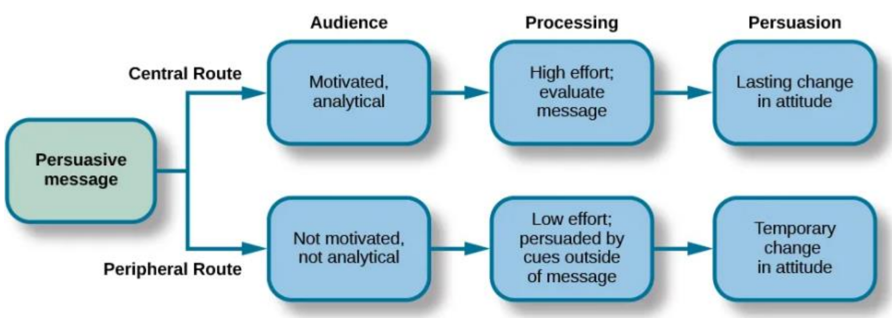


Figure 14 Elaboration Likelihood Model

The two most important aspects when forming the argument would be the message and the source of the message.

Peripheral messaging is effective when it attracts attention and requires relatively low cognitive effort to process. Choices include bright color, emotion, humor, sensory information, and memorable, catchy slogans. It is also important to note that Peripheral messages are intentionally limited in terms of data and should not encourage message processing.

According to a recent study, low-involvement people prefer highly likable sources that trigger positive feelings. (Wood & Schulman, 2021) Since the advertisement is judged by quick authority cues instead of close assessment, sources that have high credibility and likability are preferable. In the context of Humana, republican leaders that have adopted the vaccine would be one of the top choices as a message source. One strong candidate would be Mitt Romney, a Republican senator, who himself publicly announced that it is an enormous error for anyone to suggest that we shouldn't be taking vaccines. We recognize that it could be difficult to persuade these political leaders to take on an apparent pro-vaccine stance, even if that is what they truly believe in, but one of the essential characteristics of a peripheral message is that it does not contain any strong messages, and thus would be easier for these leaders to get on board.

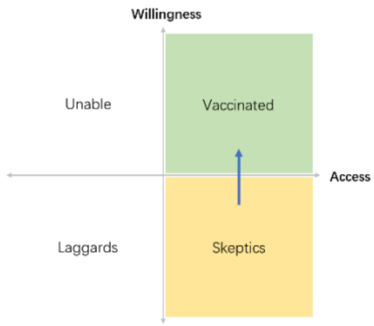
Such a campaign also targets the skeptics quadrant, and especially those who live in states that can be identified as "Trump State". This approach differs from the previous one in that it takes the softer approach to tackle a smaller population segment with a more conserved political view, while the online advertisement campaign targets a wider audience.

Our group came up with the *Kiss the Air* Campaign, a peripheral route towards vaccination coverage that features a Republican endorser. The campaign would consist of a website that provides information on the overall campaign goal – to achieve herd immunity and highlight benefits of her immunity – masks free, no more social distancing. Our endorsers would have their own page that includes information on vaccination status and the rationale of becoming vaccinated. It is important to avoid strong pro-vaccination statements on the websites, instead focus on highlighting the benefits of the end goal and personal anecdotes of the political leaders, thus making it hard for the audience to refute due to no clear message. The promotion of the website would rely on outdoor advertisement (banner ads, billboards, etc.) portraited in different languages, accompanied with a large image of our Republican endorser with a message on the side that highlights his/her vaccination status. An URL or Q.R. code that links to the campaign landing page for people interested in learning more would also be included in the ad.

Example advertisement designs are shown in 9.2Appendix B: Sample Endorsement Campaign.

Unlike the previous digital advertisement campaign, an endorsement campaign directly addresses the skeptics quadrant and raises willingness through an implicit soft sale that doesn't deter people with deep hesitancy.

5.3.5 Community Outreach: Clinics



Up to this point, our recommendations have been focusing on individuals in a specific segment, however, humans are social creatures, we live in communities that we cherish and honor. Studies have shown that social norms arise as internal motivations and as external influences, signaling that in additional to personal preferences, social norms also affect the likelihood of vaccination. (Brewer, Chapman, Rothman, Leask, & Kempe, 2017) Cluster of individuals that our model predicts with a low probability of getting vaccinated might represent an anti-vaccine social norm presence in the community. Quite often, local clinics and family doctors with a close social network to the community are the best breakthroughs in these cases. Vaccination-related social surveys revealed that providers are in a unique position to promote vaccination. (Ibid) Compared to the healthcare payer, local healthcare providers do not have apparent monetary incentives to promote the vaccine, combined with the expertise of the staff would have high credentials and persuasiveness.

We recommend Humana promote vaccine adoption in areas with low vaccination coverage through partnered primary care clinics, dental clinics, and eye clinics. To ensure results, it is important that these promotions are voiced by the clinics and spoken in the language of the community. For these targeted communities, we can choose to expand the network of healthcare providers or offer better deals to the in-network providers, so as to encourage vaccination pitches through their channel. As vaccination protects a person’s unvaccinated primary contacts as well as his or her secondary contacts, a common useful pitch would be that vaccine is for the protection of the people you love. Social networks and social norms have powerful influences on health behavior, and by partnering with local clinics, Humana would be able to shift community social norms from low vaccination to high vaccination, effectively driving up vaccination coverage.

The effectiveness of such a campaign is hard to measure but can be generalized by the following formula:

$$\frac{P_{t,c}}{V_{t,c}}$$

Where $P_{t,c}$ is the number of pitches made within a set community over a period of time, and $V_{t,c}$ represent the amount of patient visitors in the respective community over the same period of time.

Similar to the endorsement campaign, this approach to cooperate with clinics also targets skeptics, who are unwilling to get vaccinated due to a myriad of reasons. A recommendation by someone "in-group" is a good entry point to raise the community's knowledge and willingness of the vaccine.

5.4 Financial Implications

5.4.1 Estimated Potential Saving

We calculated the expected cost saving of targeting a likely vaccine rejector, should the person, in turn, decide to get vaccinated in the end by the following formula:

Cost Saving = Cost of claims without vaccine – Cost of claims with vaccine

$$C = (R_i \times R_h - R_{iv} \times R_{hv}) \times C_h + (R_i \times R_h \times R_c - R_{iv} \times R_{hv} \times R_{cv}) \times C_c$$

Where in the equation, each letter is explained in the following table:

	Description	*Value Range*
C	Expected cost saving***	\$461.23 - \$15,005
R_i	Infection rate without vaccine*	10% - 81%
R_{iv}	Infection rate with vaccine**	2.7% - 21.9%
R_h	Hospitalization rate without vaccine	21% - 31%
R_{hv}	Hospitalization rate with vaccine	2.1% - 3.1%
R_c	Critical care rate	5% - 27%
R_{cv}	Critical care rate with vaccine	0.5% - 2.7%
C_i	Cost of moderate symptom claim	\$19,000
C_h	Cost of severe symptom claim	\$59,000

Table 4 Values Adopted in Cost Saving Estimation

(National Council on Compensation Insurance, 2020)

*Since the above rates are widely speculated and have a wide range of variability, we choose to report the range on estimated rates. Especially for the contract rate of COVID, due to levels of uncertainty in data collection including, but not limited to

- Short data collection time
- Incomplete data collection due to testing capacities
- Change in conditions and environment (social distancing)

The National Council on Compensation Insurance give us a glimpse on the variation of COVID contract rate:

Rate	Source (Date of Estimate)	Comments
Less than 10%	Institute of Health Metrics and Evaluation (4/8/20)[1,2]	US Rate, assumes strict infection controls
20% - 60%	Marc Lipsitch, professor of epidemiology at Harvard T.H. Chan School of Public Health (3/4/20)[3]	Global Adult Population Rate
40% - 80%	NY Gov. Andrew Cuomo (3/21/20)	New York Rate
56%	CA Gov. Gavin Newsom (3/18/20)	California Rate
81%	Imperial College COVID-19 Response Team (3/16/20)[4]	Assumes no infection controls

Table 5 Projected Infection Rate by Source

(National Council on Compensation Insurance, 2020)

** We further calculated contract rate given the member is fully vaccinated, using Pfizer COVID Vaccine as an approximation: "for fully vaccinated individuals, effectiveness against SARS-CoV-2 infections was 73% (95% CI 72–74) and against COVID-19-related hospital admissions was 90% (89–92)." (Tortof, et al., 2021) We can hence calculate the rate of contract rate post vaccine as contract rate × (1 – 73%), and rate of hospitalization rate post vaccine as hospitalization rate × (1 – 90%)

*** Many assumptions are taken here, these include, but not limited to:

- We assumed all cases were reported and claims were filed to cover their medical expenses, and the insurance company approved all the claims. We make this assumption because this seems to be the status quo for larger corporations.

- We assumed there will be significantly less, or no claim related to light symptoms COVID contract. This could have biased our estimate towards the low end.
- We ignored the effect of fatal COVID cases, this could have a negative, but no significant influence on our averaged figure.

As calculated above, the expected cost saving is $4540 per member whom we successfully targeted and turned to vaccine acceptance. According to the results report in 2019, Humana's total Medicare Advantage (individual and group) membership is more than 4.5 million members. (Humana, 2019) Hence, we assume the calculation base of the population to be 4.5 million. Based on the dataset provided by Humana and our deployment goal, we also assume the hesitant rate for the whole is 83% and the conversion rate (The attitude of a member towards COVID vaccine is successfully converted through our campaigns) of our campaigns is 9% (also outlined in chapter 6.1)

Based on the assumptions above, the total saving of all our campaigns is $1,526,309,244.

$$Saving_T = Saving\ /\ person\ \times Member\ Count\ \times Hesistency\ Rate\ \times\ Conversion\ Rate$$

If we control the profit margin for Humana as 50%, then the money that Humana could utilize for campaigns is $847,949,580. With this money, we took a top-bottom approach to budget for the five campaigns. Employer Driven Compliance Campaign and "Close the Distance" Campaign are bottom-up campaigns of which costs could be calculated directly. For the other three campaigns whose costs could not be measured directly, we use a top-down way to allocate our money to them.

5.4.2 Estimated Cost for the Employer Driven Compliance Campaign

According to statistics provided by the U.S. Department of Labor, an employee's total compensation package costs a private employer an average of $28.89 per hour. (White, n.d.) Of that amount, wages account for roughly 70 percent and benefits 30 percent. The cost of all paid leave benefits to a private industry employer – vacation, holidays, sick and personal leave -- averages $1.98 per hour or almost 7 percent of total compensation. With one normal workday being 8 hours, an estimated cost for one paid day off would be $15.84. Assuming each employee takes 2 days off to take a dose of vaccination and receives 7 days off for side effects caused by the vaccine, totaling in 18 paid days off, this will cost the employer $285.12 per person. Even if

Humana fully compensates for the additional cost, it will still receive an estimated $4255 in potential COVID claim savings.

To calculate the total cost of this campaign, we need to get the proportion of members who are actively employed. Since there is no proper variable representing it, we use the proportion of members who are younger than 65 instead. The cost is calculated to be $230,471,104.

$$C_T = \ Cost\ per\ person \times Population \times Hesitant\ Rate \times Employment\ Rate$$

5.4.3 Estimated Cost for the "Close the Distance" Campaign

Using the estimate from section 6.34 Endorsement: "Kiss the Air" Campaign, the travel cost reimbursement for vaccination is $400 per person. We chose the median of *atlas_pct_laccess_lowi15* (Low income & low access to store), which is 6.17%, as the proxy to estimate the low access rate within the member population. To measure total cost of this campaign, we estimated an adoption rate that represents the conversion rate of this single campaign. For people with low access to vaccination, the adoption rate is assumed to be 20%, while for people of sufficient access, the adoption rate is 6%. Therefore, the cost of this campaign could be calculated as the following:

Let A represent Accessibility, where A = 0 means low access, and A = 1 means sufficient access.
R_A represents the Adoption Rate, where R_{A0} = 20% and R_{A1} = 6%.
R_H represents Hesitant Rate, where $R_{.H.}$ = 83%. C represents cost per person for the campaign

$$C_T = \ C \times Pop \times \ R_H \times [(R_{A0} \times P(A=0) + \ R_{A1} \times P(A=1)]$$

The total cost of "Close the Distance" Campaign is $102,545,172.

5.4.4 Estimated Cost for Other Campaigns

Since that online keyword search advertising reaches the widest member spectrum, and is likely to achieve the most visible result, we would advise devoting most resources to this campaign.

Following this guideline, we tried to allocate our remaining budget to Digital Advertisement, Peripheral Route to Persuasion, Community Outreach on a 30% - 20% - 12.5% basis based on the expected scenario total savings ($1,526 mil), the dollar amount should remain the same throughout the scenario analysis conducted below.

We conducted a scenario analysis using a conversion rate of 8%, 9%, and 10%, and calculated potential profit margins, respectively. The following table shows the final allocation of the budget and the corresponding result profit margin. The three charts show the variation of profit margin from 5% (conversion rate of 8%), 16% (conversion rate of 9%) and 24% (conversion rate of 10%)

Campaign	Amount($mil)	% Of Total savings
Total Savings	$1,526	100%
Employer Driven Compliance	$230	15.1%
"Close the Distance"	$103	6.72%
Digital Advertisement	$257	30%
"Kiss the Air"	$154	20%
Community Outreach - Clinic	$103	12.5%
Profit	$234	16%
Profit as % of Net Profits in 2020		7.11%

Table 6 Allocation of Budget on Projects and Expect Profit based on Expected Conversion Rate (9%)

Campaign	Amount($mil)	% Of Total savings
Total Savings	$1,696	100%
Employer Driven Compliance	$230	13.6%
"Close the Distance"	$103	6.05%
Digital Advertisement	$257	27%
"Kiss the Air"	$154	18%
Community Outreach - Clinic	$103	11.25%
Profit	$234	24%
Profit as % of Net Profits in 2020		12.15%

Table 7 Allocation of Budget on Projects and Expected Profit based on Good Conversion Rate (10%)

Campaign	Amount(mil)	% Of Total savings
Total Savings	$1,356	100%
Employer Driven Compliance	$230	17%
"Close the Distance"	$103	7.56%
Digital Advertisement (50%)	$257	33.75%
"Kiss the Air"	$154	22.5%
Community Outreach - Clinic	$103	14.06%
Profit	$234	5%
Profit as % of Net Profits in 2020		2.07%

Table 8 Allocation of Budget on Projects and Expected Profit based on Bad Conversion Rate (8%)

6 Limitations & Risks

Our group based our recommendations on insights generated from our predictive model and secondary marketing research. In this section, we would like to discuss the limitations and risks associated with our recommendations.

One of the biggest challenges we face during model building and tuning is limited computational power. Due to limited computational resources and time, we can leverage neither space nor time from the tradeoff. We had to refrain from fine tuning complex and computationally intensive models such as Support Vector Machine, K-Means Clustering, Neural Network, etc. This might lead to potential overlooking of better performing models, thus losing predictive power in the process. Another limitation is the availability of efficient yet powerful model algorithms. Given time, we believe that better algorithms can be deployed to achieve better model performance.

In addition to model limitation, we have also identified potential dataset related problems. Class imbalance issue is noticeable in the training set. Only 17 % of the records are vaccinated, while most of the vaccinated records are associated with older people, since the vast majority of Humana's customers are over 65. This may result in adverse impacts on models' learning performance. Another problem is related to data imputation. XGB comes with a built-in algorithm that will impute the missing values, but it requires the holdout set to follow the same distribution as the training set for a more accurate prediction. Lastly, due to the ambiguity in the data dictionary, we may misunderstand the meaning of several features and consequently implement a wrong methodology when processing these data.

With the above constraints, other risks are present in deploying this model and the suggestions derived from it.

Assumptions are made throughout the report to simplify the calculation of our suggestions. They can add variation to our figure estimates and final suggestions. Some assumptions made in our recommendation framework include:

- Simplified model of potential cost saving, and its source figures
- Cost estimation of each campaign deployment
- Likelihood of campaign execution and success

- The potential impact of targeting campaign
- …

The above figures are often hard to measure, not to mention that they all need adequate expertise in the healthcare insurance industry, advertising industry, and many more. Given the anterior nature of this report, we suggest using this as a prior study and conducting individual experiments to achieve greater accuracy.

7 Discussion

7.1 Religion as a Potential Identifier of Vaccine Hesitancy

In 2019, there are over 74% of people in the U.S. are with religious identity, (Pew Research Center, 2021) and most of them embrace worship as an important part of their life and have a strong faith in their communities. (Centers for Disease Control and Prevention, 2021) Based on this observation, we conducted some in-depth interviews with a convenience sample aged from 23-30, with religious beliefs. However, the response shows strong impacts of the religious community on individuals, especially older generations. So we interpret that in the context of a religious community, if religious leaders get vaccinated and speak up for the benefits of vaccines, community members will probably understand how vaccination can help to protect the community and follow their leaders.

Our strong hunch is that it can be an effective campaign to influence people who have conservative/negative attitudes on COVID vaccination. However, we are not able to identify this customer segment and evaluate the effectiveness based on our current dataset at this stage. We recommend Humana to further collect data to validate this social norm and consider conducting similar campaigns on selected customer groups.

7.2 Future advancements:

Given the short time frame, most of the recommendations and campaigns our team proposed focused on single platform/channel communications. With the new delta variant and potential future variants, it is possible that the battle between humans and COVID is going to be a long-lasting seesaw war. Moving forward, Humana should consider expanding on its channel of communication, eventually creating an omnichannel unified voice. Integrated Marketing Communication (IMC) campaigns would make more effective use of various marketing channels.

8 Conclusion

Herd immunity against COVID-19 is the ultimate goal for the world. Achieving herd immunity with safe and effective vaccines makes diseases rarer and safer. Based on past experience, a rough estimate of 95% vaccination coverage would be sufficient to achieve herd immunity in the U.S.

Our model demonstrated that age, accessibility, financial status are all crucial factors in determining vaccine acceptance. We have established effective ways to target identified vaccine hesitancy members with our recommendations. We also provided actionable insights and measurable metrics to evaluate our deployment methods. In addition, we have demonstrated that our recommendations are not only effective but also financially sound with our financial analysis. To effectively overcome barriers of vaccination and achieve a 9% increase in vaccination rate among the members who are hesitant to receive the vaccine, we suggest that Humana adopt our quadrant model when evaluating member hesitancy, as well as our five campaigns.

Our group firmly believes that by adopting our recommendation, Humana would save potential COVID-related claims and, more importantly, become one of the fundamental driving forces that accelerates the process towards herd immunity and thus fulfill its purpose of helping people achieve lifelong wellbeing.

9 Appendices

9.1 Appendix A. Estimated cost for weekly COVID tests

Total Cost = Cost of toolkit * Annuity Adjustment

$$T_e = c_{tk} * \frac{1-(1+i)^{-nt}}{\mathrm{i}}$$

	Description	*Value Range*
T_e	Cost per employee	\$918.2 - \$39,026
c_{tk}	COVID test cost*	\$20 - \$850
i	Interest Rate	0.25% annually
t	Length of program**	1 year
nt	Total number of payments	52

Table 9 Figures used in COVID Test Cost Estimation

The Cost per employee

*The cost of a COVID test is highly fluctuant depending on the specific tool an employer tries to employ, according to research done be Johns Hopkins University of Medicine, cost of a test can range anywhere from $20 to $850 per test. (Sharfstein, 2021)

**We only estimated the cost for the length of our proposed deployment period, in reality, the cost could be more or less depending on how long President Biden keeps the new rule.

9.2 Appendix B: Sample Endorsement Campaign Design

Figure 15 sample of Mitt Romney endorsement campaign – highway billboard

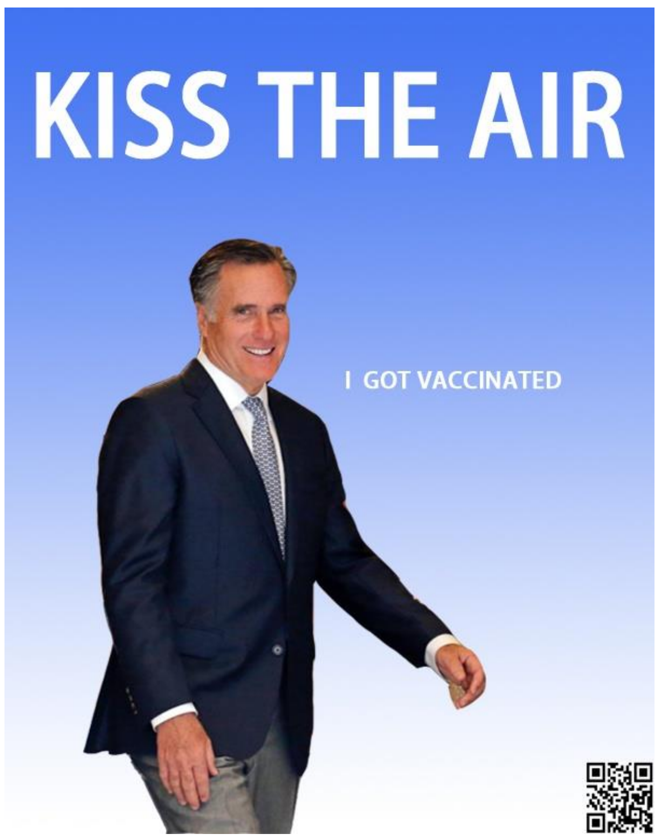


Figure 16 sample of Mitt Romney endorsement campaign – street banner

9.3 Appendix C: Supplementary Graphs and Charts

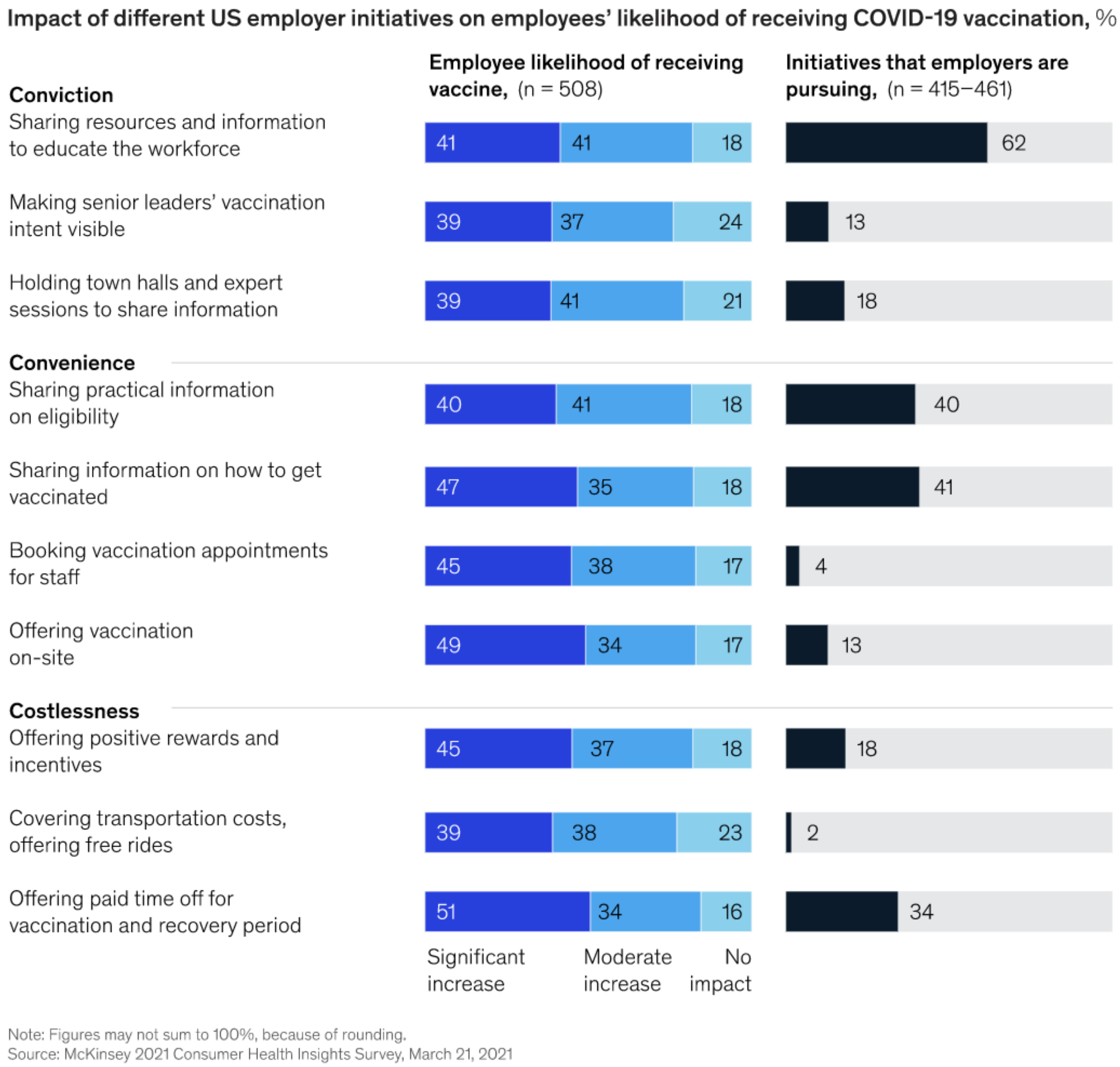


Figure 17 McKinsey Consumer Health Insights Survey

(Azimi & Cordina, 2021)

10 Works Cited

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