Humana-Mays Healthcare Analytics

2020 Case Competition

Social Determinants of Health Transportation Challenges

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1. Executive Summary

This study focused on helping Humana overcome the barrier to accessing care and achieving their best health due to Members facing Transportation Issues. Our goal was to develop a classification model to predict the likelihood of a patient experiencing Transportation Issues in the future. More importantly, we wanted to generate actionable insights and key indicators aligned to Humana's business needs.

For this study, firstly, we identified the target variable i.e.Transportation Issues (1 if the Member faces at least one Transportation Issue in the future, 0 otherwise) and we noticed the classes to be imbalanced. Secondly, we did some data preprocessing to drop highly correlated columns and to deal with NULL values to better capture the underlying trends in the data. After data processing, we tested different model architectures on our data to find the optimal model. We obtained the end result of our best performing classification model - LightGBM implementation of GBM with the optimised hyperparameters. We trained an Light GBM classifier using some hyperparameters, and got a Receiver Operating Characteristic (ROC) Area Under Curve (AUC) of 0.7402 and accuracy of 0.8557. We arrived at this model by maximising the ROC-AUC and minimising the False Positive Rate.

We discovered interesting insights and found that Member Age, Member Part D Spend, Member Disability Description and Member Credit History were among the most significant features. We also learnt that Total Maternity Admit Days did not matter in predicting Transportation Issues.

We then proposed 2 avenues for reducing these Transportation Issues - Bringing Patients to Healthcare and Bringing Healthcare to Patients. Some focus areas of the first pathway include - Chronic Diseases & Behavioral Health and Low Income Access to Affordable Healthcare. Some focus areas of the second pathway include - Using Community Health Workers and Care Coordinators.

By using the recommendations of our key indicators and model predictions, Humana will be able to save ~ $36 million annually in Reimbursements Costs. Humana will also undergo a Digital Transformation to improve their service offerings and have better Data Security; thus gaining a competitive advantage.

2. Case Background

Humana is a leading healthcare company that offers a wide array of insurance products and health & wellness services. It serves around 16.6 million members nationwide. Moreover, social Determinants of Health are a key component of Humana's integrated value-based health ecosystem. The aim of this analysis is to help Humana better understand the determinants or key-indicators of one such social determinant - 'Transportation Challenges' that prevent access to healthcare, and propose solutions for overcoming these barriers to accessing care and achieving their best health.

In order to understand the magnitude of the problem that Humana is tackling, it is worthwhile to look at a few statistics:

[1] Each year, 3.6 million people in the United States do not obtain medical care due to transportation issues. In 2017 alone, 5.8 million persons in the United States (1.8%) delayed medical care because they did not have transportation [2]. Transportation barriers to health care have a disproportionate impact on individuals who are poor and who have chronic conditions. These transportation barriers include lack of vehicle access, inadequate infrastructure, long distances and lengthy times to reach needed services, transportation costs and adverse policies that affect travel. Moreover, transportation challenges affect both rural and urban communities. Another research has shown that only 20 percent of health

can be attributed to medical care, while social and economic factors—like access to healthy food, housing status, educational attainment and access to transportation—account for 40 percent [3]. Therefore, it is necessary to make innovative progress and proactively address the issues due to inadequate transportation support, either by bringing the care to the patient, or by delivering patients to the places of care. This will assist members of the Humana insurance network in achieving their best health as well as aid Humana's vision of building upon their integrated value-based health ecosystem.

3. Data Preparation

3.1. Data Understanding

To perform our analysis, we were given a training dataset of 69,572 rows and 826 columns. The provided data was rolled-up at the customer level with information provided on 8 different types of events including demographics, medical claims, pharmacy claims, lab claims, credit data, cms features, condition related features and other features, with each event having its own set of attributes, for a total of 824 attributes. The age-range for 69,572 unique patients in the data was from age 18 to 101. Following are some of the data nuances that we observed during processing the data:

- The data was highly imbalanced with the target variable in the ratio of 59375 for class 0, i.e people who do not face any transportation issues; and 10197 for class 1, i.e. people who face transportation issues.
- Majority of the values for the field 'zip_cd' (58,571) listed as 'others'.
- The variable PDC value which represents the ratio of number of days the patient is covered by the medication in a period to the total number of days in the period, has a value greater than 1.

3.2. Target Modelling

Our aim is to identify the Humana Medicare Members who are most likely to experience a Transportation Issue and to propose relevant solutions for them to overcome this barrier to accessing care and achieving their best health.

These transportation issues include but are not limited to - medical appointments, meetings, work, and from getting things needed for daily living.

Any member experiencing a transportation issue at least once anytime in the future would come up as a positive outcome.

3.3 Feature Engineering

We explored and extracted those feature columns where the variance was greater than zero. Columns which have a variance of zero do not influence the target features of ‘transportation_issues’. Hence, we removed the following feature columns:

- 'Med_ip_ltach_admit_days_pmpm',
- 'Med_ip_maternity_admit_days_pmpm',
- 'Med_ip_mhsa_admit_days_pmpm',
- ‘Total_ip_ltach_admit_days_pmpm',
- ‘Total_ip_maternity_admit_days_pmpm',
- 'Hlth_pgm_slvrsnkr_refer_status','hedis_ami'

Next, we segregated the features as numerical and categorical features. Some examples of the Numerical features were the Credit_ and Count_ features. For the categorical variables we included features such as Indicator Features, Sex_cd, FCI_score, and Est_age to name a few. We handled each numerical and categorical features in a different way.

For the numerical features:

- We imputed the missing features values ‘Na’, based on the number of outliers. For features with a high number of outliers, we replaced their missing values with the Median Value, and for the rest of the numerical features, we replaced the missing values with the Mean of the rest of the values for that feature.

For the categorical features:

- We divided our estimated age into self_defined bins from age 18 to 101, with intervals of 5 years. This was followed by label encoding the bins to preserve ordinality. For the handling of missing features values ‘Na’, we created a new label 0.0, to give it least weightage as per the ordinality.
- For categorical features, we imputed the missing values such as ‘*’ or ‘Na’, with a new Category _X. We also dropped some features with a very high number of missing values such as 'state_cd' , 'cnty_cd' , 'zip_cd'.
- We used label-encoding for features which had ordinality and one-hot encoding for the rest of the variables.

Finally, for selecting the features we created a correlation matrix and a heatmap. We removed the feature pairs which had high absolute correlation (>0.8) and we selected only one of the features from the pair. For eg: ‘med_ip_snf_admit_ct_pmpm’ is highly correlated with ‘total_ip_snf_admit_ct_pmpm’ and the value is 0.9590506444783953, we kept only one of these features.

4. Modelling

We tried the following 3 models on our dataset:

1. Weighted Random Forest
2. Weighted XGBoost
3. LightGBM

For modelling our dataset, we trained all our models on a 80-20 train-test split, with 5 fold cross-validation. To validate our model we used the accuracy, ROC-AOC metric and the log-loss metric since our problem is a binary classification problem. Our focus was to minimize the number of false positives.

<u>Weighted Random Forest</u>

We used the Weighted Random Forest Classifier on our dataset in order to deal with the high dimensionality of the data, as well as the imbalance with respect to the target class. This model generates an internal unbiased estimate of the generalization error as the forest building progresses, and it combines more than one algorithms of the same or different kind for classifying objects, and hence is an ensemble technique. It runs on the principle of individual decision tree prediction on a subset of features and then taking vote for final consideration of class for test object. Weighted Random Forest Classifier can handle thousands of input variables without variable deletion. It also provides estimates of the variable importance in the classification.

For our model, the hyperparameters which gave us the highest values of ROC-AUC were:

n_estimators = 100

random_state = 0,

criterion = 'entropy',

class_weight="balanced"

After training our model, and using the model to predict the output on our test data, we got the following validation values:

Accuracy = 0.8528206970894718

Log-loss = 0.3790863283715298

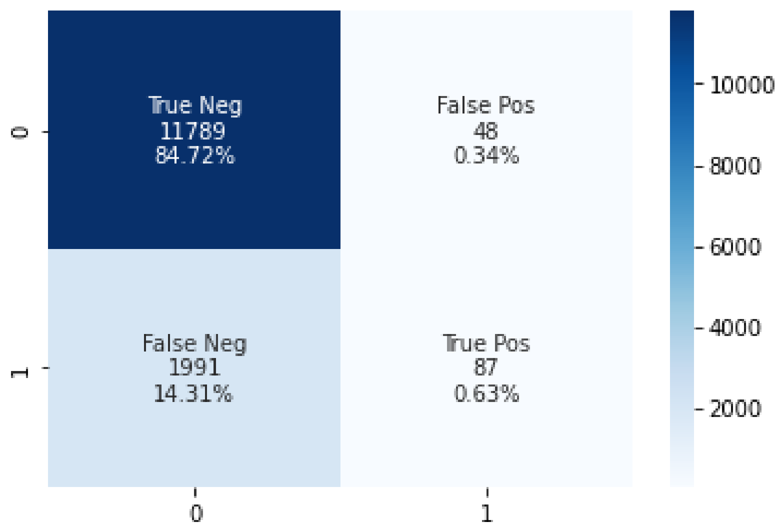


Fig 1.Confusion Matrix for Classification with Weighted Random Forest Model

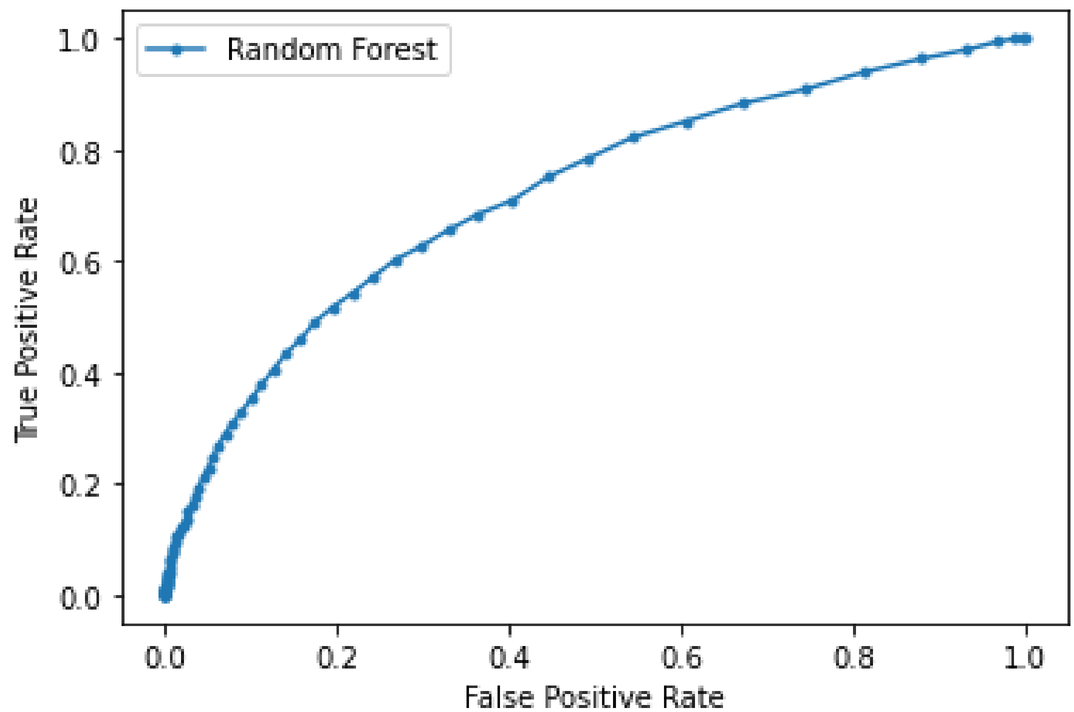


Fig 2. ROC-AUC Curve for Classification with Weighted Random Forest Model

ROC-AUC = 0.7278988625005214

XGBoost

The XGBoost model is an efficient implementation of the stochastic gradient boosting algorithm. This modified version of XGBoost is referred to as Class Weighted XGBoost or Cost-Sensitive XGBoost and can offer better performance on binary classification problems with a severe class imbalance. Boosting takes slower steps, making predictors sequentially instead of independently. It repetitively leverages the patterns in residuals, strengthens the model with weak predictions, and makes it better. By combining the advantages from both random forest and gradient boosting, XGBoost gave a higher accuracy as well as ROC-AUC value compared to weighted random forests. It also gave a lower value of log-loss error, and hence proved to be a better model for analysis than Weighted Random Forest on our dataset overall. XGBoost also provides estimates of the variable importance in the classification.

For our model, the hyperparameters which gave us the highest values of value of ROC-AUC were the default hyperparameters. After training our model, and using the model to predict the output on our test data, we got the following validation values:

Accuracy = 0.8551922385914481

Log-loss = 0.3697201494403261

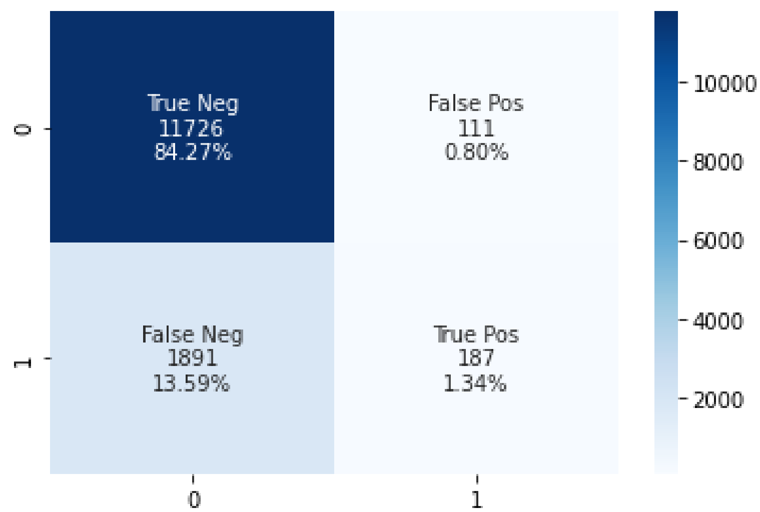


Fig 3.Confusion Matrix for Classification with XGBoost Model

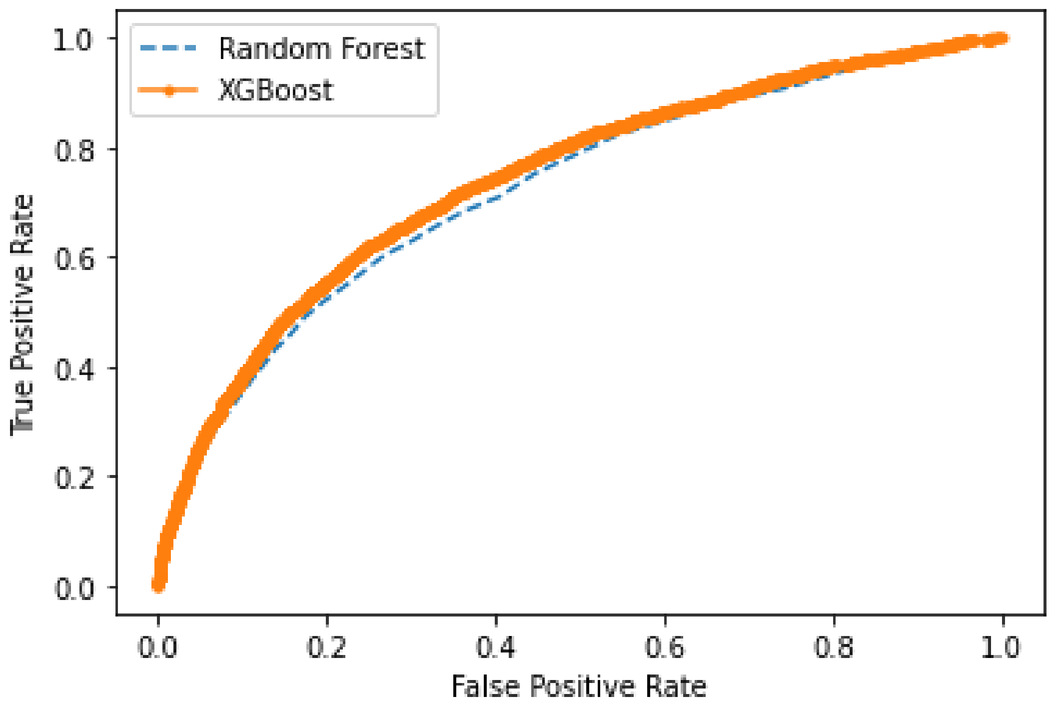


Fig 4. ROC-AUC Curve for Classification with XGBoost Model and Weighted Random Forest Model

ROC-AUC = 0.7378278462281

LightGBM

LightGBM uses a novel technique of Gradient-based One-Side Sampling (GOSS) to filter out the data instances for finding a split value while XGBoost uses a pre-sorted algorithm & Histogram-based algorithm for computing the best split. Histogram-based algorithm splits all the data points for a feature into discrete bins and uses these bins to find the split value of histogram. LightGBM can also handle categorical features by taking the input of feature names. It does not convert to one-hot coding, and is much faster than one-hot coding. However, for our dataset, without one-hot encoding the categorical features the LightGBM model did not produce very accurate results. We believe that is because it uses some kind of modified mean encoding for categorical data which caused overfitting. Hence, we input one-hot encoded categorical features similar to the other models we used.

Moreover, it achieves a high accuracy with much faster speed as compared to the XGBoost and Weighted Random Forest Classifier.

For our model, the hyperparameters which gave us the highest values of value of ROC-AUC were:

params['learning_rate']=0.02

params['num_leaves']: 1000

params['is_unbalance'] = False

params['boosting_type']='gbdt' #GradientBoostingDecisionTree

params['objective']='binary' #Binary target feature

params['metric']='binary_logloss' #metric for binary classification

params['max_depth']=30

params['min_child_samples']: 78

params['lambda_l1']: 4.5710796637344755

params['lambda_l2']: 2.9721923015218796

params['num_leaves']: 31

params['feature_fraction']: 0.7822395507451473

params['bagging_fraction']: 0.5614815105648284

params['bagging_freq']: 6

After training our model, and using the model to predict the output on our test data, we got the following validation values:

Accuracy = 0.8557671577434424

Log-loss = 0.3700827202424268

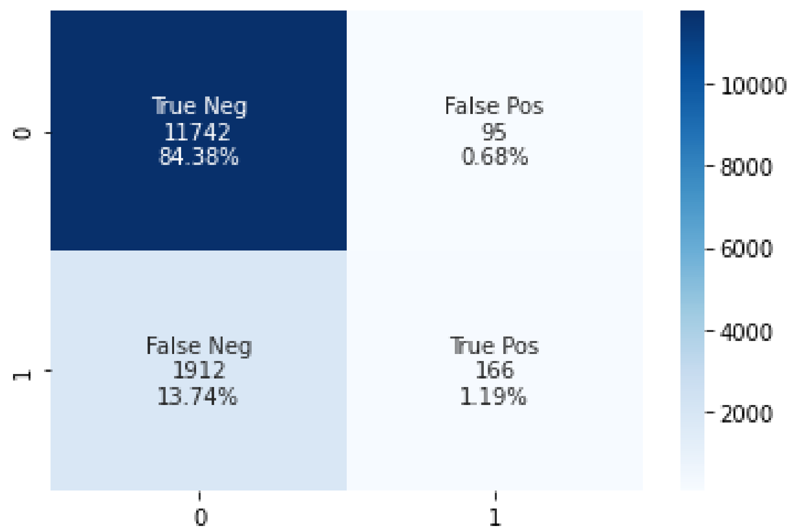


Fig 5.Confusion Matrix for Classification with LightGBM Model

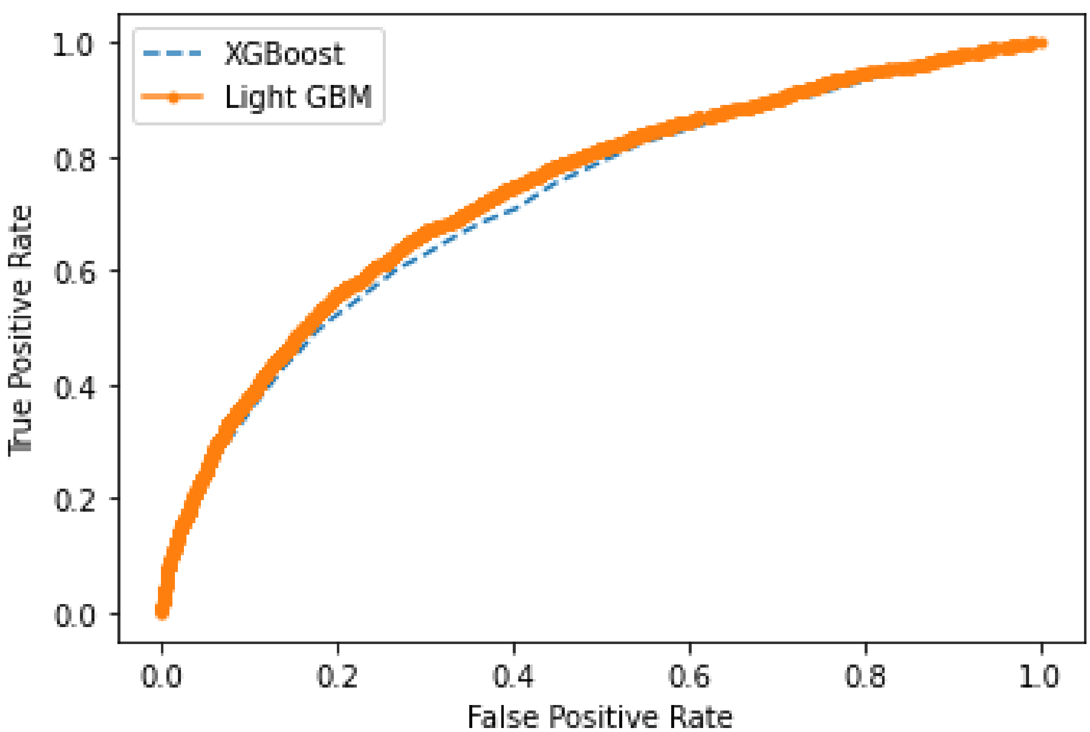


Fig 6. ROC-AUC Curve for Classification with LightGBM Model in comparison with XGBoost Model

ROC-AUC = 0.7402235352306754

The LightGBM model performed better than the XGBoost and produced higher accuracy and higher ROC-AUC values, albeit slightly. Furthermore, as seen from the confusion matrices, the LightGBM model produces a lower number of False Positives when compared to XGBoost, 95 as compared to 111. Hence, we can firmly state that the LightGBM model gave us the best result out of the 3 models.

OVERSAMPLING USING SMOTE:

In order to improve the accuracy of the minority class prediction, we used the data augmentation technique of Synthetic Minority Oversampling Technique, or SMOTE. SMOTE works by selecting examples that are close to the minority class in the feature space, by drawing a line between the examples in the feature space and drawing a new sample at a point along that line.

We applied the SMOTE technique and fed this balanced data into Random Forests, XGBoost and Light GBM. We achieved 90%+ accuracy, ROC-AUC scores > 0.90. However, after some visual analysis and cross validation tests, we concluded that our SMOTE models were not generalized as they suffered from extreme overfitting.

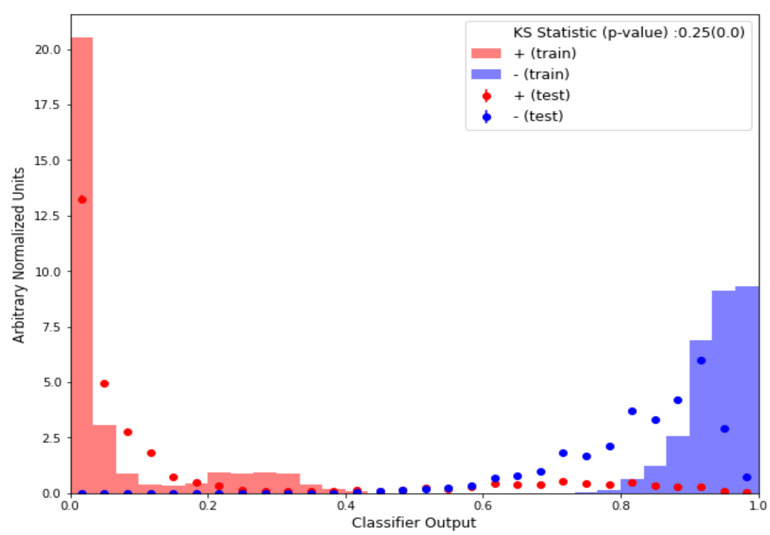


Fig 7. Overfitting shown through KS Statistic Graph for XGBoost

	Random Forest (SMOTE)	Random Forest	XGBoost (SMOTE)	XGBoost	LightGBM (SMOTE)	LightGBM
Accuracy	0.916	0.853	0.916	0.855	0.915	0.856
ROC-AUC Score	0.960	0.728	0.956	0.738	0.956	0.740
False Positive Rate	0.0071	0.0023	0.0075	0.0091	0.0082	0.0080

Table 1: Evaluation Metric Chart for Models

5. Key Performance Indicator Analysis:

5.1. Overall Feature Importance

In order to interpret the effects of the different features on the probability of Transportation Issues, we decided to go forward with a LightGBM Feature Importance Plot.

The following chart illustrates the overall feature importance of the top 50 most impactful features as identified by our model. Their importance was calculated based on the 'Split Value' - The Number of Times a Feature is used in the LightGBM Tree.

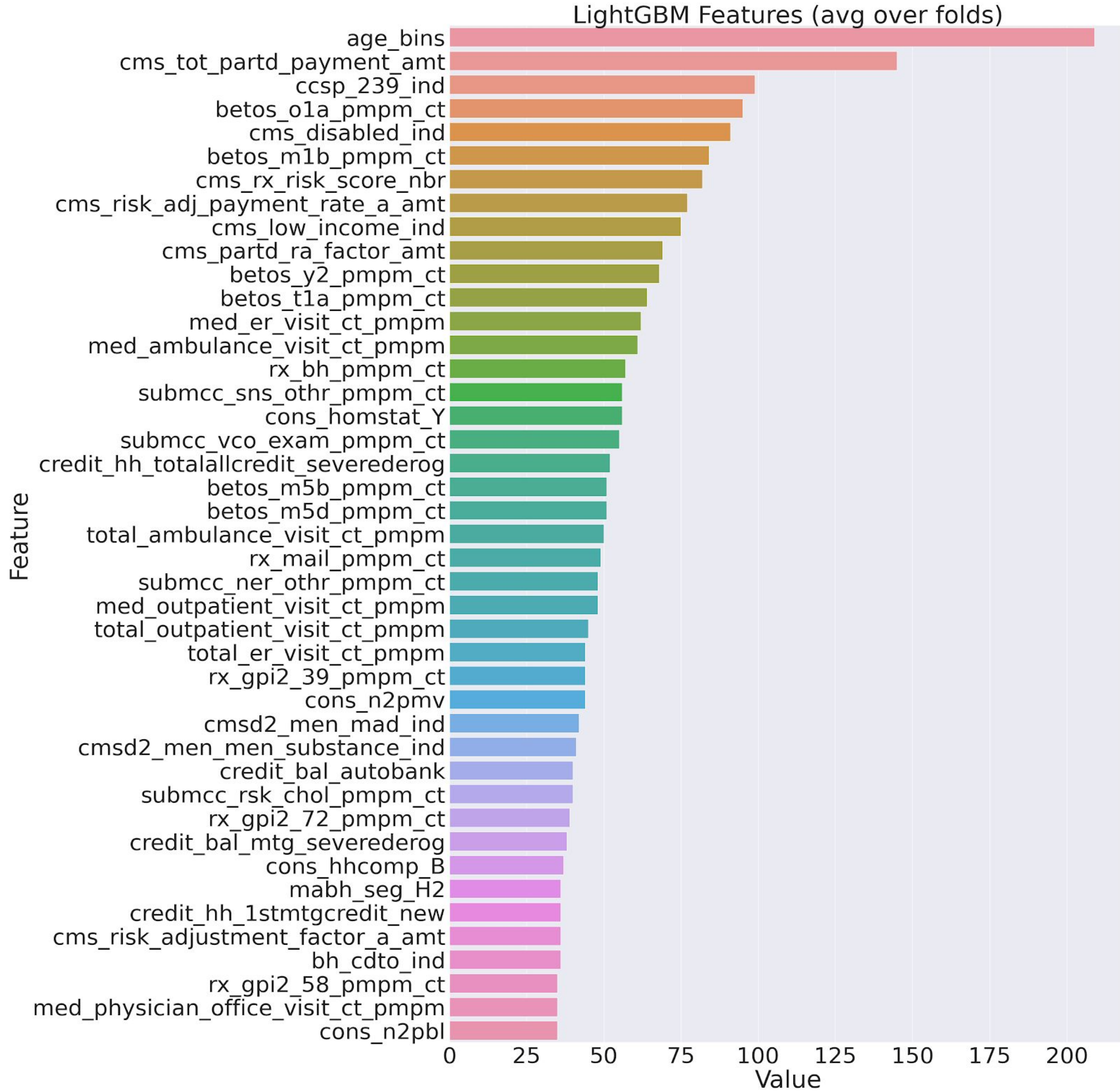


Fig 8. 50 most important features by the LightGMB.feature_importance function

Some important features learned by our model are - Member Age, Member Part D Spend, Member Disability Description and Member Credit History.

5.2. Relationship with the Response Variable

Below, we have presented some features that seem to align well with the business definition and look like key determinants of transportation issues. Thus, these plots help provide an initial validation to our model.

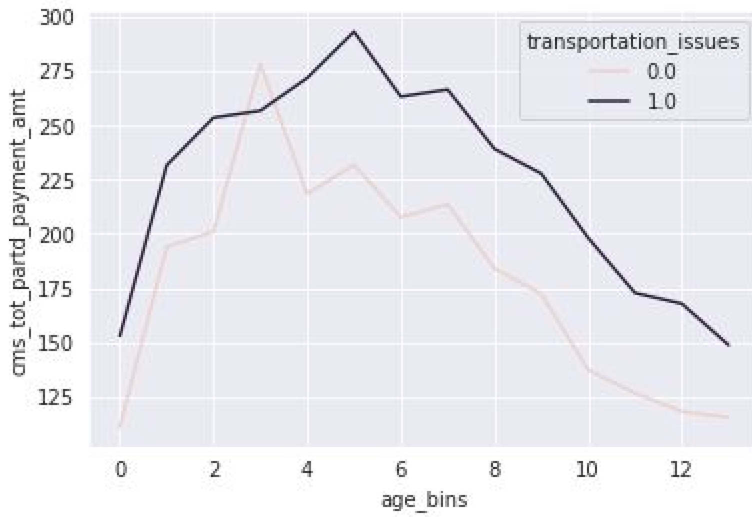


Figure 9: Average CMS Total part-d payment amount VS. age_bins

The average CMS Total PART-D Payment Amount is relatively higher for members who have Transportation Issues in most age groups. However, for the age group 35-40 years (Age Bin 3), the average CMS Total PART-D Payment Amount is more for the people without transportation issues. Overall, members with transportation issues are those who belong to the age group of 45-50 years and have the maximum average CMS Total PART-D Payment Amount.

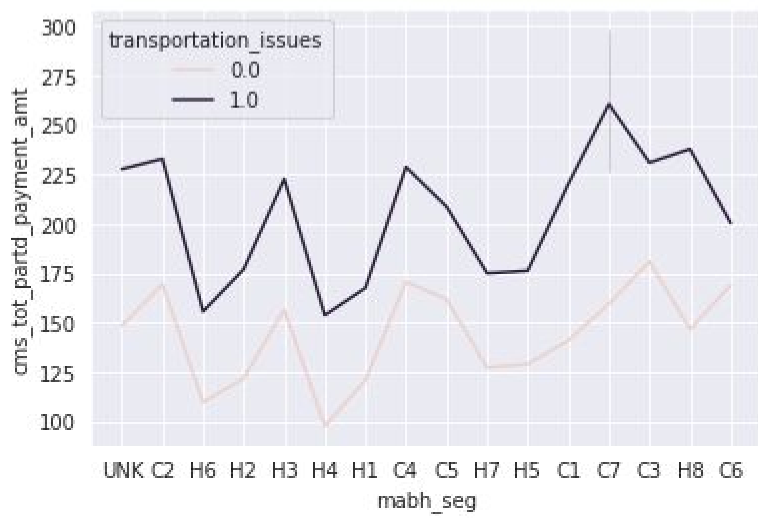


Figure 10: Average CMS Total part-d payment amount VS. mabh_seg

The average CMS Total PART-D Payment Amount is relatively higher for members who have Transportation Issues across all the MABH Segments. Majority average amount peaks exist for the people who have Chronic Conditions. Among the people with transportation issues, the maximum average CMS Total PART-D Payment Amount is highest for Chronic Overwhelmed and Reluctant Reactors. Among the people without transportation issues, the maximum average CMS Total PART-D Payment Amount is highest for Chronic Health Services Maximizers. People in the C7 category who are overwhelmed and reluctant reactors with chronic illness, have ‘High’ activity on the web, ‘Medium’ inbound calls and ‘Low’ preventive visits. [4]

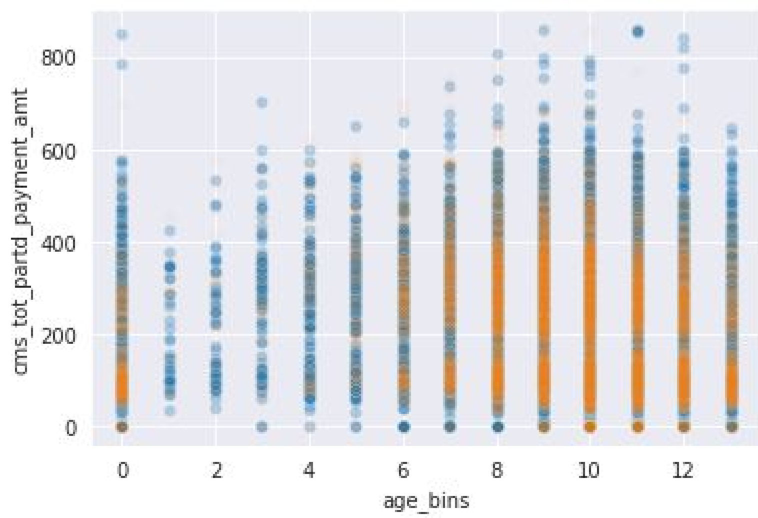


Figure 11: CMS Total part-d payment amount VS. age_bins

People in age groups 65-85 years (Age Bins: 8-12) and having an CMS Total PART-D Payment Amount below $400 - have the maximum transportation issues.

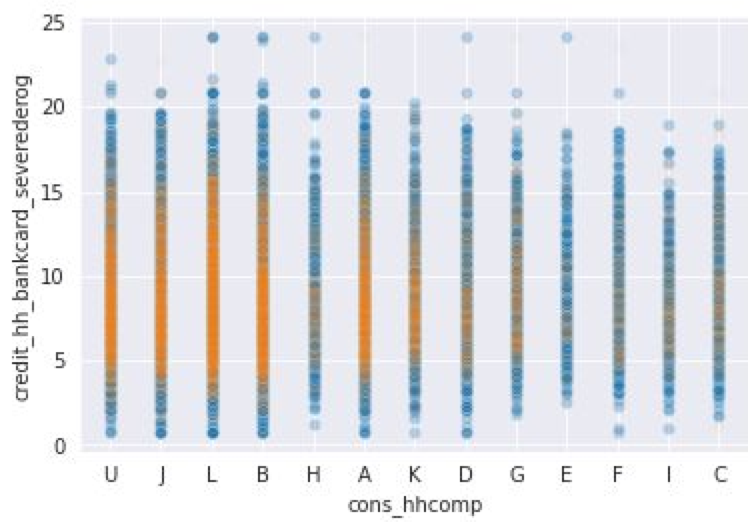


Figure 12: credit_hh_bankcard_severederog VS. cons_hhcomp

People who are in house composition categories J, L, B, A, and with 'Severe Derogatory' credit status on all their household credit accounts between 5 - 15% - have maximum transportation issues. These household categories encompass people who are either male person(J) or female person(L) with no children present, married(husband & wife) with no children(B) and children present (A).

6. Business Value Creation for Humana

6.1 Introduction

As referenced earlier, each year, 3.6 million people in the United States do not obtain medical care due to transportation issues. The transportation challenges affect healthcare consumers both, in rural and urban communities. Moreover, healthcare consumers today are gaining control over how - and with whom - they spend their healthcare dollars, and have become more empowered than ever before. These new-age customers want better products, higher quality service and a better overall experience with healthcare payers.

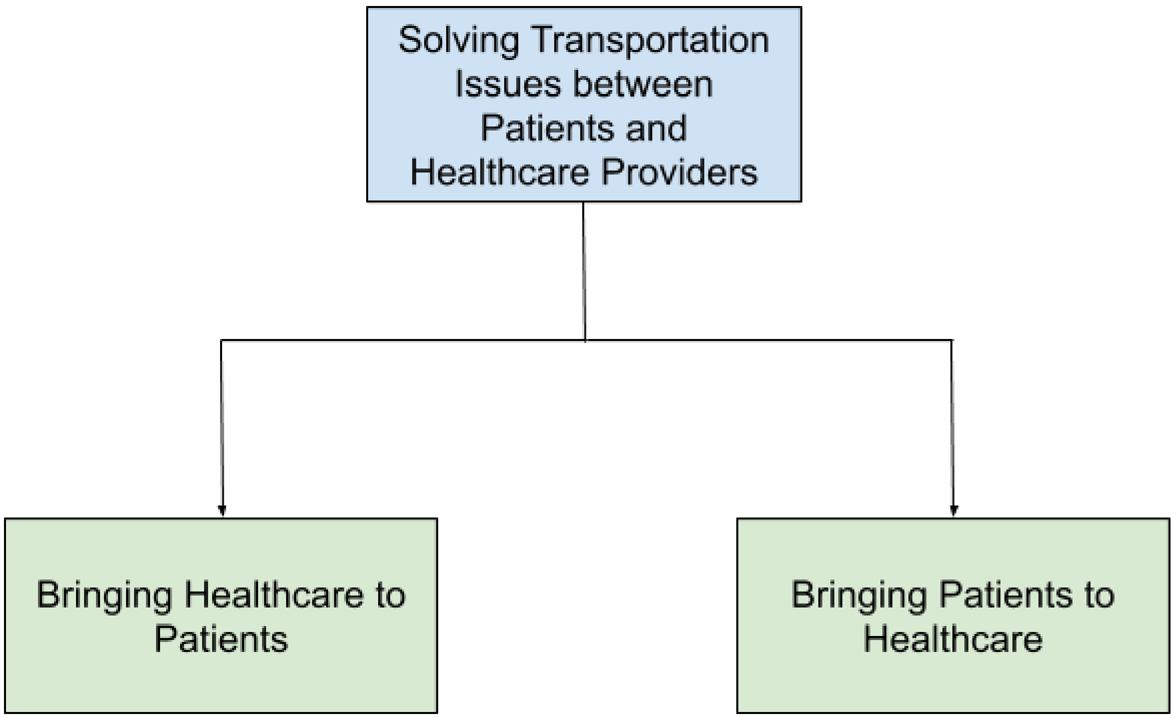
As seen from our analysis, people with chronic conditions, disability, high-debts and those who are elderly face the greatest barrier in accessing healthcare due to transportation issues. In addition to overcoming these transportation barriers, an increasing focus on customer experience is at the heart of transformation. The healthcare landscape is more competitive than ever before with an increased focus on providing better service offerings.

Figure 13. Changing Healthcare Landscape

Some Key Statistics [11]

- 59% of healthcare consumers want to see their healthcare experiences reflect those they have in the retail space
- 78% of respondents said digital consumer experience needs improved technological support
- 50% said they would leave their current providers for one that promises better technology

It has now become more necessary than ever to increase the accessibility to healthcare services, and not rely solely on the age-old hospital visit practice. In order to bridge the accessibility gap, we need to take advantage of digitization by using virtual means to bring healthcare to patients, and more efficiently utilize pre-existing resources to overcome the physical transportation barriers in bringing the patients to healthcare.



6.2 Bringing Healthcare to Patients - Virtual Health

Virtual Healthcare is instrumental in alleviating the distance and transportation barriers involved in healthcare. While virtual healthcare adoption has been slower in the past, COVID 19 has been a catalyst in its widespread adoption. Some known telemedicine service offerings are home monitoring, chronic care management, e-ICUs, emergency care, long-term care, online therapy and counseling, telepharmacy services, interpreter services, and patient-provider communication facilitation.

Virtual Healthcare can be categorized into the following:

- **Synchronous**: Live interaction based services between providers and patients eg: Video Call

- **Asynchronous**: Amongst providers and provider-to-patient transfer of health history and patient information eg: Electronic Health Records to generate patient phenotypes such as skin disease reporting through Smart Phone Camera, vitals transmission, health tracking and medication adherence.

Widespread Expansion and Adoption of Virtual Healthcare in the healthcare service workflow can be a very promising solution for combating the transportation barriers among members.

Chronic Diseases and Behavioral Health:
On the basis of our data analysis and features contributing to our prediction, we observed that Heart, Diabetes, behavioral health and psychiatry are amongst the major reasons contributing towards transportation issues. People in the C7 category who are overwhelmed and reluctant reactors with chronic illness, have ‘High’ activity on the web, ‘Medium’ inbound calls and ‘Low’ preventive visits.

Chronic care management (including mental health conditions). Healthcare utilization is more than twice as high among chronic disease patients as among those without chronic disease; inpatient utilization is as much as four-fold higher. Chronic conditions compound the stress on patients to attend frequent appointments, undergo regular diagnostics, and maintain complex medication regimens.

Solutions:
- Enabling home-based diagnostics and equipment
- Virtual applications, interoperability with systems of engagement (for example, electronic health record, revenue cycle, digital front door) and supporting infrastructure.
- Blood glucose monitors or Bluetooth-enabled blood pressure cuffs

Low Income Access to Affordable healthcare:
On the basis of our data analysis and features contributing to our prediction, we observed that Low Income Subsidy Availing status, Motor Vehicle Ownership, Household Composition and Homeownership Status are among the major reasons contributing towards transportation issues.

According to the CDC, more than 13 million patients in 2017 went without care in just one year. The reasons why people are not able to avail the benefits of programs such as Medicare and Medicaid can be attributed to the lack of awareness about their eligibility to avail such benefits.

Solutions:

- Increase awareness of telehealth as a convenient, and affordable method of treatment for the elderly and people in rural area and people with low income
- Reach to accessible, cheap gadgets and technology devices such as smartphone and tablets possessed by some family members
- Free Internet access through community wifi hotspots or libraries

Ambulatory, Acute & Routine Test Workflows:
Our model suggests a high contribution of Count of Logical Claims for Ambulatory Services, Medical and BH Ambulance Visits, Routine Venipuncture and VCO Exams towards the prediction of Transportation Issues.

Virtual healthcare includes clinical assessment and treatment for non-life-threatening concerns reducing the pressure on ambulatory and Medical Testing services
Solutions:

- Telephone triage - disposition of symptoms via smartphone by experienced clinicians and licensed medical professionals.
- Problem-solving strategies eg: pattern recognition, assessment to formulate a working diagnosis.
- Electronic intensive care unit (e-ICU) programs, allowing nurses and physicians to remotely monitor the status multiple patients in ICUs in multiple hospitals
- On the wheel Medical Testing Facilities

Secure Digital Identity and blockchain based services:
A broader ecosystem with virtual care is challenging within the limits of current identity management, patient matching and data provenance issues, blocking the trust needed for providers to collaborate on care delivery in this increasingly distributed environment. It also poses increasing challenges as patients expand the types of encounters and providers they engage in, as well as where their data resides.

A blockchain based system would help establish a **digital patient identity.** This encrypted digital identity, would contain the entire medical history for the patient, and would enable them to share it directly with a registered medical practitioner after authorization. For the patient, ability to share and manage their own health records through.a digital identity also provides on-the-go access to healthcare services and prescriptions. For Humana, a secure digital identity would introduce identity verification, and thus eliminate identity fraud.

Blockchain's capabilities can help ensure accuracy, verification and immutability in the secured access for the following data types, which also align for data included in virtual care services:

- Individual transaction information, such as patient name, provider credentials, device identifiers, billing and reimbursement codes
- Transaction ownership timeline, or data provenance, such as sequence of diagnostic services provided and location of services provided
- Transaction verification statement, such as guaranteeing that data access is only granted to authorized parties and streamlining the reimbursement audit process

For the system as a whole, a blockchain based system would streamline claims processing with greater transparency and enable provider interoperability, and would be beneficial for Humana. Moreover, this would make the stored data highly secured, and prevent confidential patient data leaks through hacks.

6.3 Bringing Patients to Healthcare:

After a diagnosis via virtual means such as telehealth, some patients would still need to avail the services of an hospital in person due to major complication and diseases, requirement of physical specialized tests or equipment. To do so, in a quick and effective manner, without breaking the bank, much thought is needed to be put into increasing the efficiency of use of pre-existing resources.

Community Health Workers:
In order to tackle the issues of healthcare access for patients due to transportation issues, healthcare providers employ community health workers (CHWs). CHWs with healthcare backgrounds assist patients in navigating the entire health care system. CHWs can also engage in transportation coordination for patients.They can help patients in transportation to and from appointments, motivate them to implement good lifestyle habits and take medications. However, the issue arises that the patients have little to no means of connecting to such CHWs.

Hospitals and physicians aso use care coordinators, who are trained in the healthcare field and are most often social workers or nurses. These healthcare coordinators cater to chronically ill or low-income patients with understanding their care plans. They also help the patients schedule primary care visits, thus reducing the trips to the E.R.

Solution: Establish a platform for network healthcare providers to enable communication among CHWs and care coordinators, healthcare providers and the members of Humana (patients).

Healthcare for Disabled:
We realised the high contribution of Disability, Substance Consumption and Tobacco Consumption Disorder factors to our model to predict the transportation issues. 40% of the total senior population in the US has at least one disability. In addition, the CDC reports that one in 4 US adults is living with a disability and mobility issues are most common.

Solution: Humana can deploy awareness and information programs to educate specifically the disable people about healthcare services, catering to their special needs.

Non-emergency medical Transport:
Humana offers Non-emergency medical Transport (NEMT) as a benefit on a limited number of MA plans and all Medicaid plans. This service in essence solves the transportation limitations with a providing direct transportation service to the patient, although its practical use is limited to efficiency and ease of scheduling such a ride. Most elderly and low-income patients who rely on such services are currently unaware [10] of the existence of such service, or its long-scheduling times.

Solution: Increase awareness of the patients about the NEMT service and provide a user-friendly and optimized scheduling application, with less wait times. Access to such service would have a profound impact on resolving the transportation issues for patients largely unaware of such service.

6.4 Potential Business Impact

Number of people facing Transportation Issues per year in US: 3.6 Million **(A)**

[5] Humana's Market Share in US (2019): 8.4% **(B)**

Humana members facing Transportation Issues per year in US: 302,400 **(A*B)**

[6]Average Reimbursement per member per year: $ 3,857 **(C)**

Assuming 15% (conservative estimate based on point 26 in [7]) members do not need hospitalisation after a video consultation. **(D)**

Total Number of Telehealth Visits [8] per year: 22 million: **(E)**

Total Number of Telehealth Users at Humana: 1.848 million **(F)=(B*E)**

Telehealth cost per visit: $38 **(G)**

Total Telehealth cost per year: $70.3 million **(H) = (G*F)**

Telehealth Integration Cost - Blockchain[9]: $ 44 Million **(I)**

Telehealth Setup Cost - Medical Devices: $ 25 Million **(J)**

Total Reimbursement Amount Saved: $ 175 Million **(A*B*C*D)**

Total Costs: $ 139.3 Million **(H+I+J)**

<u>Reimbursement Amount Saved per year: $35.7 Million</u> **((A*B*C*D)-(H+I+J))**

7. Stakeholder Analysis

	Member	Humana	Hospital
Advantages	Transparent Process Stay-at-Home Comfort Early Diagnosis Medical Data Consolidation Cost Saving (Potential)	Reduced Reimbursements Digital Transformation Better Service Offering Improved Data Security More Active Customer Base Competitive Advantage	More Active Customer Base Enhanced Patient Tracking Medical Data Consolidation Resource Distribution
Disadvantages	Increased Premium (Potential)	Infrastructure Setup Establish Hospital Tie-Ups	Infrastructure Setup

Table 2. Stakeholder Analysis

8. References

[1] https://journals.sagepub.com/doi/abs/10.1177/0361198105192400110

[2] https://ajph.aphapublications.org/doi/10.2105/AJPH.2020.305579.

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