The Impact of Workplace Factors on Mental Health Treatment Decisions in the Tech Sector

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***Abstract*— The prevalence of mental health issues within the tech industry poses significant challenges, not only due to their impact on individual employees but also on overall organizational productivity. This study leverages data from the Open Sourcing Mental Illness (OSMI) Mental Health in Tech Survey to analyze the factors influencing tech workers' likelihood to seek mental health treatment. Through comprehensive data preprocessing and visualization, the research identifies key factors such as work interference, family history of mental illness, and the availability of employer-supported mental health resources that significantly affect treatment-seeking behaviors. Our approach utilizes various predictive models to examine these relationships, with a decision tree model providing the most insightful results. The findings emphasize the critical role of supportive workplace environments and accessible mental health resources in encouraging employees to seek help, ultimately enhancing both personal well-being and workplace productivity.**

***Keywords*— Mental Health, Tech Industry, Workplace Support, Predictive Modeling, Employee Well-being**

I. Introduction

Mental health issues are prevalent in the workforce, with the National Institute of Mental Health estimating that over 20% of U.S. adults have a mental illness [1], and globally, 15% of working-age adults are affected by mental disorders [2]. These issues significantly impact the economy; for instance, depression and anxiety alone cost the global economy nearly $1 trillion annually in lost productivity due to decreased performance and approximately 12 billion lost workdays each year [2].

Investing in mental health care, such as through psychosocial counseling and antidepressant medication, offers substantial economic benefits. Studies estimate that improving treatment accessibility could result in a 5% increase in labor force participation and productivity, which translates to $399 billion in economic gains, and an additional $310 billion from improved health outcomes [3].

In the tech industry, demand for professionals remains robust, especially in software development and IT support, despite some layoffs. This resilience highlights the sector's growth, as detailed in the "State of the Tech Workforce 2024" report by CompTIA [4].

Additionally, the importance of mental health support in the workplace is increasingly recognized. According to the APA's 2022 Work and Well-Being Survey, more employees now believe their employers are genuinely concerned about their mental health, reflecting a significant cultural shift [5]. This perception is becoming crucial for employee satisfaction and influences both retention and recruitment in the tech industry, emphasizing the need for companies to prioritize mental health to attract and retain top talent.

Poor mental health can dramatically reduce an individual's ability to perform tasks efficiently and effectively, leading to increased absenteeism and reduced productivity. However, effective treatments, such as psychotherapy or medication, help improve focus and motivation, thereby enhancing work performance [6].

According to the CDC, proactive mental health strategies in the workplace, such as promoting a supportive environment, offering mental health resources, and providing training for stress management, can prevent the development of severe mental health issues and enhance overall employee well-being and productivity [6]. These efforts not only mitigate the incidence of mental health problems but also improve work engagement and productivity, benefiting both the individuals and the organization.

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 [7]. 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 OSMI Mental Health in Tech Survey dataset was refined by removing non-essential columns. 'Country' and 'state' columns were excluded to prevent biased interpretations due to limited comparative and geographical relevance. Similarly, 'timestamp' and 'comments' sections were omitted for their lack of relevance and utilization, respectively. Data on age was adjusted to exclude outliers, setting a range from 18 to 100 years. 'Gender' entries were corrected and categorized into male, female, and other. For missing data, 'self_employed' was defaulted to 'No', reflecting its minor presence in the dataset, and 'work_interfere' was filled with 'Don't know', accounting for the unspecified impact on work.

C. Visualization

Figure 1 displays a bar chart that illustrates the distribution of respondents who have sought treatment for mental health issues versus those who have not. The chart effectively highlights that the survey population is almost evenly split, with about 50% of respondents having sought treatment and 50% not. This visual representation underscores the balanced dichotomy within the tech industry, setting the stage for a deeper analysis of the factors influencing these treatment decisions.

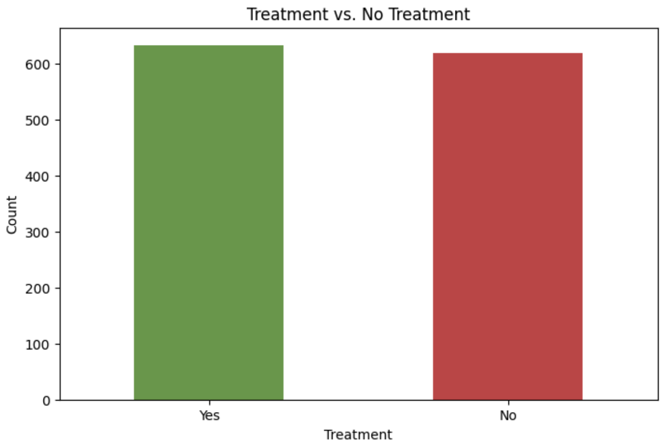

Fig. 1 Bar chart of treatment vs no treatment

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? Family history of mental illness significantly influences treatment-seeking behavior, as shown in Figure 2. Individuals with a family history are more likely to seek treatment (74%) compared to those without (35.4%). This suggests that awareness of familial mental health issues may increase the likelihood of seeking help, possibly due to heightened vigilance or greater openness to addressing these concerns.

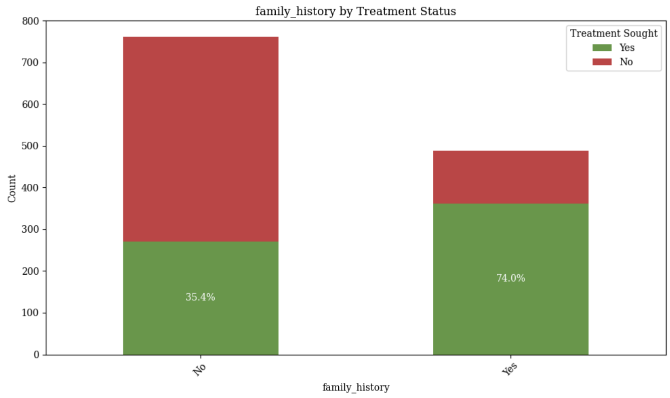

Fig. 2 Family History's Impact on Mental Health Treatment

work_interfere: If you have a mental health condition, do you feel that it interferes with your work? Work interference due to mental health issues correlates with the likelihood of seeking treatment, as depicted in Figure 3. Individuals reporting occasional interference are most likely to seek help (76.9%), while those reporting no interference have the lowest engagement (14.2%). A clear pattern shows that as work interference increases, so does the inclination to seek treatment. Those unsure of interference ("Don't Know") show lower treatment-seeking behavior, suggesting that more frequent disruptions heighten the recognition of needing help.

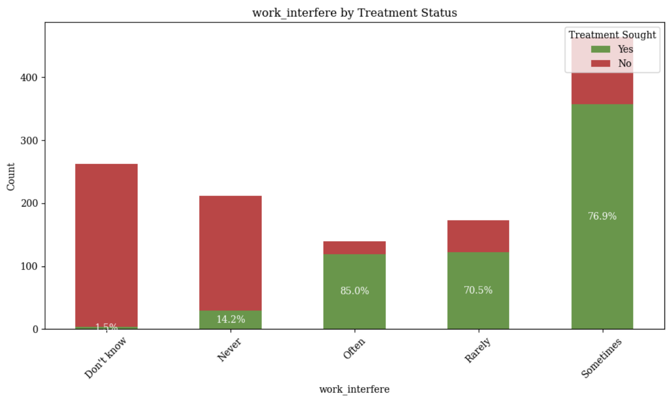

Fig. 3 Work interference vs. mental health treatment seeking

wellness_program: Has your employer ever discussed mental health as part of an employee wellness program? Wellness programs significantly influence mental health treatment-seeking behavior. Data indicates that 59.0% of employees with access to these programs actively seek treatment, compared to 49.8% in workplaces without them. Uncertainty about program availability leads to lower engagement, with only 43.3% seeking help. This suggests a strong link between the presence of wellness programs and proactive treatment-seeking, emphasizing the importance of clear communication and awareness of such resources for enhancing employee health initiatives.

leave: How easy is it for you to take medical leave for a mental health condition? The ease of taking medical leave for mental health varies widely. Individuals unsure about leave policies ("Don't Know") are less likely to seek treatment, with fewer than half pursuing it. Interestingly, those who find it "Very difficult" to take leave are most likely to seek treatment (68%), while rates for those finding it "Somewhat easy" to "Very easy" hover around 50%. This suggests a complex relationship between the ease of obtaining leave and the motivation to seek treatment, with additional factors influencing the decision beyond just policy clarity.

mental_vs_physical: Do you feel that your employer takes mental health as seriously as physical health? Many employees are uncertain whether their employers value mental health as much as physical health, with only 45.1% of this unsure group seeking treatment. However, those who feel mental health is less prioritized than physical health are more likely to seek help (59.2%), possibly due to greater awareness or stigma concerns. Conversely, employees who believe mental and physical health are equally valued show a balanced treatment engagement at 51.0%. These findings indicate that perceptions of employer attitudes towards mental health influence treatment decisions, alongside a range of other significant factors.

benefits: Does your employer provide mental health benefits? The availability and awareness of mental health benefits significantly impact treatment-seeking behavior. According to Figure 4, 63.8% of employees aware of their benefits seek treatment, compared to 48.2% without benefits and 37.1% unsure of their benefit status. Those with a clear understanding of their benefits are most likely to seek help. The data reveals that even a lack of clarity around benefits doesn't completely deter treatment efforts, highlighting the complex factors at play. This emphasizes the importance of employer transparency and the provision of mental health support to enhance employee engagement with these services.

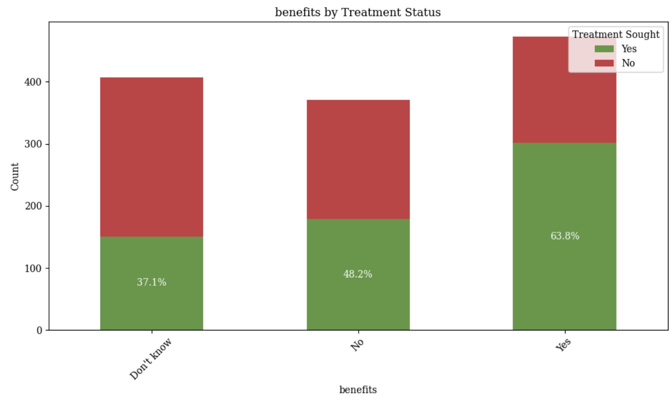

Fig. 4 Employer benefits and mental health treatment uptake

obs_consequence: Have you heard of or observed negative consequences for coworkers with mental health conditions in your workplace?

Observing negative consequences for coworkers with mental health issues appears to influence personal treatment decisions. Data shows that 69.1% of employees who witness such effects seek treatment themselves, compared to only 47.4% who haven't observed negative consequences. This suggests that seeing peers face mental health challenges can increase an individual's propensity to seek help, possibly due to heightened awareness or concerns about similar issues. This trend underscores the impact of workplace dynamics on personal health decisions and highlights how observed treatment of coworkers' mental health can affect one's own approach to wellbeing.

In the pursuit of understanding the factors influencing treatment-seeking behavior for mental health issues among employees, a correlation matrix was employed as seen in Figure 5. 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.

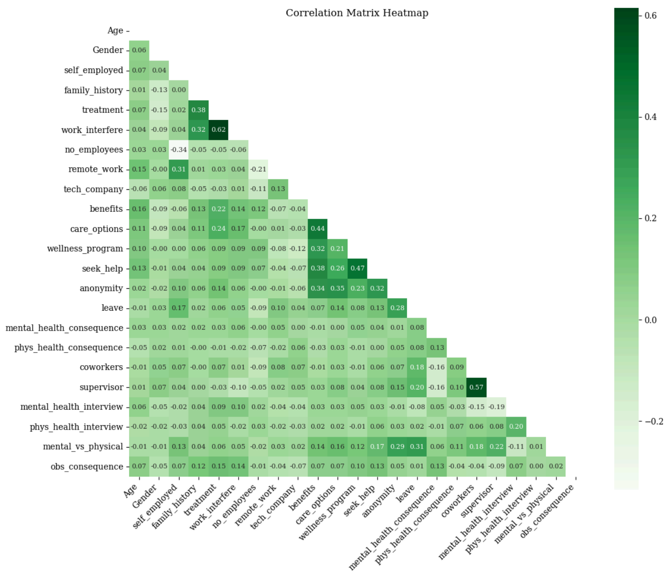

Fig. 5 Correlation matrix heatmap

D. Model Building

Several classification models were used to investigate relationships indicated by the initial correlations, focusing on predicting 'treatment' using variables like 'work interference', 'benefits', and 'care_options'. We tested models including Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, and SVM, assessing them based on Accuracy, Recall, Precision, and F1 Score. These evaluations, detailed in Table 1, highlighted the decision tree's superior performance, prompting further analysis.

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. Decision Tree Paths

Model Performance: The decision tree in Figure 6 achieves an accuracy of 82.5%, precision of 79.7%, and a recall of 91.3%, effectively predicting treatment-seeking behavior with a balanced F1-score of 85.1%. These metrics confirm its reliability in workforce behavior analysis.

Decision Paths Overview: The tree's depth was capped at three levels for readability. It primarily splits based on 'work_interference', indicating it as a critical predictor for seeking treatment. Lower interference generally leads to no treatment, while higher levels increase the likelihood of seeking help.

Deeper Analysis: Further splits on 'care_options' for low interference and on 'benefits' for high interference highlight their influence on treatment decisions. The decision tree demonstrates that while work interference is a key factor, the availability of care options and benefits also significantly affects the likelihood of seeking treatment.

Gini Impurity and Node Details: The Gini impurity measures prediction certainty, with lower values indicating stronger predictions. Nodes vary from balanced outcomes to strong predictors of treatment behavior, exemplifying the model's analytical precision.

Conclusions from Tree Analysis: Work interference is confirmed as a primary factor influencing treatment-seeking. Enhancing benefits and care options could significantly impact treatment decisions, particularly for those with greater work-related mental health challenges.

C. 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

A 2023 IEEE study [8] used the OSMI Mental Health in Tech Survey to analyze workplace mental health, highlighting the importance of fostering relationships and wellness programs to reduce mental stress, particularly in urban tech settings where stress levels are higher. This aligns with findings that continuous work pressures affect mental health significantly. Another 2022 IEEE study [9] also found that interpersonal rapport and wellness programs help mitigate workplace mental stress, especially in urban tech environments with infrequent breaks and non-remote working conditions. Both studies underscore the need for comprehensive mental health strategies and suggest using hybrid machine learning techniques to enhance predictive accuracy and intervention effectiveness.

V. Conclusions

This study has systematically explored the intricate dynamics between workplace conditions and the propensity for tech industry employees to seek treatment for mental health issues. Our findings reveal that work interference, awareness of mental health benefits, and availability of care options are crucial factors influencing employees' decision-making processes regarding mental health care. Notably, employees facing higher levels of work interference are more likely to seek treatment, highlighting the critical role of supportive workplace environments in fostering mental well-being. Additionally, the presence of structured mental health benefits and clear communication about available care options significantly enhance treatment-seeking behaviors. This research underscores the imperative for tech companies to implement comprehensive mental health strategies that not only reduce work-related stress but also promote a culture of support and openness. By addressing these key factors, organizations can not only improve individual employee health but also enhance overall productivity and workplace harmony.

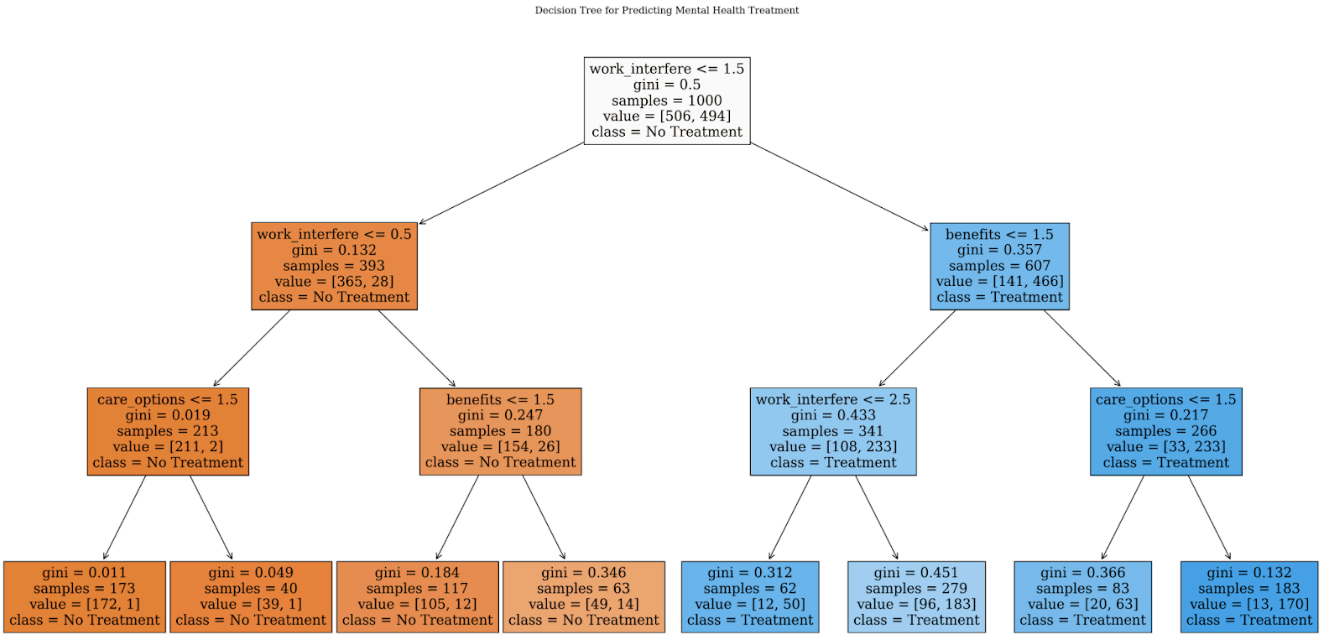

Fig. 6 Decision tree analysis of workplace factors affecting mental health treatment

References

[1] National Institute of Mental Health, “Mental Illness,” National Institute of Mental Health, Mar. 2023. https://www.nimh.nih.gov/health/statistics/mental-illness

[2] “Mental health in the workplace,” www.who.int. https://www.who.int/teams/mental-health-and-substance-use/promotion-prevention/mental-health-in-the-workplace#:~:text=Twelve%20billion%20working%20days%20are

[3] “Investing in treatment for depression and anxiety leads to fourfold return,” www.who.int. https://www.who.int/en/news-room/detail/13-04-2016-investing-in-treatment-for-depression-and-anxiety-leads-to-fourfold-return

[4] “Tech employment holds steady heading into 2023, CompTIA analysis reveals,” CompTIA, Jan. 06, 2023. https://www.comptia.org/newsroom/tech-employment-holds-steady-heading-into-2023-comptia-analysis-reveals (accessed Apr. 26, 2024).

[5] H. Stringer, “Worker well-being is in demand as organizational culture shifts,” American Psychological Association, Jan. 01, 2023. https://www.apa.org/monitor/2023/01/trends-worker-well-being#:~:text=URL%3A%20https%3A%2F%2Fwww.apa.org%2Fmonitor%2F2023%2F01%2Ftrends,100 (accessed Apr. 26, 2024).

[6] “Mental Health in the Workplace,” www.cdc.gov, May 05, 2021. https://www.cdc.gov/workplacehealthpromotion/tools-resources/workplace-health/mental-health/index.html#print

[7] “Mental Health in Tech Survey,” www.kaggle.com. https://www.kaggle.com/datasets/osmi/mental-health-in-tech-survey/data

[8] A. Lohia, A. Ranjith, A. Sachdeva and A. Bhat, "An Ensemble Technique to Analyse Mental Health of Workforce in the Corporate Sector," 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2023, pp. 1245-1251, doi: 10.1109/ICICCS56967.2023.10142470. keywords: {Training;Machine learning algorithms;Employment;Urban areas;Mental health;Production;Ensemble learning;Ensemble Technique;Machine Learning;KNN;Decision Trees;Logistic Regression;Random Forest Classifier;Psychological Disorder;Mental Health Analysis;Mental Well-being;Precision;False Positive (1);XG Boost;GLMNet;Bagging;Boosting.},

[9] S. BH et al., "Mental Health Analysis of Employees using Machine Learning Techniques," 2022 14th International Conference on COMmunication Systems & NETworkS (COMSNETS), Bangalore, India, 2022, pp. 1-6, doi: 10.1109/COMSNETS53615.2022.9668526. keywords: {Machine learning algorithms;Mood;Anxiety disorders;Mental health;Companies;Machine learning;Stability analysis;Mental Health;Mental Health Analysis;Disorders;Machine Learning Algorithms},