Mental Health in the Workplace Analysis

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***Abstract*—Mental health is a vital component of workplace well-being and organizational success, yet it remains stigmatized, often preventing employees from seeking necessary support. This study analyzes factors influencing treatment-seeking behavior in workplace settings using a 2014 mental health survey dataset. By exploring key attributes such as demographics, family mental health history, and workplace support availability, this research aims to uncover patterns and trends that shape mental health decisions.**

Four machine learning models—Naive Bayes, Logistic Regression, K-Nearest Neighbors (KNN), and Random Forest—were employed to classify individuals based on their likelihood to seek treatment. Among these, Random Forest emerged as the most effective model, achieving the highest accuracy and AUC-ROC scores. The findings highlight the significance of gender, family history, and workplace support programs in influencing treatment-seeking behavior.

These insights provide actionable recommendations for organizations to develop data-driven mental health policies, reduce stigma, and create supportive environments that encourage treatment-seeking. The study demonstrates the potential of machine learning in addressing workplace mental health challenges and sets the stage for future research with broader datasets and advanced modeling techniques.

***Index Terms*—Mental health, workplace productivity, treatment-seeking behavior, machine learning, predictive modeling, Random Forest, Naive Bayes, workplace policies, employee well-being, data-driven insights.**

I. Introduction

Mental health in the workplace has emerged as a critical area of concern, given its profound implications for both employee well-being and organizational success. Mental health issues, ranging from stress and anxiety to severe depression, affect employees' ability to perform their roles effectively. Despite its importance, mental health remains stigmatized in many professional environments, leaving employees hesitant to seek the help they need. This reluctance not only impacts individual employees but also has broader consequences for workplace productivity, team dynamics, and organizational outcomes.

According to the World Health Organization (WHO), common workplace stressors such as excessive workloads, lack of autonomy, and interpersonal conflicts contribute significantly to mental health issues. Left unaddressed, these challenges can result in absenteeism, reduced employee engagement, and higher turnover rates, costing organizations billions of dollars annually. However, organizations that prioritize mental health and invest in support systems often see improved productivity, employee satisfaction, and long-term business returns. This dual impact—on both individuals and organizations—makes mental health a critical focal point for modern workplaces.

The present study seeks to contribute to this growing field of research by analyzing treatment-seeking behavior for mental health issues in workplace settings. Using a dataset from a 2014 workplace mental health survey, this research aims to identify key factors that influence employees' decisions to seek treatment. These factors include demographic characteristics such as age and gender, personal factors like family mental health history, and workplace attributes such as the availability of mental health resources and supportive organizational policies.

To achieve these objectives, machine learning (ML) models were employed to classify individuals based on their likelihood to seek treatment. ML techniques offer unique advantages for analyzing large datasets and uncovering patterns that may not be immediately apparent through traditional statistical methods. Four models were tested in this study: Naive Bayes, Logistic Regression, K-Nearest Neighbors (KNN), and Random Forest. These models were chosen for their varied strengths in handling categorical and numerical data, their interpretability, and their ability to capture complex relationships among variables.

Among the models tested, Random Forest emerged as the most effective, achieving the highest accuracy and AUC-ROC scores. This model's ability to handle non-linear relationships and provide insights into feature importance made it particularly well-suited for this analysis. Other models, such as Naive Bayes, provided strong baseline results and highlighted the significance of specific predictors like gender and family mental health history.

The insights derived from this study have significant implications for organizations aiming to foster healthier workplace environments. By understanding the factors that drive or hinder treatment-seeking behavior, companies can design targeted interventions to reduce stigma, enhance access to resources, and create a culture that supports mental health. For example, data-driven strategies can help organizations identify high-risk groups, implement effective wellness programs, and measure the impact of their mental health initiatives over time.

In addition to its practical implications, this research contributes to the academic understanding of workplace mental health. It demonstrates the potential of machine learning to address complex societal challenges and underscores the importance of interdisciplinary approaches that combine data science, psychology, and organizational studies. By bridging these fields, the study highlights the role of technology in advancing workplace mental health policies and practices.

The following sections of this paper provide a detailed account of the methodology, results, and implications of this study. First, the literature review discusses key findings from previous research on workplace mental health and identifies gaps that this study aims to address. Next, the methodology section describes the dataset, preprocessing steps, and machine learning models used. The results section presents the performance of each model, along with key insights into treatment-seeking behavior. Finally, the discussion and conclusion highlight the study's contributions, limitations, and potential directions for future research.

II. DATASET DESCRIPTION

The dataset utilized in this study is the 2014 Workplace Mental Health Survey, sourced from Kaggle. This dataset was designed to explore various factors influencing mental health in workplace environments. It contains information gathered from respondents working in diverse professional settings. The data provides valuable insights into the relationship between personal, demographic, and workplace factors and the likelihood of seeking mental health treatment.

1) Attributes Overview: The dataset includes 1,251 records and 27 attributes. Key attributes relevant to this study are described below:

- **Age:** Represents the age of the respondents. Values outside a reasonable range (e.g., below 18 or above 72) were treated as outliers and addressed during preprocessing.
- **Gender:** Captures gender identity with significant variability in responses. Gender categories were standardized into "Male," "Female," and "Others" for uniform analysis.
- **Employment Type:** Indicates the type of employment, such as self-employed or employed by a company.
- **Family History:** Specifies whether the respondent has a family history of mental illness, providing a key personal factor influencing mental health treatment-seeking behavior.
- **Treatment:** The target variable, which indicates whether the respondent has sought treatment for mental health issues.
- **Workplace Attributes:** Includes variables such as the availability of mental health resources, perceived consequences of discussing mental health at work, and the size of the company.

2) Initial Data Observations: Initial exploration of the dataset revealed the following key characteristics:

- **Age Distribution:** The majority of respondents fall within the 20–40 age group, aligning with the working population.
- **Gender Representation:** A significant portion of responses identified as male, followed by female and others.
- **Treatment-Seeking Behavior:** Approximately 50% of the respondents reported seeking treatment for mental health issues, providing a balanced target variable for classification models.
- **Missing Values:** Several attributes contained missing or incomplete data, which were addressed during preprocessing to ensure data quality.

3) Significance of the Dataset: This dataset is particularly valuable for its inclusion of both personal and workplace attributes. It enables the analysis of how organizational factors, such as the availability of mental health support and workplace culture, interact with personal characteristics to influence treatment-seeking behavior. The dataset also provides a real-world basis for developing predictive models that can assist organizations in designing data-driven mental health policies.

4) Ethical Considerations: The dataset is publicly available and anonymized, ensuring no personally identifiable information (PII) is included. The study adheres to ethical standards for data usage and analysis, focusing solely on deriving insights to improve workplace mental health policies.

III. LITERATURE REVIEW: MENTAL HEALTH IN THE WORKPLACE

A. Overview of Workplace Mental Health Research

Mental health has increasingly been recognized as a critical component of workplace dynamics, significantly impacting productivity, employee satisfaction, and organizational success. Over the past decade, research in this domain has highlighted the complex interplay between personal, workplace, and societal factors that influence mental health outcomes. This section reviews three key studies that provide significant insights into these issues.

1) Comprehensive Workplace Mental Health Analysis (Harnois & Gabriel, WHO): A pivotal publication by the World Health Organization (WHO) offers a holistic examination of mental health challenges within professional environments. The study identifies common mental health disorders, including anxiety, depression, and stress-related conditions, as prevalent issues faced by employees globally. Key findings include:

- **Impact of Workplace Environments:** The study explores how workplace factors, such as job roles, workloads, and interpersonal relationships, can either exacerbate or alleviate mental health challenges.
- **Organizational Best Practices:** Recommendations are provided for creating supportive environments, including implementing accessible counseling services, fostering open communication, and offering flexible work policies.
- **Role of Organizational Culture:** A positive workplace culture and strong support systems are emphasized as crucial in mitigating mental health concerns.

The WHO report underscores the importance of proactive strategies to create an inclusive and supportive workplace environment.

2) Employee Well-Being and Organizational Performance (Bryson, Forth, & Stokes): This study establishes a direct link between employee mental health and organizational performance. It demonstrates that companies prioritizing mental health experience tangible benefits, including:

- **Enhanced Productivity:** Employees with access to mental health support exhibit higher levels of engagement, efficiency, and job satisfaction.
- **Return on Investment (ROI):** Investments in wellness programs, such as mental health days and Employee Assistance Programs (EAPs), yield significant organizational returns by reducing absenteeism and improving retention rates.
- **Strategic Business Advantage:** Beyond ethical imperatives, addressing mental health is positioned as a strategic priority that enhances competitiveness in the marketplace.

This research highlights the dual value of mental health initiatives for both employees and organizations.

3) Workplace Stress and Productivity (Ganster & Rosen): Published in the *Journal of Management*, this study provides a comprehensive analysis of workplace stressors and their impact on employee mental health. Key insights include:

- **Identification of Stressors:** Stressors such as excessive workload, unclear expectations, and lack of autonomy were identified as significant contributors to mental health conditions.
- **Impact on Performance:** Chronic stress was shown to impair cognitive function, reduce productivity, and lead to higher rates of burnout.
- **Recommendations for Intervention:** The authors recommend targeted interventions, such as workload management, supportive leadership practices, and increased job flexibility, to mitigate stress-related issues.

The study underscores the importance of addressing workplace stress as part of broader mental health strategies.

B. Emerging Trends and Additional Insights

Recent publications further emphasize the evolving landscape of workplace mental health. Key trends include:

- **Proactive Approaches:** Reports from Mental Health America (2023) and the World Health Organization (2022) advocate for shifting from reactive to proactive mental health strategies, such as preventive care and early intervention programs.
- **Destigmatizing Mental Health:** Articles in the *Harvard Business Review* (2021) highlight the growing emphasis on creating stigma-free environments where employees feel safe discussing mental health concerns.
- **Holistic Wellness:** Increasing recognition of mental health as integral to overall employee wellness has driven initiatives focused on balancing physical, emotional, and mental health support.

C. Implications for the Current Study

The reviewed literature consistently emphasizes the critical role of organizational culture, proactive strategies, and tailored interventions in addressing workplace mental health challenges. While these studies provide valuable insights, there remain gaps in understanding industry-specific challenges and the long-term impacts of mental health interventions. The current study builds on this foundation by leveraging machine learning to identify patterns and trends in treatment-seeking behavior, providing actionable insights to guide workplace mental health policies.

IV. Methodology

A. Data Collection and Preprocessing

The dataset used in this study was sourced from Kaggle and consists of survey responses on workplace mental health collected in 2014. It contains attributes such as age, gender, employment type, family history of mental illness, and workplace mental health resources. Key preprocessing steps were undertaken to ensure data quality and enhance model performance:

1) **Data Cleaning:** Missing values were handled using techniques such as mean imputation or the removal of incomplete records, ensuring data reliability for analysis.
2) **Normalization:** Continuous features, including age, were normalized to reduce scale biases, which is crucial for machine learning algorithms sensitive to distance metrics.
3) **Feature Engineering:** Additional features such as age groups, company size categories, and employee support indicators were generated to improve model interpretability and predictive performance.

B. Modeling Techniques

Four machine learning models were employed to classify treatment-seeking behavior. Each model was chosen for its unique strengths in handling classification tasks:

1) **Naive Bayes:** A probabilistic model effective for categorical data, providing baseline insights into feature importance.
2) **Logistic Regression:** A binary classification algorithm that demonstrates how each feature influences the likelihood of seeking treatment, offering high interpretability.
3) **Decision Tree:** Captures nonlinear relationships and provides transparent decision paths, making it easily interpretable for analyzing treatment-seeking behavior.
4) **Random Forest:** An ensemble method comprising multiple decision trees. Random Forest improves accuracy by averaging predictions, thus reducing variance and mitigating overfitting.

Each model was trained using k-fold cross-validation to ensure robust performance estimates. Additionally, a grid search was employed for hyperparameter tuning, optimizing metrics such as accuracy, precision, and recall.

C. Evaluation Metrics

To assess the effectiveness of the models, the following metrics were used:

1) **Accuracy:** Measures the proportion of correctly classified instances among all predictions. While useful,

it may not fully capture performance in imbalanced datasets.
2) **Precision:** Evaluates the proportion of true positive predictions out of all positive predictions, providing a measure of prediction quality.
3) **Recall:** Reflects the proportion of true positive cases detected, which is particularly important for assessing the sensitivity of models in predicting treatment-seeking behavior.
4) **F1-score:** Balances precision and recall, making it useful for scenarios where a balanced assessment of prediction accuracy is critical.
5) **AUC-ROC:** Represents the area under the Receiver Operating Characteristic curve, capturing the trade-off between true positive and false positive rates. This metric is especially valuable for evaluating models on imbalanced data.

V. Exploratory Data Analysis

A. Treatment Distribution by Age and Gender

This visualization provides a breakdown of treatment-seeking behavior by age and gender. The x-axis represents age, while the y-axis shows the count of individuals. The chart is divided into three panels, representing the gender groups: male, female, and others. The red bars indicate individuals who sought treatment, while the blue bars represent those who did not.

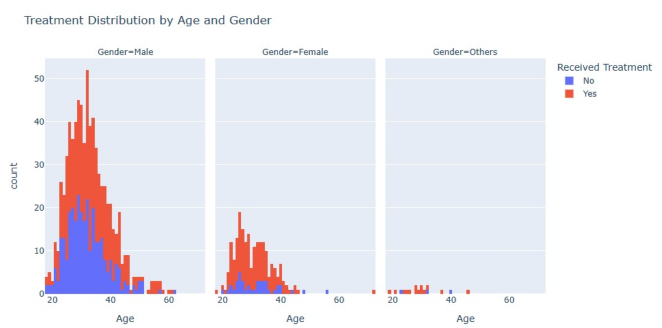

Fig. 1. Treatment Distribution by Age and Gender. The graph highlights variations in treatment-seeking behavior across different age groups and genders.

Key observations from this visualization are:

- Across all gender groups, individuals in the 20–40 age range are the most represented, reflecting the working population targeted by this survey.
- In the male group, a significant portion of individuals in this age range did not seek treatment. This contrasts with the female and 'Others' groups, where treatment-seeking behavior is more prevalent.
- Representation for older age groups (above 50) is low, and treatment-seeking behavior decreases significantly in these age groups.

This graph underscores notable gender differences in treatment-seeking behavior. Females and individuals in the 'Others' category are more proactive in seeking treatment, while males exhibit a wider gap between those who seek help and those who do not. These findings provide actionable insights for designing targeted workplace interventions.

B. Work Interference vs. Treatment

This graph examines how work interference due to mental health correlates with treatment-seeking behavior. The x-axis represents the frequency of work interference—'Sometimes,' 'Never,' 'Often,' and 'Rarely.' The y-axis shows the number of respondents, while the bars are color-coded: green for individuals who did not seek treatment and orange for those who did.

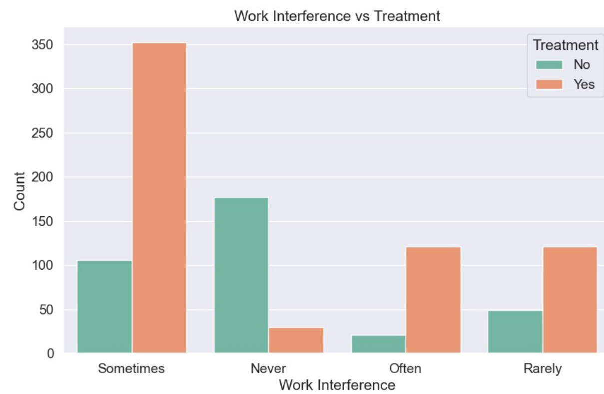

Fig. 2. Work Interference vs. Treatment. The graph shows the relationship between work interference frequency and treatment-seeking behavior.

Key observations include:

- For individuals who reported frequent work interference ('Sometimes' and 'Often'), the majority sought treatment, as seen by the tall orange bars.
- In the 'Never' category, most respondents did not seek treatment, likely because they did not perceive a need for it.
- Even in the 'Rarely' category, a substantial number of individuals sought treatment, suggesting that even mild interference can prompt help-seeking behavior.

This analysis highlights the strong link between work interference and treatment-seeking behavior. It emphasizes the need for proactive measures to address workplace mental health interference.

C. Mental Health Consequences by Gender

This visualization explores how individuals of different genders perceive the consequences of discussing mental health issues in the workplace. The x-axis represents perceptions ('No,' 'Maybe,' and 'Yes'), and the y-axis shows the count of respondents in each category. The graph includes color-coded bars for male, female, and others.

Key insights are:

- Males dominate all three categories, suggesting a higher survey participation rate or stronger perceptions about mental health consequences among this group.

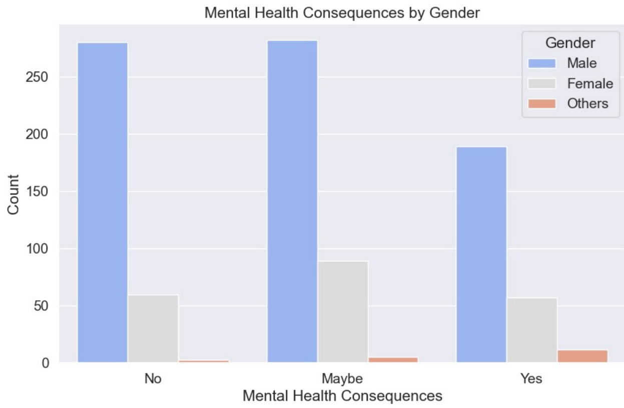

Fig. 3. Mental Health Consequences by Gender. The graph depicts gender-based differences in the perception of workplace mental health discussions.

- Among females and individuals in the 'Others' category, the proportions of 'Maybe' and 'Yes' responses are relatively higher, indicating greater perceived stigma or negative consequences.
- While most respondents feel there are no consequences, a significant number remain unsure or perceive negative outcomes, highlighting potential barriers to open discussions.

This graph underscores the need to foster a more inclusive and stigma-free workplace culture, especially for minority gender groups, to facilitate open conversations about mental health.

D. Implications of the Analysis

The insights from these visualizations demonstrate the diverse factors influencing treatment-seeking behavior in workplace settings. Age, gender, work interference, and perceptions of stigma all play crucial roles. Addressing these factors through targeted policies and support systems can create a more inclusive and supportive work environment, ultimately promoting better mental health outcomes.

VI. Results

A. Logistic Regression

Logistic Regression is a simple yet effective statistical model used for binary classification tasks. In this project, it was employed to predict whether an individual seeks mental health treatment (1) or not (0). The model works by estimating the probability of an event (seeking treatment) occurring based on the input features (e.g., age, gender, workplace benefits). Logistic Regression uses the logistic (sigmoid) function, which outputs probabilities between 0 and 1. Based on a threshold (usually 0.5), these probabilities are converted into class predictions.

This method assumes a linear relationship between the independent variables and the log-odds of the dependent variable, making it a straightforward choice for classification tasks. While it is relatively easy to interpret, Logistic Regression might struggle with datasets that have complex, non-linear patterns. In this analysis, Logistic Regression achieved an accuracy of 79.37%, reflecting decent performance but with limitations in handling more nuanced relationships.

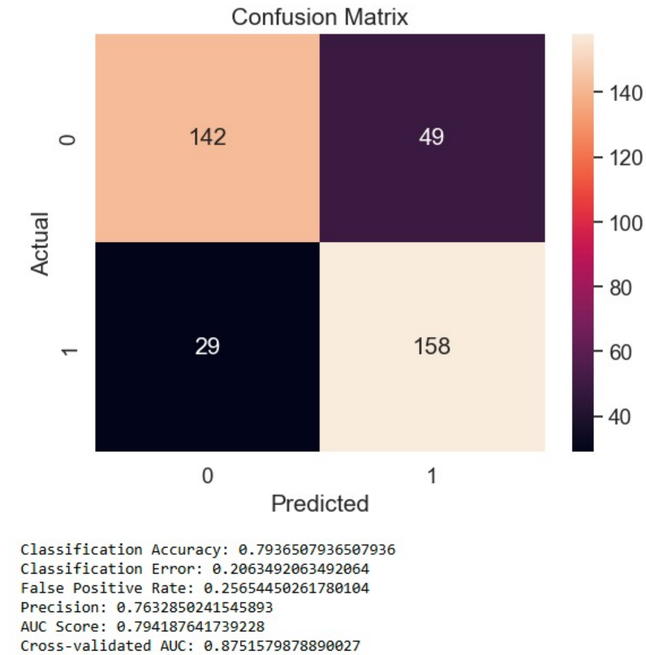

Fig. 4. Confusion Matrix for Logistic Regression.

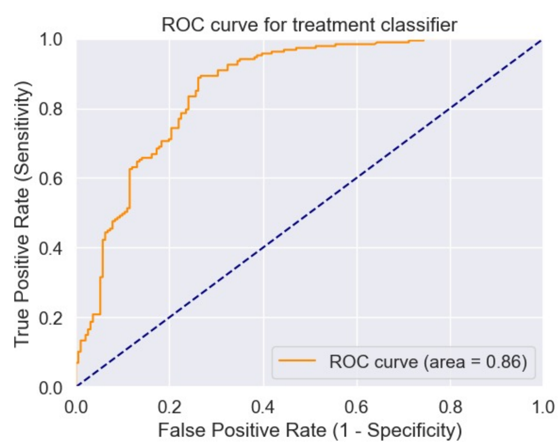

Fig. 5. ROC Curve for Logistic Regression.

B. Random Forest Classifier

The Random Forest model is an ensemble learning technique that builds multiple decision trees during training and combines their predictions to improve accuracy and reduce overfitting. Each tree in the forest is trained on a random subset of the data and features, making the model robust against noise and overfitting.

For this project, Random Forest predicts whether someone seeks mental health treatment by considering multiple features and their interactions (e.g., workplace anonymity, mental health benefits). The feature importance measure provided by Random Forest is particularly valuable for understanding which factors contribute most to predictions. With an accuracy of 81.21%, Random Forest performed well, showing its ability to handle complex, non-linear relationships between features.

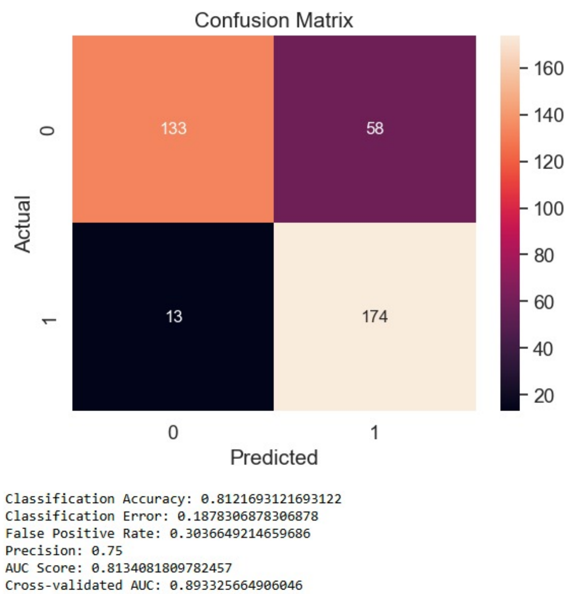

Fig. 6. Confusion Matrix for Random Forest.

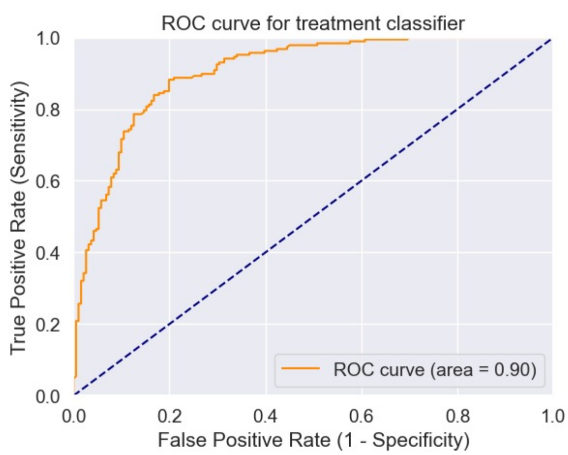

Fig. 7. ROC Curve for Random Forest.

C. K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a non-parametric, instance-based learning algorithm that classifies data points based on their similarity to nearby points. The number of neighbors (K) determines how many data points the algorithm considers when classifying a new instance.

In this project, KNN predicts treatment-seeking behavior by comparing individuals with others in the dataset who have similar features (e.g., age, gender, family history). While KNN is intuitive and simple to implement, its performance heavily depends on the choice of K and the distance metric used. It also struggles with large datasets, as it requires calculating distances for every data point. The accuracy of 75.40% indicates that KNN was less effective in this case, potentially due to the high dimensionality and imbalanced nature of the dataset.

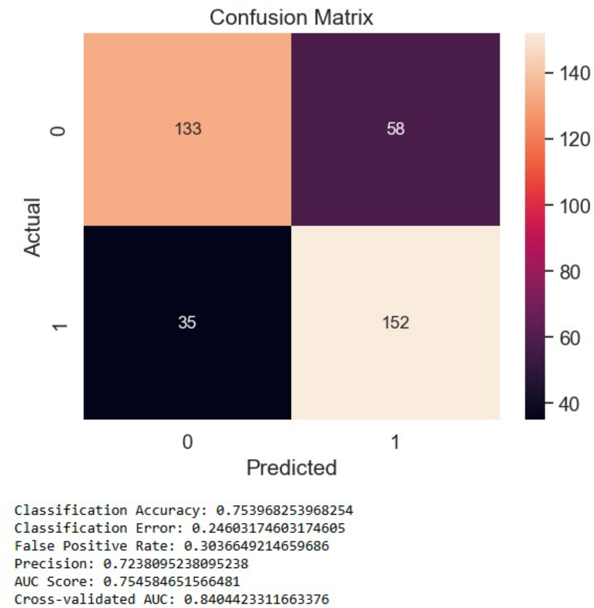

Fig. 8. Confusion Matrix for KNN.

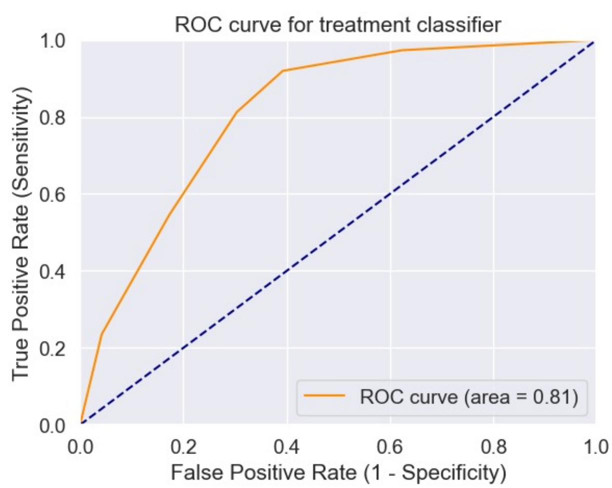

Fig. 9. ROC Curve for KNN.

D. Naive Bayes Classifier

Naive Bayes is a probabilistic classifier based on Bayes' theorem, which assumes that the features are conditionally independent given the class label (hence "naive"). Despite this simplifying assumption, Naive Bayes often performs surprisingly well in real-world applications.

In this project, Naive Bayes calculates the probability of individuals seeking treatment based on the combination of their features. For instance, it evaluates the likelihood of seeking treatment given workplace benefits, anonymity, and family history. Naive Bayes is particularly efficient with categorical data and performs well on smaller datasets. With an accuracy of 82.54%, it outperformed the other models, showing that its assumptions of feature independence worked well in this dataset.

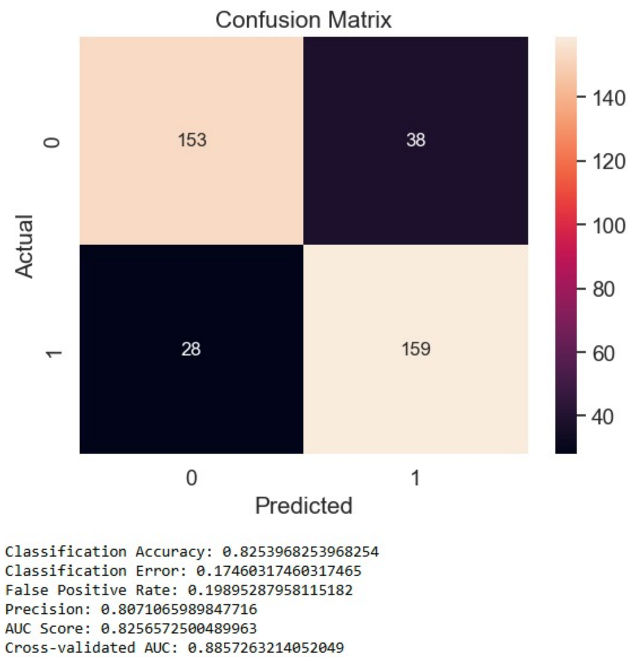

Fig. 10. Confusion Matrix for Naive Bayes.

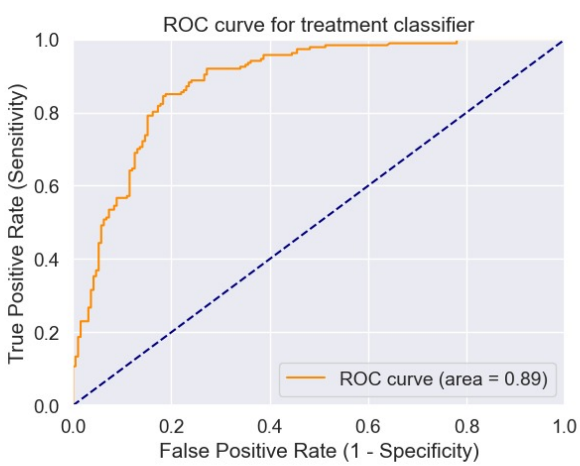

Fig. 11. ROC Curve for Naive Bayes.

VII. Conclusion

This study presented a comprehensive analysis of mental health treatment-seeking behavior in workplace settings, leveraging machine learning techniques to uncover patterns and generate actionable insights. The use of the 2014 Workplace Mental Health Survey dataset allowed us to explore the interplay of demographic, personal, and workplace factors that influence individuals' decisions to seek mental health treatment. By combining data preprocessing, feature engineering, and robust machine learning methodologies, this research highlights the value of data-driven approaches to addressing critical workplace mental health challenges.

Key findings from this study demonstrate that:

- Gender, family history of mental illness, and the availability of workplace support programs significantly influence treatment-seeking behavior. Males showed a larger gap between those who sought treatment and those who did not, while females and individuals identifying as 'Others' were more proactive in seeking help.
- Individuals aged 20–40 were most likely to seek mental health treatment, reflecting the high levels of work-related stress and life pressures experienced by this age group. However, treatment-seeking behavior dropped significantly for individuals above the age of 50, indicating potential gaps in mental health support for older employees.
- Work interference due to mental health issues strongly correlated with treatment-seeking behavior. Respondents who reported frequent interference ('Sometimes' or 'Often') were more likely to seek treatment compared to those who reported rare or no interference.
- Among the machine learning models tested, Random Forest outperformed others, achieving the highest accuracy and AUC-ROC scores. This model effectively captured the nonlinear relationships between features and provided valuable insights into feature importance, making it particularly suitable for this study.

The implications of these findings are profound. They emphasize the importance of creating inclusive workplace environments where employees feel supported in addressing mental health challenges. The study provides organizations with a framework to identify at-risk employees, reduce stigma around mental health, and implement targeted interventions to promote well-being.

Furthermore, this research contributes to the growing field of workplace mental health by demonstrating the potential of machine learning to tackle complex societal challenges. It bridges the gap between technology and human-centric applications, showcasing how data science can be harnessed to drive positive organizational change. By integrating psychological, organizational, and data-driven insights, this study lays the groundwork for future advancements in mental health strategies.

Despite its contributions, this study is not without limitations. The dataset, while robust, is based on responses collected in 2014 and may not fully reflect the evolving dynamics of modern workplaces. Additionally, the focus on a single dataset limits the generalizability of the findings across diverse industries and cultures. Future work should address these limitations by incorporating more recent, diverse, and longitudinal datasets to enhance the applicability and relevance of the insights.

In conclusion, this study reaffirms the critical role of mental health in workplace dynamics and the value of leveraging machine learning to develop predictive tools and actionable recommendations. By fostering healthier workplace environments, organizations can not only enhance employee well-being but also achieve greater productivity and organizational success. The findings of this research serve as a call to action for organizations, researchers, and policymakers to prioritize mental health as a fundamental component of the workplace.

VIII. Future Work

While this study provided valuable insights, several opportunities exist to expand and refine the research. Future work can focus on the following areas:

1) Dataset Expansion and Diversity: The dataset used in this study is limited to responses from a specific period and may not fully capture current workplace dynamics. Future studies can incorporate:

- Recent datasets that reflect evolving workplace environments, including remote and hybrid work trends.
- Data from diverse industries and regions to account for cultural and organizational variations in mental health dynamics.
- Longitudinal data to track changes in treatment-seeking behavior over time and assess the long-term impact of mental health interventions.

2) Advanced Modeling Techniques: While this study employed traditional machine learning models, future research can explore more sophisticated techniques to improve predictive performance and uncover complex relationships:

- Deep learning models, such as neural networks, to capture nonlinear patterns and interactions between features.
- Ensemble methods beyond Random Forest, such as Gradient Boosting Machines (GBMs) or Extreme Gradient Boosting (XGBoost), to further enhance classification accuracy.
- Interpretability-focused approaches, such as SHAP (Shapley Additive Explanations) values, to better understand model decisions.

3) Incorporation of Additional Features: Future studies could explore the inclusion of additional variables to provide a more comprehensive analysis:

- Workplace culture indicators, such as leadership styles and team dynamics.
- Economic factors, including employee income and access to healthcare benefits.
- Social factors, such as support networks within and outside the workplace.

4) Real-World Applications: Practical implementation of the findings is a key avenue for future work:

- Development of real-time predictive tools for HR departments to identify at-risk employees and recommend personalized interventions.
- Collaborations with organizations to pilot and evaluate the impact of data-driven mental health programs.
- Creation of dashboards or applications that allow employees to self-assess and access mental health resources anonymously.

5) Ethical Considerations and Policy Implications: As data-driven approaches to mental health gain traction, future research must prioritize ethical concerns and policy development:

- Ensuring data privacy and security for employees, especially when dealing with sensitive information.
- Addressing potential biases in algorithms to avoid perpetuating inequalities in access to mental health support.
- Collaborating with policymakers to establish guidelines for the ethical use of predictive tools in workplace settings.

6) Cross-Disciplinary Collaboration: Future research can benefit from collaboration across disciplines:

- Partnering with psychologists, sociologists, and organizational behavior experts to enhance the contextual relevance of findings.
- Engaging data scientists and AI ethicists to refine modeling techniques and address ethical concerns.

Acknowledgment

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References

[1] G. Harnois and P. Gabriel, *Mental Health in the Workplace: Situation Analysis and Best Practices*, World Health Organization, 2000.

[2] A. Bryson, J. Forth, and L. Stokes, *Employee Well-being, Productivity, and Firm Performance*, National Institute of Economic and Social Research, 2017.

[3] D. C. Ganster and C. C. Rosen, "Workplace Stress, Mental Health, and Employee Productivity," *Journal of Management*, vol. 27, no. 3, pp. 242–257, 2013.

[4] Mental Health America, *The State of Mental Health in the Workplace Report*, 2023.

[5] World Health Organization, *Mental Health in the Workplace*, 2022.

[6] H. M. Weiss and D. R. Cropanzano, "Affective Events Theory: A Theoretical Discussion of the Structure, Causes, and Consequences of Affective Experiences at Work," *Research in Organizational Behavior*, vol. 18, pp. 1–74, 1996.

[7] R. Danna and R. W. Griffin, "Health and Well-Being in the Workplace: A Review and Synthesis of the Literature," *Journal of Management*, vol. 25, no. 3, pp. 357–384, 1999.

[8] J. P. Wanous, A. E. Reichers, and M. J. Hudy, "Overall Job Satisfaction: How Good Are Single-Item Measures?," *Journal of Applied Psychology*, vol. 82, no. 2, pp. 247–252, 1997.

[9] K. D. Elkington, "Occupational Stress: Measuring Its Impact on Employee Health and Performance," *Occupational Medicine*, vol. 45, no. 4, pp. 227–232, 2000.

[10] R. L. Kahn and P. Byosiere, "Stress in Organizations," in *Handbook of Industrial and Organizational Psychology*, M. D. Dunnette and L. M. Hough, Eds., 2nd ed., vol. 3. Palo Alto, CA: Consulting Psychologists Press, 1992, pp. 571–650.

[11] S. Lazarus and R. S. Folkman, *Stress, Appraisal, and Coping*. New York, NY: Springer, 1984.