# Exploring Mental Health Contributing Factors in the Tech Industry

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***Abstract*— BRUH idk**

***Keywords*— Include at least 5 keywords or phrases**

## I. Introduction

The National Institute of Mental health estimates "that more than one in five U.S. adults live with a mental illness" Also "more than half the world's population are currently in work and 15% of working-age adults live with a mental disorder." According to a study by the World Health Organization, depression and anxiety disorders alone cost the global economy nearly $1 trillion annually in lost productivity. This large figure underscores the significant economic toll that poor mental health can have on overall economic output, largely due to decreased performance and the loss of workdays. Further analysis shows that every year, approximately 12 billion workdays are lost due to depression and anxiety, which highlights the widespread effect of these mental health issues on workforce efficiency and economic productivity. Addressing mental health in the workplace is not only a critical health concern but also a significant economic imperative. By investing in mental health care and support, businesses can improve their productivity and reduce economic losses, with studies "estimated costs of scaling up treatment, primarily psychosocial counselling and antidepressant medication, amounted to US$ 147 billion. Yet the returns far outweigh the costs. A 5% improvement in labour force participation and productivity is valued at US$ 399 billion, and improved health adds another US$ 310 billion in returns." Furthermore, according to the "State of the Tech Workforce 2024" report by CompTIA, U.S. tech employment remained strong into 2023. Even with layoffs, the number of tech job postings and hiring in December 2022 continued to reflect a demand for tech professionals, particularly in software development and IT support roles. APA's 2022 Work and Well-Being Survey indicates a shift in employee expectations regarding mental health support, with a large majority believing that their employers are more concerned about employees' mental health than in the past. It suggests that how employers support mental health is becoming a crucial consideration for current and prospective employees. Poor mental health significantly affects job performance by reducing individuals' ability to perform tasks efficiently and effectively. Mental health disorders such as depression and anxiety can lead to increased absenteeism and reduced productivity. Additionally, employees struggling with mental health issues often experience decreased cognitive performance, which can affect their daily work tasks. Studies have shown that treating depression and anxiety can reduce symptoms that interfere with work, such as lack of motivation or focus. Effective treatments, such as psychotherapy or medication, help employees regain their ability to perform at their best, which benefits both the individuals and the organization. According to the CDC, Proactive mental health strategies in the workplace can prevent the development of severe mental health issues and enhance overall employee well-being. Preventive measures include promoting a supportive work environment, offering mental health resources, and providing training for stress management. These efforts not only help in reducing the incidence of mental health problems but also improve work engagement and productivity.

## II. Approach

*A. Problem Understanding and Dataset Acquisition*

The dataset used in this study is from Open Sourcing Mental Illness (OSMI) Mental Health in Tech Survey, a survey on mental health in the tech workplace in 2014 [10]. The survey gathers data on a variety of factors such as family history of mental illness, personal mental health conditions, employer support for mental health, and the impact of mental health on work performance and it comprises more than 1200 responses. This comprehensive set of questions allows for a thorough analysis of how different factors relate to the likelihood of seeking treatment for mental health issues among tech workers.

*B. Data Preprocessing*

The dataset from the Open Sourcing Mental Illness (OSMI) survey was initially streamlined by removing certain columns that did not contribute to the analysis objectives. The 'country' column was dropped to avoid assumptions about mental health conditions across different nations due to insufficient comparative data. Similarly, the 'state' column, applicable only to the U.S., was also removed following the exclusion of the 'country' column. The 'timestamp' column, detailing the exact date and time of survey responses, was deemed irrelevant for the study's purposes and thus discarded.

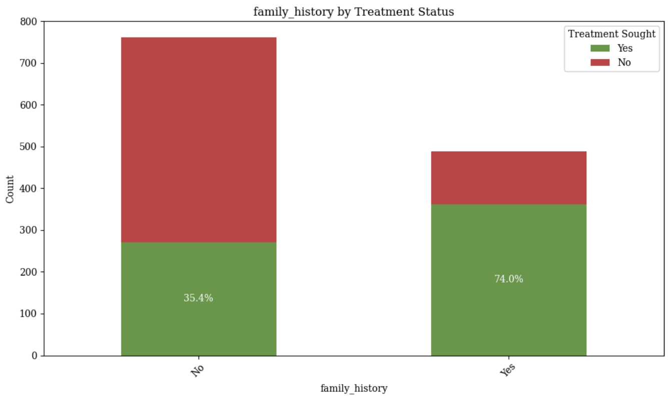
Further simplifications included the removal of the 'comments' section, which was optional and largely unused by respondents, thereby providing little analytical value. The age data contained outliers, prompting the setting of an age range from 18 to 100 years to maintain demographic relevancy. The 'gender' variable, initially presenting numerous spelling errors and variant entries, was standardized into three categories: male, female, and other, reflecting the open-ended nature of the original question.

To address missing data, a strategic approach of imputation was employed. The 'self_employed' column, where null values predominated, was imputed to 'No' based on the observation that only a small percentage (1.4%) of respondents identified as self-employed, making it a reasonable assumption for the majority. The 'work_interfere' column, which had missing entries, was uniformly imputed with 'Don't know' to reflect uncertainty in cases where respondents did not specify how mental health conditions impacted their work. These preprocessing steps were critical in shaping a coherent dataset ready for further analysis and model building.

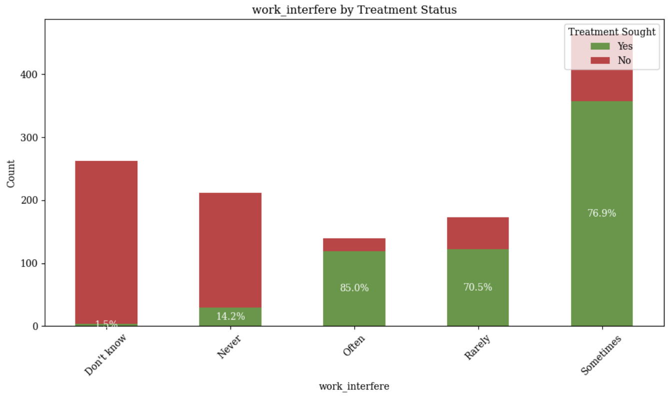
*C. Visualization*

Stacked bar charts were employed to illustrate the proportions of respondents seeking treatment for mental health conditions, segmented by factors such as family history of mental illness. These charts clearly displayed differences in treatment-seeking behavior, using color differentiation for visual clarity. This visualization technique quantified the impact of various factors on mental health treatment decisions, enhancing the interpretability of the dataset's patterns.

*family_history: Do you have a family history of mental illness?* The data indicates a notable link between family history and the pursuit of mental health treatment; 74% of individuals with such a history have sought help, contrasting with 35.4% without. Those without a family history represent a larger portion of the survey population, regardless of treatment status. This pattern suggests that awareness of familial mental health challenges could heighten individuals' propensity to seek treatment, possibly due to increased vigilance or a greater openness to acknowledging and addressing mental health concerns.




*work_interfere: If you have a mental health condition, do you feel that it interferes with your* *work?* Analysis of the data reveals that individuals experiencing work interference from mental health issues "Sometimes" have the highest rate of seeking treatment, with 76.9% addressing their concerns professionally. In contrast, only 14.2% of those in the "Never" category have sought help, marking the least engagement with treatment services. A discernible pattern emerges, showing an increased inclination for treatment as the occurrence of mental health-related work interference rises. Additionally, the "Don't Know" response is associated with lower treatment-seeking behavior. This information points to a probable link between the regularity of mental health challenges affecting work and the pursuit of treatment, suggesting that more frequent disruptions may prompt a greater recognition of the need for assistance.

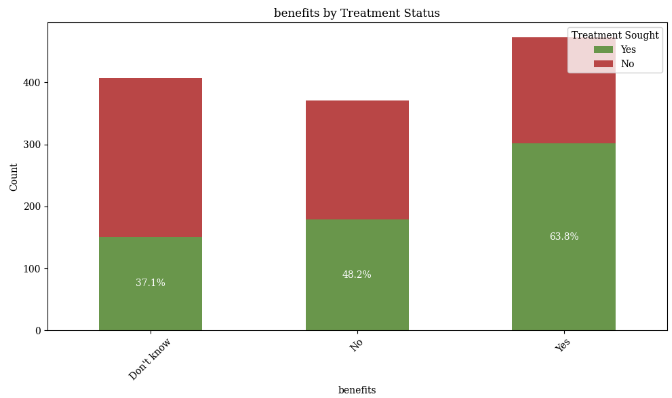



*wellness_program: Has your employer ever discussed mental health as part of an employee wellness program?* The data shows that wellness programs may be a significant factor in mental health treatment-seeking behavior. Individuals with access to wellness programs are the most proactive in seeking help, with 59.0% pursuing treatment. In workplaces without such programs, the decision to seek treatment is more divided, with a marginal majority of 49.8% reaching out for help. Uncertainty about the existence of wellness programs correlates with a reduced likelihood of treatment-seeking, as only 43.3% of employees in this category have sought assistance. This pattern implies a potential link between wellness program availability and employee engagement with mental health services, stressing the need for awareness and clear communication about such resources. These insights could be instrumental for companies looking to bolster their health benefits with wellness initiatives.

*leave: How easy is it for you to take medical leave for a mental health condition?* The uncertainty surrounding mental health leave is prevalent, as the "Don't Know" category dominates, with under half of these individuals seeking treatment. Intriguingly, those who find it "Very difficult" to take mental health leave are the most likely to seek treatment, at a rate of 68.0%. Treatment-seeking rates are notably consistent, hovering around the 50% mark for those who consider leave-taking "Somewhat easy" to "Very easy." This data hints at a complex relationship between the perceived ease of leave and treatment-seeking behavior; those facing or fearing greater obstacles may be more motivated to seek help. Additionally, the 50% treatment rate among those who find leave-taking straightforward suggests that factors other than the ease of leave play a significant role in the decision to seek treatment.

*mental_vs_physical: Do you feel that your employer takes mental health as seriously as physical health?* A significant portion of the workforce is unsure if their employers value mental health as much as physical health, with only 45.1% of this group seeking treatment. Among those who perceive mental health as less prioritized than physical health, a majority (59.2%) have sought help, which might reflect a proactive stance due to increased awareness or concerns about mental health stigma. Contrastingly, individuals who view mental and physical health as equally recognized by their workplace exhibit a near-even split regarding treatment, with a marginal majority of 51.0% engaging in treatment. These observations suggest that while perceptions of workplace mental health attitudes are associated with seeking treatment, there's a broader spectrum of factors influencing this critical health decision.

*benefits: Does your employer provide mental health benefits?* The presence and awareness of mental health benefits are evidently linked to treatment-seeking behaviors, with 63.8% of those aware of their benefits seeking treatment, surpassing the 48.2% without benefits and the 37.1% unsure of their benefit status. Notably, those certain of their mental health benefits are most likely to seek treatment. Even without clarity on benefit availability, over a third still pursue treatment, highlighting the complex dynamics influencing such decisions. This pattern underscores the role of employer-provided mental health support and suggests that increased transparency and access to benefits may promote greater utilization of mental health services among employees.




*obs_consequence: Have you heard of or observed negative consequences for coworkers with mental health conditions in your workplace?* The data indicates that witnessing negative repercussions for coworkers dealing with mental health issues may have a ripple effect, with 69.1% of those observing such outcomes seeking treatment for themselves. In contrast, less than half of the individuals who haven't seen negative consequences, at 47.4%, have taken similar steps. This pattern suggests that firsthand observation of the challenges faced by peers can heighten an individual's likelihood of seeking help, potentially spurred by greater awareness or concern over facing similar issues. The trend hints at the influence of workplace dynamics on personal health decisions, where the observed treatment of coworkers' mental health can shape one's approach to their own wellbeing.

In the pursuit of understanding the factors influencing treatment-seeking behavior for mental health issues among employees, a correlation matrix was employed. This matrix was generated after label encoding was applied to convert categorical variables into a numerical format suitable for correlation analysis. The matrix divulged that, alongside work interference which displayed a substantial correlation coefficient of 0.62, there were notable correlations between treatment and other predictors. Specifically, the provision of mental health benefits showed a correlation coefficient of 0.22 with treatment-seeking behavior, while the awareness of care options was slightly more correlated at 0.24. These findings suggest that both the availability of benefits and knowledge of care options are relevant predictors of treatment-seeking behavior, albeit to a lesser extent than work interference, thereby meriting consideration in the comprehensive evaluation of mental health initiatives within the workplace.

### *D. Model Building*

Upon identifying notable correlations, an array of classification models was employed to further explore this relationship. The independent variables 'work interference', ‘benefits’, and ‘care_options’ were utilized to predict the dependent variable 'treatment'. The predictive performance of various algorithms—namely, Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, and Support Vector Machine (SVM)—was assessed. Evaluation metrics included Accuracy, Recall, Precision, and F1 Score, providing a comprehensive analysis of each model's effectiveness. The results of this comparative analysis are systematically presented in Table 1. Based on these results, a decision tree was chosen for further evaluation.

TABLE I
CLASSIFICATION MODEL RESULTS

| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Logistic Regression | 0.784861 | 0.800000 | 0.811594 | 0.805755 |
| Decision Tree | 0.824701 | 0.797468 | 0.913043 | 0.851351 |
| Random Forest | 0.824701 | 0.797468 | 0.913043 | 0.851351 |
| Gradient Boosting | 0.796813 | 0.788079 | 0.862319 | 0.823529 |
| SVM | 0.824701 | 0.776471 | 0.956522 | 0.857143 |

## III. Evaluation

### *A. Evaluation Goals*

The evaluation section of this study focuses on identifying the workplace conditions that most influence employees' decisions to seek mental health treatment. Through a detailed analysis of factors like work interference, availability of mental health benefits, and awareness of care options, the goal is to pinpoint which elements are most effective in encouraging treatment pursuit. This understanding will help in crafting more supportive workplace mental health policies.

### *B. Metrics*

The decision tree model exhibits strong performance with an accuracy of 82.5%, indicating that it correctly predicts treatment-seeking behavior in a majority of cases. The precision of 79.7% confirms that a high proportion of positive predictions are accurate, while a recall of 91.3% demonstrates the model's ability to identify most actual positive cases. The F1-score of 85.1% further highlights the model’s balance between *precision* and recall, ensuring its reliability in scenarios where accurate detection is crucial. These metrics collectively validate the model's effectiveness in analyzing treatment-seeking behavior within the workforce.

### *C. Decision Paths*

Primary Splits: The decision tree splits first on work_interfere <= 0.5 and then on work_interfere <= 1.5. This suggests that the level of work interference due to mental health issues is a significant predictor for seeking treatment. Lower levels of interference seem to correlate with not seeking treatment, while higher levels show a mixture but lean more towards seeking treatment.

Secondary Splits: After the initial split on work interference, the tree considers other variables: On the left side, where work interference is low (work_interfere <= 0.5), it further splits on care_options <= 1.5. This suggests that availability and awareness of care options play a role in the decision-making process for individuals with lower work interference due to mental health issues. However, the majority of the leaf nodes indicate 'No Treatment,' which reinforces the idea that individuals with lower work interference are less likely to seek treatment regardless of care options. On the right side, where work interference is higher (work_interfere <= 1.5), the tree splits on benefits <= 1.5 and again on care_options <= 1.5. This indicates that for individuals experiencing more significant interference with work, the presence of benefits and care options are important factors in the decision to seek treatment.

Gini Impurity: The Gini impurity is a measure of how often a randomly chosen element would be incorrectly identified. Nodes with higher Gini impurity suggest greater uncertainty in the classification. Nodes with lower Gini values indicate more homogeneous groups. For example, nodes with Gini close to 0 are very pure, meaning almost all samples belong to one class. The initial node has a high Gini impurity of 0.5, indicating a balanced split between the classes, whereas some leaf nodes have low Gini impurity, indicating a strong correlation with one of the classes.

Sample Sizes and Value Counts: Each node lists the number of samples that fall into each category. For example, the leftmost leaf node shows that 173 samples resulted in 'No Treatment' with a Gini impurity of 0.011, which is very low, indicating that this path is a strong predictor for not seeking treatment.

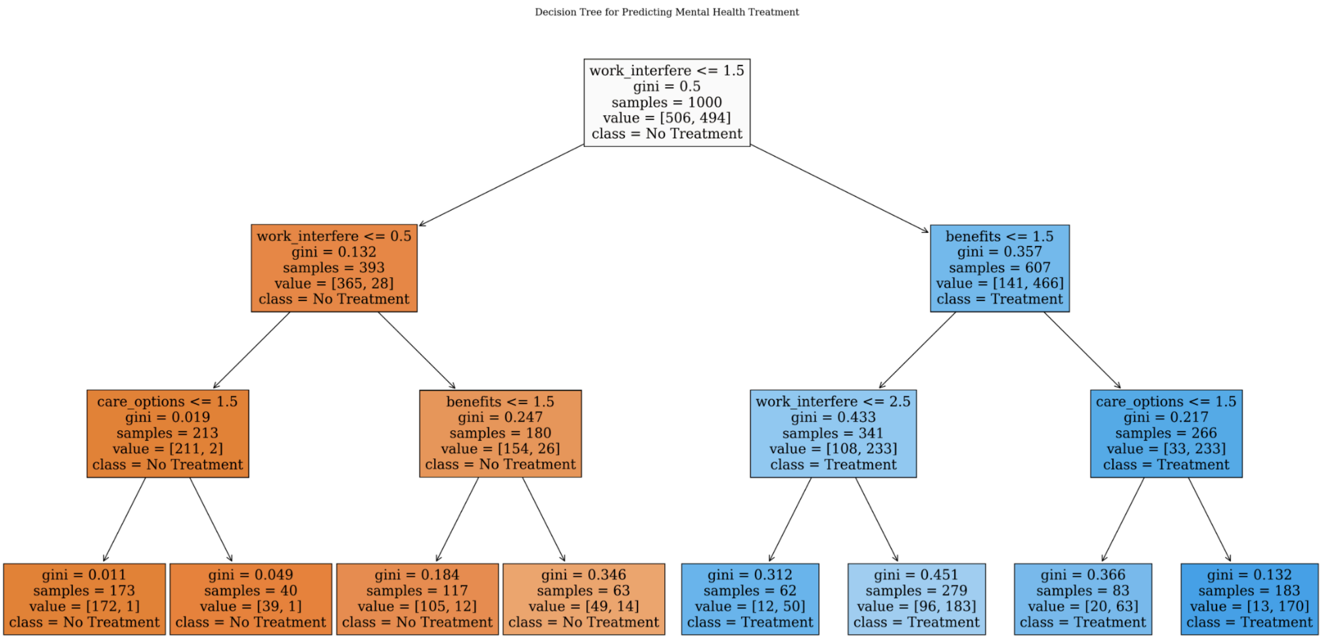
Predicted Class: The class label at each node tells us the majority class of the samples at that point. It can be seen that 'No Treatment' is the majority class in several leaf nodes, especially on the left side of the tree.

Class Distribution: The value attribute in each node represents the distribution of the classes. For instance, the rightmost node on the first level shows a distribution of [506, 494], meaning the samples are almost evenly split between not seeking treatment and seeking treatment.

From these observations, we can conclude that work interference is a key variable in predicting whether individuals in the tech industry will seek mental health treatment. The presence and awareness of benefits and care options are also important, especially for those experiencing a higher level of work interference. The decision tree suggests that as work interference increases, the likelihood of seeking treatment also increases, but the availability of benefits and care options significantly influences this decision.

## *E. Practical Implications*

Tech companies can utilize the insights from the decision tree analysis by implementing early detection measures for work-related mental health interference and enhancing awareness of available care options. Strengthening mental health benefits is crucial, particularly for those with higher interference levels, and should be part of a supportive work environment that encourages treatment-seeking behavior. Education initiatives on mental health can demystify treatment processes, promoting a culture of openness and support. Continuous policy evaluation with such data-driven approaches ensures that mental health interventions remain effective and responsive to employee needs.




# IV. Related Work

# V. Conclusions


# Acknowledgment


# References


[1] REFERENCES FR BRUH