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Explainable Machine Learning Approach for Burnout Risk Classification in Technology Workers

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Abstract−Burnout among technology workers has become a significant occupational health concern due to increasing workload demands, rapid technological changes, and high-performance expectations. This study proposes an explainable machine learning framework for burnout risk classification using mental health and workplace indicators. The dataset consists of 3,000 samples derived from a larger mental health dataset, incorporating psychological variables such as stress, anxiety (GAD-7), and depression (PHQ-9), as well as workplace-related factors including work hours, sleep duration, work-life balance, social support, and job satisfaction. A balanced random sampling approach was applied by selecting 750 samples from each burnout class. The data were split into training and testing sets using an 80:20 stratified approach. Three machine learning algorithms Logistic Regression, Random Forest, and Extreme Gradient Boosting (XGBoost) were evaluated using accuracy, F1-score, and ROC-AUC with default hyperparameter settings. Feature importance analysis was applied to enhance model interpretability. The results show that Logistic Regression achieved the highest accuracy of 88.2% with an F1-score of 0.88 and the best discriminative performance with an AUC of 0.96, consistently outperforming Random Forest and XGBoost across all evaluation metrics. The findings indicate that psychological factors, particularly stress, anxiety, and depression, are the most influential predictors of burnout risk. Overall, the proposed framework demonstrates strong predictive performance and interpretability, making it suitable for early burnout detection in technology work environments.

Keywords: Burnout Prediction; Machine Learning; Explainable Artificial Intelligence; Occupational Health; Technology Workers; Mental Health

1. INTRODUCTION

Burnout has become a major occupational health issue in modern workplaces due to increasing digital transformation, high workload demands, and continuous performance pressure (Zhang et al., 2025). It is characterized by emotional exhaustion, reduced professional effectiveness, and psychological detachment, which negatively affect employee well-being and organizational productivity (Petitta & Ghezz, 2023). Therefore, early detection of burnout is essential to support timely intervention and prevention (Leclercq & Hansez, 2024). Technology workers are particularly vulnerable to burnout due to intensive cognitive demands, long working hours, tight deadlines, and rapidly changing technologies (Leclercq & Hansez, 2024). These conditions often lead to psychological distress such as stress, anxiety, depression, sleep disturbance, and poor work-life balance (Ayar et al., 2022). Hence, effective predictive models are required to identify burnout risk at an early stage in technology work environments (Ayar et al., 2022). Recent advances in machine learning (ML) have enabled more accurate prediction of burnout by learning complex patterns from psychological and workplace data (Adamopoulos et al., 2025). In addition, explainable artificial intelligence (XAI) enhances model transparency by identifying key variables that influence predictions, making ML models more applicable in real-world occupational health decision-making (Adamopoulos et al., 2025).

Several studies have demonstrated the effectiveness of machine learning techniques in burnout prediction. (Adapa et al., 2022) proposed an explainable supervised machine learning approach for predicting burnout among healthcare professionals and reported an Area Under the Curve (AUC) of 0.81. (Feher et al., 2024) applied machine learning techniques to predict burnout among teachers and achieved an AUC of 0.811, highlighting the importance of psychological indicators in burnout detection. (Magdalena et al., 2024) developed a machine learning model to identify burnout and emotional exhaustion risk factors among nursing staff, demonstrating the relevance of occupational and psychological variables in prediction tasks. Meanwhile, (Trinkenreich et al., 2023) investigated burnout among software developers and emphasized organizational and individual contributors to burnout in software engineering environments.

Table 1. Comparison of Previous Studies and Proposed Research

Study	Domain	Method	Main Finding	Research Gap
Adapa et al. (2022)	Healthcare Professionals	Explainable Machine Learning	AUC = 0.81; interpretable burnout prediction	Limited to healthcare domain
Feher et al. (2024)	Teachers	Machine Learning	AUC = 0.811; psychological factors highly influential	Limited workplace factor integration
Magdalena et al. (2024)	Nursing Staff	Machine Learning	Identified burnout risk factors in nurses	Not focused on technology workers
Trinkenreich et al. (2023)	Software Developers	Conceptual Analysis	Burnout determinants in developers	No predictive ML framework

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Study	Domain	Method	Main Finding	Research Gap
Proposed Study	Technology Workers	Logistic Regression, Random Forest, XGBoost + Explainability	Burnout risk classification framework using mental + workplace indicators	Integrates domain, features, comparison, and explainability

As summarized in Table 1, existing studies mainly focus on healthcare, education, and nursing domains, while technology workers remain underrepresented (Adapa et al., 2022; Feher et al., 2024; Magdalena et al., 2024). Moreover, most studies analyze psychological and workplace variables separately and lack a unified modeling approach (Feher et al., 2024; Magdalena et al., 2024). In addition, few studies provide a systematic comparison of multiple machine learning algorithms combined with explainability techniques (Adapa et al., 2022; Trinkenreich et al., 2023). Therefore, there remains a need for an explainable machine learning framework that integrates mental health and workplace indicators for burnout risk prediction in technology-intensive work environments. To address these gaps, this study proposes an Explainable Machine Learning Framework for Burnout Risk Classification Among Technology Workers Using Mental Health and Workplace Indicators. The proposed framework integrates psychological measures, including stress score, anxiety score (GAD-7), and depression score (PHQ-9), together with workplace-related indicators such as work hours, deadline pressure, sleep duration, work-life balance, social support, and job satisfaction. Three machine learning algorithms, namely Logistic Regression, Random Forest, and Extreme Gradient Boosting (XGBoost), are evaluated and compared using multiple performance metrics, including accuracy, precision, recall, F1-score, confusion matrix analysis, cross-validation, and ROC-AUC. The novelty of this study lies in the development of a domain-specific and explainable predictive framework that combines mental health and workplace factors within a unified pipeline. Unlike previous studies that focused on healthcare professionals, teachers, nursing staff, and software developers (Adapa et al., 2022; Feher et al., 2024; Magdalena et al., 2024; Trinkenreich et al., 2023), this study integrates mental health indicators and workplace-related factors within a unified predictive framework. Furthermore, while previous studies primarily investigated burnout prediction within specific occupational settings or lacked a comparative predictive framework (Adapa et al., 2022; Magdalena et al., 2024; Trinkenreich et al., 2023), this study performs a comprehensive comparison of Logistic Regression, Random Forest, and XGBoost to identify the most suitable model for burnout risk classification. Feature importance analysis is further incorporated to improve model transparency and provide actionable insights into the factors contributing to burnout risk. Therefore, the proposed framework not only delivers accurate classification performance but also supports evidence-based decision-making for occupational mental health management. This study contributes to the growing body of research on explainable machine learning in occupational health and provides a practical framework for early burnout risk detection among technology workers.

2. RESEARCH METHODS

2.1 Basic Research Framework

This study adopts a quantitative, machine learning-based experimental research design to classify burnout risk among technology workers (Kundur et al., 2025). The proposed research framework consists of four main stages, namely data preprocessing, feature selection, model training, and explainability analysis. The framework is designed to systematically transform raw data into meaningful predictions while ensuring interpretability of the model outputs. Three machine learning algorithms Logistic Regression, Random Forest, and XGBoost are applied for comparative analysis to identify the best-performing model in burnout risk classification. The proposed research framework consists of seven sequential stages: data collection, data preprocessing, domain-based feature selection, stratified train-test splitting, machine learning model development, model evaluation, and explainability analysis. In the preprocessing stage, missing values and irrelevant features are removed, followed by normalization where necessary. Feature selection is performed to identify the most influential variables contributing to burnout prediction. Subsequently, machine learning models, including Logistic Regression, Random Forest, and XGBoost, are trained and evaluated using a train-test split validation approach. Finally, model interpretability is achieved through feature importance analysis to explain the prediction outcomes.

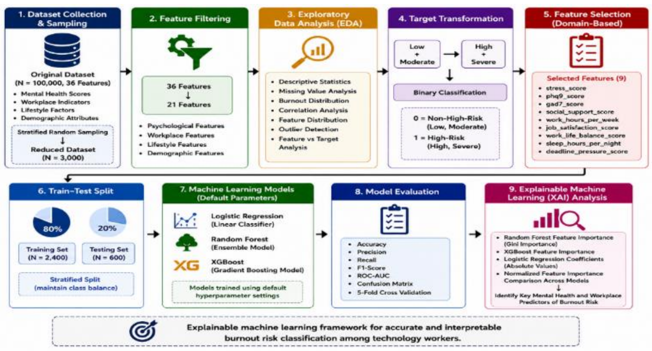

Figure 1. Research Framework for Burnout Risk Classification

Figure 1, illustrates the proposed end-to-end machine learning framework for burnout risk classification among technology workers. The framework consists of sequential stages, including dataset collection and sampling, data preprocessing, feature filtering, domain-based feature selection, stratified train-test splitting, machine learning model development, model evaluation, and explainable machine learning analysis. During preprocessing, burnout levels were transformed into a binary classification problem by grouping Low and Moderate levels as non-burnout (0) and High and Severe levels as burnout (1). The original dataset containing 36 features was first reduced to 21 features through feature filtering and subsequently narrowed to 9 domain-relevant predictors through domain-based feature selection. Three machine learning algorithms, namely Logistic Regression, Random Forest, and XGBoost, were implemented and compared using default hyperparameter settings. Model performance was evaluated using Accuracy, Precision, Recall, F1-Score, ROC-AUC, Confusion Matrix, and 5-Fold Cross-Validation. Finally, explainable machine learning techniques, including Random Forest feature importance, XGBoost feature importance, Logistic Regression coefficients, and normalized cross-model importance comparison, were employed to identify the most influential predictors of burnout risk. Overall, the framework provides a systematic and interpretable pipeline for burnout risk classification among technology workers.

2.2 Dataset Description

The dataset used in this study was obtained from the Kaggle repository titled “Mental Health and Burnout in Tech Workers 2026”. The dataset consists of 100,000 synthetic records containing 36 features representing mental health indicators, workplace conditions, and demographic attributes of technology workers. To ensure a balanced class distribution and maintain computational efficiency, a stratified random sampling strategy was applied to obtain a representative subset of 3,000 samples from the original dataset (Wu et al., 2024). The dataset was subsequently balanced between burnout and non-burnout classes after stratification. This approach preserves the proportional distribution of burnout classes and reduces potential sampling bias, ensuring that the reduced dataset remains representative of the original population.

The target variable, burnout level, originally consists of four categories: Low, Moderate, High, and Severe. For classification purposes, these categories were transformed into a binary format, where Low and Moderate represent class 0 (non-burnout), while High and Severe represent class 1 (burnout). The input features include stress score, PHQ-9 score, GAD-7 score, social support score, work hours per week, job satisfaction score, work-life balance score, sleep duration, and deadline pressure score.

2.3 Data Preprocessing and Feature Selection

Initially, the dataset contained 36 features, including demographic, psychological, and workplace-related variables. To simplify the classification task and improve model interpretability, the target variable was transformed into a binary format by merging Low and Moderate into class 0 (non-burnout) and High and Severe into class 1 (burnout), reflecting a clinically meaningful distinction between non-critical and high-risk burnout conditions.

During preprocessing, irrelevant and non-predictive attributes were removed, reducing the feature set from 36 to 21 variables. Subsequently, domain-based feature selection was performed to identify the most relevant predictors of burnout risk. Based on findings from previous burnout and occupational mental health studies, nine features were selected for model development, namely stress score, PHQ-9 score, GAD-7 score, social support score, work hours per week, job satisfaction score, work-life balance score, sleep hours per night, and deadline pressure score. This feature selection process aims to reduce dimensionality and improve model interpretability while maintaining predictive relevance.

2.4 Dataset Splitting

After feature selection, the final dataset consisted of 3,000 samples with 9 selected features. The dataset was partitioned into training and testing sets using an 80:20 stratified split strategy, a widely adopted approach in machine learning to ensure robust and unbiased model evaluation (Kiran & Rajendran, 2026). This resulted in 2,400 training samples and 600 testing samples, while stratification preserved the proportional distribution of burnout classes across both subsets.

2.5 Machine Learning Models

This study employs three machine learning algorithms for burnout risk classification, namely Logistic Regression, Random Forest, and XGBoost. Logistic Regression is used as a baseline model due to its simplicity and interpretability in binary classification tasks (Kiran & Rajendran, 2026). Random Forest is applied as an ensemble learning method capable of handling nonlinear relationships and reducing overfitting through bootstrap aggregation (Alam, 2025). XGBoost is utilized as the main advanced ensemble method because of its high performance, regularization capability, and efficiency in handling complex structured data (Amjad et al., 2022).

The models are trained using an 80:20 train-test split strategy. Evaluation metrics include accuracy, precision, recall, and F1-score to ensure a balanced assessment of classification results. In addition to the train-test split evaluation, a 5-fold cross-validation procedure was performed to assess model stability and generalization capability (Ismail et al., 2026). The average accuracy across the five folds was used as an additional performance indicator for comparing the evaluated models.

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2.6 Explainability Method

To enhance model interpretability, feature importance analysis was conducted using the Random Forest model due to its intrinsic capability to provide Gini-based feature importance measures. Although Logistic Regression achieved the highest classification performance, Random Forest was selected for explainability analysis because it offers a direct and intuitive mechanism for quantifying the contribution of individual features to classification decisions. Feature importance scores were used to identify the most influential predictors associated with burnout risk among technology workers. Furthermore, a comparative feature importance analysis was performed across Random Forest, XGBoost, and Logistic Regression. Gini-based importance scores were extracted from the tree-based models, whereas absolute coefficient values were obtained from Logistic Regression. The resulting importance values were subsequently normalized to facilitate a fair comparison across model (Ismail et al., 2026; Matta & Bolli, 2023).

Feature importance analysis is recognized as an intrinsic explainability approach that provides model-level transparency by quantifying the relative contribution of each predictor to classification outcomes, consistent with the broader principles of explainable machine learning (Adamopoulos et al., 2025; Mokheleli & Bokaba, 2025).

3. RESULTS AND DISCUSSION

This section presents the experimental results and discussion of the proposed explainable machine learning framework for burnout risk classification among technology workers. The performance of Logistic Regression, Random Forest, and XGBoost is evaluated using cross-validation, accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC analysis. In addition, feature importance analysis is conducted to identify the most influential factors contributing to burnout prediction and to enhance model interpretability. The findings are discussed in relation to their implications for occupational mental health management (Pereira et al., 2021).

3.1 Experimental Results Overview

This section presents the experimental results of machine learning models for burnout risk classification among technology workers. Three models are evaluated, namely Logistic Regression, Random Forest, and XGBoost, using a stratified test set of 600 samples. The performance is assessed using accuracy, precision, recall, and F1-score to provide a balanced evaluation of classification capability. The results of each model are presented in the following subsections.

3.2 Validation Performance Analysis

Cross-validation was conducted to evaluate the stability and generalization capability of the proposed machine learning models. A 5-fold cross-validation strategy was employed, where the dataset was divided into five subsets and each subset was used as a testing set once while the remaining subsets were used for training. Figure 2 presents the mean accuracy obtained by Logistic Regression, Random Forest, and XGBoost across the five folds.

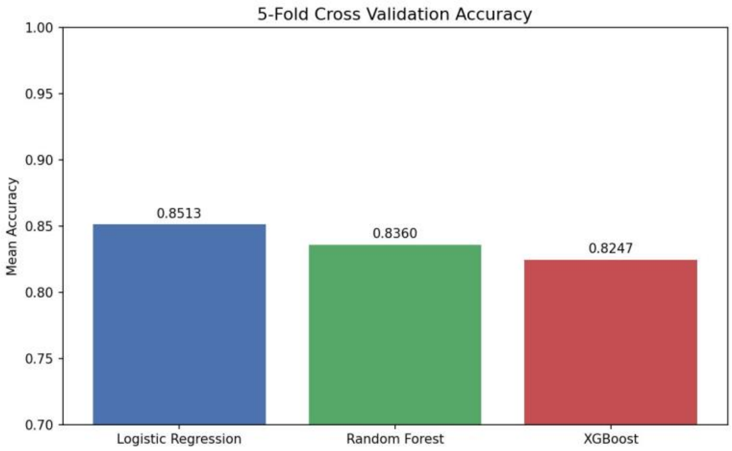

Figure 2. Cross-Validation Performance

The results indicate that all models achieved consistently high accuracy values, demonstrating strong generalization performance across different data partitions. Logistic Regression achieved the highest mean cross-validation accuracy (85.1%), followed by Random Forest (83.6%) and XGBoost (82.5%). The relatively small differences among the models suggest that the selected mental health and workplace indicators provide robust predictive information for burnout risk classification. Furthermore, the consistency of the cross-validation results confirms that the proposed framework is stable and not overly dependent on a specific train-test split.

The discrepancy between cross-validation and test set results is attributed to the sensitivity of ensemble methods to data distribution. While Logistic Regression demonstrates more stable performance across folds, Random Forest

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benefits from variance reduction on the specific test set distribution, yet still falls slightly below Logistic Regression in overall performance. This finding strengthens the reliability of the classification performance observed in the hold-out testing phase.

3.3 Model Performance and Comparative Analysis

The first analysis focuses on comparing the predictive performance of the three machine learning models. The results are summarized in Table 2

Table 2. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.882	0.873	0.893	0.883
Random Forest	0.875	0.869	0.883	0.876
XGBoost	0.863	0.859	0.870	0.864

Table 2, shows the comparative performance of Logistic Regression, Random Forest, and XGBoost for burnout risk classification. The results indicate that Logistic Regression achieves the highest accuracy (88.2%), followed by Random Forest (87.5%) and XGBoost (86.3%). This finding suggests that the burnout classification task exhibits predominantly linear separability that can be effectively captured by a simpler model. Notably, Logistic Regression consistently outperformed the ensemble methods across all evaluation metrics including accuracy, precision, recall, and F1-score, demonstrating that model complexity does not always correlate with improved predictive performance in structured datasets.

XGBoost recorded the lowest performance among the three models, which may be attributed to the use of default hyperparameter settings and the relatively structured nature of the feature space, where the sequential boosting strategy provides limited additional benefit. Overall, the results demonstrate that Logistic Regression provides the most stable and effective classification performance, confirming its suitability as both a baseline and competitive model for burnout risk classification.

3.4 Confusion Matrix Analysis

Confusion matrix analysis was performed to provide a detailed evaluation of the classification results obtained by each machine learning model. Figures 3 present the confusion matrices of Logistic Regression, Random Forest, and XGBoost, respectively.

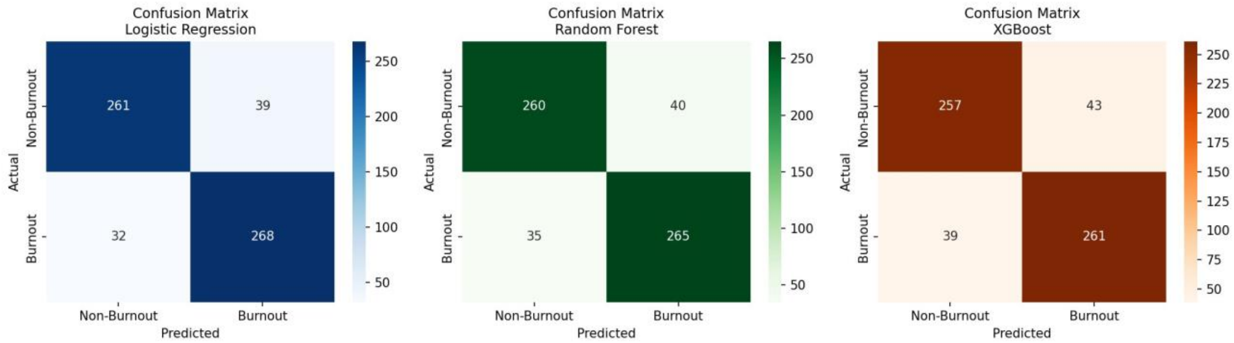

Figure 3. Confusion Matrices of Logistic Regression, Random Forest, and XGBoost

As shown in Figure 3, the Logistic Regression model correctly classified 261 non-burnout cases and 268 burnout cases, with 39 false positives and 32 false negatives, representing the highest number of correctly classified instances and the best balance between true positive and true negative predictions among the three models. The Random Forest model correctly identified 260 non-burnout cases and 265 burnout cases, with 40 false positives and 35 false negatives, producing slightly more classification errors compared to Logistic Regression. Meanwhile, XGBoost correctly classified 257 non-burnout cases and 261 burnout cases, with 43 false positives and 39 false negatives, representing the highest number of misclassifications among the three models, consistent with its lower accuracy values reported in Table 2.

Overall, the confusion matrix analysis demonstrates that Logistic Regression provides the most balanced classification performance, with the highest number of correctly classified instances and the lowest number of false negatives. Since false negatives represent burnout cases that remain undetected, minimizing this type of error is particularly important in occupational health applications. Therefore, Logistic Regression was identified as the most suitable model for burnout risk prediction among technology workers based on overall classification performance.

3.5 ROC Curve and AUC Analysis

Receiver Operating Characteristic (ROC) analysis was performed to evaluate the ability of each model to distinguish between burnout and non-burnout classes across different classification thresholds.

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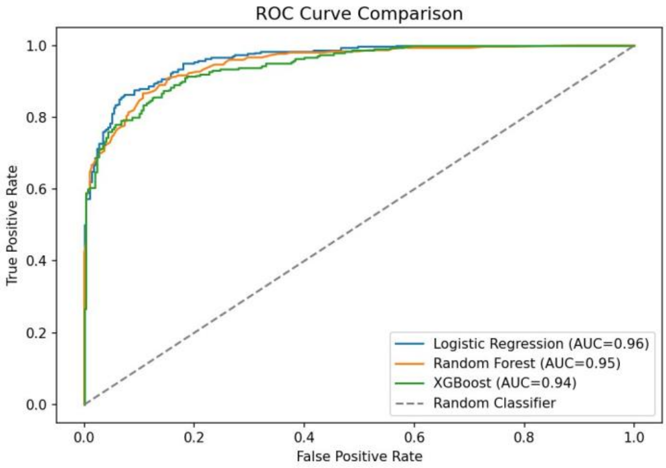

Figure 4. ROC Curves of the Evaluated Machine Learning Models

Figure 4 presents the ROC curves of Logistic Regression, Random Forest, and XGBoost. The results indicate that all three models achieved excellent classification performance, with AUC values greater than 0.94. Logistic Regression achieved the highest AUC score (0.96), followed by Random Forest (0.95) and XGBoost (0.94). The ROC curves are positioned close to the upper-left corner of the graph, reflecting high sensitivity and specificity across a wide range of classification thresholds. These results further confirm that Logistic Regression demonstrates the strongest discriminative capability across all evaluation dimensions, consistently outperforming the other models in both accuracy and AUC.

3.6 Feature Importance Analysis

To enhance model interpretability, feature importance analysis was performed using the Random Forest classifier due to its inherent capability to provide Gini-based feature importance measures, enabling direct quantification of each feature's contribution to burnout risk classification. Although Logistic Regression achieved the highest overall accuracy, Random Forest was selected for explainability analysis because it provides more robust and interpretable feature importance scores compared to logistic coefficients. The importance scores were calculated using the Gini Importance (Mean Decrease in Impurity) method (Chen et al., 2025).

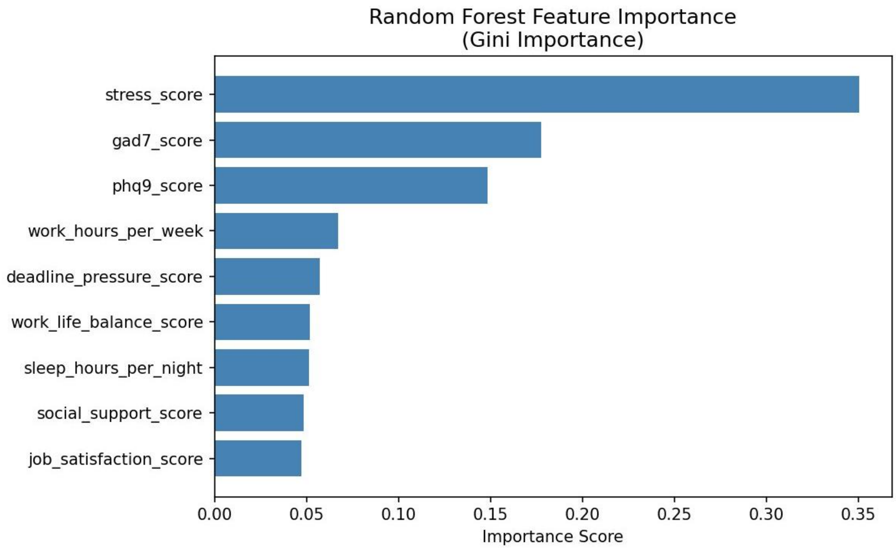

Figure 5. Random Forest Feature Importance Ranking

Figure 5, presents the feature importance ranking of the selected variables. The results indicate that stress_score is the most influential feature in predicting burnout risk. This finding suggests that perceived stress is the primary factor driving burnout classification, highlighting the critical role of stress management in preventing burnout among technology workers. The second and third most important features are gad7_score and phq9_score, which represent anxiety and depression symptoms respectively.

In contrast, workplace-related variables such as work_hours_per_week, deadline_pressure_score, sleep_hours_per_night, work_life_balance_score, social_support_score, and job_satisfaction_score demonstrate lower importance values. This result suggests that mental health conditions have a stronger direct impact on burnout risk than workplace characteristics alone.

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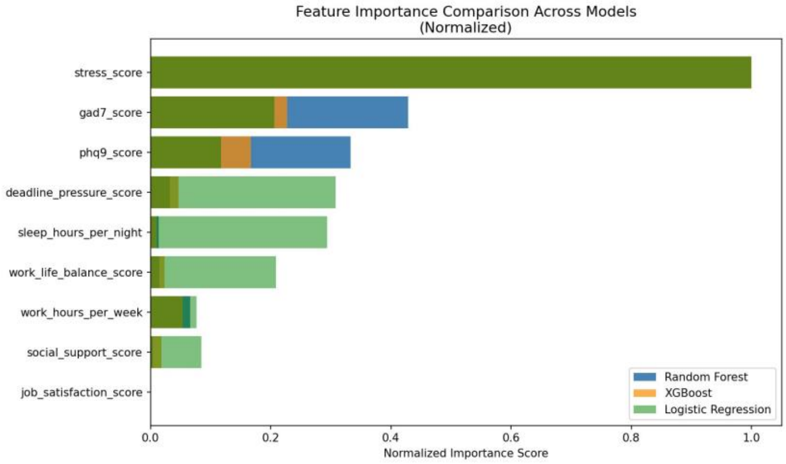

Figure 6. Feature Importance Comparison Across Models (Normalized)

Figure 6, presents a normalized comparison of feature importance across all three models. While the relative ranking varies slightly between models, stress_score, gad7_score, and phq9_score consistently emerge among the most influential predictors, reinforcing the conclusion that psychological indicators play a dominant role in burnout risk classification across different modeling approaches

3.7 Discussion

The experimental results demonstrate that machine learning techniques can effectively classify burnout risk among technology workers using a combination of mental health and workplace indicators. Among the evaluated models, Logistic Regression achieved the highest classification accuracy (88.2%), followed by Random Forest (87.5%) and XGBoost (86.3%). Logistic Regression also obtained the highest AUC score (0.96) and cross-validation accuracy (85.1%), demonstrating consistent superiority across all evaluation metrics. These results suggest that the burnout classification task exhibits predominantly linear separability, where a simpler model is sufficient to capture the underlying patterns effectively (Adapa et al., 2022; Magdalena et al., 2024).

The cross-validation results further confirm the robustness and stability of the proposed framework. The relatively consistent performance across the five folds indicates that the selected features capture meaningful and stable patterns related to burnout risk. The discrepancy between cross-validation and test set results is attributed to the sensitivity of ensemble methods to data distribution. While Logistic Regression demonstrates more stable performance across folds, Random Forest benefits from variance reduction on specific data partitions, yet still falls slightly below Logistic Regression in overall performance.

A key finding from the feature importance analysis is the dominance of psychological indicators in predicting burnout risk. Stress score emerged as the most influential feature, followed by anxiety (GAD-7) and depression (PHQ-9). This indicates that burnout among technology workers is more strongly driven by psychological distress than by workplace-related factors alone. Although variables such as work hours, deadline pressure, and work-life balance contribute to the prediction process, their relative influence is significantly lower compared to mental health indicators.

These findings are consistent with previous studies reporting that chronic stress, anxiety, and depressive symptoms are among the primary determinants of occupational burnout. This reinforces the understanding that burnout should not be viewed solely as an organizational workload issue but also as a psychological health condition requiring early detection and intervention (Sarkar & Kudapa, 2024). Therefore, organizations should prioritize integrated mental health monitoring systems and preventive strategies to reduce burnout risk and improve employee well-being. (Rodrigues et al., 2025)

From a methodological perspective, the results also demonstrate that increasing model complexity does not necessarily improve predictive performance. Despite being a more advanced ensemble learning algorithm, XGBoost did not outperform Random Forest or Logistic Regression. This outcome can be attributed to several factors. First, the relatively small sample size of 3,000 records may limit the ability of boosting algorithms to iteratively correct residual errors effectively. Second, no hyperparameter tuning beyond default settings was performed, meaning that XGBoost may not reflect its optimal configuration. Third, the dataset exhibits relatively structured and partially linear patterns where simpler models are sufficient.

It is important to acknowledge that the dataset used in this study consists of synthetic data obtained from a public repository, which may affect the external validity of the findings. Synthetic datasets, while useful for controlled experimentation and model development, may not fully capture the complex and heterogeneous patterns present in real-world occupational settings. Consequently, the generalizability of the proposed framework to actual technology workers across different organizational contexts, cultures, and industries remains to be validated. Future studies are encouraged to replicate this framework using real-world organizational datasets to assess its practical applicability.

Future work may incorporate SHAP-based explainable AI techniques to provide more robust and globally consistent interpretations of model predictions. Unlike impurity-based feature importance, SHAP values can offer both local and global explanations, improving transparency and interpretability in high-stakes occupational health applications.

4. CONCLUSION

This study proposed an explainable machine learning framework for burnout risk classification among technology workers using mental health and workplace indicators. The experimental results demonstrated that machine learning techniques can effectively identify burnout risk, with Logistic Regression achieving the highest classification accuracy of 88.2%, the highest AUC score of 0.96, and the best cross-validation accuracy of 85.1%, consistently outperforming Random Forest and XGBoost across all evaluation metrics. In addition, feature importance analysis revealed that stress score, anxiety (GAD-7), and depression (PHQ-9) were the most influential predictors of burnout risk, indicating that psychological factors play a more significant role than workplace-related variables in the classification process. These findings suggest that the proposed framework can serve as a practical decision-support tool for organizations seeking to detect burnout risk at an early stage and implement targeted interventions to improve employee well-being. Nevertheless, this study has several limitations. First, the dataset used consists of synthetic data obtained from a public repository, which may not fully represent real-world technology workers. Second, all models were trained using default hyperparameter settings without extensive tuning. Future research may utilize real-world organizational datasets, investigate additional psychological and workplace variables, and explore advanced explainable artificial intelligence techniques such as SHAP to further improve predictive performance and interpretability.

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