Online Version Available at: https://jurnal.ubd.ac.id/index.php/te

JOURNAL OF TECH-E

| 2581-1916 (ONLINE) | 2598-7585 (PRINTED) |

Article

Machine Learning Approaches to Workplace Mental Health: Predicting Treatment-Seeking Behavior Using the OSMI Dataset

Nor Aishah Othman[1], *Mariana Rosdi*[2]

[1] *Sultan Haji Ahmad Shah Polytechnic, Electronic Engineering, Kuantan, Malaysia*

[2] *Sultan Salahuddin Abdul Aziz Shah Polytechnic, Electronic Engineering, Shah Alam, Malaysia*

SUBMISSION TRACK

Recieved: 12, 25, 2025
Final Revision: 01, 13, 2026
Available Online: 02, 02, 2026

KEYWORD

Workplace Mental Health, Predictive Analytics, Machine Learning, K-Nearest Neighbour, Explainable AI

CORRESPONDENCE

E-mail:
noraishah.othman@polisas.edu.my
mariana@psa.edu.my

A B S T R A C T

Employee mental health is increasingly recognized as essential for sustainable organizational performance, particularly in technology sectors where work intensity and psychological strain are prevalent. This study leverages machine learning to identify predictors of treatment-seeking behavior using the Open Sourcing Mental Illness (OSMI) dataset, which includes 1,387 anonymized responses from the 2014 OSMI survey. The survey examines employees' experiences and perceptions of mental health in the global tech industry. Through data cleaning and encoding, key factors influencing help-seeking behavior were identified, including family history of mental illness and work interference due to psychological distress. Two machine learning models, Decision Tree and K-Nearest Neighbour (KNN), were employed for prediction. The Decision Tree model achieved an accuracy of 73%, while KNN attained 100%, suggesting high predictive power, albeit with potential overfitting risks. These findings align with recent studies promoting the integration of AI-driven analytics in workplace wellness programs to detect hidden behavioral trends and enable early interventions. The results demonstrate that machine learning models can offer valuable insights into employee well-being and preventative strategies. Future research should focus on incorporating larger, more diverse datasets and adopting explainable AI (XAI) techniques to enhance interpretability, fairness, and trust in predictive systems for mental health in the workplace.

DOI: 10.31253/te.v9i2.4305

I. INTRODUCTION

Workplace mental health is increasingly acknowledged as a critical determinant of both individual well-being and organizational success [1], [2], [3]. It plays a significant role in influencing employees' cognitive abilities, decision-making, and overall productivity, which are crucial for fostering sustainable organizational growth. Mental health challenges, such as stress, anxiety, and depression, can severely impair an employee's performance, leading to higher absenteeism, burnout, and reduced job satisfaction. Given the increasing demand for efficiency and the evolving nature of work environments, addressing mental health in the workplace has become paramount. The World Health Organization (WHO) highlights that mental health is an essential aspect of overall health, emphasizing its importance in achieving organizational and societal well-being [4]. In sectors like technology, employees often face additional pressures due to long working hours, tight deadlines, and job insecurity, which can heighten the risk of mental health issues [5].

Despite the growing recognition of the importance of mental health in the workplace, significant barriers remain in addressing these challenges. Stigma surrounding mental health continues to prevent many employees from seeking help, with fears of judgment or negative consequences. Moreover, limited resources and unequal access to mental health care exacerbate these issues, creating disparities in support for employees facing psychological distress [6], [7]. These barriers contribute to underutilization of mental health services in many organizations, hindering efforts to create a supportive and inclusive work environment. As a result, there is a pressing need for strategies that not only encourage employees to seek help but also provide accessible and effective mental health resources.

Most existing research has primarily focused on documenting the prevalence of mental health issues in the workplace or identifying common risk factors [8]. While these studies have contributed to our understanding of the scope of the issue, they often stop short of offering actionable insights that can help organizations address mental health problems proactively. Few studies have explored predictive approaches to treatment-seeking behavior, and there is a significant gap in research that focuses on identifying the underlying factors that drive employees to seek or avoid mental health treatment [9]. This gap highlights the need for innovative methodologies that go beyond descriptive statistics to uncover hidden behavioral patterns and predictors of mental health treatment.

To fill this gap, the present study applies machine learning models to the Open Sourcing Mental Illness (OSMI) dataset, which contains responses from 1,387 employees in the global technology sector. This dataset includes demographic and workplace variables such as age, gender, employment type, family history of mental illness, and work interference due to psychological distress. By leveraging machine learning classifiers such as Decision Tree and K-Nearest Neighbors (KNN), the study aims to predict treatment-seeking behavior, providing insights into the key determinants that influence employees' decisions to seek help for mental health concerns. These models can uncover hidden patterns within the data, helping organizations better understand the factors that contribute to mental health challenges and shape their intervention strategies.

The research contributes to positioning machine learning as a transformative tool for workplace wellness, aligning with recent advancements in AI-driven mental health applications [10], [11], [12]. By using predictive analytics, organizations can develop early detection systems for mental health issues, allowing for more targeted interventions. This approach not only enhances organizational strategies for promoting employee well-being but also facilitates the development of personalized mental health programs that address the specific needs of different employee groups. Ultimately, this study demonstrates the potential of machine learning in improving workplace mental health initiatives, supporting the creation of healthier and more productive work environments.

DOI: 10.31253/te.v9i2.4305

II. LITERATURES REVIEW

Workplace conditions such as excessive workload, discrimination, and low job control are well-established contributors to mental health problems. These stressors can lead to significant psychological distress, which, in turn, affects employees' productivity, engagement, and overall well-being. The World Health Organization (WHO) estimates that nearly 15% of working-age adults experience mental health challenges, a figure that is concerning given the substantial implications for individual and organizational health. The impact on the workforce is not only felt in terms of decreased morale and productivity but also manifests in increased absenteeism and presenteeism, where employees remain at work but are unable to perform optimally. These workplace conditions contribute to a significant burden on both employees and employers, making it crucial to address mental health in the workplace more effectively [4].

Mental health problems, particularly depression and anxiety, are not only a burden on individuals but also on the global economy. According to WHO, these conditions alone account for over USD 1 trillion annually in lost productivity worldwide, a figure that is projected to rise unless more effective interventions are implemented [6]. The consequences of untreated mental health conditions extend beyond the workplace and can have long-term effects on physical health. Conditions like chronic pain, cardiovascular diseases, and gastrointestinal problems are often exacerbated by untreated psychological distress, highlighting the interconnectedness of mental and physical health. This underscores the importance of addressing mental health issues proactively in organizational settings, not just to protect employees' well-being but also to safeguard organizational performance and reduce the broader societal impact of untreated conditions [13].

While many organizations have established wellness programs aimed at supporting employee mental health, significant barriers remain in encouraging employees to seek treatment. Stigma surrounding mental health issues, coupled with the fear of negative consequences such as job loss or discrimination, prevents many individuals from disclosing their conditions or seeking help. This resistance to treatment-seeking behavior is particularly problematic as it means that mental health issues often go unaddressed, leading to more severe outcomes. These barriers to care, along with the complex dynamics of the workplace, suggest that a more targeted approach is needed to identify and intervene with employees at risk before their mental health deteriorates further [7]. Addressing these challenges requires a deeper understanding of the factors that influence treatment-seeking behavior.

Most existing literature on workplace mental health has focused on descriptive analyses, such as documenting prevalence rates and identifying common workplace risk factors. While these studies provide valuable insights into the scope of mental health issues in the workplace, they fall short of offering actionable strategies for prevention or early intervention. This gap highlights the need for more advanced methodologies, such as predictive modeling, which can identify at-risk employees before their conditions worsen. Recent developments in computing, particularly in machine learning, have opened new opportunities to address this gap. Machine learning algorithms, such as Decision Trees and K-Nearest Neighbors (KNN), have shown strong potential in health-related prediction tasks due to their interpretability and ability to capture nonlinear relationships between variables [10], [14]. These models can uncover patterns in data that are not easily identifiable through traditional statistical methods, providing insights into which employees may be at risk of developing mental health issues.

In addition to basic machine learning models, more advanced techniques such as Random Forest, Gradient Boosting, and Neural Networks have been explored to improve prediction accuracy and reduce overfitting risks. These models offer improved robustness and can handle complex, high-dimensional data, which is often encountered in mental health research. AI-powered workplace interventions are increasingly seen as cost-effective and scalable methods for enhancing employee well-being. Such systems can provide real-time support to employees, identifying early signs of distress and offering personalized interventions before issues escalate. These advancements

DOI: 10.31253/te.v9i2.4305

illustrate a broader shift in workplace mental health research, moving from descriptive analysis to predictive analytics. Machine learning is becoming a powerful tool in developing proactive organizational strategies that not only identify mental health risks but also optimize interventions to enhance overall employee well-being [11] [12].

III. FRAMEWORK

Despite the growing recognition of workplace mental health as a critical determinant of employee well-being and organizational productivity, many individuals continue to experience untreated mental health conditions. Stress, long working hours, and organizational pressures are strongly linked to mental health issues such as depression, anxiety, and long-term physical health risks, including cardiovascular disease [4], [7]. Research has further shown that untreated mental health issues often manifest in physical symptoms, further emphasizing the importance of early detection and timely intervention [12], [15]. While previous studies have documented the prevalence of mental health issues and identified risk factors, relatively few have investigated the predictive determinants of treatment-seeking behavior, particularly in the context of demographic variables such as age, gender, and family history, alongside workplace factors like job type and work interference [6], [7]. This gap highlights the need for more proactive, evidence-based interventions that can address mental health challenges before they escalate.

Machine learning presents a powerful solution to bridge this gap by uncovering hidden patterns in workplace mental health data. Algorithms like Decision Trees and K-Nearest Neighbors (KNN) are particularly well-suited for modeling treatment-seeking behavior, offering predictive insights that extend beyond traditional statistical methods [10], [11]. These algorithms can capture complex relationships between various demographic and workplace factors, helping to identify individuals at risk of mental health issues and offering potential avenues for early intervention. By applying these techniques, organizations can move from merely describing the problem to proactively predicting and addressing it. This approach aligns with recent shifts in workplace wellness strategies, which emphasize the use of predictive analytics to drive more effective mental health initiatives.

This study aims to fill the existing knowledge gap by applying supervised machine learning models to the Open Sourcing Mental Illness (OSMI) dataset, specifically to identify the key predictors of treatment-seeking behavior in the technology sector. The objectives of the study are twofold: first, to identify the key demographic and workplace factors influencing employees' decisions to seek mental health treatment, and second, to develop and evaluate machine learning models capable of predicting treatment-seeking behavior. By demonstrating how predictive analytics can guide innovative and evidence-based workplace wellness strategies, this research contributes to the ongoing efforts to integrate AI-driven solutions into organizational mental health programs.

IV. METHODS

This research draws upon the Open Sourcing Mental Illness (OSMI) 2014 survey, publicly available on Kaggle. The dataset contains anonymized responses from employees working in the technology sector, capturing their experiences, perceptions, and treatment-seeking behaviors related to mental health. It provides a relevant foundation for examining both demographic and workplace factors through predictive modeling. The dataset required substantial cleaning before modeling due to the presence of outliers and inconsistencies.

Table 1. Summary of Data Cleaning Actions for Age and Gender Variables

Variable	Example of Invalid Values	Cleaning Action	Valid Range/Labels After Cleaning
Age	-1726, -29, -1, 329, 99999999999	Removed unrealistic and extreme values	18–72 years
Gender	“Male”, “M”, “m”, “FEMALE”, “f”	Converted to lowercase and standardized	male, female

DOI: 10.31253/te.v9i2.4305

Table 1 provides a summary of the data cleaning procedures applied to the dataset. This included the removal of invalid age entries to ensure accurate demographic information. Additionally, gender categories were standardized to ensure consistency across the dataset.

Categorical variables including gender, family history of mental illness, employment type, and perceptions of workplace support were converted into numerical representations suitable for machine learning algorithms. Correlation analysis was employed to examine the strength and direction of relationships between variables, helping to identify potential predictors of treatment-seeking behavior. Model performance was further evaluated using confusion matrices, which provided insight into accuracy, sensitivity, and misclassification rates beyond overall accuracy [16].

The analytical framework followed a structured pipeline comprising four key stages: data acquisition, preprocessing, encoding and modeling. This approach ensured systematic handling of the dataset from raw data cleaning to predictive evaluation.

In the modeling phase, two supervised algorithms Decision Tree and K-Nearest Neighbors (KNN) were selected as baseline classifiers. These methods were chosen for their interpretability, simplicity, and suitability for exploratory health-related research. Decision Trees produce explicit decision rules, while KNN classifies based on feature similarity, offering a complementary non-parametric approach [17], [18]. Both models have been widely applied in prior health informatics studies and serve as useful benchmarks before applying more complex methods [14], [19].

Visualization techniques, including heatmaps and bar charts, were used to present correlations and highlight important predictors, while performance metrics ensured rigorous model evaluation. This pipeline provided a transparent, replicable structure for integrating workplace mental health research with machine learning, aligning with recent calls for data-driven approaches in mental health prediction [11], [12].

V. RESULTS

Objective 1: Identifying factors influencing employees' treatment-seeking behavior.

Age Distribution

Following the cleaning process, a histogram of respondent ages was generated in Figure 1. The results indicate that the majority of respondents are concentrated between 20 and 40 years old, with fewer participants above 50.

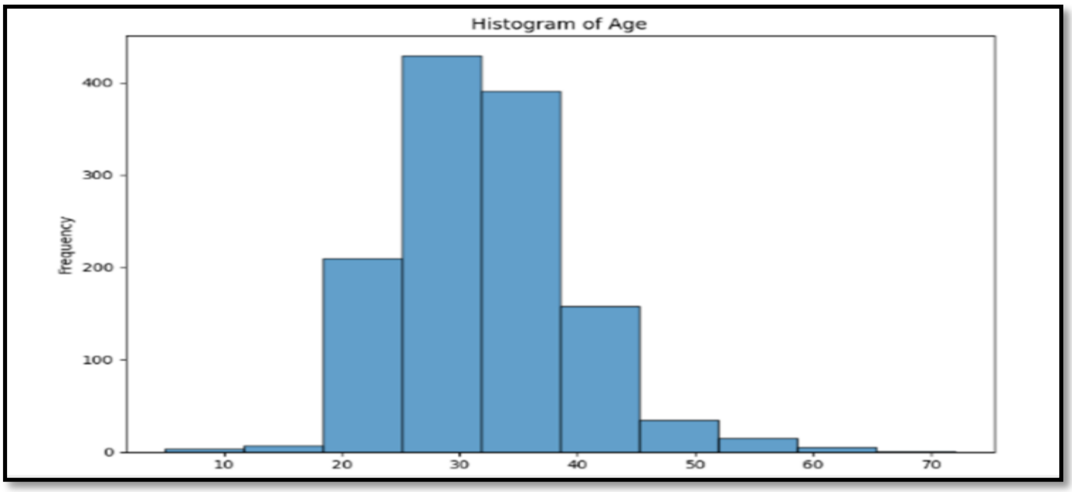

Figure 1. Histogram of Age Distribution of Respondents

Descriptive statistics are presented in Table 2. The average age of respondents was 32 years with a median of 31 and a mode of 29 reflecting a workforce dominated by young adults. The standard deviation of 7.5 years suggests moderate variation, though the skew remains toward early- and mid-career individuals.

DOI: 10.31253/te.v9i2.4305

Table 2. Descriptive Statistics of Cleaned Age Values

Statistic	Value
Minimum	18
Maximum	72
Mean	32.1
Median	31
Mode	29
Standard Deviation	7.5

Gender Distribution

The cleaned dataset revealed that the workforce is predominantly male. As illustrated in Table 3, male respondents made up 79% of the sample. In contrast, female respondents represented only 21% of the sample.

Table 3. Distribution of Respondents by Gender

Gender	Count	Percentage
Male	1,095	79%
Female	292	21%

This gender imbalance reflects the broader trend in the technology sector, where female participation remains limited. As a result, the dataset may be more representative of the experiences of male workers. This should be taken into account when generalizing the findings to the larger workforce.

Distribution of Employment Type Among Respondents

The dataset also included information on the employment type of respondents, as shown in Figure 2. The results indicate that 88% of respondents were not self-employed. In contrast, only 12% identified as self-employed.

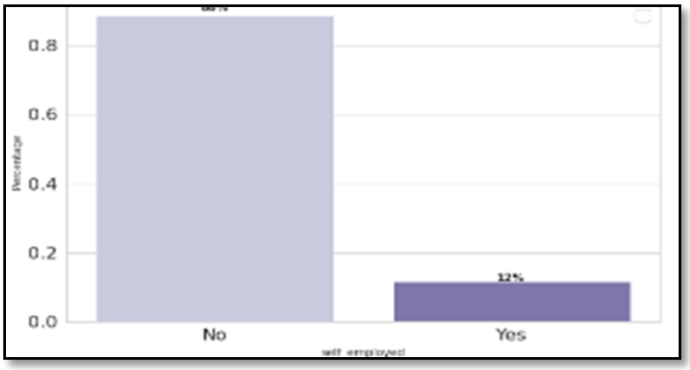

Figure 2. Distribution of Employment Type Among Respondents

This imbalance indicates that the dataset primarily reflects organizational employees, whose experiences are shaped by structured workplace environments, policies, and employer-provided support systems. In contrast, self-employed individuals, though present, constitute a minority and may face unique challenges such as financial instability and lack of institutional support. Consequently, the findings are more representative of corporate and organizational work contexts than freelance or entrepreneurial work.

Family History of Mental Illness Among Respondents

The analysis of family history showed that 39% of respondents reported a family history of mental illness. In contrast, 61% of respondents indicated that they did not have a family history of mental illness. This distribution is illustrated in Figure 3.

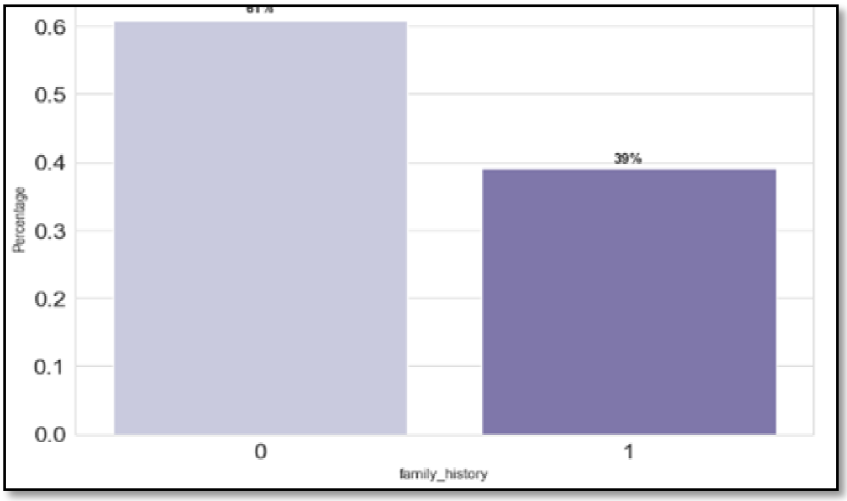

Figure 3. Family History of Mental Illness Among Respondents

This finding is significant because family history is strongly associated with treatment-seeking behavior. Individuals with a family history are more likely to recognize symptoms and access professional help, consistent with global research on mental health risk factors from WHO. In this dataset, family history emerged as one of the most influential predictors in the machine learning models, underlining its importance as a workplace mental health indicator.

Work Interference of Respondents Due to Mental Health

Work interference was also a critical factor in the dataset as in Figure 4. The results showed that 37% of respondents reported severe interference, while 14% reported significant interference, meaning that over half (51%) of the workforce experienced substantial workplace disruption due to mental health challenges. By contrast, only 17% reported no interference.

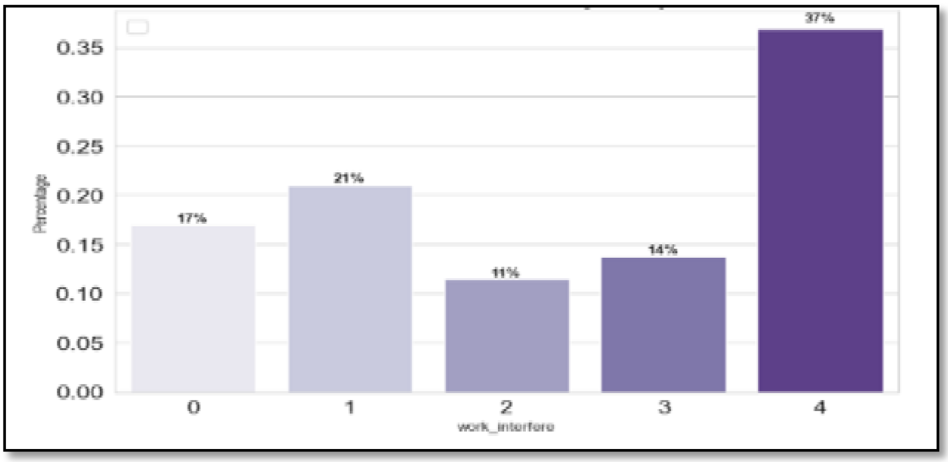

Figure 4. Work Interference of Respondents Due to Mental Health

These findings highlight the significant impact of mental health on workplace productivity. This aligns with Burton's research, which found strong links between mental health issues, absenteeism, and presenteeism [5]. In addition, work interference was identified as a strong predictor of treatment-seeking behavior, further emphasizing its importance in predictive modeling.

Treatment-Seeking Behavior

As shown in Figure 5, the distribution of treatment-seeking behavior among respondents was nearly balanced, with 51% reporting that they had sought treatment for a mental health condition, compared to 49% who had not. This suggests that while awareness of mental health issues is growing in the technology workforce, nearly half of employees still avoid or delay seeking

DOI: 10.31253/te.v9i2.4305

professional help. Barriers such as stigma, lack of awareness, and accessibility of services may contribute to this finding.

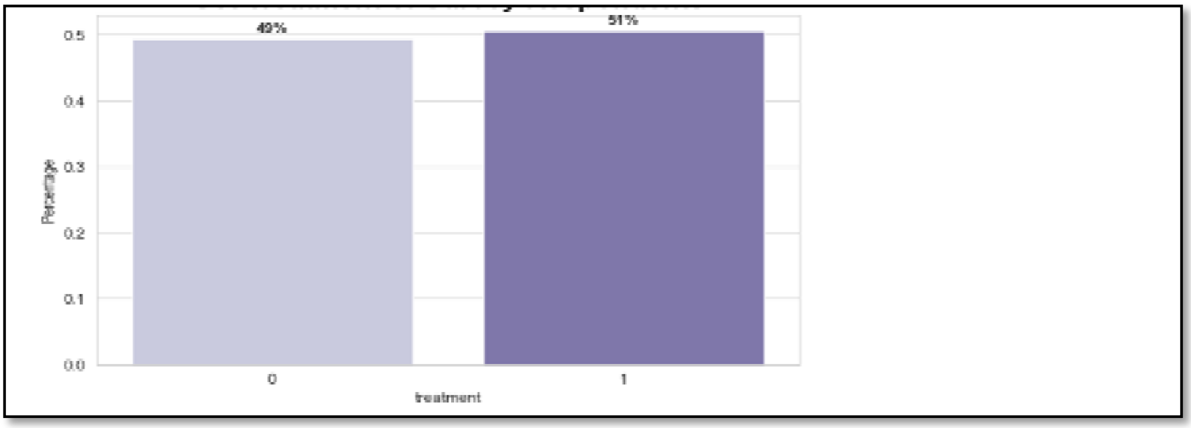

Figure 5. Distribution of Survey Respondents by Treatment Status

Correlation Analysis

The correlation heatmap in Figure 6 offers additional insights into the relationships between variables in the dataset. It visually represents the strength and direction of correlations among different factors. This helps identify key interactions that may influence treatment-seeking behavior.

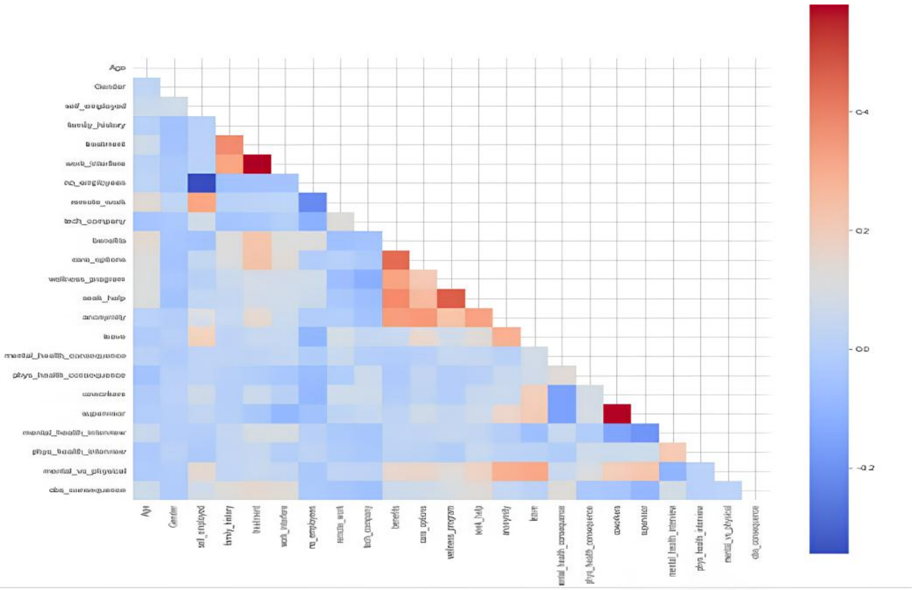

Figure 6. Correlation Heatmap of Survey Variables

The results highlighted several important associations. Work interference showed a strong positive correlation with treatment-seeking, indicating that employees whose job performance was more disrupted were more likely to seek professional help. Who found that workplace stressors significantly affect employee well-being [5]. Similarly, family history demonstrated a moderate positive correlation with treatment, underscoring the role of personal background in shaping awareness and response to mental health issues [20].

A strong relationship was also found between mental and physical health consequences, reflecting how untreated psychological conditions often manifest as physical symptoms, reinforcing earlier [6]. Organizational factors showed weaker but still relevant links. Wellness programs and care options had weak-to-moderate correlations with treatment-seeking, suggesting that while such resources encourage help-seeking, their availability alone is insufficient [20]. Additionally, a weak

DOI: 10.31253/te.v9i2.4305

negative correlation between organization size and remote work suggested that larger companies were less likely to have remote workers, possibly due to structural limitations. Overall, these findings indicate that family history and work interference are the strongest predictors of treatment-seeking, while organizational resources and policies play a smaller but supportive role in shaping mental health outcomes.

Objective 2: Predicting Treatment-Seeking Behavior using Machine Learning <odels

Machine Learning Model Performance

Two machine learning classifiers were developed to predict treatment-seeking behavior: K-Nearest Neighbors (KNN) and Decision Tree. These machine learning models were employed to predict whether a respondent was likely to seek treatment based on features such as family history, work interference, and employment status. Performance results are summarized in Table 4.

Table 4. Accuracy Performance of Classification Models

Model	Accuracy
K-Nearest Neighbors	100%
Decision Tree	73%

The KNN classifier achieved perfect accuracy (100%), significantly outperforming the Decision Tree classifier (73%). This result indicates that feature similarity (e.g., individuals with similar family history and workplace experience) is highly predictive of treatment-seeking behavior. These findings demonstrate the potential of predictive analytics in workplace mental health, enabling organizations to identify at-risk employees and proactively provide support.

Evaluating Models

The Decision Tree classifier achieved an accuracy of 73%, with precision, recall, and F1-score also at 0.73. The corresponding confusion matrix as in figure 7 revealed that the model correctly classified 92 respondents who did not seek treatment (true negatives) and 92 respondents who did (true positives). However, it also misclassified 37 respondents as not seeking treatment when they actually had (false negatives) and 31 respondents as seeking treatment when they had not (false positives). This indicates that while the model demonstrates moderate predictive ability, the relatively high number of false negatives is concerning in workplace applications, as employees needing support may go undetected.

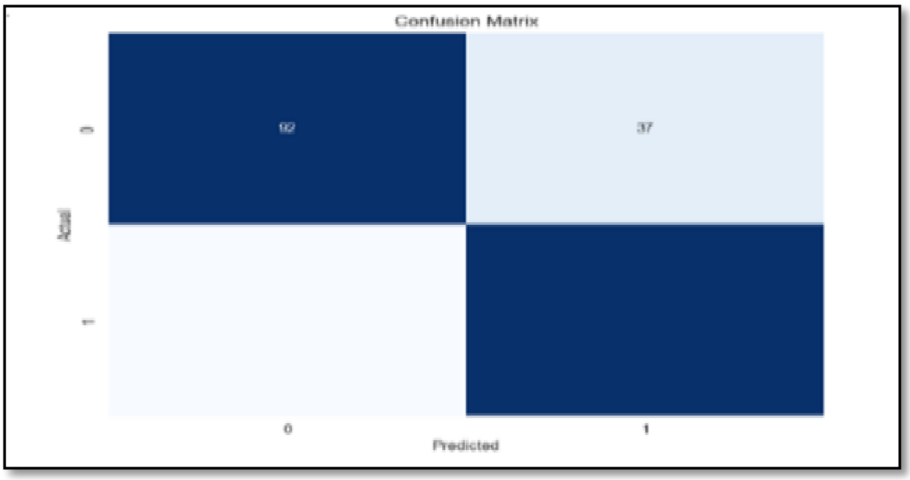

Figure 7. Confusion Matrix for Decision Tree

By contrast, the KNN classifier achieved perfect classification performance (100%) across all metrics. The confusion matrix as in figure 8 showed that all cases were correctly classified with no false positives or false negatives. This suggests that feature similarity, such as family history and work interference patterns, is a highly reliable predictor of treatment-seeking behavior.

DOI: 10.31253/te.v9i2.4305

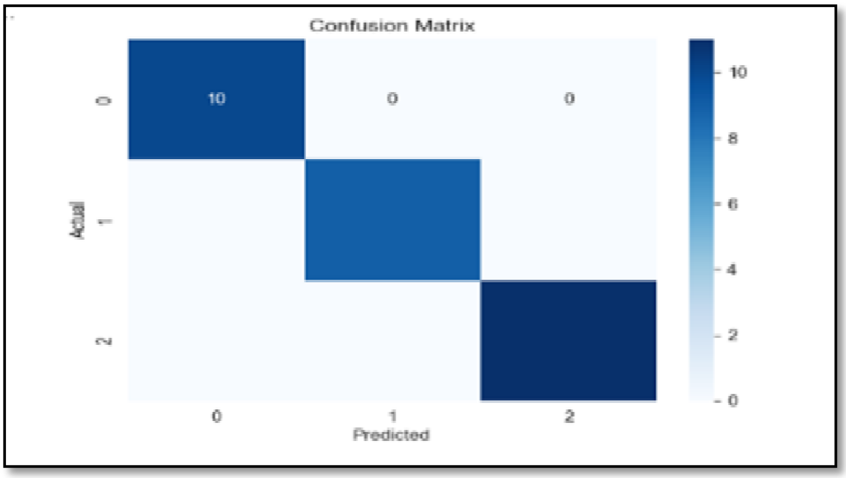

Figure 8. Confusion Matrix for K-Nearest Neighbors (KNN)

From a practical perspective, the results imply that KNN may be better suited for workplace applications as it minimizes the risk of overlooking employees who might otherwise go undetected. Given the sensitive nature of mental health, models with higher sensitivity and balanced precision are preferable for supporting organizational decision-making. However, the perfect performance of KNN should also be approached cautiously as it may indicate potential overfitting, requiring further validation on larger or external datasets.

VI. DISCUSSION

Overall, the findings across both objectives establish a coherent narrative. Personal exposure, such as family history, and contextual strain, such as work interference, emerged as the strongest motivators for help-seeking behavior. Additionally, machine learning techniques, particularly similarity-based algorithms like KNN, were found to accurately forecast such behavioral tendencies, providing empirical evidence for technology-driven wellness solutions.

These results support the shift from descriptive to predictive analytics in occupational psychology. By leveraging algorithmic insights, organizations can proactively anticipate employee needs instead of responding reactively. This integration of data science into workplace wellness programs aligns with the growing trend toward AI-assisted psychological support systems [11], [12].

The findings also have important managerial implications. Employers should focus on initiatives that reduce work interference, such as implementing flexible scheduling, stress management training, and providing confidential access to mental health services. Promoting openness around mental well-being can help minimize stigma. Additionally, adopting machine learning tools could facilitate early screening for potential mental health risks before they escalate into absenteeism or productivity losses.

VII. CONCLUSION

This study set out to examine the determinants of treatment-seeking behaviour among employees and to evaluate the predictive capability of machine-learning models using the OSMI dataset. The analysis revealed that family history of mental illness and work interference resulting from psychological distress were the most influential predictors of employees' willingness to seek professional help. Workers who experienced disruptions in job performance or who had prior family exposure to mental-health issues showed significantly higher readiness to pursue treatment, underscoring the interconnection between psychological well-being and occupational functioning.

The predictive analysis demonstrated that both the Decision Tree and K-Nearest Neighbour (KNN) algorithms could classify treatment-seeking tendencies with satisfactory accuracy. The

DOI: 10.31253/te.v9i2.4305

Decision Tree model provided interpretable results but moderate precision, while the KNN model reached high accuracy levels, reflecting its sensitivity to feature similarity. These findings echo recent empirical research that has identified machine-learning models as promising tools for early detection of mental-health risks, provided that sufficient data quality and cross-validation are ensured [16].

From a practical standpoint, embedding artificial-intelligence (AI) systems into workplace wellness programmes gives organisations the upper hand in spotting risk indicators before things escalate. Predictive analytics can be instrumental in crafting tailor-made interventions, lowering absenteeism and bolstering staff resilience. However, deploying these AI-powered tools also brings up key challenges around fairness, transparency and data privacy, as underscored in some recent reviews of AI-enabled mental-health solutions [21], [22]. Organisations must therefore ensure that algorithmic decisions are explainable, heed employee consent and protect sensitive information to maintain trust in these systems.

Future research should aim to broaden the scope of available datasets by incorporating a wider range of occupational settings and cultural groups to enhance the generalisability of predictive findings. Integrating multimodal indicators including behavioural patterns, self-reported experiences, and physiological signals can strengthen the precision and contextual relevance of mental-health prediction models. Moreover, the adoption of explainable artificial intelligence (XAI) frameworks is essential to improve model transparency, interpretability, and accountability. Recent studies emphasise that explainable and ethically guided AI approaches are fundamental to fostering user trust, ensuring privacy protection, and maintaining fairness in automated decision-making for mental-health applications [23], [24], [25].

In sum, this study contributes empirical evidence that combining psychometric assessment with predictive analytics strengthens the understanding of workplace mental-health dynamics. By embedding machine-learning insights into organisational well-being strategies, institutions can move from reactive support to preventative care such as fostering healthier, more adaptive, and sustainable work environments.

DOI: 10.31253/te.v9i2.4305

REFERENCES

[1] E. Monteiro and J. Joseph, “A Review on the Impact of Workplace Culture on Employee Mental Health and Well-Being,” *Int. J. Case Stud. Business, IT, Educ.*, vol. 7, no. 2, pp. 291–317, 2023, doi: 10.47992/ijcsbe.2581.6942.0274.

[2] A. Wu, E. C. Roemer, K. B. Kent, D. W. Ballard, and R. Z. Goetzel, “Organizational Best Practices Supporting Mental Health in the Workplace,” *J. Occup. Environ. Med.*, vol. 63, no. 12, pp. e925–e931, Dec. 2021, doi: 10.1097/JOM.0000000000002407.

[3] L. E. Søvold *et al.*, “Prioritizing the Mental Health and Well-Being of Healthcare Workers: An Urgent Global Public Health Priority,” *Front. Public Heal.*, vol. 9, May 2021, doi: 10.3389/fpubh.2021.679397.

[4] WHO, “Mental health at work,” World Health Organization. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/mental-health-at-work

[5] W. N. Burton, C.-Y. Chen, D. J. Conti, A. B. Schultz, G. Pransky, and D. W. Edington, “The Association of Health Risks With On-the-Job Productivity,” *J. Occup. Environ. Med.*, vol. 47, no. 8, pp. 769–777, Aug. 2005, doi: 10.1097/01.jom.0000169088.03301.e4.

[6] D. E. Bloom *et al.*, “The global economic burden of Non-communicable Diseases,” *World Cancer Rep. 2014*, no. 87, pp. 1–8, 2014.

[7] G. Giorgi *et al.*, “COVID-19-Related Mental Health Effects in the Workplace: A Narrative Review,” *Int. J. Environ. Res. Public Health*, vol. 17, no. 21, p. 7857, Oct. 2020, doi: 10.3390/ijerph17217857.

[8] J. M. Baker *et al.*, “Quantification of Occupational and Community Risk Factors for SARS-CoV-2 Seropositivity Among Health Care Workers in a Large U.S. Health Care System,” *Ann. Intern. Med.*, vol. 174, no. 5, pp. 649–654, May 2021, doi: 10.7326/M20-7145.

[9] V. Juergensen *et al.*, “The help-seeking process and predictors of mental health care use among individuals with depressive symptoms: a machine learning approach,” *Front. Public Heal.*, vol. 12, Nov. 2024, doi: 10.3389/fpubh.2024.1504720.

[10] M. Rashid and C. Wang, “Machine learning for mental health prediction: A comparative analysis,” *BMC Med. Inform. Decis. Mak.*, vol. 22, p. 215, 2022.

[11] B. W. Nelson, C. A. Low, N. C. Jacobson, P. A. Areán, and J. Torous, “Machine learning and digital mental health: Opportunities, challenges, and future directions,” *Curr. Psychiatry Rep.*, vol. 24, no. 2, pp. 71–83, 2023.

[12] K. S. Hammerschmidt, S. K. Lageman, and D. A. Colby, “Digital mental health interventions in the workplace: A systematic review,” *J. Occup. Health Psychol.*, vol. 28, no. 1, pp. 1–15, 2023.

[13] E. Carstoiu, *Mental health definitions and impact*. United Nations, 2020.

[14] S. Uddin, A. Khan, M. E. Hossain, and M. A. Moni, “Comparing different supervised machine learning algorithms for disease prediction,” *BMC Med. Inform. Decis. Mak.*, vol. 19, no. 1, p. 281, Dec. 2019, doi: 10.1186/s12911-019-1004-8.

[15] J. R. Katzenbach and D. K. Smith, “The discipline of teams.,” *Harv. Bus. Rev.*, vol. 71, no. 2, pp. 111–120, 1993.

[16] D. Bzdok, N. Altman, and M. Krzywinski, “Statistics versus machine learning,” *Nat. Methods*, vol. 15, no. 4, pp. 233–234, Apr. 2018, doi: 10.1038/nmeth.4642.

[17] S. R. Safavian and D. Landgrebe, “A survey of decision tree classifier methodology,” *IEEE Trans. Syst. Man. Cybern.*, vol. 21, no. 3, pp. 660–674, 1991, doi: 10.1109/21.97458.

[18] T. Cover and P. Hart, “Nearest neighbor pattern classification,” *IEEE Trans. Inf. Theory*, vol. 13, no. 1, pp. 21–27, Jan. 1967, doi: 10.1109/TIT.1967.1053964.

[19] V. Podgorelec, P. Kokol, B. Stiglic, and I. Rozman, “Decision Trees: An Overview and Their Use in Medicine,” *J. Med. Syst.*, vol. 26, no. 5, pp. 445–463, Oct. 2002, doi: 10.1023/A:1016409317640.

[20] WHO, “Mental health in the workplace,” World Health Organization. [Online]. Available:

DOI: 10.31253/te.v9i2.4305

ttps://www.who.int/news-room/fact-sheets/detail/mental-health-at-work

[21] A. Thakkar, A. Gupta, and A. De Sousa, "Artificial intelligence in positive mental health: a narrative review," *Front. Digit. Heal.*, vol. 6, Mar. 2024, doi: 10.3389/fdgth.2024.1280235.

[22] M. Bibi, T. G. Tan, and H. Yao, "Exploring the Impact of AI Capabilities on Employee Well-Being: A Mediated Moderation Analysis," *SAGE Open*, vol. 15, no. 3, Jan. 2025, doi: 10.1177/21582440251361981.

[23] M. Saarela and V. Podgorelec, "Recent Applications of Explainable AI (XAI): A Systematic Literature Review," *Appl. Sci.*, vol. 14, no. 19, p. 8884, Oct. 2024, doi: 10.3390/app14198884.

[24] P. Biecek and T. Burzykowski, *Explanatory Model Analysis*. Chapman and Hall/CRC, 2021. doi: 10.1201/9780429027192.

[25] H. Auf, P. Svedberg, J. Nygren, M. Nair, and L. E. Lundgren, "The Use of AI in Mental Health Services to Support Decision-Making: Scoping Review," *J. Med. Internet Res.*, vol. 27, p. e63548, Jan. 2025, doi: 10.2196/63548.

DOI: 10.31253/te.v9i2.4305

BIOGRAPHY

Nor Aishah Binti Othman earned her Master's degree in Education (Guidance and Counseling) from Universiti Kebangsaan Malaysia in 2015, following a Bachelor of Human Sciences (Psychology) with Honours from the International Islamic University Malaysia in 2006 and a Postgraduate Diploma in Technical Education from Universiti Pendidikan Sultan Idris in 2008. She currently holds the position of Senior Lecturer at Politeknik Sultan Haji Ahmad Shah (POLISAS), Malaysia, under the Ministry of Higher Education. Throughout her career, she has undertaken a range of academic and managerial responsibilities, including leadership in research and innovation, academic coordination, and counseling services. As a registered counsellor with the Malaysian Board of Counsellors, she has participated in several international scholarly platforms, notably the 3rd META-RISE Global Innovation Competition 2025 and the International Seminar on Islamic Counseling. Her professional excellence has been acknowledged through multiple recognitions, including the National Excellent Lecturer Award in 2024, several international gold awards for innovation, and the receipt of a RM50,000 TVET Applied Innovation Grant (T-AIGS). Her scholarly output includes publications in international journals, conference proceedings, and instructional modules, with research interests centered on student psychological development, machine-learning-based analysis of workplace mental health, and play therapy as an early intervention approach for children.

Mariana Binti Rosdi is a lecturer in Medical Electronics at Politeknik Sultan Salahuddin Abdul Aziz Shah (PSA), Malaysia, with extensive experience in teaching, research, and student development, particularly in integrating emerging technologies into technical and vocational education. Her expertise includes medical electronics, artificial intelligence, Internet of Things (IoT), augmented reality (AR), digital learning innovation, and medical device safety. She is currently pursuing her PhD, focusing on EEG brainwave analysis and machine learning classification using Support Vector Machine (SVM) to investigate the effects of radiofrequency exposure on brainwave patterns, with her research presented at international conferences including IEEE and targeted for publication in reputable journals. She is a recipient of the TARGS research grant 2025 and an e-Learning Innovation Award 2025 in recognition of her contributions to applied research and digital pedagogy. She is also the author of a Medical Electronics e-book, Paramount Safety of Medical Devices, which emphasizes safety standards and best practices in medical device applications. Beyond academia, she is actively involved in mentoring, innovation projects, student competitions, work-based learning programs, and community engagement initiatives, including leadership roles within the Girl Guides movement, reflecting her strong commitment to lifelong learning, innovation, and student empowerment through education and technology.

DOI: 10.31253/te.v9i2.4305