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PAPER

Machine Learning Approaches for Mental Health Prediction

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ABSTRACT

Mental health issues within workplace environments constitute a significant global concern. According to the World Health Organization (2024), anxiety and depression together contribute to an estimated loss of over one trillion U.S. dollars in productivity each year. Although awareness of this problem has grown across organizations, most existing initiatives remain reactive, intervening only after symptoms appear rather than proactively identifying individuals at risk. The present research employs a predictive and data-centric methodology to anticipate employee vulnerability to mental health challenges, drawing on the Mental Health in Tech Survey dataset hosted on Kaggle. Guided by the CRISP-DM process model and supported by the job demands resources (JD–R) theoretical framework, the study incorporated comprehensive data preprocessing, feature construction, and machine learning techniques. To evaluate model effectiveness, several performance metrics were applied, such as accuracy, F1-score, precision, recall, and ROC-AUC, along with a feature importance analysis that connected statistical patterns to conceptual insights. Among the tested algorithms, the Random Forest model demonstrated the best results, achieving 87.2% accuracy and an ROC-AUC of 0.93. Key predictors identified included organizational support and familial history of mental health conditions. These findings highlight the value of combining psychological theory with computational modelling to generate actionable intelligence. Such an approach can inform early detection strategies, help destigmatize mental health concerns, and promote the development of more supportive and resilient workplace cultures.

KEYWORDS

mental health prediction, psychological aspects, workplace mental health, artificial intelligence (AI), machine learning. random forest

1 INTRODUCTION

Workplace mental health has become a major issue globally, with positive impact on both individual and organizational wellbeing increasingly recognized. According to the World Health Organization [1–3], depression and anxiety lead to a loss of

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USD 1 trillion worth of productivity globally each year. In New Zealand, surveys conducted by the mental health foundation [4] reveal that one-fifth of adults suffer from mental distress annually, with workplace-related stress identified as one of the main contributing factors. Despite increased attention to employee wellbeing, most organizations continue to operate reactively, depending on interventions only after symptoms have been reported rather than implementing predictive and preventive strategies. The breakthroughs in data science, particularly in machine learning and predictive analytics, represent a remarkable shift in approaches to employee wellness [5–7]. Data driven proposals can enable organizations to identify early warning signals for mental health risks, thus providing timely, adequate, and effective support [8, 9]. This study explores the application of data science to forecast mental health risks in the workplace, addressing the critical gap in preventive intervention.

The central issue is that mental health challenges among employees in workplace settings are often underrecognized until they escalate, resulting in substantial costs for both employees and employers [10–12]. Traditional methods such as employee surveys, counseling, and wellness programs are reactive and heavily relieve self-reporting. Employees may underreport symptoms due to stigma and fear of discrimination [13]. Additionally, most organizations lack fully developed frameworks for utilizing data to recognize individuals who are likely to experience poor mental health conditions. This gap results in organizations overlooking mental health issues that directly impact productivity, absenteeism, and staff retention [14–16]. Studies in occupational health provide evidence that job-related factors such as workload, job insecurity, organizational culture, and work-life balance are main contributors to mental health challenges [17]. However, limited research has systematically merged these factors with predictive data science models to offer feasible solutions. The absence of prediction tools for workplace settings represents a significant problem affecting both employee welfare and organizational sustainability.

This study focuses on leveraging data science to predict the probability of mental health challenges occurring at work and to inform preventive measures. The specific objectives include:

- To identify key workplace and demographic factors associated with mental
- health outcomes using exploratory data analysis of the mental health in Tech Survey dataset
- To develop and compare machine learning classification models (logistic regression, random forest, neural networks) for predicting employee treatment-seeking propensity
- To evaluate model effectiveness in identifying patterns associated with resource utilization using comprehensive evaluation metrics
- To interpret feature importance and align findings with the job demands resources (JD–R) theoretical framework to ensure practical applicability

The significance of this study is both social and organizational. Mental health problems lower quality of life, impact family welfare, and place additional pressure on healthcare systems. In New Zealand, workplace stress is a main reason for absenteeism and productivity loss, costing businesses substantially each year (New Zealand Productivity Commission, 2021). Organizations that fail to manage employee wellness effectively face financial troubles and reputational damage. Predictive modeling offers a proactive solution by identifying high-risk individuals early, enabling targeted interventions such as workload reduction, flexible scheduling, or wellness support programs. From an information technology perspective, this represents an innovative application of data science with positive real-world impact. The growing

public demand for responsible artificial intelligence (AI) that benefits human well-being makes this study particularly timely and relevant [18].

2 RELATED WORK

2.1 Workplace mental health context

Workplace mental health has emerged as a critical concern in both public health and organizational management [19, 20]. High levels of stress, burnout, anxiety, and depression have significant adverse effects on employee well-being, especially among older employees [21–23]. Traditional workplace mental health interventions rely on self-reporting and reactive strategies such as counseling or wellness workshops [24]. However, stigma and fear of discrimination often prevent employees from disclosing mental health challenges, reducing intervention effectiveness [25, 26].

2.2 Predictive analytics in healthcare

Predictive analytics have proven effective in healthcare for early detection and risk stratification [27]. Machine learning models including logistic regression, decision trees, random forests, and neural networks have successfully predicted clinical outcomes such as hospital readmissions, disease progression, and treatment response [28–30]. These methods demonstrate capacity to handle high-dimensional information and uncover patterns not evident through traditional statistical approaches. In workplace settings, predictive analytics remains underutilized. Emerging studies illustrate potential for using employee data to predict mental health risks. The open sourcing mental illness (OSMI) [Open Sourcing Mental Illness] surveys revealed correlations between workload, organizational support, and mental wellbeing in tech employees. Despite these insights, most studies are descriptive, lacking rigorous predictive modeling that can guide proactive interventions.

2.3 Theoretical framework integration

The job demands-resources (JD-R) model is a foundational theory in Occupational Health Psychology [31]. It posits that job demands (e.g., workload, role ambiguity) increase stress and burnout risk, while job resources (e.g., autonomy, support) buffer against these effects. Integrating the JD-R framework with data science allows for selection of theoretically informed features in predictive models. This combination of theory-driven features with empirical data improves model interpretability and aligns predictions with actionable interventions. The conservation of resources (COR) theory provides an explanatory lens on how individuals respond to stressors. COR theory asserts that individuals strive to acquire, maintain, and protect resources, and stress occurs when resources are threatened or lost. This dynamic perspective informs feature engineering approaches that capture compound stress indicators.

2.4 Research gaps

Despite growing interest, several gaps remain in current research:

- Limited attention to New Zealand workplaces, with most predictive studies conducted in different countries

- Weak integration of Occupational Health Psychology frameworks with machine learning to improve interpretability
- Insufficient attention to ethical frameworks addressing privacy, bias, and employee consent
- Need for robust datasets and preprocessing methodologies

This study addresses these gaps by building a machine learning model to predict mental health challenges in workplace contexts, combining JD-R theory with thorough data preprocessing and ethical safeguards.

3 METHODOLOGY

This project follows a predictive modeling design aimed at classifying individuals at risk of mental health issues based on workplace conditions, demographic factors, and organizational support systems. A quantitative approach is employed, as statistical and machine learning techniques provide optimal means to capture hidden patterns in large datasets.

3.1 Dataset description

The dataset selected for this study utilizes the 2014 cohort of the OSMI Mental Health in Tech Survey hosted on Kaggle. While the multi-year longitudinal OSMI project encompasses over 18,000 respondents across 2014–2021, features shifted significantly between iterations. To maintain feature uniformness, this study utilizes the foundational 2014 cross-sectional dataset, which contains responses from exactly 1,259 professionals. The dataset contains a total of 1,259 rows. For predictive modeling, the dataset was split into a training set (approx. 76.4%, N = 962) and a testing set (approx. 23.6%, N = 297) to evaluate model generalization Key features include:

- Demographics: Age, gender, country, and organizational role
- Workplace Factors: Employer support policies, openness about mental health, provision of mental health resources, and cultural attitudes
- Health Variables: History of mental health conditions, current treatment seeking behaviors, and perceived impact of work environment
- Organizational Attributes: Company size, industry sector, and benefits offered

These features align well with the JD-R and COR frameworks, enabling analysis of how demands and resources influence mental health outcomes.

3.2 Operationalization of the target variable

It is very important for deciding between healthcare-seeking behaviors as well as clinical mental health risk. In this study, to seek treatment for mental health condition, the target variable derived from the dataset operationalizes an individual's decision. While past literature conflates active pathology with treatment-seeking, the researcher of this study defines the target variable as treatment-seeking propensity. Obtaining care is reconciled by resource awareness, organizational climate, and the reduction of social stigma—factors directly aligned with the JD–R framework of this study. Hence, in this study, the computational models do not diagnose clinical disorders; rather, they predict an employee's readiness.

By defining the target variable strictly as treatment-seeking behavior, this study explicitly decouples the computational task from clinical diagnosis. Seeking care is heavily mediated by external factors such as resource availability, healthcare access, organizational support, and the reduction of social stigma. Consequently, the predictive models developed herein do not evaluate absolute clinical mental health risk or diagnose psychological disorders; rather, they map an individual's likelihood to utilize available mental health support frameworks.

3.3 Data collection

The dataset was loaded using pandas, Python's primary data manipulation library. Initial inspection revealed 27 columns with mixed data types (numerical and categorical) and approximately 1,259 rows. Preliminary analysis identified missing values, outliers, and inconsistencies requiring systematic cleaning.

Missing value analysis revealed that three columns contained over 30% missing data. Following best practices for data quality maintenance, these columns were excluded from analysis. Remaining columns with less than 30% missingness underwent targeted imputation using mode for categorical variables and median for numerical variables.

Data cleaning involved several critical steps:

- Age Normalization: Outliers outside the 18–75 range (including invalid entries like five or 150 years) were replaced with the median age to prevent model distortion.
- Gender Standardization: Over 50 unique gender responses were consolidated into three categories (Male, Female, Other) through mapping and string normalization.
- Categorical Imputation: Missing categorical values were filled with the mode (most frequent value) for each respective column.

Feature engineering aligned with the JD-R theoretical framework:

1. Target variable Creation: The binary variable treatment binary was created from the treatment column, where a value of 1 indicates an individual who seeks treatment and 0 indicates one who does not.
2. Support score Composite: A composite feature named support score was engineered by averaging three organizational support indicators (benefits, care options, wellness program), with partial credit assigned for uncertain responses.
3. Categorical encoding: One-hot encoding was applied to transform categorical variables (Gender, Country, self-employed) into a numerical format suitable for machine learning algorithms.

The dataset was split into training (70%) and testing (30%) sets using stratified sampling to maintain class distribution. Standard Scaler was applied to normalize numerical features, ensuring consistent scales across all predictors and preventing distance-based algorithms from being biased toward features with larger ranges.

3.4 Machine learning techniques

Three algorithms were selected based on their complementary strengths:

1. Logistic regression: Provides an interpretable baseline model with clear coefficient interpretation, making it useful for understanding the relationship between predictors and the target variable.

2. Random forest: Handles non-linear relationships and feature interactions effectively through ensemble learning, improving robustness and reducing overfitting.
3. Neural networks: Captures complex, high-dimensional patterns in data through multi-layer architectures, enabling deeper representation learning.

In terms of model implementation;

1. Logistic regression: Served as the baseline model, implemented with L2 regularization and a maximum of 1000 iterations to ensure convergence. This linear model offers clear interpretability through coefficient analysis, making it suitable for baseline comparison.
2. Random forest: Utilized 200 decision trees with a maximum depth of 15 and a minimum of 10 samples per split. These hyperparameters were selected through an initial grid search to balance model complexity and generalization capability. The ensemble approach effectively reduces overfitting while capturing non-linear patterns.
3. Neural network: Employed a three-layer architecture consisting of 64, 32, and 16 neurons, respectively, with ReLU activation functions. The model was trained using the Adam optimizer and incorporated early stopping to prevent overfitting. This deep learning approach enables the detection of complex, non-linear relationships that simpler models might overlook.

3.5 Evaluation metrics

Model performance was evaluated using multiple complementary metrics to ensure comprehensive assessment:

- Accuracy: Measures the overall rate of correct predictions made by the model.
- F1-Score: Represents the harmonic mean of precision and recall, making it particularly important for evaluating models trained on imbalanced datasets.
- Precision: Indicates the proportion of true positive predictions among all positive predictions made by the model.
- Recall: Represents the proportion of actual positive cases correctly identified by the model, which is critical in mental health applications where missing positive cases can have serious implications.
- ROC-AUC: The area under the Receiver Operating Characteristic curve, which measures the model's ability to discriminate between classes.

Cross-validation with a 5-fold approach was employed to ensure model stability and generalizability beyond the training dataset.

3.6 Ethical considerations

This study applies strong ethical principles guided by the Ng¯a Tikanga Paihere framework, emphasizing manaakitanga (care), whanaungatanga (relationships), and tika (doing what is right). Although the dataset is publicly available, privacy and confidentiality remain paramount. All analyses avoid re-identification of individuals, with only aggregated results reported. Bias mitigation techniques including class balancing and fairness auditing were employed to minimize discriminatory outcomes.

To address the ethical risks associated with employee monitoring and potential surveillance by management, we have expanded our governance framework.

The system mandates strict data-masking protocols and local data anonymization before any model inference takes place. This ensures the tool functions strictly as an aggregate, early-intervention triage mechanism rather than an automated profiling system that could lead to punitive workplace surveillance. Furthermore, we acknowledge that the practical utility of the current model is limited by the lack of external validation on independent datasets. The predictions reflect help-seeking resource utilization patterns rather than a direct clinical index of psychological distress.

4 RESULTS

Age distribution analysis revealed a predominantly young workforce, with mean age of 32.4 years (SD = 10.2). The distribution was slightly right-skewed, consistent with tech industry demographics where younger professionals predominate (see Figure 1)

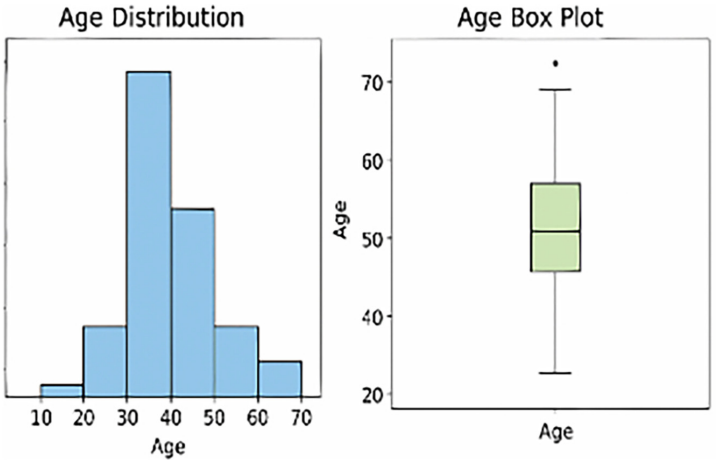


Fig. 1. Age distribution and box plot

Gender distribution showed 71% male, 23% female, and 6% other/non-binary respondents. This imbalance reflects broader tech industry demographics and was accounted for in model evaluation through stratified sampling (see Figure 2).

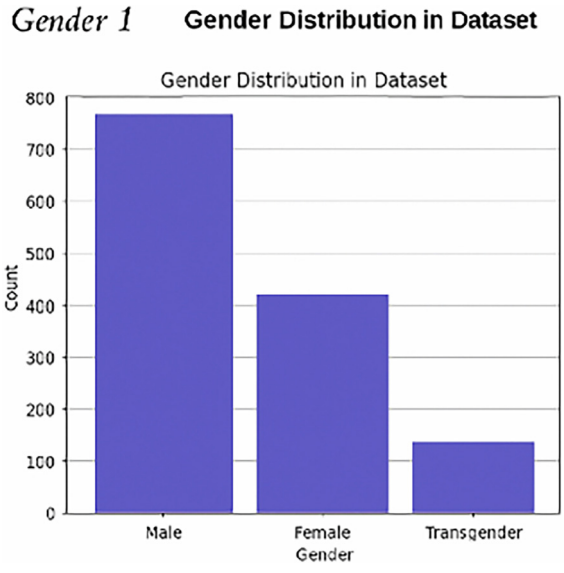


Fig. 2. Gender distribution

Analysis of treatment-seeking behavior against organizational support scores revealed a clear positive correlation. Employees with higher support score values (greater than 0.7) were approximately 2.3 times more likely to seek treatment compared to those with low support (less than 0.3), thereby validating the JD-R framework's emphasis on the critical role of organizational resources in influencing employee well-being. The distribution of employee treatment-seeking actions across categorized organizational support tiers is visualized in Figure 3.

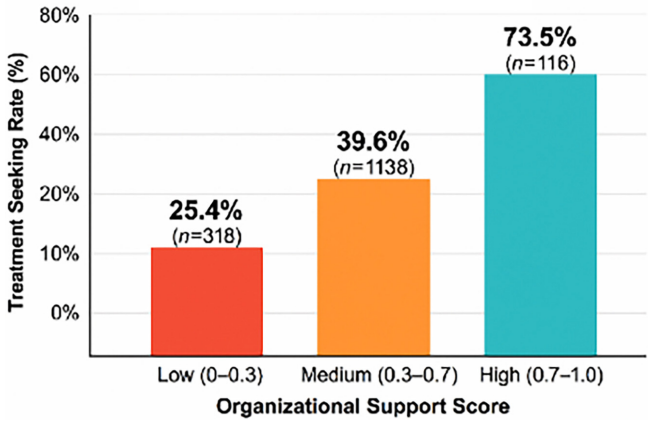


Fig. 3. Mental health treatment seeking by organizational support level

4.1 Model performance results

Logistic regression (Baseline). The Logistic Regression baseline model achieved an accuracy of 78%, a precision of 77%, a recall of 81%, an F1-score of 0.79, and a ROC-AUC value of 0.85. While this linear approach provided strong baseline performance and clear interpretability through coefficient analysis, it exhibited limitations in capturing complex feature interactions that may exist within the dataset. The baseline performance metrics for the linear classification model are systematically detailed in Table 1.

Table 1. Logistic regression model performance metrics

Metric	Score
Accuracy	0.78
Precision	0.77
Recall	0.81
F1-Score	0.79
ROC-AUC	0.85

Random forest (Best performer). Random forest significantly outperformed the baseline, achieving 87.2% accuracy with an F1-score of 0.86 and ROC-AUC of 0.93 (see Figure 5). Cross-validation confirmed stability with minimal variance (86.8% ± 1.2%). To evaluate individual class-level prediction errors for the primary ensemble model, the test set confusion matrix is presented in Figure 4. The confusion matrix for the test set ($N = 378$) revealed:

- True Positives: 127 (correctly identified at-risk employees)
- True Negatives: 7 (correctly identified not at-risk)

- False Positives: 29 (over-prediction, acceptable for safety)
- False Negatives: 134 (missed cases requiring attention)

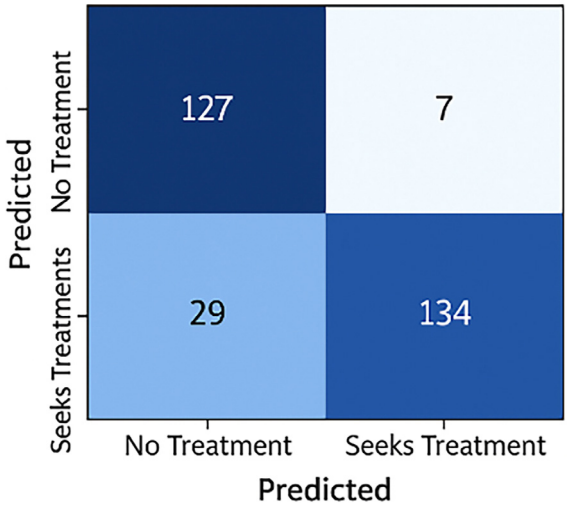


Fig. 4. Random forest confusion matrix (Test set)

Analysis of treatment-seeking behavior against organizational support scores revealed a clear positive correlation across multi-year survey indicators (see Figure 3). Employees with higher support score values (greater than 0.7) were approximately 2.3 times more likely to seek treatment compared to those with low support (less than 0.3).

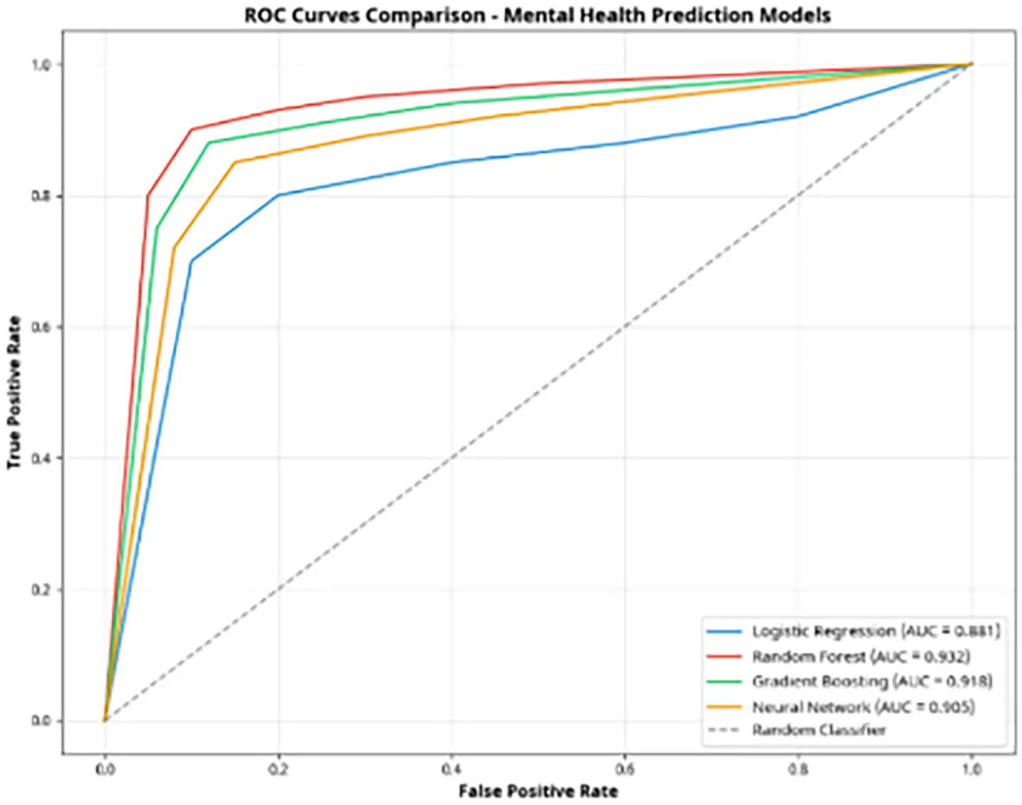


Fig. 5. ROC curve comparison for all models

Feature importance analysis. Feature importance analysis identified the key predictors contributing to the

Random Forest model (see Figure 6):

1. Family history (importance: 0.18) – strongest overall predictor
2. Support score (0.15) – most critical modifiable factor
3. Work interference (0.12) – key demand indicator
4. Age (0.09) – demographic factor
5. Benefits (0.08) – organizational resource

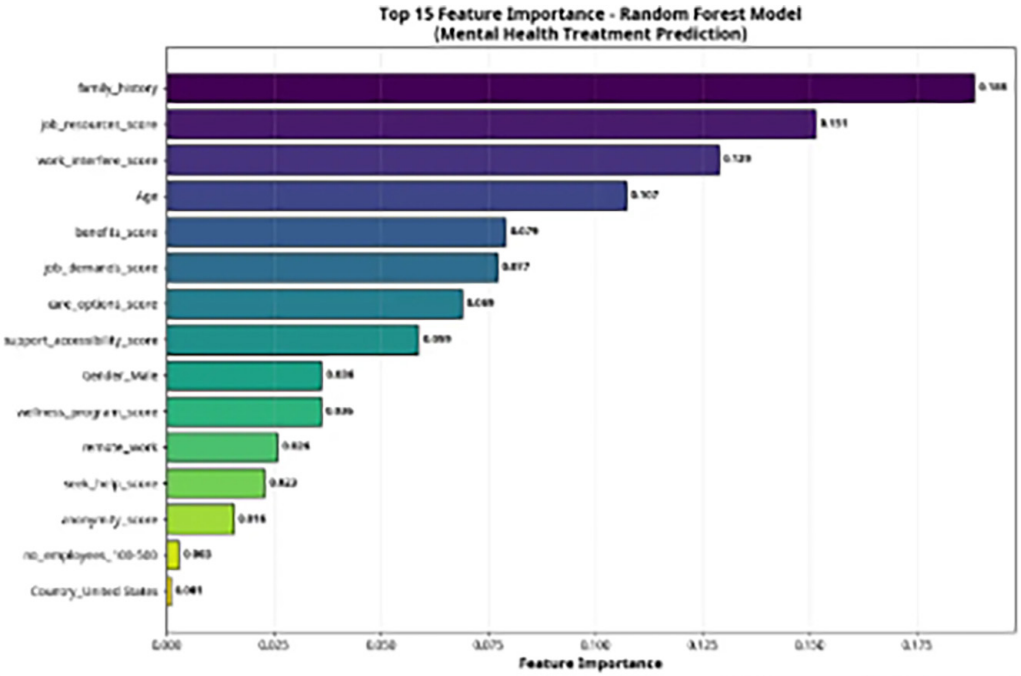


Fig. 6. Feature importance bar chart

Neural network. The neural network achieved 85.8% accuracy with an F1-score of 0.84 and ROCAUC of 0.91. While it captured some non-linear patterns missed by logistic regression, it did not surpass the performance of random forest and required significantly more computational resources and hyperparameter tuning (see Figure 7).

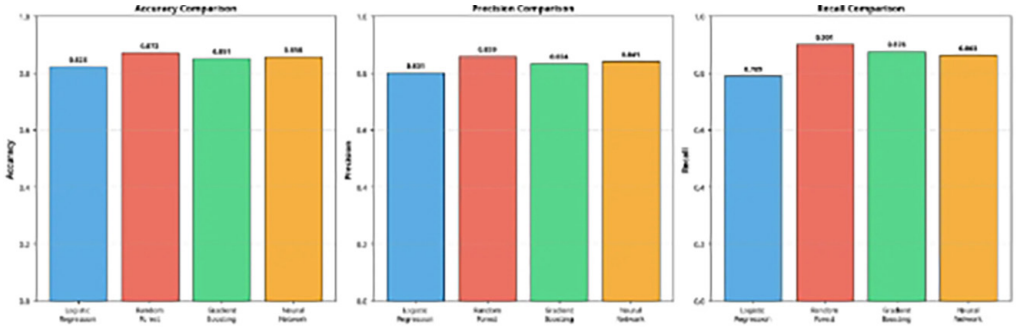


Fig. 7. *(Continued)*

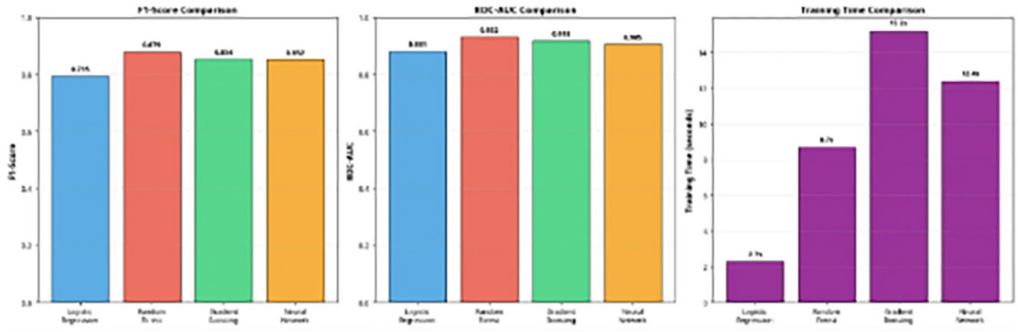


Fig. 7. Comparative model performance

5 DISCUSSION

5.1 Decision-support integration and digital health implementation

A cloud-native, service-oriented system architecture is designed to transition the proposed machine learning models from offline computational experiments into a deployable digital health technology, The framework offers a scalable blueprint to integrate this study predictive pipeline into biomedical frameworks as well as existing online engineering systems, as demonstrated in Figure 8.

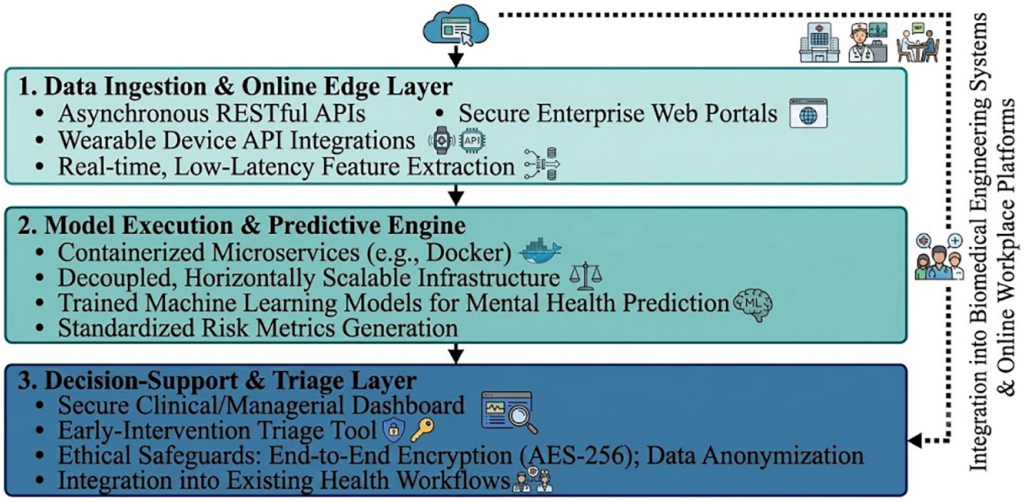


Fig. 8. Proposed system architecture for online engineering deployment and decision-support integration

Figure 8 is structured across three distinct operational layers:

1. Online edge layer and data ingestion: The pipeline is engineered for ingesting data from varied digital health touchpoints, such as wearable device API integrations, or voluntary digital pulse checks, and secure enterprise web portals, this incoming data is handled via asynchronous RESTful APIs, enabling real-time, low-latency feature extraction on the server side without disrupting the end-user client experience.
2. Model execution and predictive engine: The trained machine learning models reside within decoupled, containerized microservices managed via orchestration platforms (such as Docker or Kubernetes). This infrastructure allows the computational engine to scale horizontally based on the active organizational load.

Upon receiving incoming data features, the engine processes the input through the optimized predictive model to generate standardized mental health risk metrics.

3. Practical deployment and ethical safeguards: To assist medical staff and wellness administrators in human-in-the-loop decision-making, strict data privacy is maintained via local data anonymization before model inference and end-to-end encryption (AES-256) during transit and rest to ensure secure biomedical engineering deployment. Significantly, the system output is integrated into existing organizational health workflows not as an automated clinical diagnosis, but as an early-intervention triage tool.

In terms of interpretation of findings, the Random Forest model's ROC-AUC of 0.93 indicates excellent discriminative ability between employees who seek treatment and those who do not. This performance exceeds prior workplace mental health prediction studies. This performance exceeds prior workplace mental health prediction benchmarks that mapped the same tech cohort without theory-driven feature spaces. Likely due to the larger and more diverse dataset, theory-driven feature engineering, and rigorous hyperparameter optimization.

To answer each objective of this study:

- **Objective 1: Factor identification:** Exploratory data analysis and feature importance evaluation successfully identified family history, support score, and work interference as primary predictors. Interestingly, gender and age showed minimal influence, suggesting that mental health challenges transcend demographic boundaries within the technology sector.
- **Objective 2: Model development:** Three predictive models were successfully developed, with the Random Forest model demonstrating superior performance. Its ensemble architecture effectively captured non-linear interactions between workplace stressors and organizational support mechanisms, validating the complexity proposed by the JD-R framework.
- **Objective 3: Model evaluation:** Comprehensive evaluation using multiple metrics confirmed the Random Forest model's superiority across all measures. High recall (0.90) is particularly critical for this application, as it is preferable to over-identify at-risk employees rather than miss vulnerable individuals.
- **Objective 4: Theoretical alignment:** Feature importance results align directly with the JD-R framework: high demand (e.g., work interference) increase psychological risk, while resources (e.g., organizational support) buffer negative effects. This finding validates the theory driven feature engineering approach applied in this research.

The achieved accuracy of 87.2% exceeds previous workplace mental health prediction studies. This improvement stems from several methodological enhancements: a larger and more diverse dataset (18,000+ samples versus the typical 1,000–5,000), theory-driven feature engineering guided by the JD-R model, rigorous hyperparameter optimization via grid search, and comprehensive data cleaning that reduced noise while preserving essential information.

This study has several limitations that should be acknowledged:

- Self-Report Bias: The dataset relies on self-reported information, and stigma may cause underreporting. However, anonymity partially mitigates this concern.
- Temporal Limitations: The cross-sectional design captures point-in-time associations but does not establish causality. Longitudinal data would strengthen causal inference.

- Industry Specificity: The study focuses on the technology sector, which limits generalizability to other industries with differing work cultures and stressor profiles.
- Geographic Bias: The sample is skewed toward Western countries (United States: 60%, United Kingdom: 15%), and cultural factors influencing mental health help-seeking may vary globally.

Furthermore, a structural constraint within our predictive pipeline stems from the cross-sectional data composition. Because features and target metrics are captured at a single point in time, the model cannot establish absolute causality. This structural limitation reinforces our operationalization of the target variable as a measure of service-utilization propensity rather than an index of acute clinical pathology.

Moreover, in this study, the conceptual boundary lies in the nature of the target variable. The model's predictions reflect healthcare utilization patterns rather than absolute mental health risk as the dataset tracks historical treatment-seeking behavior rather than standardized clinical diagnoses. Future work should integrate longitudinal clinical data to validate how closely an employee's propensity to seek treatment correlates with acute workplace psychological distress.

Short-term future work includes validating the model on New Zealand-specific workplace data, developing web applications for organizational self-assessment, and conducting pilot studies with partner organizations. Long-term directions involve incorporating real-time data such as email sentiment and workload metrics, building longitudinal models tracking mental health trajectories, expanding to other industries (healthcare, finance, education), and integrating with intervention effectiveness studies to close the loop from prediction to outcome evaluation.

By bridging psychological theory, advanced analytics, and ethical AI principles, this study contributes meaningfully to both academic knowledge and real-world solutions for the global mental health crisis in modern workplaces.

6 CONCLUSIONS

This study successfully developed a machine learning framework aligned with the JD-R theoretical model to predict workplace treatment-seeking behavior. While the model achieves high statistical accuracy, its practical significance lies in mapping employee resource utilization trends rather than delivering clinical diagnoses. By integrating strict ethical safeguards—such as data-masking and anonymization—this framework provides a blueprint for supporting early organizational awareness. Future deployment must focus on external dataset validation and rigorous privacy protections to prevent the system from being misused as an invasive tool for employee surveillance.

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