Mental Health in the Tech Industry: Final Paper

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GitHub Repository: https://github.com/kkellygu/ds3001Project/tree/main

Abstract

The tech industry's fast-paced, high-pressure environment significantly impacts employees' mental health. This project explores mental health dynamics among tech employees using the "Mental Health in Tech 2016" dataset. The dataset includes survey responses from employees regarding their mental health history, healthcare insurance/benefits, how their company addresses mental health, and more. The primary goal is to understand how workplace resources and conditions influence employees' comfort in discussing mental health issues with supervisors. Logistic regression, decision tree, and random forest models were applied, achieving accuracies of 58-63% and highlighting key predictors, such as workplace psychological safety and the perceived consequences of discussing mental health issues.

Feature importance analysis revealed that employees' comfort levels in discussing mental health with coworkers strongly correlate with their openness to supervisors, emphasizing the role of team dynamics and psychological safety. Limitations, such as data imbalances and generalizability, underscore the need for more comprehensive data collection and preprocessing to enhance model performance and insights. It should be noted that it is extremely difficult to

capture the nuances of a person's relationship with mental health and their workplace situation in a single dataset or survey.

Key recommendations to improve the rate of employees who feel comfortable talking to their supervisor about mental health include fostering a supportive workplace culture that normalizes mental health discussions and increasing awareness of available mental health resources. Future research should incorporate qualitative data to address ambiguities and improve predictive accuracy. This study provides actionable insights for tech employers to prioritize mental health, enhancing both employee well-being and organizational productivity.

Introduction

The tech industry is known for its fast-paced and demanding environments, which can significantly impact mental well-being. As future professionals in this field, understanding the mental health landscape is crucial to fostering healthier workplaces. Research shows that a positive workplace environment significantly influences employee health, which in turn drives productivity and well-being (Hafeez et al.). Using the Kaggle dataset "Mental Health in Tech 2016," this project aims to identify trends and patterns related to mental health among tech employees, examine how workplace conditions and resources influence mental health outcomes, provide actionable insights to improve employee well-being, and reduce stigma surrounding mental health in the tech sector.

The target variable we are predicting is “Would you feel comfortable discussing a mental health disorder with your direct supervisor(s)?” Our predictive question asks, “Can workplace mental health resources predict the self-reported likelihood of employees seeking help for mental health issues within the tech industry?”

Our analysis revealed that workplace environments and mental health resources significantly influence employees’ comfort levels in discussing mental health concerns with their employers. Some of the key factors include support from co-workers and employers and the availability of mental health resources. The project utilized machine learning models, including logistic regression, decision trees, and random forests, to predict the comfort levels of discussing mental health based on workplace conditions. These models were chosen because of the categorical nature of the dataset. We utilized logistic regression to understand the relationships between workplace environment factors and employee comfort. Additionally, a decision tree and random forest added further depth to our analyses by capturing non-linear relationships and interactions among features. Metrics including accuracy, precision, and F1 score were all used to evaluate and compare the performance of these models. By using a combination of approaches, we aimed to create a variety of results to analyze, balancing predictive accuracy and interpretability.

The results of this analysis provided valuable insights into the analyses. Each model yielded different levels of predictive power with the random forest performing the best overall, with an accuracy of 63% and an F1 score of 0.70 for “No” responses. However, similar to the other models, the random forest had challenges predicting “Maybe” responses accurately. Logistic regression had a balanced performance with an accuracy of 60% and performed the best for “Yes” responses with an F1 score of 0.69. Decision trees, while less accurate overall, provided valuable visualizations of feature importance and pathways leading to specific outcomes. Across all models, the most critical factors included perceptions of employer attitudes toward mental health, resource accessibility, and team dynamics. These findings highlight the power of workplace culture in how it affects employee comfort levels in discussing mental health concerns.

While the models provided meaningful insights, they also faced many challenges and limitations due to the nature of the dataset and the analysis. The categorical nature of the data, with many yes/no/maybe responses, limited the models’ ability to capture the relationship of the variables entirely. Additionally, there were missing values that complicated the analysis, potentially introducing biases into the results. As mentioned above, all of the models conducted had difficulties predicting “Maybe” responses, reflecting the nuances of middle-ground attitudes toward engaging in mental health discussions. Addressing these limitations in future research, like incorporating more qualitative data like surveys or interviews or expanding the dataset to include a more diverse population, could enhance the robustness and applicability of the findings.

Data

As computer science and data science students about to enter the tech field, understanding the mental health landscape within our industry is crucial. This dataset on mental health in tech provides an opportunity to explore trends and patterns related to the well-being of those already in the industry. By analyzing self-reported mental health statuses and workplace conditions, we can first address any common patterns in the findings and then assess whether any improvements can be made for the future of the industry to both improve employee mental health and expand upon existing resources related to mental health in the tech industry.

This dataset comes from the "2016 Mental Health in Tech" survey, found publicly available on Kaggle here, and contains about 1400 observations and 63 variables. The data was collected from a voluntary, online survey conducted by Open Sourcing Mental Illness (OSMI), an organization dedicated to raising awareness and providing resources about mental health in tech. Thus, it is not a random sample, but rather a convenience sample since the participants are likely self-selected and voluntarily filled out the form. This is representative of the targeted population because although it is not randomly sampled, it does offer different perspectives from a diverse group of tech workers. The survey likely reached employers working in a variety of tech or information technology fields, making it reflective of the broader industry trends.

The dataset will help us identify practices that contribute to better mental health outcomes and uncover stigma surrounding mental health issues. By gaining these insights, we can advocate for healthier work environments and foster a more inclusive culture in our future workplaces. Ultimately, this knowledge equips us to contribute positively to the tech industry, prioritizing mental well-being alongside innovation and productivity. Additionally, this survey data offers insights into the attitude towards mental health in the tech workplace, exploring the frequency of mental health disorders among tech workers. The data is compiled by volunteers driven by raising awareness for mental health and supporting those who have mental health disorders. The data collected from the survey was compiled into a CSV file that includes demographic statistics like the individual age, gender, and country/state of residence, as well as other questions regarding the work conditions, insights into the employer, and the stigma surrounding mental health in a work environment. The figures below visualize some of the key survey data, providing insights into how the varied responses are distributed for the measured variables.

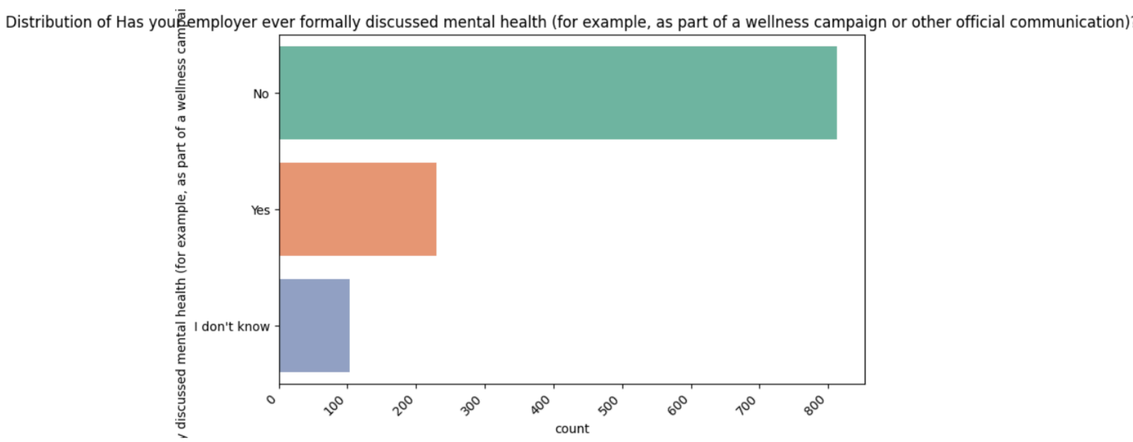


Figure 1. Formal Discussions of Mental Health From Employers

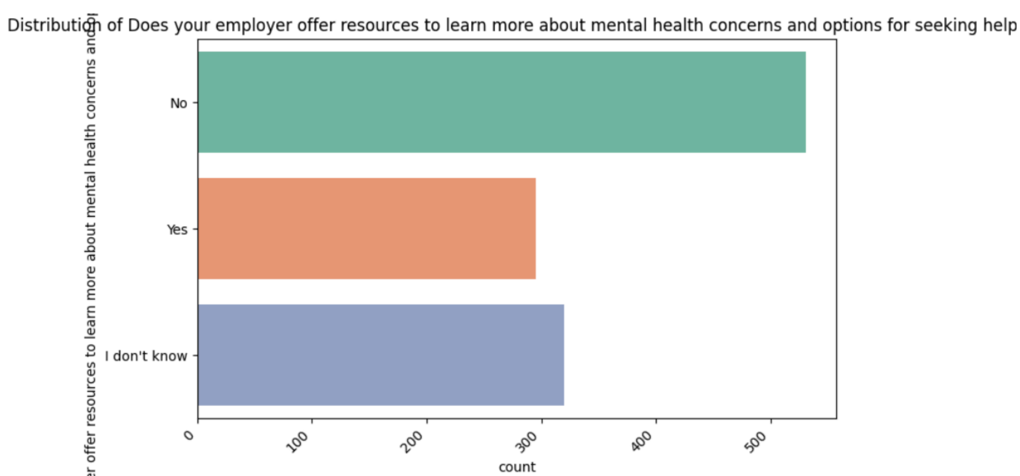


Figure 2. Mental Health Resources Provided by Employer

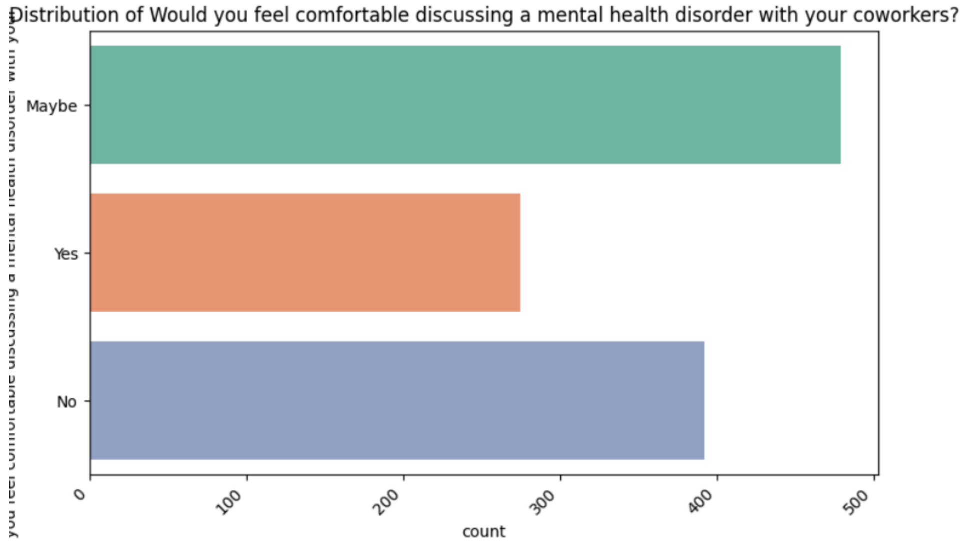


Figure 3. Comfort Regarding Mental Health Discussions with Coworkers

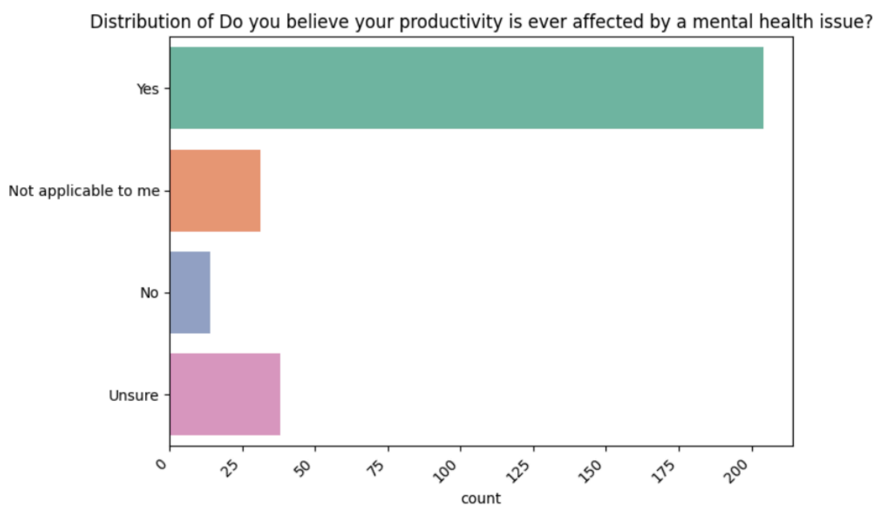


Figure 4. Rated Productivity Level Under Mental Health Issue

Looking at the data, more people responded positively to feeling comfortable addressing mental health issues with their supervisor and employer. However, many people replied “no” or “I don’t know” to questions related to whether they would feel comfortable disclosing information about their mental health to their coworkers or clients, and also whether their company provided additional mental health resources. It is also important to note that a vast majority of people said that their productivity has at some point been affected by a mental health issue. This suggests that providing a safe environment to discuss and seek help for mental health issues may also boost productivity levels and benefit employers.

While the dataset offers significant insights, a key concern to be aware of is the data quality and completeness, as this data is self-reported, it may be prone to errors. This required us to figure out how to deal with possible missing values or any inconsistencies and carefully clean the data up to maintain the integrity of our analyses. Since the data was gathered through a convenience sample of volunteers, it may not be fully representative of the grand overall population of professionals in the tech industry, which poses a challenge to the generalizability of the findings.

To address these potential challenges, we plan to categorize the variables into predictors and outcomes to then apply a consistent prediction framework. Given the categorical nature of most data points ("yes" or "no" responses), we will use methods such as decision trees and random forest models to help predict our outcome variables. These models are effective in capturing non-linear relationships and handling categorical features, making them a better fit than logistic regression in this context. In addition, the ensemble learning method of the random forest would allow a more accurate reading of the dataset due to the complexities of the model. From here, we will be able to compare the performance of these different frameworks across multiple outcomes and see which one(s) performs the best and can offer us the best insights throughout our analysis process.

Through this analysis, we aim to uncover trends and actionable insights that can contribute to healthier workplaces in the tech industry. By leveraging a variety of metrics and tree-based models tailored to the dataset's categorical nature, we ensure a robust and in-depth understanding of the mental health landscape within this industry.

Methods

In this study, each observation is represented by an individual survey response. These responses include data on employees' workplace conditions and mental health status. A possible observation might capture employees who report experiencing high levels of stress, anxiety, poor management, lack of support leading to burnout, or possible depressive symptoms. On the other hand, other observations may reflect employees who experience a more positive and healthy working environment with greater access to mental health resources.

The primary goal of this study was to predict mental health status based on workplace conditions and other features. Specifically, the target variable is whether employees feel comfortable sharing mental health concerns with their supervisors, a categorical variable with three possible values: ("yes", "no", and "maybe"). Given our dataset, the study employed supervised learning for classification, focusing on decision trees and random forest models which were valuable in modeling the more complex, non-linear relationships between our variables like workplace conditions and employees' comfort in discussing mental health concerns with their supervisors. Utilizing tree-based models proved advantageous for us because most of the predictors were either categorical or binary variables because of the nature of survey data being question and response. These methods allow us to delve into the data and visualize our results through decision splits.

The study utilized decision trees, random forests, and logistic regression, where decision trees provided a visual understanding of how different factors contributed to specific outcomes, random forests helped to reduce overfitting complications by averaging decision tree results and overall enhance the thoroughness of analysis, and logistic regression was used for binary classification, as most of the data consisted of yes/no responses. Through these methods, we could evaluate model performance through various aspects such as estimating the likelihood of specific outcomes based on independent variables and measuring metrics like accuracy, precision, recall, and F1 score. By gathering multiple metrics from our data, we can gain a more comprehensive understanding of our model's effectiveness in prediction. For one, measuring F1 scores, which capture the harmonic mean between precision and recall, is insightful in understanding performance from more imbalanced datasets.

Data preparation involved cleaning missing values and encoding categorical variables, such as whether an employer provides mental health benefits or whether employees know their options for mental health care. One-hot encoding transformed these variables into binary features for analysis. While Principal Component Analysis (PCA) could be used for numeric variables like company size, the dataset's predominantly categorical nature limited its application.

Challenges anticipated included responses that dominated the dataset. For example, if a large company has responses from a majority of its employees, this may impact the results of cluster analysis, which could be mitigated through oversampling or undersampling techniques. Another challenge was the reliance on self-reported data, which oversimplified nuanced mental health dynamics and significantly limited what we were able to work with. Namely, "yes" or "no" responses may oversimplify underlying issues, as there's no room for further elaboration or different degrees of a participant's response. A mere one-word response doesn't offer deep, meaningful insights beyond surface-level content, which could lead to superficial conclusions, and thus not fully accurate of the greater population.

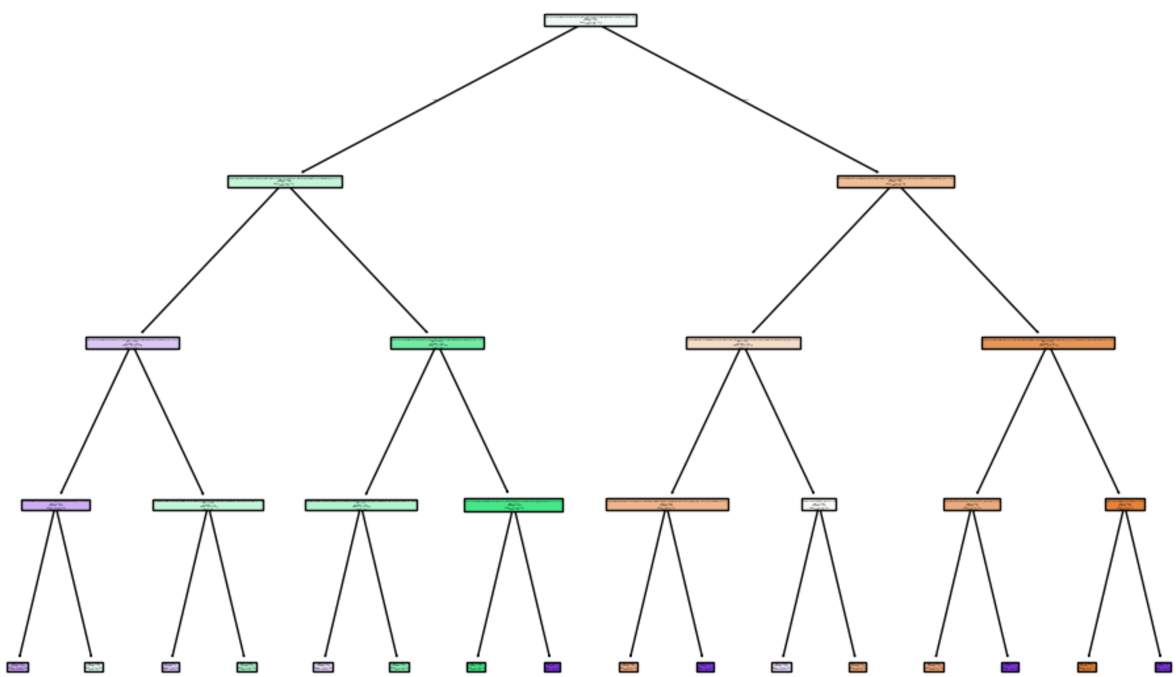
The results of this study were communicated through a confusion matrix to present the accuracy and F1 scores, feature importance from tree-based models, and a summary of performance metrics. This approach provided clarity on model performance, allowing for further adjustments based on the nature of the findings, and highlighted key components of what influences employees' level of comfort in discussing mental health with employers or supervisors. By leveraging a methodical approach to understanding workplace mental health dynamics, we aim to contribute actionable insights and foster healthier, more inclusive environments in the tech industry.

Results

Model Performance Overview

Model	Accuracy	Class	Precision	Recall	F1 Score
Logistic Regression	0.60	No (0)	0.61	0.55	0.58
		Yes (1)	0.67	0.72	0.69
		Maybe (2)	0.50	0.51	0.51
Decision Tree	0.58	No (0)	0.69	0.46	0.55
		Yes (1)	0.64	0.73	0.68
		Maybe (2)	0.46	0.53	0.49
Random Forest	0.63	No (0)	0.67	0.72	0.70
		Yes (1)	0.64	0.64	0.69
		Maybe (2)	0.54	0.41	0.47

Decision Tree



Overall, the logistic regression model provided balanced performances across all the classes with an accuracy of 0.60. It performed reasonably well for "Yes" predictions with an F1 score of 0.69, and the predictions for "Maybe" were slightly lower with an F1 score of 0.51. This suggests room for improvement when predicting more ambiguous responses. As a baseline model, the logistic regression provided a suitable baseline. The decision tree model had an accuracy of 0.58, which was slightly lower than the logistic regression. It achieved its highest F1 score of 0.68 with the "yes" class but performed worse for the "maybe" class with 0.49. Lastly, the random forest model outperformed both the logistic regression and the decision tree model with an accuracy of 0.63. Its strongest performance was for the "no" class, which had an F1 score of 0.70, due to the high recall value of 0.72. However, it struggled with the "maybe" class, which provided the lowest F1 score out of all the models at 0.47. Despite the overall higher accuracy for the random forest class, its difficulties in predicting the "maybe" class suggest that ensemble learning methods alone are not sufficient to address the complexity of ambiguous responses. However, this framework performed best for our outcomes of interest.

Feature Importance Overview

Feature	**Importance**
Do you think that discussing a mental health disorder with your employer would have negative consequences? (No)	0.106479
Do you think that discussing a mental health disorder with your employer would have negative consequences? (Yes)	0.068377
Do you feel that your employer takes mental health as seriously as physical health? (Yes)	0.060997
Do you know the options for mental health care available under your employer-provided coverage? (No)	0.050659
Have you ever sought treatment for a mental health issue from a mental health professional?	0.050477

Do you work remotely? (Sometimes)	0.046187
Do you have a family history of mental illness? (Yes)	0.046149
Does your employer offer resources to learn more about mental health concerns and options for seeking help? (No)	0.045763
Do you feel that your employer takes mental health as seriously as physical health? (No)	0.044742
Is your anonymity protected if you choose to take advantage of mental health or substance abuse treatment resources provided by your employer? (Yes)	0.043685

Based on feature importance, we found that the most important feature by far was: “Would you feel comfortable discussing a mental health disorder with your coworkers?_No”, followed by: “Do you think that discussing a mental health disorder with your employer would have negative consequences?_No”, and finally: “Would you feel comfortable discussing a mental health disorder with your coworkers?_Yes”. Thus, the effect of feeling comfortable discussing mental health with coworkers is very highly correlated with feeling comfortable discussing mental health with supervisors. This is likely because coworkers contribute a lot to the workplace environment. With a work environment that feels unsafe and doesn’t foster open communication, it is unlikely that an employee would be comfortable being vulnerable to their supervisor.

Another way to look at this is that the supervisor also sets the tone for the team, so the employees on the team will likely follow this dynamic. The second most important feature makes sense when we consider that people who believe that discussing mental health with employers will have negative consequences are likely to feel uncomfortable talking about these issues with their direct supervisors. This discomfort may arise from fears of putting their jobs in jeopardy, concerns about associated stigma, or worries about potential negative impacts on their careers.

Therefore, it seems that the things that contribute most to an open discussion about mental health in the workplace are the team environment (accounting for both coworkers and employers/supervisors) and psychological safety, knowing they are cared for. Other issues like whether or not the company has good healthcare benefits were not deemed as important by the model. Again, this makes sense as talking to a supervisor about mental health does not necessarily mean the person will be required to receive treatment for it.

Conclusion

This project aimed to explore mental health outcomes in the tech industry by using predictive models like decision trees, random forests, and linear regression. While the models offered some insights into trends and were somewhat effective at classifying mental health outcomes, there were limitations to their performance, which presents room for improvement and further exploration in the future.

One of the main challenges was with balancing precision and recall, likely due to data imbalances and feature complexities. The categorical nature of the data primarily contained binary yes/no responses, which may have oversimplified the complex workplace and mental health dynamics, which in turn limited the model's ability to adequately capture such nuanced relationships. Both workplace and mental health experiences are multifaceted and cannot properly be measured with binary variables to define their relationship to one another. Incorporating more quantitative features or continuous variables like levels of stress reported, degrees of workplace satisfaction, or other measurable responses may help improve the model's ability to identify patterns better.

Additionally, there was a lot of missing data which may have affected the model's ability to make reliable predictions. For our study's purposes, our model could be used as a starting point for future research that may use enhanced data collection methods to help reduce the effects of missing data. It's also possible that utilizing techniques like SMOTE or other resampling strategies could help with imbalanced data complications in future research.

Another limitation was the possibility of multicollinearity among features specific to workplace conditions, such as employer support and access to mental health resources. These variables may have potentially overlapped and reduced the distinct predictive power of individual features, making it harder to identify exactly which factor was most influential.

Generalizability was another concern, as the dataset primarily represented tech industry workers from specific regions, which may not be applicable or relevant to other industries or global contexts. Expanding this dataset to include a broader range of geographical regions and demographics of respondents would help provide a more comprehensive view of the trends found within this smaller population. It could also be worth exploring how mental health outcomes have evolved in response to workplace culture and practices.

Despite these challenges, results from our overall analysis indicate that machine learning models like logistic regression, decision trees, and random forests provide helpful insights and offer a foundation for identifying trends related to mental health patterns among employees in the tech industry. It is worth noting that our desired thresholds for model validity weren't quite met, which enforces the need for further improvements in areas like data preprocessing, feature engineering, and model optimization to better account for missing or inadequate data that may affect the model's predictions. Additionally, incorporating more quantitative data analytics could provide richer insights in tandem with the current data. To address the ambiguity of "maybe" responses, incorporating additional qualitative data like performance evaluations or other surveys could increase the predictive accuracy of future analyses. It could also be more insightful to obtain quantitative metrics to further support our efforts to measure employees' affinity with seeking mental health resources.

From the analysis conducted, a few recommendations came to mind. Firstly, employers in the tech industry should implement and prioritize workplace initiatives that foster a supportive culture of trust and openness where discussing mental health is normalized and supported, helping to reduce the stigma around the topic and encourage employees to seek help without fear of judgment. Additionally, employers should increase the accessibility and visibility of mental health resources, like counseling services or support groups. These types of initiatives can help companies create environments where employees feel valued, supported, and comfortable with both coworkers and leaders, ultimately improving well-being and productivity.

By combining predictive insights with actionable recommendations, this project offers many ways for tech companies to foster an environment where the mental health of their employees is prioritized and recognized. While our models fell short on highly accurate predictions, their outputs can still be used as a benchmark to give employers base insights as to whether their employees feel comfortable discussing mental health with them and what employers can do to improve in that regard. When mental health is treated with the same urgency as physical health, the workplace environment can ultimately progress towards a healthier, more productive workforce, fostering more harmony between leadership and employees worldwide. This project highlights the importance of data-driven methods to better address and understand workplace cultures surrounding mental health and improvements that can be made. With improved data collection in future exploration, the findings throughout this project can help employers take actionable steps to a more supportive environment to make a meaningful impact and contribute to a more open culture in the tech industry.

References

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