Predicting Perceived Importance of Mental Health

Analysis of Factors Affecting if Employees Feel their Employers Value Mental Health

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ABSTRACT

People have become more aware of mental health/issues over the years, as the focus on higher education and mentally intensive jobs grow. About “1 in 5 Americans will experience a mental illness in a given year” and “more than 50% will be diagnosed with a mental illness or disorder at some point in their lifetime” [1]. Do not forget the added loneliness and stress people had to face during the COVID-19 pandemic. Although mental illness affects a large proportion of people, it often goes undiagnosed or untreated because of the stigma surrounding it.

In our research paper, we look at mental health in the tech industry where metal health is a growing issue. Specifically, we seek to understand and predict how important mental health is to employers as perceived by employees through use of several different machine learning models and anonymous data from Open Source Mental Illnesses (OSMI).

The models that were produced in our research are documented in the following github repository: https://github.com/RealLazBaz/DSCI_Final_Project

CCS CONCEPTS

•Computing methodologies~Machine learning~Learning paradigms~Supervised learning~Supervised learning by classification

•Computing methodologies~Machine learning~Machine learning approaches~Classification and regression trees

•Computing methodologies~Machine learning~Machine learning approaches~Kernel methods~Support vector machines

•Computing methodologies~Machine learning~Machine learning algorithms~Ensemble methods~Bagging

•Computing methodologies~Machine learning~Machine learning algorithms~Feature selection•Computing methodologies~Machine learning~Cross-validation

•Computing methodologies~Modeling and simulation~Model development and analysis~Model verification and validation

•Applied computing~Life and medical sciences~Health informatics

KEYWORDS

Mental Health, Tech Industry, Data Science, Exploratory Data Analysis, KNN, SVM, Decision Trees, Random Forest

1 Introduction

Mental health is a growing concern in many areas of society, and can have extensive impacts on individuals. As defined by the CDC, mental health includes “emotional, psychological, and social well-being,” and impacts how we handle stressors and other changes in our lives [1]. Mental and physical health are equal aspects of health, and although physical health is often prioritized, mental illness and poor mental health can lead to physical health complications as well as decreased standards of living.

More than 50% of people in the United States will be diagnosed with a mental illness at some point in their lifetime, and in any given year, about 20% of Americans will experience a mental illness [1]. The amount of individuals experiencing debilitating mental illness is also steadily increasing and will affect current children far more than their parents.

The effects of mental health disorders have only been amplified by the effects of the COVID-19 pandemic. Among adults living in the United States, the effects of the pandemic have resulted in the rates of depression or anxiety, substance abuse, stress-related symptoms, and suicidal ideation nearly doubling [3]. This is a staggering and worrying number, and brings about a new urgency in the understanding of mental health related struggles across a variety of fields.

Mental health was already a concerning topic for people working in the technology industry. Specifically in technical areas, mental health has a profound impact on individuals and their ability to be productive at work. Additionally, a recent study showed that professionals working in the technology industry were more likely to see declines in mental health during the pandemic when compared to those working in other industries [4].

Open Sourcing Mental Illness (OSMI) was founded in 2013 with a specific focus on mental health of individuals working in the tech industry [2]. The organization conducts research, puts out information, and speaks at conferences with the ultimate goal of changing the experiences of individuals with mental health disorders working in technology industries [2]. Their research is the most significant research done in this area.

The OSMI Mental Health in Tech Survey was first administered in 2014, and has been administered every year since, with the survey being slightly adapted over time to its current form, which was first administered in 2017 [2]. The data collected between 2017 and 2020 is the basis for our exploration into mental health effects within the tech community.

2 Related Work

There has been significant work done to analyze the data collected by OSMI by a number of groups. The analysis has included both statistical models and machine learning models, which provided a significant amount of useful information to get us started.

A statistical analysis was performed by Pratik B. Patel at the University of South Florida to determine the statistically significant factors that would result in an individual working in the tech industry seeking out mental health resources [5]. The goal of this analysis was specifically focused on determining if people were getting the help that they needed when they developed a mental illness. This statistical analysis found five statistically significant indicators of individuals seeking out mental health services: age, how much mental illness affected that person at work, family history of mental illness, if benefits were offered to employees, and if the employee had observed negative consequences for seeking out mental health services. Patel came to the conclusion that the existence of benefits on their own was often not enough to encourage people to make use of services, and often pressures from work were needed to motivate use. However, investing in employee benefits may encourage the use of mental health services, and in turn result in lower downtime and less productivity loss for employees struggling with mental illness.

A machine learning analysis was performed by Xiaodi Wang at West Connecticut State University with the help of Meera Sharma, Sonok Mahapatra, and Adeethyia Shankar, and similar to Patel's statistical analysis, chose to focus on whether individuals struggling with mental illness were seeking out treatment [6]. This group implemented a number of algorithms, including a Support Vector Machine, k-Nearest Neighbors, Decision Tree, Random Forest, Naive Bayes, and Logistic Regression. This group found that, for their data, the Support Vector Machine algorithm was the most accurate on the test set. Then, using Principal Component Analysis, this group was able to determine the most important factors in their machine learning algorithms. This group found similar important factors to Patel's statistical analysis, identifying age, gender, family history, whether a mental illness was affecting an individual's work, and the benefits that were offered by a company as the most important factors. The similar indicators across both studies validate the results of both studies. Wang's research group came to the conclusion that such data could be used to develop a shorter questionnaire to be distributed to employees to identify those in need of treatment or likely to seek out treatment.

3 Methods

The dataset we used to perform machine learning algorithms was a combination of data from the OSMI Mental Health in Tech Survey from the years 2017 through 2020. We chose to focus on the data from these four years because the survey did not change over those four years, so the same attributes were shared across the four surveys. The original dataset included 75 attributes and over 1700 observations.

3.1 Data Cleaning and Feature Engineering

Cleaning the data presented a number of challenges. One initial challenge was that the survey itself branched into different questions depending on the answers to previous questions. For example, the first question asked to those taking the survey was if they were employees of a company or if they were self-employed. Following that question, a different set of questions were asked to those who indicated they were employees of a company and those who indicated they were self-employed. As a result, there was a significant amount of missing data, as a number of questions were not asked to every respondent.

Additionally, we found that a number of the questions offered a spot for freeform answers. The freeform answers allowed for the respondents to type in answers, which led to a large number of unique responses. This was the case for questions that asked about the age and gender of responding individuals. There were also a number of questions that asked respondents to elaborate on previous answers by asking them to explain why they answered a question a certain way.

Another major challenge was that a number of the responses were collected categorically. For example, a question may have responses of “yes,” “no,” and “maybe,” or responses ranging from “strongly agree” to “strongly disagree,” with significant variety. To perform a number of our models, those responses would need to be encoded.

Our first step in data cleaning was we removed the observations of the individuals who indicated they were self-employed. About 85% of respondents indicated that they were employees of a company, so we had significantly more data. By removing both the self-employed respondents and the questions they were asked, we removed the vast majority of the missing data.

Next, we cleaned the age and gender variables. Both of these attributes had the potential to be significant indicators, so we did not want to drop them, but needed to be cleaned because of the freeform nature of the responses. We removed the unreasonable ages (below 18 or above 80, which we assumed would place them out of the range of the workforce), and replaced those values with the median age for the dataset. For the gender responses, we categorized all of the free responses indicating a respondent identified as male or female into male or female, and labeled the rest of the responses as “other”.

For the remaining freeform questions, we removed the attribute. We were not able to get significant encodable information from the responses to why individuals felt a certain way, so we chose not to include those attributes in our model.

For questions about the country where a respondent worked or lived, we dropped responses from countries where we had less than 30 observations. Therefore, we could preserve the country variable as encodable to our model.

Finally, we encoded all of our categorical variables into numerical values so that they could be run through our algorithms. We had positive answers (i.e. “yes” or “strongly agree”) as the highest value responses in our encoding.

3.2 Algorithms

Our selected target variable was the perception employees had of how important mental health was to their employers. We chose to predict this variable because that aligned specifically with the goals of OSMI, who are focused on changing the discussion of mental health and the experience of those with mental health disorders. Whether or not mental health is a priority for a company is important in addressing mental health concerns throughout the tech community.

We simplified our classification problem by reducing the target variable’s classes from 11 classes ranging from 0 to 10 to 2 classes. The first class combined classes 0 to 5, and the second class combined classes 6 to 10. The higher the class the more importance the employees believed their employer gave mental health.

Splitting Data

The cleaned data set was randomly split to be 80 percent training data and 20 percent testing data. The training set was further used in cross validation with three folds to select the best parameters for each of the models.

Decision Trees

The Decision Tree algorithm is a classification algorithm that employs a tree-like structure to move through attributes to ultimately reach a response. For each response to a given attribute, it may look at different responses to ultimately come to a decision.

The original dataset employed a branching structure, so we decided that it would be a good option as it would potentially allow us to use some of the questions specifically asked to self-employed individuals or to employees before we employed data cleaning. Even after we dropped some of those attributes, we still felt it would be a powerful algorithm to employ because a number of responses still seemed to follow that branching structure.

Random Forest

The Random Forest algorithm operates much like the decision tree algorithm, but enlists multiple, random decision trees to determine a final classification. For the same reasons we chose to use a Decision Tree algorithm, we decided that using a Random Forest algorithm would be a good option.

Random Forest algorithms also enable us to run an Out of Bag (OOB) classification error to determine the significant features and how many features to include in the algorithm.

k-Nearest Neighbors

The k-Nearest Neighbors algorithm for classification looks at the responses that have the most similar attributes and uses those similarities to classify a given attribute. We decided kNN would be another strong option because, much like the Decision Tree and Random Forest algorithms, it can still classify non-linear relationships well. Similarity also is a powerful tool, so it seemed like a strong candidate to explore. Before we inserted our data, we used Z-score standardization to normalize all of our data.

Support Vector Machine Classification

The Support Vector Machine (SVM) Classification uses responses to create a hyperplane between responses to classify them into outputs. The goal of the hyperplane is to draw a line between specific linearly separable responses to group similar answers. Previous works employed an SVM classification algorithm, and it was the most successful algorithm for Wang's research group, so we felt it would also be a good option. Before we inserted our data, we used Z-score standardization to normalize all of our data.

4 Results

The following results were produced from code that can be found at the following github repository: https://github.com/RealLazBaz/DSCI_Final_Project

Table 1. Accuracy and F1 Score by Algorithm; Target Variable Importance of Mental Health

Algorithm	Mean CV Training Accuracy	Test Accuracy	F1 Score
Decision Tree	0.837	0.745	0.681
Random Forest	1	0.784	0.702
kNN	0.752	0.740	0.711
SVM	0.832	0.753	0.685

The accuracy values for the Decision Tree algorithm are taken from the Decision Tree parameters selected from the highest cross-validation scores.

For our target variable determining how important employees perceived mental health to be to their employers, the kNN classifier performed strongest when considering both accuracy and F1 score. The Random Forest algorithm had a stronger accuracy than the kNN algorithm, but a significantly lower F1 score. However, Random Forest still outperformed the SVM and Decision Tree algorithms in F1 score.

Table 2. Correlation and Feature Importance; Selected Features, Target Variable Importance of Mental Health

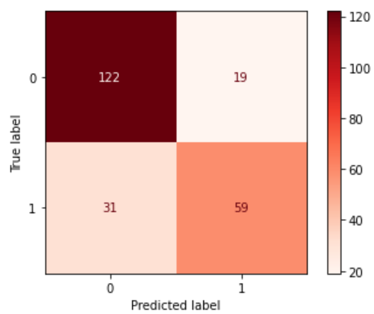
Variable	Correlation	Random Forest Feat. Importance
PHImportance	0.469	0.149
employerDiscussMH	0.369	0.060
coworkersMHstigma	0.318	0.063
MHwithSupervisor	0.299	0.038
resourcesOffered	0.299	0.034
askingForLeave	0.293	0.047
age	0.008	0.050

Variables

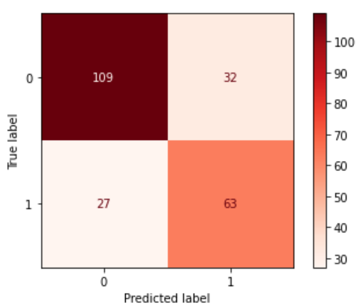
- PHImportance: the perceived importance that a company places on physical health.
- employerDiscussMH: whether or not an employer has formally discussed mental health with their employees.
- coworkersMHstigma: how employees would expect their coworkers to react if they were to disclose a mental illness
- MHwithSupervisor: employee's comfort discussing a mental health issue with a supervisor
- resourcesOffered: whether or not an employer provides resources to learn more about mental health benefits that are available
- askingForLeave: ease of asking for leave from work due to a mental health issue
- age: the reported age of the respondent

There was strong agreement between the important features in our models and the features that were highly correlated with our target variable. One striking difference was that age of the respondent had very low correlation with our target variable, but ranked very highly in feature importance for our models.

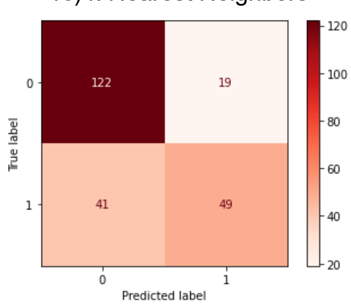
1a) Random Forest



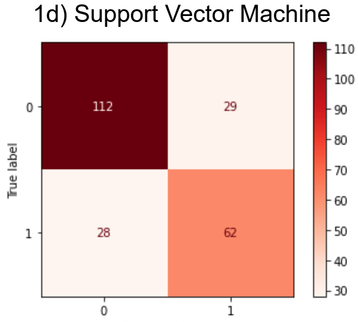
1b) Decision Trees



1c) k-Nearest Neighbors



1d) Support Vector Machine



Figures 1a-1d: Confusion matrices for the machine learning models.

The confusion matrices show the results for each algorithm's parameters that performed the best in cross validation, in order to compare overall performance.

5 Discussion

In analyzing our data and models, we used correlation heat maps and Out of Bag classification error to determine the significant features that impact whether employees feel their companies value mental health. The significant features that were identified were a company's value of physical health, if a company discussed mental health with employees, the perceived stigma that coworkers held about mental illness, and the ease of discussing mental health with a supervisor, including asking for leave due to a mental illness. Identifying these top features is significant because it offers an opportunity for companies to understand how they can help their employees feel most supported.

One surprising top feature that we identified was that a company's perceived value of physical health was strongly tied to their perceived value of mental health. This indicates that companies who prioritize the health of their employees often highlight both mental and physical health. This result was surprising because mental health has traditionally taken a back seat to physical health, but it is exciting to see that both are prioritized here.

Another top feature that impacted the perceived importance of mental health was whether a company had discussed mental health with their employees. Although not a surprising result, this is an easy actionable first step for companies to show employees that they care about mental health. It also underlines that companies must take action and be willing to get into potentially uncomfortable issues to create lasting changes in their company culture.

The significance of the stigma that coworkers hold about mental illness indicates another actionable step for companies to address concerns about company culture. It is again not surprising that the attitude of coworkers has a significant impact on how employees perceive their company. However, it also shows that changes at the higher levels are not enough. Programming must reach out to people at all levels and work to address mental illness, even for those who do not struggle with it, to make the workplace a supportive one for those who do struggle.

That said, the ability to talk to a supervisor about mental health struggles is also a significant indicator. Both coworkers and supervisors work to create the perception an employee has of their company, and both must be addressed to create the positive changes in the perception of mental health that can help employees feel better supported.

Our models all had accuracy scores in the seventies, and we were hoping to build models with higher accuracy, especially for a binary classifier. The F-1 scores of each of the classifiers were a little less than the accuracy scores which suggest some models struggled to identify one class over the other. Looking at Figure 1a and 1c, the random forest model and K-Nearest Neighbor Model struggled to identify cases where employees rated their employer's value of mental health to be greater than 5 or above average. This could be due to less observations belonging to that class.

Another thing to notice is that most of the train accuracies are not high. This may be because the model is underfitting to the data. In this case, adding more meaningful features may be helpful. Considering the pandemic impacted so many tech employee's lives, questions surrounding COVID policies may be helpful.

One of the reasons for a lower accuracy score than expected is the subjective nature of some of the questions in the survey. Two employees who work in the same workplace may potentially rank how much their employers value mental health very differently. This can make it harder to predict what subject answers without more meaningful features.

Something to consider is how much bias is in the survey. Since employees voluntarily take the survey, it can lead to selection bias. Those people who care more about mental health will be more likely to take the survey voluntarily. This can lead to more people with mental illnesses than what is representative of the tech industry. Going in the other direction, it is also possible that there may be survivorship bias in that those with mental illnesses may drop out of the tech industry leading to an undersampling of those with mental illness.

One of things we would like to tackle in the future is an analysis of this bias as it does affect how well our results generalize to the tech industry. Other possible next steps are some type of feature selection to find important features, use of nonlinear features to make the model more complex, dimensionality reduction to analysis where most of the variance comes from, exploration of other target variables, and use of oversampling for target variables with unbalanced classes.

6 Conclusion

We employed machine learning algorithms to predict whether or not employees feel their company values mental health. We were able to construct algorithms with up to 78.4% accuracy. We also were able to identify significant factors in creating that perception among employees, which can be used to inform actionable changes that companies can make to show employees that they value mental health in the workplace.

The machine learning algorithms that we have employed do not have the degree of accuracy that we would have hoped for in predicting the perception that employees have of how important mental health is to their employers. To employ these machine learning algorithms in a predictive manner, additional work on the models would be necessary. Additional data may help to make the models more accurate. Specifically, the OSMI survey could potentially branch into more questions about the workplace environment to get a better picture of the ultimate result.

Further research beyond improvements to our models could go in many directions to determine ways to support people struggling with mental health issues. Our dataset focuses specifically on individuals working in technology industries. Gathering data and running models on employees from other industries can help determine if the results from technology industries are applicable to those working in other industries.

Additionally, more work could be done to address actionable steps companies can take to make the experiences of those struggling with mental illness better. For example, the OSMI survey asks about how people feel that living with a mental illness affects their career. Running additional models that look into specific predictive factors affecting the experience of those with mental illness would be an interesting next step. Companies need to show they care about mental illness before they can make meaningful changes for their employees, and that is a good first step. However, looking into the specific experiences of employees is the logical next step to continue improving the workplace environment.

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CONTRIBUTIONS

We would like to highlight the contributions of both team members.

Jarrett worked on the data cleaning and exploratory data analysis for the 2016 data. Although we ultimately decided to use the 2017-2020 data, as it was more applicable to our ultimate goals, some of that work was used for the 2017-2020 data. Jarrett also worked implementing the initial machine learning algorithms. Jarrett also wrote the project proposal and a significant amount of the final report

Bazin worked on the data cleaning and exploratory data analysis for the 2017-2020 data. Bazin then worked extensively on improving the models we implemented, including implementing cross-validation and grid search algorithms. Bazin also worked to produce visualizations of the model results, including the creation of confusion matrices. Although not shown here, he also ran models on other potential target variables.

Both members worked on the documentation of the final project. Jarrett wrote a larger portion of the final report, though both contributed, and both members worked together for the midterm and final presentations.