EQUA: PERSONALIZED BURNOUT RISK ASSESSMENT USING MACHINE LEARNING AND LLM-BASED COACHING

TECHNICAL REPORT

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ABSTRACT

Burnout is an increasingly prevalent issue in modern workplaces, impacting employee well-being, productivity, and organizational health. This report presents **Equa**, a comprehensive system for burnout detection that leverages machine learning and large language models (LLMs) to provide a proactive approach to workplace wellness. The system uses a Gradient Boosting Regressor model, trained on a real-world dataset of employee metrics, to predict an individual's burnout score. This quantitative analysis is integrated into a user-friendly Streamlit application that provides an AI-powered wellness coach. The coach, driven by the *Mistral-7B* model via the OpenRouter API, delivers personalized, empathetic advice based on the user's predicted burnout risk and allows for interactive follow-up conversations. By combining robust predictive modeling with AI-driven guidance, Equa offers a scalable and accessible tool for early burnout detection and intervention. Experimental results demonstrate the model's high predictive accuracy (R^2 of 0.90), highlighting the potential of integrated AI solutions to foster healthier and more supportive work environments.

Keywords Burnout Detection · Machine Learning · Large Language Models · Workplace Wellness · Psychological Data

1 Introduction

Burnout is a psychological syndrome resulting from prolonged exposure to chronic stress, particularly in professional or high-demand environments. It is characterized by emotional exhaustion, reduced performance, and detachment, posing significant risks to both individuals and organizations. The increasing prevalence of burnout in modern workplaces has drawn attention to its substantial social and economic impact, including decreased productivity, higher turnover, and adverse health outcomes. As work environments become more complex and fast-paced, the need for proactive strategies to identify and mitigate burnout has never been more pressing.

Traditional approaches to identifying burnout typically rely on self-reported questionnaires or periodic evaluations. While these methods provide valuable insights, they are often subjective and reactive, identifying burnout only after it has manifested. The availability of rich datasets containing employee work metrics and self-reported wellness indicators has opened the door to modern machine learning approaches that can detect early signs of burnout, allowing for timely intervention.

In this project, we present **Equa**, a proactive, data-driven framework for detecting employee burnout risk. Equa predicts a numerical burnout score and classifies individuals into Low, Moderate, and High-risk categories based on a combination of professional and personal metrics. By integrating this predictive model with a large language model, the framework provides not only a risk score but also personalized, actionable coaching. This approach facilitates personalized interventions, empowering organizations and individuals to take preventive action and maintain well-being.

2 Dataset and Exploratory Analysis

The project utilizes the "Are Your Employees Burning Out?" dataset, an enriched collection of employee metrics sourced from a 2008 survey. The dataset provides a comprehensive view of factors influencing workplace stress and well-being.

The dataset, containing 22,750 records, was loaded and examined for its structure and statistical properties. Table 1 summarizes the key features used for modeling.

Table 1: Key features in the employee burnout dataset

Feature	Description
Designation	Employee's job level or seniority (0-5)
Resource Allocation	Number of projects or tasks handled
Mental Fatigue Score	Self-reported score of mental exhaustion (0-10)
Company Type	Type of company (Service or Product)
WFH Setup Available	Whether work-from-home is an option (Yes/No)
Gender	Employee's gender (Male/Female)
Date of Joining	The date the employee joined the company
Burn Rate	The target variable indicating burnout level (0-1)

Initial data analysis revealed missing values in 'Resource Allocation', 'Mental Fatigue Score', and the target variable 'Burn Rate'. These were handled by imputing the median value for each respective column, a robust method for dealing with skewed data.

Exploratory Data Analysis (EDA) focused on understanding the distributions of key variables and their relationships. A histogram of the 'Burn Rate' (Figure 1) showed a relatively normal distribution centered around a mean of 0.45, indicating a balanced representation of different burnout levels in the dataset.

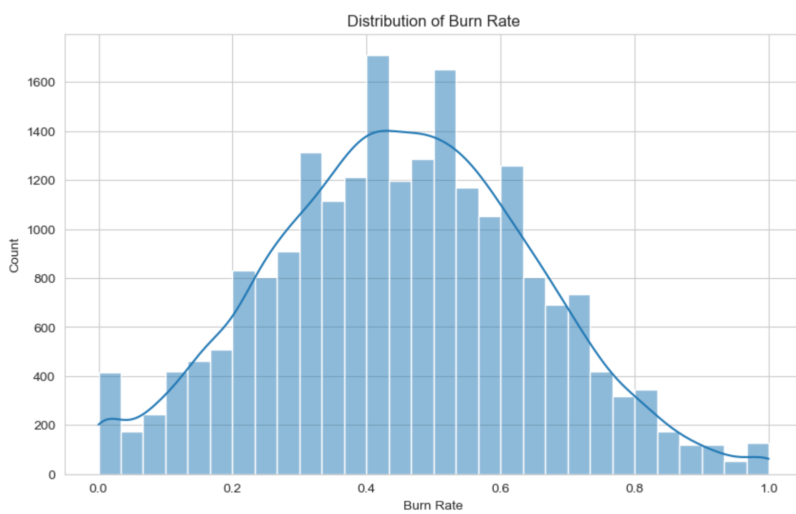

Figure 1: Distribution of Burn Rate in the dataset.

A correlation matrix (Figure 2) was generated to examine the relationships between numerical features. The analysis revealed that 'Mental Fatigue Score' had the strongest positive correlation with 'Burn Rate' (0.71), followed by 'Resource Allocation' (0.36) and 'Designation' (0.35). This confirms that higher mental fatigue and greater job responsibility are significant predictors of burnout.

2.1 Feature Engineering

To enhance the predictive power of the model, two key feature engineering steps were performed:

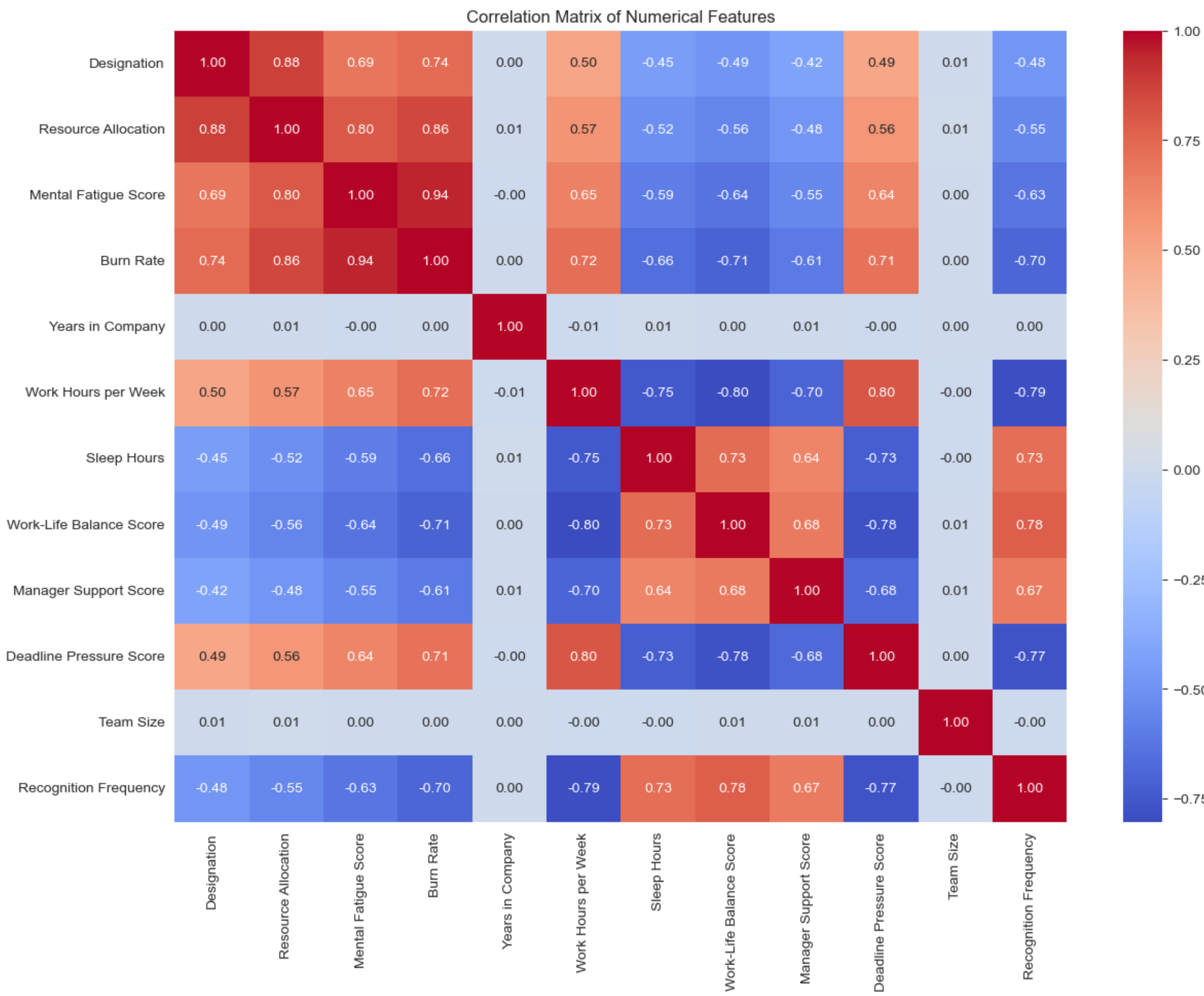

Figure 2: Correlation matrix of numerical features. ‘Mental Fatigue Score‘ shows the highest correlation with ‘Burn Rate‘.

1. **Temporal Feature Creation:** The ‘Date of Joining‘ column was converted into a numerical feature, ‘Days_Since_Joining‘, by calculating the number of days between the latest joining date in the dataset and each employee’s start date. This captures an employee’s tenure, which can influence burnout.

2. **Categorical Encoding:** The categorical features (‘Gender‘, ‘Company Type‘, ‘WFH Setup Available‘) were one-hot encoded to convert them into a numerical format suitable for machine learning algorithms.

3 Modeling Approach

The modeling process began with a comparative analysis of several regression algorithms to establish a performance baseline. The dataset was split into training (80%) and testing (20%) sets. Four models were evaluated: Linear Regression, Support Vector Regressor (SVR), Random Forest Regressor, and Gradient Boosting Regressor.

As shown in Table 2, the **Gradient Boosting Regressor** achieved the highest R-squared value and the lowest Mean Absolute Error (MAE) and Mean Squared Error (MSE), making it the best-performing model out-of-the-box.

The Gradient Boosting model was then selected for hyperparameter tuning using ‘RandomizedSearchCV‘ with 5-fold cross-validation to optimize its performance further. The best parameters identified were: ‘n_estimators: 900‘, ‘min_samples_split: 5‘, ‘min_samples_leaf: 2‘, ‘max_features: ’log2’‘, ‘max_depth: 7‘, and ‘learning_rate: 0.01‘.

Table 2: Baseline model comparison results

Model	R-squared	MAE	MSE
Gradient Boosting	0.898	0.0449	0.0037
Random Forest	0.894	0.0453	0.0038
SVR	0.870	0.0530	0.0047
Linear Regression	0.861	0.0518	0.0050

4 Results and Conclusion

The tuned Gradient Boosting model achieved a final R-squared value of **0.90** on the test set, indicating that it explains 90% of the variance in employee burnout rates. The final MAE was 0.0444, and the MSE was 0.0036, demonstrating high predictive accuracy.

A feature importance analysis was conducted on the final model to identify the most influential factors in predicting burnout. As illustrated in Figure 3, the 'Mental Fatigue Score' was by far the most significant predictor, followed by 'Days_Since_Joining' and 'Designation'. This aligns with the initial EDA findings and psychological literature on burnout.

The final tuned model and its associated column structure were saved to 'employee_burnout_model.pkl' for deployment in the web application. The project successfully demonstrates that machine learning models can accurately predict employee burnout risk from standard workplace metrics. The high performance of the Gradient Boosting model confirms the viability of this data-driven approach for proactive wellness interventions.

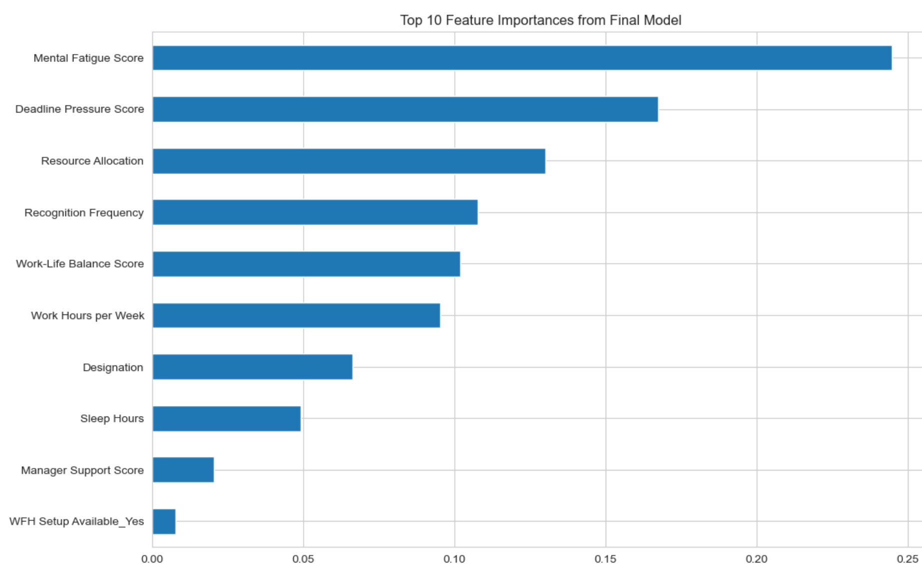

Figure 3: Feature importance scores from the final Gradient Boosting model.

5 Deployment and Application

To make the model accessible and actionable, a comprehensive system was built and deployed as a Streamlit web application, **Equa: Your Personal AI Burnout Coach**.

The application's backend is powered by the saved 'employee_burnout_model.pkl' file. User inputs from the web interface, such as job designation and mental fatigue score, are collected and preprocessed by a helper function ('prepare_input_data' in 'app.py') to match the feature format required by the model.

The core of the user experience is the AI coaching service, implemented in 'ai_service_openrouter.py'. This module uses the OpenRouter API to interface with the **Mistral-7B Instruct** large language model. Based on the user's predicted burnout score and input data, a dynamic prompt is generated to elicit a personalized, empathetic coaching plan.

The system distinguishes between an initial analysis and follow-up questions, allowing for a natural, conversational interaction with the AI coach.

The Streamlit front-end (‘app.py‘) provides an intuitive user interface. A sidebar allows users to input their work metrics using sliders and select boxes. Upon analysis, the application displays the predicted burnout score and risk category (Low, Moderate, or High). The main panel features a chat interface where the user receives the initial AI-generated advice and can ask follow-up questions. To ensure reliability, a fallback mechanism is included; if the API call fails, the application provides a set of pre-written, high-quality tips relevant to the user’s risk category.

A Code Repository

The source code and related materials for this project are publicly available on GitHub. The repository includes the Jupyter Notebook for model development, the Streamlit application code, and the AI service module.

You can access the repository at: `https://github.com/Farid-Karimi/Equa`

B Application UI

Figure 4 shows screenshots of the deployed *Equa* application, illustrating the data input sidebar, the risk analysis dashboard, and the interactive AI coaching chat.

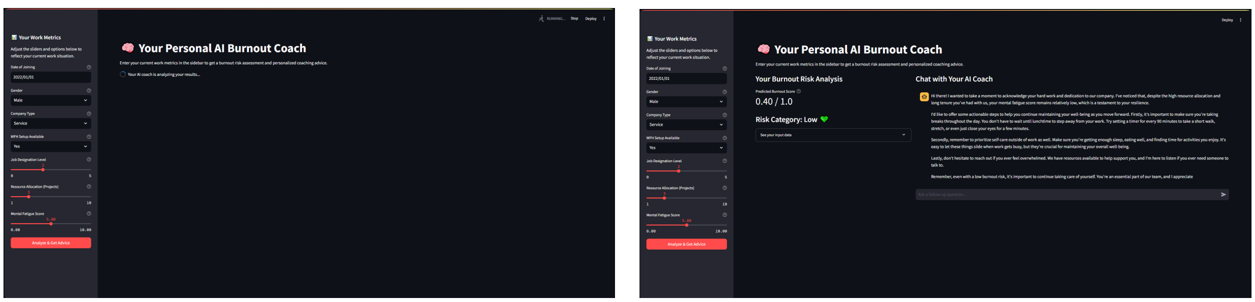

Figure 4: Screenshots of the AI Wellness Coach application user interface.

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