

**The Business of Mental Health in the Workplace:  
A Machine Learning Analysis to Inform Practices**

Holly P. Figueroa

College of Science and Technology, Bellevue University

DSC 550: Data Mining

Professor Brett Werner

November 19, 2022

A long-overdue awareness for mental health is growing in the United States and abroad (2022). For businesses that awareness includes three important assertions: mental health is a very common struggle, it impacts employee performance, and simple things can be done to help. The purpose of this analysis is to examine what business features help or hinder. An employee survey dataset was used from the non-profit, Open Source Mental Health (OSMI) to examine these features (2019). This data was sourced in 2016, a year with the highest participation, and is publicly accessible through the creative commons. To extract insights about features that foster a healthy culture for mental wellness, machine learning modeling was used to create predictions for work interference due to mental health. By examining the model results, a path for improving this aspect of culture was identified. In addition to simply offering employees a better culture for performance and morale, dedicating attention to forming a strong culture has been shown as an effective way to recruit the best talent (Pendell, 2022).

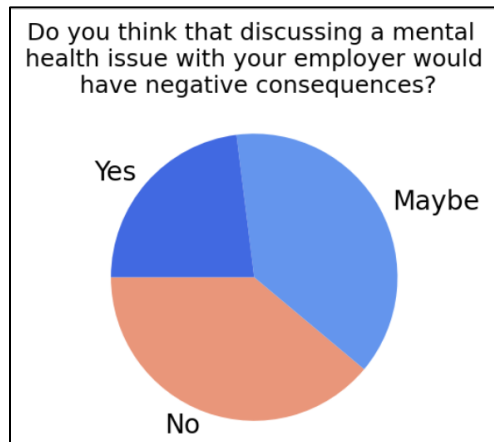
### **Exploratory Data Analysis**

The target for analysis was based on the survey question, “If you have a mental health condition, do you feel that it interferes with your work?”, with responses ranging from “never” to “often”. Of the 1259 sample, 80% responded. The response rate illustrates the commonality of mental health struggles. Plots were created to explore the assertion that workplace culture could impact employees’ ability to manage mental wellness. The survey asked if employees felt there would be negative consequences if they discussed their mental health struggles with their employer. Figure 1 revealed that the majority of employees either felt unsafe or uncertain about the prospect of talking about these struggles.

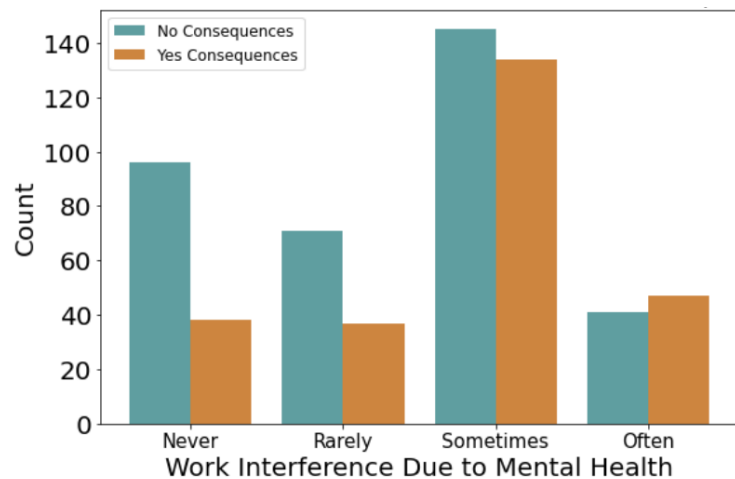
Distributions for work interference were compared between groups that felt safe to talk with their employer and those that did not (See Fig. 2). First, it was clear the safe group was larger than the unsafe group, with the “maybe” group excluded. Second, the proportion of people experiencing work

interference from mental health “never” or “rarely” was clearly higher for the safe group. Those in the unsafe group had a higher relative proportion of people reporting work interference “sometimes” or “often” in the survey.

**Figure 1**



**Figure 2**



### Data Preparation

The most significant steps taken to prepare data included choosing features to keep, handling missing values, and the import of additional data. Nearly 20% of the target values were missing. A K-Nearest Neighbors Classifier model was used to fill the roughly 200 missing values. The accuracy of predictions used on a test sample scored a modest 45%, nearly double the odds of a random guess. The survey asked respondents if their employer provided health insurance benefits, but the survey included international participants where employer health care may not have been as essential as it is in the United States. While respondents outside of the United States represented a small portion of the sample, maximizing sample size was favored. Location data was used to merge-in data from the World Health Organization that identified nations that provided care to its citizens by right. With the additional consideration included as a feature, it was hoped the model would better interpret the relationship between healthcare access and work interference.

Selecting features to include was largely based on what a company would be able to draft action from. For example, an employee's medical history, although ideal as a predictor, would not be appropriate to inform company practices. Personal information features, features reflective of protected classes, or features a business could not likely control were kept out of the prepared dataset. Those most compelling features that remained included working remotely, ease of taking leave, employer offerings for resources, employer benefits, willingness to discuss mental health with a supervisor, and perceptions if doing so would result in negative consequences.

### **Model Building and Evaluation**

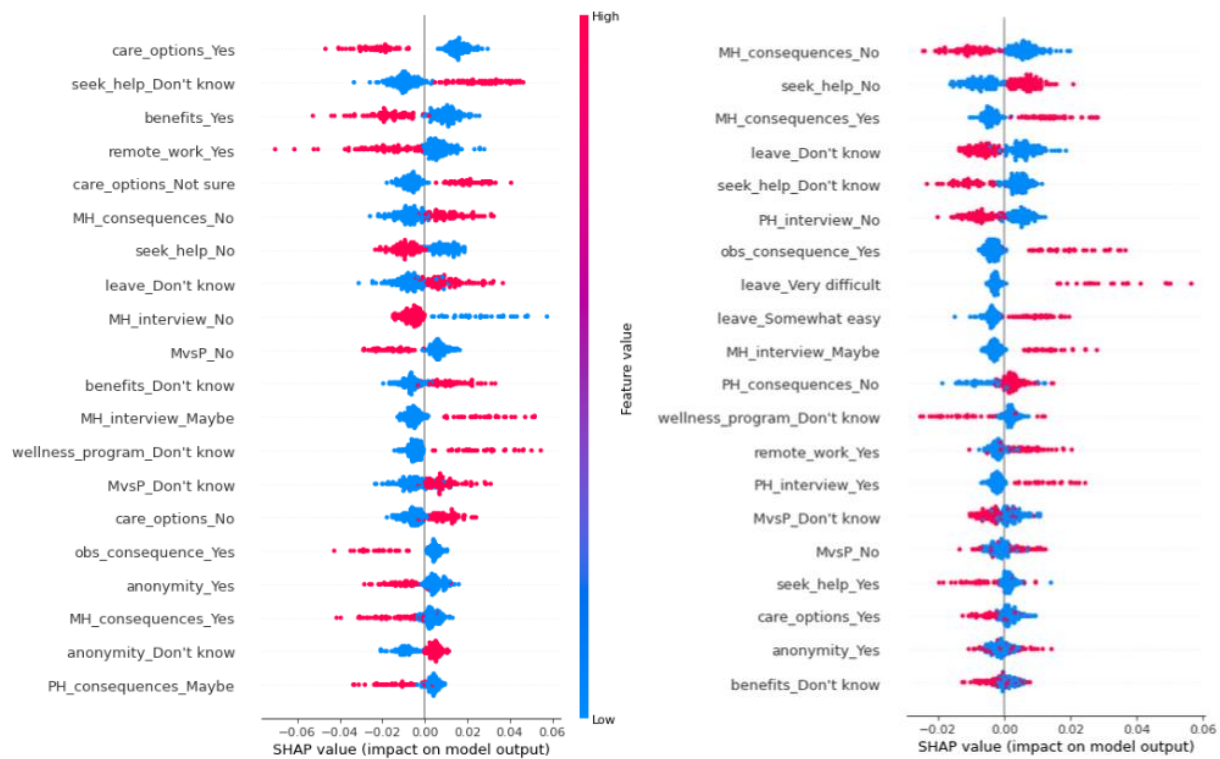
The features selected for use were compelling, but with so many features removed as they could not practically or ethically inform practices, prediction accuracy was not expected to be high. However, once the best model was in place the focus would shift to interpreting feature importance. The data was split with 80% for model training and 20% for testing. The dataset was categorical in its entirety, with a few variables encoded ordinally, including work interference. For this reason, it was desirable to use a tree model to allow for clearer interpretation. However, a grid search was chosen to aid in identifying an optimal model. The gridsearch trained and compared 3 models, a decision tree classifier, a decision tree regressor, and a random forests classifier. A variety of hyperparameters were also tested for each model to widen chances at improved accuracy. The search identified a random forests model as the optimal model with a maximum depth of 14 and minimum samples split at 15. Accuracy score was calculated at approx 47%. Features were then selected down from 42 to 30 using chi square, which did not significantly improve accuracy.

To gain insights from the model feature importance was explored using sklearn and shap libraries. Sklearn's feature importance calculated importance for all features as less than .05 with remote work being the highest. The results however, cannot say how any given feature influences the

model. The shap library however, offers more to be interpreted by an exhaustive averaging of how predictions changed based on feature values. More than that, shap values, based on game theory, are derived by gaining these averages across every possible combination of feature order. A costly, but powerful tool to examine what an opaque model is really doing. To make the best use of shap values two visualizations were created to compare top features for the highest and lowest work interference values (Fig.3).

**Figure 3**

*Top Features and SHAP Values for Work Interference When Predicting “never” (left) and “often”(right)*



*Note.* Each point represents an observation. “Yes”, “No”, and “Maybe” features represent encoded feature responses. With red representing the highest value, red would be equal to one, confirming that response was selected. The SHAP scale on the x-axis represents exactly how much a feature altered the model’s prediction.

A careful examination of plots created through the SHAP library allowed for a clearer understanding of how features were contributing to the model. Feeling safe to discuss mental health issues with your employer influenced the model to lower predictions for work interference values. Inversely, feeling there would be consequences for doing this led the model to increase prediction values for work interference. Figure 3 also shows that having employers that did not offer resources for mental health led the model to favor the high values of work interference. Some of the highest shap values in the plots were when responses indicated it was "very difficult" to take leave for mental health, pushing work interference prediction higher. Remote work also had some of the highest shap values where the model favors this feature to predict lower work interference values. While lacking benefits did not make the top list for features impacting higher work interference, it is one of the strongest features predicting low values for work interference. It would suggest that the model leads predictions to higher levels of work interference when a person reports not having mental health benefits, or not knowing what mental health care options are available to them. Many feature responses for "I don't know" topped the shap plots for work interference. When comparing these responses closely, they generally appear to neither support high nor low work interference. Instead, their role in the model appears to essentially pull predictions away from either extreme.

### **Conclusion**

The model created did not have impressive accuracy, but with very limited information regarding the workplace attitudes and offerings, the model doubled improvements from guessing. The model had several limitations. The dataset did not offer a balanced distribution for gender, making it possible gender-dependent features were not fairly emphasized. The model would likely have benefited from a larger sample size. Another disadvantage is that valuable features that would typically be desired for mental health were cut from the set prior to predicting missing values for work interference.

However, the results are intuitively sound given the nature of how mental health awareness and care access has been widely regarded as an improvement for people's wellbeing.

Human capital is a fundamental asset of any workplace. The model created would suggest a culture around mental health exists in every workplace whether a business chooses to manage it to its own benefit or not. With limited information, the model was able to communicate a path to influence a healthier workplace culture. Steps the model would appear to support most would include: making mental health resources known and available to employees, offering access to health care, creating policies to support and protect staff through mental health struggles, creating staffing structures that allow for leave to be granted when needed, and having remote work options available. These are the simple ways to help a lot of people feel better and work better.

## References

- The growth of Mental Health Awareness* (2022) *Howard Magazine*. Available at: <https://magazine.howard.edu/stories/the-growth-of-mental-health-awareness> (Accessed: November 19, 2022).
- Osmi Mental Health in Tech Survey 2016* (2019) *Kaggle*. Available at: <https://www.kaggle.com/datasets/osmi/mental-health-in-tech-2016> (Accessed: September, 1, 2022).
- Pendell, N.D.and R. (2022) *Culture wins by attracting the top 20% of candidates*, *Gallup.com*. Gallup. Available at: <https://www.gallup.com/workplace/237368/culture-wins-attracting-top-candidates.aspx> (Accessed: November 19, 2022).