Targeted Wellness Benefits Promotion

Maximizing the impact of benefits programs on member health

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ABSTRACT

Health and Welfare benefits offered by employers in the United States can be complex and difficult for employees to understand. The benefits available and how and when to use them are often not well understood by employees, and therefore are often underutilized. When employees fail to take full advantage of available benefits, they may pay more for health care out-of-pocket or miss out on valuable benefits entirely. For employers, underutilized benefits represent a poor return on the sizable investment of offering them.

The complexity of benefits offerings makes it difficult for employees to understand what benefits are available, how and why to enroll in them, and how to optimize usage based on their personal situations. Dense, technical language used to describe benefits creates an additional barrier.

This study will use data collected by the Behavioral Risk Factor Surveillance System (BRFSS) to to help address this problem. This is a national telephone survey collecting data from participants about high risk behaviors and health outcomes. I propose that, using this data, we can identify correlations between behaviors and outcomes, and use those connections to help employees identify and use the benefits available to them tailored to their personal health situations. If we can ask employees about their personal health situation, we can identify which benefits are available to them that can help most impact their overall health and wellness. I'm also proposing that we can find the minimal amount of data to collect from an employee, so that they can get recommendations with the least amount of effort and data exposure as possible.

INTRODUCTION

1 Problem

Benefits are presented to employees as a large menu of options they have to enroll in. Enrollment often happens only once a year, and can be a complex and overwhelming process. Information about benefits offerings are typically presented with technical insurance terminology that employees have difficulty understanding. These complexities are a large barrier to employees understanding the benefits that are available to them, and what their best options are to use them. In addition, employees often have benefits available to them through their employer at no cost to them. These ancillary benefits are often underutilized, usually because employees don't know that they have these benefits, or they don't know that the benefits apply to their personal situation.

This project will tackle this problem by trying to identify risk factors that employees might be able provide that we can use to promote benefits that are best suited for an employees specific, personal situation.

2 Importance

Benefits are expensive for employers to offer, and getting the best return on investment, while also providing lucrative benefits offerings to their employees is a constant balance for human resources teams.

Health and welfare is also expensive and complicated for employees to navigate. Providing easier methods for employees to identify the best options for them and to take advantage of the benefits they already have can save them money and improve their overall health and wellness.

3 Limitations of Existing Solutions

Benefits administration companies often offer tools to employees called Decision Support tools. These take some information about an employee, usually from simple questions asked about whether an employee expects specific medical procedures, or what their expected medical expenditures are for the upcoming year. Using this information, they provide some recommendations for what benefits would be best for the employee.

These tools have some problems, however. They focus mainly on Medical enrollment, missing all of the other benefits available to the employee, such as Employee Assistance Programs, Telemedicine benefits, Critical Illness insurance, etc. These tools also almost exclusively focus on initial enrollment in benefits rather than how an employee can use their benefits once they are enrolled. Therefore, the scope of these tools and the help they offer the employee is limited. In addition, these tools ask employees to forecast for the upcoming year, which is often challenging to do.

4 Contribution

This project will use the BRFSS data to help identify risk factors based on employee's current situations. Using that data, we can help employees identify benefits most appropriate for them.

RELATED WORK

There are a number of studies that have been conducted using the BRFSS data:

1 Correlative Analysis

- A 2023 study published in the Journal of Public Health and Emergency used the 2020 BRFSS dataset to investigate the association between adverse childhood experiences (ACEs) and self-reported mental health conditions in adults [1]
- A 2019 study published in Preventing Chronic Disease used BRFSS data to assess the prevalence of subjective cognitive decline in adults aged 45 years or older in 49 states [2]

2 Machine Learning Algorithms

- A 2023 study published in Patterns used the 2021 BRFSS dataset to investigate machine learning algorithms and data augmentation techniques for predicting chronic kidney disease [3]

This project will build on this by applying similar methods to the specific industry problem of collecting behavioral data from employees and health outcomes to help them connect to welfare benefits that will be most relevant to them.

PROPOSED WORK

1 Data Source

I will use the 2022 Behavioral Risk Factor Surveillance System (BRFSS) data for this project. [4]. The 2022 BRFSS data contains 445,132 records, one per survey conducted. Each survey conducted has 326 columns, where a majority of this data correspond to the response to a question asked within the survey. Each set of questions is also assigned a general category that may be useful for analysis.

2 Data Preparation & Exploratory Data Analysis

The 2022 BRFSS data consists of 326 columns numerically encoded. Because the data is encoded, it is difficult to read without referring back to a code book. I will begin EDA by transforming the numerical data into readable and interpretable values. These values will be extracted from the codebook.

The survey data doesn't specifically label which questions are behavioral in nature versus which are health outcomes. I will work through all of the questions in the survey and annotate each as either a health outcome or not. I will also align each health outcome to a common health and welfare benefit offered by employers.

I will continue by performing some simple EDA by exploring the data and values to better understand the questions and answers provided.

3 Data Mining Techniques

I intend to use the following data mining methods:

- Clustering
  I intend on using clustering to attempt to identify groups of survey results that are likely to lead to specific health outcomes.
- Association Rule Mining
  Using methods like FP-Growth and Association Rule Mining can help identify survey answers that most likely result in a specific health outcome.
- Classification
  I would like to build decision tree models that attempt to classify specific health outcomes. Decision trees will provide both a classification method, but also explainable parameters we can use to determine specific health outcomes.

4 Tools

I will be working primarily in Python. I will be using Pandas, sklearn, and Plotly as my primary libraries for this project.

EVALUATION

1 Evaluation Metrics

To evaluate each of the specific methods above:

For clustering, I intend on using silhouette coefficients to analyze how well the clustering methods perform.

For association rule mining, using support and confidence will provide methods of identifying the most relevant rules.

For classification, accuracy, precision, recall, and F1 scores will be the standard evaluation methods. In addition, a confusion matrix will help evaluate model performance.

To measure the overall success of the project, I'll be using my own domain knowledge of the problem space to evaluate whether my methods are successful. Success, here, will be determined by if we can accurately determine health outcomes and associated health and welfare benefits using behavioral questions. Implementation will also be important. Determining whether the methods can be reasonably implemented in a real-world setting is critical.

2 Experimental Setup

For methods that require training and testing, I will be using the standard 80/20 test/train split.

I will also focus in on specific health outcomes and question categories to identify specific associations and correlations.

RESULTS

1 Data Preparation

This data required multiple preparation and cleaning steps. A majority of the data are primarily survey questions with limited answers valid answers. Each answer is encoded as an integer value. In addition, the columns are represented as short, coded values that don't have a lot of intuitive meaning.

A codebook is provided with the dataset, which is an HTML file containing descriptions of each variable and descriptions of all values for that variable. In order to translate the data to something more easily read and understood, I scraped the descriptions and valid values from the codebook. I then replaced the column names and values in the file with the valid value descriptions.

In addition, there are some columns that are both numeric and categorical. I translated the categorical answers to numeric representations so the data in each column would be uniform type.

I also manually labelled each question as either being related to a health outcome (such as a specific condition) vs. not being relations to a health outcome.

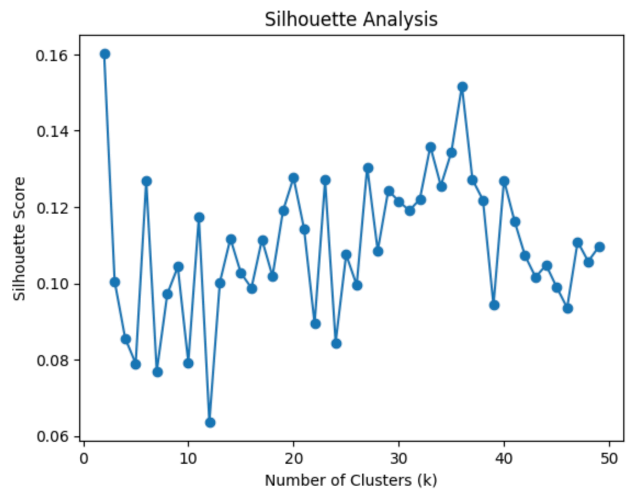
2 Clustering

My first attempt at clustering this data was to apply hierarchical clustering using Gower's Distance as my distance metric (as this data is primarily categorical, with some numerical variables). The number of records and columns in this data, however, proved this approach intractable. This method was incredibly memory intensive, and I could not proceed with this method on available hardware.

I then moved to a mini-batch K-Means approach. For this method, I selected the categorical columns, then applied MCA to reduce the dimensionality dramatically. Mini-batch K-Means was then applied to the reduced data. I experimented with two main hyperparameters: the number of MCA components to reduce to and k. I used silhouette score to determine the best k. Two of the attempts did have k=2 clusters as the highest Silhouette Score, however I discarded these since 2 clusters is not practically enough to describe this population.

Number Components	Attempted K's	Best K	Silhouette Score
20	1-50	37	0.210
30	1-50	34	0.167
40	1-50	36	0.151

Silhouette analysis for Number Components = 30



Clustering, however, did not yield successful interpretable results. I attempted to interpret the clusters generated by training a decision tree using the data as features and the assigned cluster as labels, intending on using the decision tree criteria to interpret each cluster. The decision tree, however, was not sufficient to intuitively provide a description of each cluster.

3 Frequent Pattern Analysis

I initially started frequent pattern analysis and association rules using the full dataset, intending . The size of the dataset, however, prevented this from being feasible. Processing frequent patterns on this size of dataset was too memory intensive and time consuming for the resources I have available.

Given the difficulties above, I have focused in on specific combinations of data that I'm interested in performing frequent pattern analysis on. I used Frequent Pattern analysis and Association Rule mining

Chronic Conditions and Mental Health

I began looking at data where users answered the question "(Ever told) you had a depressive disorder (ADDEPEV3)", as "1 - Yes", (consequent) and the associations to other chronic health conditions (antecedents). Through this analysis, I found that 9.3% of people surveyed indicated that they both had arthritis and had a depressive disorder. The Lift between these two survey answers is 1.33, meaning that those with arthritis are 1.33 times more likely to have a depressive disorder compared to the overall population.

People who have multiple chronic conditions indicate similar and more extreme results. People who have a chronic respiratory disease, arthritis, and asthma were 2.43 times more likely to have a depressive disorder. Diabetes, asthma, and arthritis were 2.3 times more likely to have a depressive disorder.

Disability and Mental Health

Similarly, I explored associations between respondents that had a depressive disorder and disability.

Among the interesting association rules: I found that 6.5% of respondents both responded that they had difficulty concentrating or remembering and that they had been told they had a depressive disorder. Respondents who said they had difficulty concentrating or remembering were 2.8 times more likely to also have a depressive disorder.

Respondents who have difficulty walking or climbing stairs were 1.6 times more likely to have a depressive disorder. Respondents that responded that they had difficulty doing errands alone were 2.4 times more likely to have a depressive disorder.

Sexual Orientation, Gender Identity, and Mental Health

I also looked at relationships between Sexual Orientation, Gender Identity and Mental Health.

13.81 % of men who identify as straight had been told that had a depressive disorder and 24.49% of women who identify as straight had been told they had a depressive disorder. Straight men are less likely to have been diagnosed with a depressive disorder than the overall population, while straight women are 1.19 times more likely to have been diagnosed.

31.68% of men who identify as gay responded that they had been diagnosed with depression (1.54 times overall population), while 38.74% of women who identify as lesbian also had depression (1.88 times overall population).

I found that women who identify as bisexual are 2.75 times more likely to have a depressive disorder than the overall population. And bisexual men and 1.9 times more likely.

Of the transgender population surveyed, 49.7% of male-to-female transgender respondents were diagnosed with depression (2.42 times), while 46.21% of female-to-male respondents were diagnosed (2.25 times). 59% of gender non-confirming respondents reported having been told they have a depressive disorder (2.9 times).

4 Classification

In an effort to determine relationships between survey questions that relate to respondents answering ‘Yes’ to the question ‘(Ever told) you had a depressive disorder’, I trained a decision tree. The target label was the answer to the depressive disorder question. I limited the features to those that occurred in my previous analysis above (chronic conditions, disability, and sexual orientation/ gender identity).

After training the decision tree, I extracted the rules the decision tree learned, focused only on the rules leading to ‘Yes’, and limited rules to those based on over 400 samples to focus on the top occurring paths.

When analyzing these rules, I found the following:

- The decision tree isolated “Difficulty Concentrating or Remembering” as the most deterministic feature. A majority of the paths leading to a ‘Yes’ to the depressive disorder label begin with a ‘Yes’ to this question as well, regardless of other factors.
- “Difficulty Concentrating or Remembering” answered as “Yes” and “How often have you felt various kinds of stress (specific kinds specified in the question)?” answered as “Always”, plus the absence of some other features predicts a ‘Yes’ answer to depressive disorders with 92.41% probability (n=488)
- “Difficulty Concentrating or Remembering” answered as “Yes” and “How often have you felt various kinds of stress (specific kinds specified in the question)?” answered as “Usually”, plus the absence of some other features predicts a ‘Yes’ answer to depressive disorders with 82.79% probability (n=639)
- “Difficulty Concentrating or Remembering” answered as “Yes” and “Difficulty Doing Errands Alone” answered as “Usually”, plus the absence of some other features predicts a ‘Yes’ answer to depressive disorders with 82.79% probability (n=639)
- “Difficulty Concentrating or Remembering” answered as “Yes” and “Female Sexual Orientation” answered as “Straight”, plus the absence of some other features predicts a ‘Yes’ answer to depressive disorders with 67.6% probability (n=1,543)
- “How often have you felt various kinds of stress (specific kinds specified in the question)?” answered as “Usually”, plus the absence of some other features predicts a ‘Yes’ answer to depressive disorders with 65.23% probability (n=558)

DISCUSSION

1 Project Timeline

The project was time boxed to an 8 week period total. The project will be divided into the following phases:

Phase 1 (1 week): Data acquisition, basic data ingestion, and beginning EDA

Phase 2 (1 week): Extended EDA. Beginning clustering methods.

Phase 3 (1 week): Beginning Association Rule Mining.

Phase 4 (1 week): Beginning Classification.

Phase 5 (2 weeks): Wrapping up all methods.

Phase 6 (1 week): Conclusion of all work

Phase 7 (1 week): Final report

2 Challenges, Changes, and Lessons

Not everything worked as planned or hoped. I had hoped to use Clustering methods to help understand and segment this data, however these methods are difficult or impossible to interpret in complex categorical data situations. Choosing the correct data mining methods for the task is important, and this method did not appear to be viable for this dataset. After learning this, I decided to put this method aside and focus on the other methods in my plan.

In addition, I had started the project thinking that I was going to be able to find complex relationships across the many different features in the dataset. I quickly found that was not going to be possible with the resources (both compute and time) that I had available. After discovering these limitations, I pivoted to focus on one particular aspect of interest: how various more targeted features impact mental health, specifically depressive disorders. Shifting to this focus dramatically improved my ability to find interesting results.

CONCLUSION & FUTURE WORK

1 Conclusion

By evaluating the relationship between behaviors and health outcomes, we can find relationships. Using these relationships, we can design features to help members better utilize the health and welfare benefits available to them. This helps meet employees where they are at in their life, and tailor their recommendations to their specific current behaviors, making it easier and more reliable for them to make positive health decisions.

In addition, driving engagement in the full benefits program financially benefits both employers and employees.

In this study, I focused on how various other health and behavioral factors influence the presence of a depressive disorder. I found that a number of factors were highly related to a respondent having a depressive disorder. In my industry, we might use this as a way to help users of our product find appropriate resources that may help them. For instance, if we know that a user is in one of the risk groups for depressive disorders based on other factors, we can proactively provide them information about mental health benefits that their employer offers, getting them the help they may need.

2 Future Work

The work I've been able to accomplish here is preliminary. There are a number of way this work can be expanded on.

- Dive deeper and use more comprehensive data analysis tools to determine indicating factors for depressive disorders.
- More broadly look at combinations of data across multiple categories to find more complex connections.
- Expand data collection to our benefits administration product, collecting data on who uses benefits such as virtual therapy vendors like Talkspace and how that relates to their demographics or behavioral responses.

REFERENCES

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