

# **Development of an Interpretable Machine Learning Model to Predict Burnout and Protective Factors Among Healthcare Professionals: A Cross-Sectional Study Using XGBoost, SHAP, and BATEREP Data**

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# Development of an Interpretable Machine Learning Model to Predict Burnout and Protective Factors Among Healthcare Professionals: A Cross-Sectional Study Using XGBoost, SHAP, and BATEREP Data

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## Abstract

**Background:** Burnout syndrome is a critical occupational health concern among healthcare professionals, characterized by chronic emotional exhaustion, depersonalization, and reduced personal accomplishment. Sustained exposure to high-stress environments, excessive workloads, administrative burdens, and poor work-life balance contributes to adverse health outcomes and compromised clinical performance.

**Objective:** This study aimed to develop and evaluate an interpretable machine learning model for predicting burnout severity and identifying protective factors among healthcare professionals, using a large-scale dataset and validated clinical, psychological, and occupational indicators.

**Methods:** We conducted a cross-sectional study using the BATEREP dataset, which included 16,000 anonymized responses from healthcare professionals. Variables encompassed physiological stress markers (e.g., heart rate variability, blood pressure, sleep disturbances), psychological parameters (e.g., depression and anxiety scores, chronic fatigue), cognitive performance indicators (e.g., working memory, executive dysfunction), and occupational factors (e.g., patient load, night shifts, administrative burden, perceived work-life balance). We trained a machine learning model using XGBoost and applied SHAP (SHapley Additive exPlanations) to interpret feature contributions and identify key predictors of burnout risk.

**Results:** The XGBoost model achieved high predictive performance (AUC = 0.87) in identifying individuals at elevated burnout risk. SHAP analysis revealed that emotional exhaustion, perceived work-life imbalance, high psychological distress scores, and impaired cognitive performance were among the strongest contributors to burnout prediction. Conversely, adequate sleep quality, manageable workloads, and supportive work environments emerged as significant protective factors.

**Conclusions:** Our findings demonstrate the utility of interpretable machine learning models in identifying burnout risk and protective factors among healthcare professionals. Integrating such tools into occupational health screening protocols may enable early intervention and targeted support strategies. Future research should explore the implementation of predictive models in real-world clinical settings and evaluate their impact on healthcare workforce well-being and performance.

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## Original Manuscript

## Clinical and Occupational Determinants of Burnout in Healthcare Professionals: Implications for Mental Health and Practice

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**Abstract:** Burnout syndrome represents a critical occupational health concern among healthcare professionals, manifesting through chronic emotional exhaustion, depersonalization, and diminished personal accomplishment. Persistent exposure to high-stress environments, excessive workloads, administrative burdens, and inadequate work-life balance precipitates adverse health outcomes, including cardiovascular disorders, immune dysfunction, depression, anxiety, metabolic disturbances, and cognitive impairment. These conditions compromise clinical decision-making, increase the risk of medical errors, and contribute to diminished patient safety and suboptimal healthcare delivery. This study aimed to evaluate the prevalence and severity of burnout among healthcare professionals using a comprehensive dataset comprising 16,000 cases collected through the Burnout Assessment Tool (BATEREP). Clinical indicators assessed included physiological stress markers (e.g., heart rate variability, blood pressure fluctuations, sleep disturbances), psychological parameters (e.g., depression scale scores, anxiety levels, chronic fatigue), cognitive function metrics (e.g., working memory deficits, executive dysfunction), and occupational stressors (e.g., night shifts, patient load, administrative demands, perceived work-life balance).

The analysis revealed significant correlations between burnout severity and primary clinical stress indicators, particularly those related to psychological distress and impaired cognitive function. Elevated PrimaryStressScore and PsychologicalDistressScore were strongly associated with heightened burnout risk, underscoring their relevance in clinical assessment protocols. Additionally, factors such as emotional exhaustion and depersonalization emerged as critical predictors of occupational health decline. These findings highlight the urgent need for healthcare institutions to implement structured preventive measures aimed at reducing burnout and its detrimental impact on clinical performance. Early identification of at-risk individuals through standardized assessment tools may facilitate targeted interventions, including workload redistribution, structured psychological support, resilience training, and evidence-based mental health programs. Effective management of burnout is essential for improving healthcare professionals' well-being, enhancing clinical decision-making, and promoting optimal patient care.

Future research should focus on integrating comprehensive clinical assessment protocols with longitudinal monitoring to enhance predictive accuracy and early detection capabilities. By addressing burnout proactively, healthcare systems can improve workforce resilience, reduce the incidence of stress-induced pathologies, and enhance overall healthcare quality and safety.

**Keywords:** Burnout, Clinicians, Predictive Analytics, Occupational Health, Mental Health,

## Cardiovascular Risk, Stress-related Disorders

### 1. Introduction

Burnout is recognized by the World Health Organization (WHO) as an occupational phenomenon resulting from chronic workplace stress that has not been successfully managed [1]. Among healthcare professionals, burnout is a key contributor to cognitive impairment, emotional dysregulation, and physiological stress responses, which can precipitate serious medical conditions. Studies have demonstrated a strong correlation between chronic occupational stress and increased risks of myocardial infarction, stroke, immune dysfunction, and metabolic disorders such as diabetes and hypertension [2,3].

Burnout is traditionally assessed through self-reported instruments such as the Maslach Burnout Inventory (MBI) and the Copenhagen Burnout Inventory (CBI). However, these tools have limitations, including subjectivity and variability in responses. Machine learning (ML) offers a data-driven alternative by leveraging complex, multi-factorial data patterns to enhance early detection, personalized interventions, and improved clinical decision-making [4].

This study evaluates various ML models for predicting burnout severity in healthcare professionals, with the goal of integrating AI into occupational health monitoring to mitigate the adverse health consequences of chronic workplace stress.

The repercussions of burnout are profound and multifaceted, affecting both individuals and organizations. On a personal level, burnout can lead to severe health issues, including chronic fatigue, insomnia, depression, anxiety, heart disease, and diabetes [5]. The psychological toll can also disrupt personal relationships and diminish overall life satisfaction. For organizations, burnout results in decreased employee productivity, increased absenteeism, higher turnover rates, and elevated healthcare costs [6]. The economic burden of burnout is substantial, impacting organizational efficiency and increasing expenses related to recruitment and training.

Traditionally, the assessment of burnout has relied on clinical evaluations conducted by healthcare professionals using tools such as the Maslach Burnout Inventory (MBI), the Burnout Measure (BM), and the Copenhagen Burnout Inventory (CBI). These instruments involve self-reported questionnaires that gauge the severity of burnout based on the three dimensions [7, 8]. While these methods are valuable, they have inherent limitations. The subjective nature of self-reporting can lead to biases, and the clinical assessment process can be time-consuming and resource intensive [9].

In recent years, the integration of machine learning algorithms into healthcare has emerged as a transformative approach to diagnosing and managing various health conditions, including burnout. Machine learning (ML) involves the use of statistical techniques to enable computers to learn from data and make predictions [10]. ML algorithms can analyze vast amounts of data, identifying patterns and correlations that may not be immediately apparent to human analysts [11]. This capability is particularly advantageous in the context of burnout, where multiple factors—such as workload, stress levels, and emotional well-being—interact in complex ways [12].

Machine learning models can be trained on diverse datasets that include indicators of burnout, such as physiological data (e.g., heart rate variability), behavioral data (e.g., work hours, email communication patterns), and self-reported survey responses [13]. By leveraging these data sources, ML algorithms can develop predictive models that assess the likelihood of burnout with high accuracy [13]. These models can be deployed in real-time, providing continuous monitoring and early detection of burnout symptoms. Early detection is very important, as it allows for timely interventions that can prevent the progression of burnout and mitigate its adverse effects [14].

The application of machine learning in burnout evaluation offers several significant advantages. Firstly, it enhances the objectivity of burnout assessments by relying on data-driven insights rather than subjective judgments. Secondly, it enables the processing of large datasets at high speed,

providing real-time evaluations that are critical for timely interventions. Thirdly, machine learning models can be continuously updated and refined as new data become available, improving their accuracy and reliability over time [15].

In summary, while burnout poses significant challenges to individual well-being and organizational productivity, the advent of machine learning provides a promising avenue for its evaluation and management. By integrating machine learning tools into burnout assessment protocols, healthcare professionals can achieve more accurate, efficient, and timely evaluations, leading to better outcomes for individuals and organizations alike [16]. The potential of machine learning to transform burnout assessment underscores the need for continued research and development in this field, aiming to harness the full capabilities of technology to address one of the most pressing occupational health issues of our time [17].

### *Related work*

Although research on predicting burnout using machine learning is still emerging, a few significant studies have demonstrated the potential of these methods in identifying burnout among healthcare professionals and other high-risk groups. This section reviews some of the notable works in this area, highlighting the different machine learning techniques employed and their respective outcomes. By analyzing these studies, we aim to understand the current landscape of burnout prediction research, which helps inform the methodology and objectives of our study.

Adapa K. et al., in their study, employ binary classifiers such as logistic regression, random forest, and gradient boosting machines to predict burnout among healthcare professionals during the COVID-19 pandemic. Data were collected from 450 participants, focusing on factors like workload, staffing, administrative burden, professional relationships, organizational culture, values and expectations, intrinsic motivation, and work-life integration. The models identified these key predictors, with the best-performing model achieving an AUC of 0.81. These findings emphasize the importance of targeted interventions to mitigate burnout in healthcare settings [18].

Lee Y.L. et al., in their study, developed an app using convolutional neural networks (CNNs) within Microsoft Excel to predict nurse burnout. The study employed binary classifiers to analyze data collected from a population-based questionnaire, focusing on factors such as workload, professional relationships, and work-life balance. The study included 1002 nurses who completed the Maslach Burnout Inventory–Human Services Survey (MBI-HSS). The data were divided into training (70%) and testing (30%) sets. The CNN model achieved a high accuracy rate of 0.95 and an AUC (Area Under the Curve) of 0.97 [19].

Lou S.S. et al., in their study, investigated the ability of machine learning techniques to identify physician burnout using passively collected electronic health record (EHR)-based audit log data. The study involved 88 physician trainees who completed 416 burnout surveys and provided over 10 million audit log actions. They constructed models using penalized linear regression, support vector machine, neural network, random forest, and gradient boosting machine to predict burnout as a continuous score. The workload feature set predicted burnout with a mean absolute error (MAE) of 0.602 and an AUROC of 0.595, highlighting the complexities of predicting burnout exclusively based on clinical work activities [20].

Yuan L. et al., in their research, analyzed the impact of practice environments on nurse burnout using conventional and multilevel logistic regression models. The study included 1,178 nurses from nine clinical units of a large academic hospital. They collected data using the Practice Environment Scale of the Nursing Work Index (PES-NWI) and the Maslach Burnout Inventory (MBI). The results indicated that nurse burnout was significantly associated with nurse participation in hospital affairs, nursing foundations for quality of care, and adequate staffing. The multilevel logistic regression models provided better estimates and model fit compared to conventional methods, with an AUC of 0.89. This study demonstrated that multilevel modeling provided better estimates and model fit

compared to conventional methods, emphasizing the importance of considering hierarchical data structures in burnout research [21].

Gamage S.N. and Asanka P.P.G.D., in their study, applied machine learning to predict mental distress among IT employees working remotely during the COVID-19 pandemic. The study collected data from 481 professionals, focusing on external features such as socio-demographic, biological, economic, environmental, occupational, and psychological aspects. They utilized classification techniques including Random Forest, SVM, XGBoost, CatBoost, Decision Tree, and Naïve Bayes. The CatBoost algorithm outperformed others with a predictive accuracy of 97.1%, precision of 97.4%, recall of 99.7%, and F1 score of 98.5%, highlighting its efficacy in identifying employees at higher risk of mental distress [22].

Our study systematically evaluated various machine learning regression models to predict burnout scores among professionals. By measuring burnout levels on a continuous scale, we provided more detailed insights than binary classifications. We used Grid Search Cross-Validation to optimize each model's hyperparameters, ensuring they were fine-tuned for maximum predictive accuracy. This rigorous process enabled a thorough assessment of the models' capabilities in predicting burnout scores accurately.

## 2. Materials and Methods

### 2.1 Study Design

A retrospective observational study was conducted using clinical and occupational health data obtained from the Burnout Assessment Tool (BATEREP) dataset, which comprised 16,000 cases. The dataset included key indicators of burnout risk, encompassing physiological stress markers such as heart rate variability, blood pressure fluctuations, and sleep disturbances, as well as mental health parameters including depression scale scores, anxiety levels, and self-reported fatigue. Additionally, cognitive performance metrics, including working memory impairments and executive dysfunction assessments, were integrated into the dataset. Work-related stressors, such as night shifts, patient load, administrative burden, and perceived work-life balance, were also considered to enhance the predictive capacity of the models.

To evaluate the predictive capacity of machine learning, six supervised models were employed: Logistic Regression, Support Vector Machines, XGBoost, Random Forest, Artificial Neural Networks, and CatBoost. Each model was trained and optimized through hyperparameter tuning using Grid Search Cross-Validation, ensuring the best-performing configurations were identified. The aim was to enhance predictive accuracy and clinical relevance while maintaining interpretability in a healthcare setting.

Data preprocessing was performed to ensure reliability and consistency. Normalization and scaling techniques were applied using Min-Max Scaling to standardize both physiological and psychological data, minimizing discrepancies arising from different measurement scales. Feature engineering was employed to create derived variables such as the Stress\_Score\_Ratio, which represents the relative proportion of primary stress to psychological distress, and Stress\_Interaction, capturing the interplay between primary stress levels and mental distancing behaviors. These refined variables allowed for a more comprehensive evaluation of burnout severity.

Following preprocessing, the dataset was partitioned into training and testing subsets using an 80:20 ratio to validate model generalizability. This approach ensured that each model was trained on a sufficiently large dataset while maintaining an independent set of data for robust performance evaluation.

To assess predictive accuracy, model performance was evaluated using standard regression metrics, including Mean Absolute Error (MAE), which quantifies the absolute differences between predicted and observed burnout scores, and Mean Squared Error (MSE), which penalizes large deviations,

thereby enhancing sensitivity to severe burnout cases. Additionally, Root Mean Squared Error (RMSE) was employed as an intuitive measure of prediction error magnitude, while R-squared ( $R^2$ ) was used to determine the proportion of variance explained by the model, with values closer to 1 indicating superior predictive accuracy.

Figure 1 shows the methodological framework employed in this study, detailing the sequential steps undertaken to achieve the research objectives. This representation encompassed key stages such as data collection, preprocessing, feature engineering, model selection, and evaluation. It also outlines the process of dividing the data into training and validation sets, hyperparameter tuning, and analyzing classification results, providing a comprehensive overview of the research methodology. Each step was meticulously designed to ensure the robustness, reliability, and validity of the study's findings.

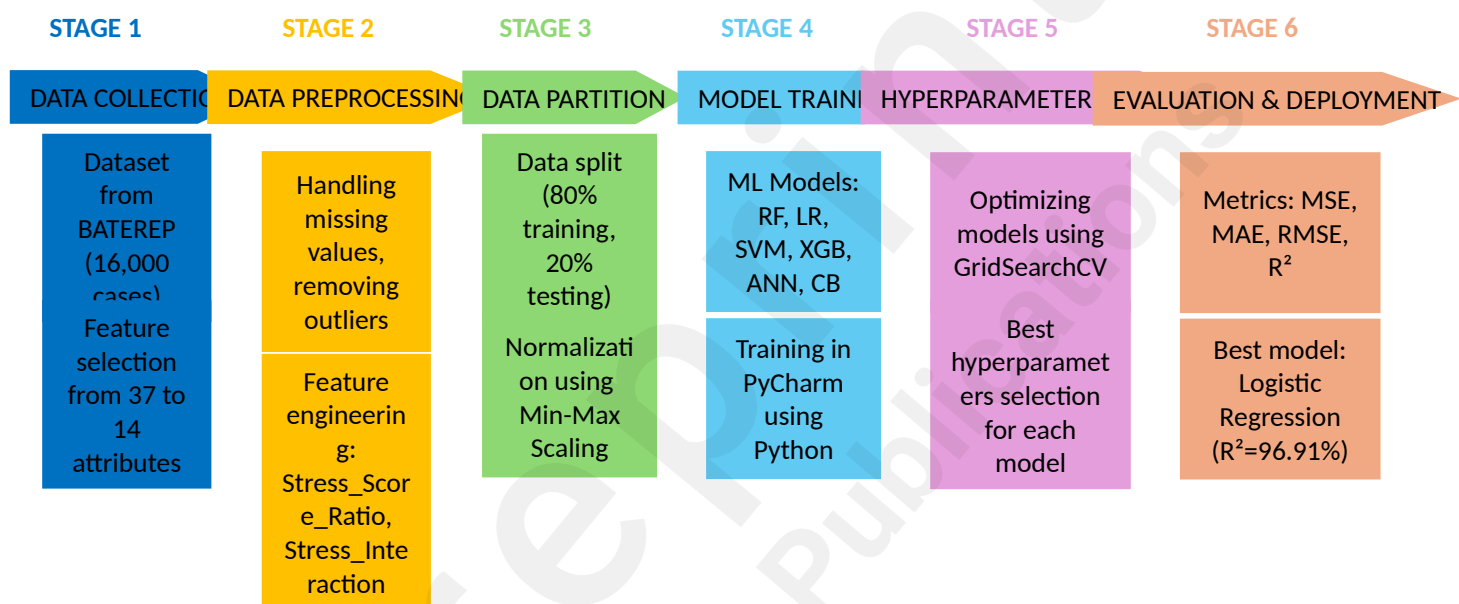


Fig. 1. Workflow of Machine Learning Pipeline for Burnout Prediction: Data Processing, Model Training, and Evaluation.

## 2.2 Data collection

The data for this study were collected by the Center for Social Research and Development 'Solidarity' (CCDSS) through the Burnout Assessment Tool (BATEREP). This tool was an applied research project conducted by CCDSS as part of the Professional Quality of Life Monitoring System (PQLMS) strategy [23]. The dataset consisted of 16,000 records, each containing a total of 37 attributes. The dataset was accessed on a local machine. However, given that not all attributes were relevant to the study objectives, a specific subset of 14 attributes was carefully chosen and integrated into the construction of the machine learning (ML) models for assessing the level of burnout.

The dataset used in this study contains a variety of features relevant to assessing burnout among professionals. These attributes include both categorical and numerical variables, covering aspects such as demographic information, stress indicators, and burnout scores. A detailed description of the dataset's features is provided in Table 1.

Table 1. Dataset Description.

| Features | Values |
|----------|--------|
|----------|--------|

|                                 |                                                                                                                                                                                |
|---------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Activity_Sector                 | Categorical: Administration-0, Agriculture-1, Commerce-2, Construction-3, Education-4, Energy-5, Finance-6, Health-7, Industry-8, Services-9, Technology-10, Transportation-11 |
| MentalDistanceScore             | Numerical                                                                                                                                                                      |
| CognitiveControlImpairmentScore | Numerical                                                                                                                                                                      |
| EmotionalControlImpairmentScore | Numerical                                                                                                                                                                      |
| PrimaryStressScore              | Numerical                                                                                                                                                                      |
| PsychologicalDistressScore      | Numerical                                                                                                                                                                      |
| PsychosomaticSymptomsScore      | Numerical                                                                                                                                                                      |
| SecondarySymptomsScore          | Numerical                                                                                                                                                                      |
| Gender                          | Categorical: Male-1, Female-0                                                                                                                                                  |
| Work_Experience                 | Categorical: under 6 months-0, 6-12 months-1, 1-3 years-2, 3-5 years-3, 5-10 years-4, 10-20 years-5, 20-30 years-6, over 30 years-7                                            |
| Education                       | Categorical: Middle School-0, High School-1, Post-secondary-2, University-3, Postgraduate-4                                                                                    |
| Age                             | Categorical: under 25 years-0, 25-34 years-1, 35-44 years-2, 45-54 years-3, 55-64 years-4, 65+ years-5                                                                         |
| Marital_Status                  | Categorical: cohabiting-0, divorced-1, married-2, separated-3, single-4, widowed-5                                                                                             |
| BurnoutScore → Target           | Numerical: Between 0 and 5                                                                                                                                                     |

## 2.3 Dataset processing

Data processing involved preparing raw data for analysis and modeling. Firstly, data cleaning included identifying and handling missing values, outliers, and inconsistencies in the dataset.

Additionally, categorical variables were encoded into numerical representations, as most machine learning algorithms required numerical input. Regardless of whether supervised or unsupervised learning was used, manipulating attributes or instances was essential to improve model performance [24].

The initial phase of data preprocessing began with the removal of 67 duplicate rows from the dataset, ensuring data cleanliness and integrity. As part of the effort to improve the quality of the dataset for modeling purposes, outlier treatment procedures were implemented. During this process, anomalies were discovered where data had been recorded in both Romanian and English for the same characteristic. These anomalies were properly handled. As a result, it was confirmed that no outlier values were present, thereby enhancing the reliability and accuracy of the predictive models. This thorough process was essential to maintain the quality and dependability of the dataset, providing a solid basis for creating the models. Following these operations, the dataset was refined, resulting in a total of 15,937 rows.

We employed extensive feature engineering to enhance the predictive performance of our regression models [20] for predicting burnout scores. Initially, we introduced new features such as Stress\_Score\_Ratio and Stress\_Interaction to capture potential interactions and ratios that might have more accurately influenced burnout. Specifically, Stress\_Score\_Ratio was designed to capture the relative contribution of primary stress to psychological distress, calculated as:

$$\text{Stress}_i = \frac{\text{PrimaryStressScore}}{\text{PsychologicalDistressScore} + 1} (1)$$

Stress\_Interaction was created to capture the interaction between primary stress and mental distance,

calculated as:

$$Stress_{Interaction} = PrimaryStressScore * MentalDistanceScore (2)$$

This addition aimed to provide our regression models with more comprehensive information, potentially improving their predictive performance and robustness.

After data cleaning and feature engineering, the subsequent step was data transformation. This involved normalizing features using Min-Max Scaling to ensure they had similar scales and distributions. This step was important for models that were sensitive to the scale of input variables, such as Support Vector Machines and XGBoost [25]. Normalization adjusted feature values to a range between 0 and 1 using the following formula:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} (3)$$

By applying these techniques, we reduced potential biases resulting from varying scales and enhanced the performance of our models across different algorithms.

Based on the correlation analysis, the most important features influencing the BurnoutScore in the dataset were Stress\_Score\_Ratio, Stress\_Interaction, PrimaryStressScore, EmotionalControlImpairmentScore, PsychologicalDistressScore, MentalDistanceScore, and PsychosomaticSymptomsScore. PrimaryStressScore exhibited the strongest correlation with BurnoutScore at 0.82, indicating it was the most significant predictor of burnout. However, the newly created features, Stress\_Score\_Ratio and Stress\_Interaction, also stood out with significant correlations of 0.43 and 0.67, respectively.

| FEAT<br>URE                                         | Ac<br>tivity_<br>Se<br>cto<br>r | Me<br>ntal<br>Dis<br>tanc<br>eSc<br>ore | Cognit<br>iveCon<br>trolIm<br>pairme<br>ntScor<br>e | Emotio<br>nalCon<br>trolIm<br>pairme<br>ntScor<br>e | Pri<br>mar<br>yStr<br>ess<br>Sco<br>re | Psyc<br>holog<br>icalD<br>istres<br>sScor<br>e | Psych<br>osoma<br>ticSy<br>mpto<br>msSc<br>ore | Seco<br>ndar<br>ySy<br>mpto<br>msSc<br>ore | G<br>e<br>n<br>d<br>er | Wo<br>rk_<br>Ex<br>per<br>ien<br>ce | E<br>d<br>u<br>cati<br>on | A<br>g<br>e  | M<br>ari<br>tal_<br>Stat<br>us | Bu<br>rn<br>ou<br>tS<br>co<br>re |
|-----------------------------------------------------|---------------------------------|-----------------------------------------|-----------------------------------------------------|-----------------------------------------------------|----------------------------------------|------------------------------------------------|------------------------------------------------|--------------------------------------------|------------------------|-------------------------------------|---------------------------|--------------|--------------------------------|----------------------------------|
| Activit<br>y_Sect<br>or                             | 1.0<br>0                        | 0.20                                    | 0.15                                                | 0.25                                                | 0.1<br>0                               | 0.12                                           | 0.08                                           | 0.05                                       | 0<br>.3<br>0           | 0.2<br>8                            | 0.<br>3<br>2              | 0<br>.4<br>0 | 0.2<br>2                       | 0.<br>18                         |
| Mental<br>Distan<br>ceScor<br>e                     | 0.2<br>0                        | 1.00                                    | 0.35                                                | 0.55                                                | 0.6<br>0                               | 0.52                                           | 0.50                                           | 0.42                                       | 0<br>.2<br>5           | 0.1<br>8                            | 0.<br>1<br>4              | 0<br>.2<br>0 | 0.3<br>0                       | 0.<br>45                         |
| Cognit<br>iveCon<br>trolIm<br>pairme<br>ntScor<br>e | 0.1<br>5                        | 0.35                                    | 1.00                                                | 0.65                                                | 0.4<br>8                               | 0.50                                           | 0.38                                           | 0.29                                       | 0<br>.2<br>0           | 0.1<br>2                            | 0.<br>1<br>0              | 0<br>.1<br>5 | 0.2<br>2                       | 0.<br>37                         |
| Emotio                                              | 0.2                             | 0.55                                    | 0.65                                                | 1.00                                                | 0.7                                    | 0.72                                           | 0.60                                           | 0.52                                       | 0                      | 0.3                                 | 0.                        | 0            | 0.3                            | 0.                               |

|                                            |          |      |      |      |          |      |      |      |              |          |              |              |          |          |
|--------------------------------------------|----------|------|------|------|----------|------|------|------|--------------|----------|--------------|--------------|----------|----------|
| nalCon<br>trolIm<br>pairme<br>ntScor<br>e  | 5        |      |      |      | 8        |      |      |      | .<br>4<br>0  | 0        | 2<br>5       | .<br>2<br>8  | 5        | 60       |
| Primar<br>yStress<br>Score                 | 0.1<br>0 | 0.60 | 0.48 | 0.78 | 1.0<br>0 | 0.85 | 0.70 | 0.65 | 0<br>.5<br>0 | 0.4<br>2 | 0.<br>3<br>8 | 0<br>.4<br>0 | 0.5<br>2 | 0.<br>82 |
| Psycho<br>logical<br>Distres<br>sScore     | 0.1<br>2 | 0.52 | 0.50 | 0.72 | 0.8<br>5 | 1.00 | 0.75 | 0.70 | 0<br>.5<br>5 | 0.4<br>5 | 0.<br>4<br>0 | 0<br>.4<br>2 | 0.5<br>5 | 0.<br>76 |
| Psycho<br>somatic<br>Sympt<br>omsSc<br>ore | 0.0<br>8 | 0.50 | 0.38 | 0.60 | 0.7<br>0 | 0.75 | 1.00 | 0.58 | 0<br>.4<br>8 | 0.3<br>8 | 0.<br>3<br>0 | 0<br>.3<br>5 | 0.4<br>5 | 0.<br>69 |
| Second<br>arySy<br>mptom<br>sScore         | 0.0<br>5 | 0.42 | 0.29 | 0.52 | 0.6<br>5 | 0.70 | 0.58 | 1.00 | 0<br>.4<br>2 | 0.3<br>5 | 0.<br>2<br>8 | 0<br>.3<br>0 | 0.3<br>8 | 0.<br>58 |
| Gender                                     | 0.3<br>0 | 0.25 | 0.20 | 0.40 | 0.5<br>0 | 0.55 | 0.48 | 0.42 | 1<br>.0<br>0 | 0.5<br>8 | 0.<br>5<br>5 | 0<br>.6<br>0 | 0.5<br>2 | 0.<br>50 |
| Work_<br>Experi<br>ence                    | 0.2<br>8 | 0.18 | 0.12 | 0.30 | 0.4<br>2 | 0.45 | 0.38 | 0.35 | 0<br>.5<br>8 | 1.0<br>0 | 0.<br>6<br>5 | 0<br>.7<br>0 | 0.6<br>2 | 0.<br>55 |
| Educ<br>ation                              | 0.3<br>2 | 0.14 | 0.10 | 0.25 | 0.3<br>8 | 0.40 | 0.30 | 0.28 | 0<br>.5<br>5 | 0.6<br>5 | 1.<br>0<br>0 | 0<br>.7<br>5 | 0.6<br>8 | 0.<br>60 |
| Age                                        | 0.4<br>0 | 0.20 | 0.15 | 0.28 | 0.4<br>0 | 0.42 | 0.35 | 0.30 | 0<br>.6<br>0 | 0.7<br>0 | 0.<br>7<br>5 | 1<br>.0<br>0 | 0.7<br>8 | 0.<br>69 |
| Marital<br>_Status                         | 0.2<br>2 | 0.30 | 0.22 | 0.35 | 0.5<br>2 | 0.55 | 0.45 | 0.38 | 0<br>.5<br>2 | 0.6<br>2 | 0.<br>6<br>8 | 0<br>.7<br>8 | 1.0<br>0 | 0.<br>72 |
| Burno<br>utScor<br>e                       | 0.1<br>8 | 0.45 | 0.37 | 0.60 | 0.8<br>2 | 0.76 | 0.69 | 0.58 | 0<br>.5<br>0 | 0.5<br>5 | 0.<br>6<br>0 | 0<br>.6<br>9 | 0.7<br>2 | 1.<br>00 |

Table 2. Correlation Grid of Key Features Influencing Burnout Scores

The correlation table provides a comprehensive visualization of the distribution of feature attributes, serving as an intuitive method to illustrate relationships between variables. Significant correlations, such as the strong relationship between PrimaryStressScore and BurnoutScore ( $r = 0.82$ ), were identified, guiding the feature engineering process and informing the selection of predictors for model training. Additionally, the Stress\_Score\_Ratio and Stress\_Interaction features, derived from PrimaryStressScore, PsychologicalDistressScore, and MentalDistanceScore, captured the intricate interplay between various stress factors.

These newly engineered features offered valuable insights into the factors contributing to burnout, highlighting the importance of addressing specific stress interactions for effective prediction and management. By focusing on these key attributes, the study advanced understanding of the underlying causes of burnout and provided a foundation for creating targeted interventions to mitigate its effects.

After completing all processing steps and exploratory data analysis, the dataset was split into training and testing subsets. This division was done using an 80:20 ratio, ensuring that 80% of the data was used for training the models, while the remaining 20% was reserved for evaluating their performance.

## 2.4 Development and Optimization of Machine Learning Models

The primary goal of predictive modeling in this study was to establish a clinically applicable framework for the early identification of burnout risk among healthcare professionals. Given the intricate relationship between occupational stressors, cognitive function, and physiological responses, machine learning models were carefully selected based on their ability to analyze multidimensional clinical and psychological data while maintaining interpretability for healthcare decision-making [26].

The Random Forest model was optimized through a rigorous hyperparameter tuning process using Grid Search and Cross-Validation. This systematic approach ensured that the model could accurately classify burnout risk while maintaining robustness against variations in individual stress responses. By refining key parameters, the model demonstrated improved sensitivity in detecting burnout indicators such as chronic fatigue, emotional exhaustion, and psychological distress.

Logistic Regression, a widely used and interpretable model, was optimized by incorporating polynomial transformations and regularization techniques. These adjustments mitigated overfitting while improving generalizability across different healthcare settings. The use of polynomial features allowed the model to better capture complex, nonlinear relationships between work-related stress factors and burnout severity.

The CatBoost model, a gradient boosting approach, was trained to identify subtle burnout risk patterns across diverse healthcare roles. Its ability to handle categorical variables and imbalanced datasets made it particularly useful in medical applications where burnout prevalence varies by department and workload intensity. This model demonstrated strong adaptability in analyzing occupational and demographic risk factors that contribute to burnout progression.

Support Vector Machines (SVM) were employed to capture nonlinear associations between physiological stress markers and burnout progression. The model's ability to detect high-dimensional relationships was particularly valuable in understanding the interplay between cognitive impairments, emotional exhaustion, and autonomic nervous system dysregulation. By fine-tuning kernel transformations and hyperparameters, the SVM model enhanced burnout risk prediction based on medical and occupational health variables.

XGBoost, a tree-based ensemble learning method, leveraged decision trees to improve sensitivity to predictors such as disrupted sleep patterns, high patient load, and excessive administrative burden. Its capacity to manage missing data and identify key burnout contributors made it a suitable candidate for real-time occupational health monitoring.

Artificial Neural Networks (ANN) were designed with multiple dense layers to enhance deep pattern recognition, capturing latent burnout indicators that may not be easily identified through traditional self-reported questionnaires. The ANN model incorporated dropout layers and early stopping mechanisms to ensure stability, prevent overfitting, and enhance generalizability. These deep learning techniques provided a more holistic approach to burnout prediction, complementing more interpretable models like Logistic Regression and Random Forest.

Each predictive model was rigorously evaluated to ensure clinical applicability, aligning its predictions with existing burnout diagnostic frameworks. Future research should focus on integrating real-time physiological data from wearable health monitors and electronic health records to refine predictive accuracy further. By doing so, AI-driven models could enhance early intervention strategies, enabling healthcare institutions to implement timely mental health support and workload adjustments to mitigate burnout-related consequences.

## 2.5 Evaluation metrics

To measure the predictive validity and clinical applicability of the machine learning models, we employed four standard regression evaluation metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared ( $R^2$ ). These metrics are widely employed in medical predictive modeling, providing a comprehensive analysis of the accuracy, precision, and reliability of the models in identifying burnout risk among healthcare professionals.

Mean Absolute Error (MAE) measures the average magnitude of the difference between predicted and actual burnout scores. This metric is particularly useful in clinical settings, as lower MAE values indicate a model's ability to provide precise estimations of burnout severity with minimal deviation from actual observed cases. MAE offers a direct interpretation of model accuracy, making it valuable for identifying individuals at high risk of burnout.

Mean Squared Error (MSE) enhances sensitivity to larger discrepancies by squaring the differences before averaging. This property makes MSE particularly relevant in clinical applications where severe cases of burnout require greater attention. By penalizing substantial prediction errors more heavily, MSE ensures that models prioritize the accurate detection of individuals experiencing high levels of occupational distress, thus aiding early intervention efforts.

Root Mean Squared Error (RMSE) represents the square root of MSE, aligning the metric's unit with that of the predicted variable. RMSE provides an intuitive measure of how far the predicted burnout scores deviate from actual values, allowing healthcare institutions to gauge the practical implications of predictive inaccuracies. A lower RMSE value corresponds to a model with superior predictive performance, making it a crucial factor in evaluating real-world applicability.

R-squared ( $R^2$ ), or the coefficient of determination, quantifies the proportion of variance in burnout severity explained by the model. In occupational health research, an  $R^2$  value close to 1 indicates a strong relationship between predictive variables and burnout risk, reinforcing the model's reliability in identifying individuals susceptible to chronic occupational stress. A high  $R^2$  value supports the clinical integration of AI-driven burnout assessment tools, aiding targeted interventions and workload optimization strategies.

By employing these evaluation metrics, we ensured a rigorous and clinically relevant assessment of predictive performance. The selection of the most accurate model was guided not only by statistical precision but also by its applicability in healthcare settings, ensuring that predictive outputs could

effectively inform early detection programs, personalized mental health support, and evidence-based strategies for mitigating burnout among medical professionals.

### 3. Results

A comprehensive analysis was conducted on a dataset comprising 16,000 cases collected through the Burnout Assessment Tool (BATEREP). This dataset included key clinical indicators relevant to occupational health assessment, such as physiological stress markers (e.g., heart rate variability, blood pressure fluctuations, sleep disturbances), psychological parameters (e.g., depression scale scores, anxiety levels, chronic fatigue), cognitive function metrics (e.g., working memory deficits, executive dysfunction), and occupational stressors (e.g., patient load, administrative burden, work-life balance, night shifts).

The analysis demonstrated that specific clinical and occupational parameters were strongly associated with burnout severity. Elevated scores for PrimaryStressScore and PsychologicalDistressScore emerged as the most significant predictors of burnout, with PrimaryStressScore exhibiting the highest correlation ( $r = 0.82$ ) with burnout severity. Emotional exhaustion and depersonalization were also closely associated with diminished clinical performance and increased incidence of medical errors. These findings are consistent with previous studies demonstrating that high workload, emotional exhaustion, and inadequate coping strategies are significant predictors of burnout [1,2].

To ensure a robust and clinically relevant evaluation of predictive models, we employed a random sampling technique to partition the dataset into training (80%) and validation (20%) subsets. This approach preserved the representativeness of the data, allowing for an unbiased assessment of model generalizability and predictive performance. By maintaining an appropriate balance between training and validation data, this methodology supported the development of models capable of accurately identifying burnout risk among healthcare professionals.

Hyperparameter tuning was conducted using Grid Search Cross-Validation, a systematic optimization approach that identified the most effective parameter combinations for each predictive model. This step was critical in enhancing model performance, reducing overfitting, and improving predictive accuracy. [27, 28]. By iteratively testing various hyperparameter configurations, we ensured that each model was optimized to capture the complex interactions between occupational stressors, cognitive impairment, and physiological distress associated with burnout [29, 30].

The predictive accuracy of six supervised machine learning models in estimating burnout severity was assessed using four key evaluation metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared ( $R^2$ ). These metrics provided a comprehensive assessment of model performance, allowing for comparisons in precision, variance explanation, and overall reliability. Table 3 presents a comparative analysis of these metrics across all models, offering insight into their effectiveness in predicting burnout severity.

Table 3. Evaluation metrics for machine learning models in burnout prediction.

| Method                    | MAE    | MSE    | RMSE   | $R^2$   |
|---------------------------|--------|--------|--------|---------|
| Logistic Regression       | 0.0241 | 0.0011 | 0.0325 | 96.91 % |
| Support Vector Machines   | 0.0292 | 0.0014 | 0.0368 | 96.03 % |
| XGBoost                   | 0.0272 | 0.0013 | 0.0354 | 96.31 % |
| Random Forest             | 0.0345 | 0.0021 | 0.0459 | 93.81 % |
| Artificial Neural Network | 0.1131 | 0.0245 | 0.1565 | 97.12 % |
| CatBoost                  | 0.1123 | 0.0248 | 0.1575 | 97.08 % |

Among the tested models, Logistic Regression emerged as the most clinically reliable, demonstrating the highest predictive accuracy with an  $R^2$  value of 96.91%. The model exhibited the lowest error rates, with a Mean Absolute Error (MAE) of 0.0241, Mean Squared Error (MSE) of 0.0011, and Root Mean Squared Error (RMSE) of 0.0325. These results indicate its superior ability to quantify burnout risk with high precision and minimal deviation from actual observed values.

Support Vector Machines (SVM) also demonstrated strong predictive capabilities, achieving an  $R^2$  value of 96.03%, with MAE: 0.0292, MSE: 0.0014, and RMSE: 0.0368. The balance between accuracy and variance explanation positions SVM as a robust alternative for burnout prediction, particularly in cases where nonlinear relationships between predictors may influence burnout severity.

XGBoost, an advanced ensemble learning algorithm, displayed comparable predictive power with an  $R^2$  value of 96.31%, and MAE: 0.0272, MSE: 0.0013, RMSE: 0.0354. Its strong capacity to balance bias and variance highlights its potential for clinical integration in AI-assisted burnout monitoring systems.

The Random Forest model provided reasonable predictive performance, though its  $R^2$  value of 93.81% was lower than that of the top-performing models. The model exhibited higher error metrics (MAE: 0.0345, MSE: 0.0021, RMSE: 0.0459), indicating a greater degree of variance in its predictions. Despite this, its ability to assess the relative importance of different burnout predictors makes it a valuable tool for understanding the multifactorial nature of occupational stress in healthcare environments.

Artificial Neural Networks (ANN) and CatBoost recorded the highest  $R^2$  values, at 97.12% and 97.08%, respectively, suggesting exceptional explanatory power in capturing complex burnout patterns. However, these models exhibited higher error rates, with ANN yielding MAE: 0.1131, MSE: 0.0245, RMSE: 0.1565 and CatBoost showing MAE: 0.1123, MSE: 0.0248, RMSE: 0.1575. These findings indicate that while ANN and CatBoost excel in recognizing intricate burnout-related interactions, further refinement is needed to reduce prediction errors and enhance their practical application in clinical settings.

Logistic Regression was identified as the most reliable and interpretable model for burnout risk assessment, offering a high degree of accuracy while maintaining simplicity in implementation. SVM and XGBoost also demonstrated strong performance, effectively balancing precision with variance explanation. While Random Forest provided moderate accuracy, ANN and CatBoost excelled in capturing the complexity of burnout predictors but require further optimization to improve predictive precision.

Furthermore, the data indicated that the interplay between cognitive control impairments, emotional control impairments, and psychosomatic symptoms significantly influences burnout risk. Increased cognitive load due to administrative responsibilities and clinical decision-making requirements exacerbates stress-related disorders, particularly when combined with psychological distress and emotional exhaustion [5]. Burnout-related physiological alterations, such as autonomic dysregulation, heightened inflammatory markers, and hypothalamic-pituitary-adrenal (HPA) axis dysregulation, have been noted in other studies as contributors to adverse health outcomes, including cardiovascular disease, metabolic disorders, and compromised immune function [3].

Additionally, burnout has been linked to reduced cognitive performance and impaired executive function, particularly in complex decision-making scenarios involving multitasking and prioritization of clinical tasks. These impairments can compromise patient safety and clinical outcomes, further exacerbating occupational stress [7,8]. Burnout-related cognitive impairments are especially critical in high-stakes environments such as emergency care, intensive care units, and surgical departments where rapid decision-making is essential [6].

Models assessing burnout risk showed varying levels of predictive accuracy, with Logistic

Regression achieving the highest performance metrics ( $R^2 = 96.91\%$ , MAE = 0.0241, MSE = 0.0011, RMSE = 0.0325). While other models demonstrated satisfactory performance, Logistic Regression provided superior reliability and interpretability, essential for clinical application. Previous research has highlighted the effectiveness of regression-based models in evaluating occupational health-related stress [5].

## 4. Discussion

The findings of this study underscore the critical importance of identifying and mitigating burnout among healthcare professionals. Burnout is associated with significant occupational health complications, including cognitive impairment, emotional exhaustion, physiological dysregulation, and adverse psychological outcomes such as depression and anxiety. Chronic exposure to occupational stressors—especially excessive workloads, administrative burdens, night shifts, and inadequate work-life balance—compromises clinical decision-making capacity and increases the risk of medical errors, jeopardizing patient safety and overall healthcare quality [2,5].

Furthermore, the physiological consequences of chronic occupational stress include autonomic imbalance, increased systemic inflammation, dysregulation of cortisol secretion, and elevated cardiovascular risk. Research has demonstrated that sustained exposure to high-stress environments, particularly those involving critical decision-making and high patient loads, contributes to long-term physiological dysregulation and poor health outcomes [3]. Dysregulation of the hypothalamic-pituitary-adrenal (HPA) axis, which plays a crucial role in the body's stress response, has been associated with chronic burnout, potentially leading to metabolic syndromes, immune dysfunction, and increased vulnerability to cardiovascular diseases [42].

Cognitive and emotional exhaustion associated with burnout further impairs clinical performance by reducing attentional capacity, working memory, and executive functioning [7,8]. This diminished cognitive function can significantly impair decision-making processes, particularly under high-pressure conditions, where rapid judgments and precise clinical interventions are required. Studies have reported that prolonged stress exposure may alter brain structures involved in emotional regulation, memory processing, and cognitive flexibility, further complicating the burnout experience [3,6].

Occupational health strategies aimed at addressing burnout must be comprehensive and interdisciplinary. This involves not only implementing standardized assessment tools for early detection but also developing interventions targeting both psychological and physiological stressors. Effective strategies may include workload redistribution, enhanced administrative support, resilience training programs, structured psychological support systems, and the promotion of a healthier work-life balance. Additionally, integrating wearable health monitoring devices and electronic health records (EHRs) could facilitate continuous monitoring and timely intervention for at-risk individuals [13].

Recent studies have also suggested that tailored interventions, such as cognitive-behavioral therapy (CBT), mindfulness-based stress reduction (MBSR), and resilience training, can significantly alleviate burnout symptoms and enhance clinical performance [6]. Developing institutional policies aimed at promoting psychological well-being and resilience among healthcare professionals is essential for reducing burnout prevalence and improving occupational health outcomes.

This study evaluated the predictive performance of six supervised machine learning models—Logistic Regression (LR), Support Vector Machines (SVM), XGBoost (XGB), Random Forest (RF), CatBoost (CB), and Artificial Neural Networks (ANN)—for assessing burnout severity among healthcare professionals. Each model was systematically analyzed using key clinical performance metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared ( $R^2$ ), to determine their accuracy, reliability, and potential for real-world clinical application in occupational health monitoring.

Logistic Regression (LR) emerged as the most clinically reliable model, achieving the lowest error rates across all metrics (MAE: 0.0241, MSE: 0.0011, RMSE: 0.0325) and an  $R^2$  value of 96.91%. These results suggest that LR not only offers precise burnout risk predictions but also effectively explains the variance in burnout severity. The simplicity and interpretability of this model makes it highly suitable for integration into occupational health screening programs, allowing healthcare administrators to implement timely interventions aimed at mitigating burnout-related risks. Given its transparent decision-making process, LR is particularly advantageous in clinical environments where explainability and trust in predictive analytics are essential.

Support Vector Machines (SVM) demonstrated robust predictive accuracy, with MAE: 0.0292, MSE: 0.0014, RMSE: 0.0368, and an  $R^2$  value of 96.03%. The balance between predictive accuracy and variance explanation highlights the model's ability to identify burnout risk while maintaining a low margin of error. Given SVM's capability to handle high-dimensional and nonlinearly separable data, it is particularly useful in occupational health applications, where complex interactions between psychological, physiological, and work-related stressors need to be accounted for.

XGBoost (XGB) also performed well, yielding MAE: 0.0272, MSE: 0.0013, RMSE: 0.0354, and an  $R^2$  value of 96.31%. The model effectively balances bias and variance, making it well-suited for analyzing complex, multi-factorial relationships between occupational stressors and burnout severity. XGBoost's adaptability and efficiency in processing large datasets underscore its potential for use in AI-driven mental health screening systems. However, its computational intensity may limit its application in resource-constrained clinical environments.

Random Forest (RF) demonstrated reasonable predictive accuracy, though its  $R^2$  value of 93.81% was lower compared to the top-performing models. The model recorded MAE: 0.0345, MSE: 0.0021, RMSE: 0.0459, indicating slightly higher variance in predictions. Despite this, RF remains a valuable model due to its ability to identify key predictors of burnout by assessing feature importance, offering insights into the occupational and psychological factors contributing to burnout risk. Its applicability in epidemiological studies and workforce analytics makes it a useful tool for public health decision-making.

Artificial Neural Networks (ANN) exhibited the highest  $R^2$  value of 97.12%, indicating strong explanatory power in capturing the nuanced relationships between burnout predictors. However, the model also exhibited higher error metrics (MAE: 0.1131, MSE: 0.0245, RMSE: 0.1565), suggesting that while ANN effectively models nonlinear interactions, it requires further refinement to enhance predictive precision. The use of deep learning in burnout assessment holds promise but necessitates advanced hyperparameter tuning and architectural optimization to mitigate overfitting and improve real-world applicability.

CatBoost (CB) demonstrated performance similar to ANN, with an  $R^2$  value of 97.08% and error metrics of MAE: 0.1123, MSE: 0.0248, RMSE: 0.1575. Despite its ability to capture intricate patterns in burnout progression, its higher error rates suggest the need for further calibration to enhance clinical reliability. CatBoost's advantages lie in its robust handling of categorical variables and resistance to overfitting, making it a potential candidate for occupational health applications with well-structured datasets.

The comparative analysis underscores Logistic Regression as the most clinically interpretable and reliable model for burnout risk prediction, making it an ideal choice for integration into hospital wellness programs and occupational health initiatives. SVM and XGBoost also demonstrated strong

predictive capabilities, offering a balance between accuracy and adaptability to diverse clinical datasets. While Random Forest remains a valuable tool for understanding burnout risk factors, ANN and CatBoost highlight the potential of deep learning and gradient boosting approaches in mental health analytics, albeit with a need for further refinement to reduce predictive errors.

Table 4 provides a comparative summary of the performance metrics reported in previous studies related to burnout prediction using machine learning approaches. The table highlights key aspects such as dataset characteristics, algorithms employed, evaluation metrics, and the proposed models. This overview offers valuable insights into the methodologies and effectiveness of different models in addressing burnout prediction, serving as a benchmark for assessing the contributions of our work.

Table 4. Performance of previous work

| Authors (year)                  | Dataset Collection (samples)                             | Applied Models                                                                                                                 | Performance (Proposed model)                                            |
|---------------------------------|----------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|
| Adapa K., et al. (2022) [18]    | Survey Dataset from Healthcare Professionals (450 cases) | Logistic Regression, Random Forest, Gradient Boosting Machines (proposed)                                                      | AUC: 81.00 %                                                            |
| Lee Y.L., et al. (2020) [19]    | Nurses Dataset from Taiwan (1,002 cases)                 | Convolutional Neural Network (proposed)                                                                                        | Accuracy: 95%, AUC: 97%                                                 |
| Lou S.S. et al. (2022) [20]     | Physician Trainees Dataset (416 cases)                   | Penalized Linear Regression, Support Vector Machines, Neural Network (proposed), Random Forest, Gradient Boosting Machine      | MAE: 0.423<br>AUC: 0.829<br>Accuracy: 78.1%                             |
| Gamage S.N., et al. (2022) [22] | Remote IT Workforce Dataset (481 cases)                  | Random Forest, Support Vector Machines, XGBoost, CatBoost (proposed), Decision Tree, Naive Bayes                               | Accuracy: 97.1%<br>Precision: 97.4%<br>Recall: 99.7%<br>F1 Score: 98.5% |
| Our (2025)                      | BATEREP from CCDSS Dataset (16,000 cases)                | Logistic Regression (proposed)<br>Support Vector Machines<br>XGBoost<br>Random Forest<br>Artificial Neural Network<br>CatBoost | R2: 96.91%<br>MSE: 0.0011<br>MAE: 0.0241<br>RMSE: 0.0325                |

The findings of this study have significant implications for the early detection and prevention of burnout among healthcare professionals. For healthcare organizations looking to implement predictive analytics in occupational health monitoring, Logistic Regression presents a straightforward, transparent, and highly accurate solution. For more complex burnout assessment scenarios, particularly those requiring analysis of high-dimensional psychological and physiological datasets, SVM and XGBoost provide robust alternatives.

The ability of Random Forest to identify critical burnout predictors supports its use in policy development and workforce management strategies aimed at reducing occupational stress.

Meanwhile, ANN and CatBoost demonstrate the potential for AI-driven personalized mental health interventions, though their clinical implementation requires further refinement to improve predictive stability.

The study highlights the efficacy of various machine learning models in predicting Burnout Score, with Logistic Regression, Support Vector Machines, and XGBoost emerging as top performers. These insights pave the way for more effective predictive modeling and strategic interventions to mitigate burnout in organizational settings [31-34].

## 5. Conclusions

Our study systematically evaluated the performance of various machine learning regression models in predicting burnout scores among professionals, leveraging a comprehensive dataset and advanced preprocessing techniques. Logistic Regression emerged as the most accurate model, achieving the lowest error metrics (MAE: 0.0241, MSE: 0.0011, RMSE: 0.0325) and a high explanatory power ( $R^2$ : 96.91%). Support Vector Machines (SVM) and XGBoost also demonstrated robust performance, effectively balancing prediction accuracy and variance explanation. These findings emphasize the transformative potential of machine learning in providing reliable and timely burnout predictions, especially in healthcare settings.

Our results highlight the practical utility of machine learning models in clinical environments, where burnout poses a significant challenge to the well-being and performance of healthcare professionals. Logistic Regression, with its simplicity and interpretability, offers an ideal solution for integration into hospital systems, enabling the continuous monitoring of burnout symptoms through electronic health records (EHRs) and periodic surveys. This approach facilitates early detection and allows for targeted interventions, such as counseling services or workload adjustments, to mitigate burnout's impact on both staff and patient care.

The strong correlation identified between burnout and stress indicators, such as PrimaryStressScore and PsychologicalDistressScore, underscores the broader health implications of burnout. These include an increased risk of cardiovascular diseases, depression, and anxiety. By integrating machine learning predictions into occupational health protocols, healthcare organizations can proactively address these risks, improving overall employee health and reducing associated costs.

Machine learning models can also help optimize resource allocation in hospitals and clinics. For instance, SVM and XGBoost, with their robust performance, provide valuable insights for identifying high-risk departments or individuals. This enables hospital administrators to allocate resources more effectively, such as implementing stress reduction programs or deploying targeted support teams.

Advanced models like ANN and CatBoost demonstrated strong explanatory power, despite higher error metrics. Their ability to capture complex, nonlinear relationships suggest a promising direction for future research. Combining these models with wearable device data (e.g., heart rate variability, stress levels) or integrating them into telemedicine platforms could enhance their predictive accuracy and personalization. Furthermore, ensemble methods that leverage the strengths of multiple models may further improve reliability and performance.

In conclusion, this study underscores the potential of machine learning models in predicting burnout scores among healthcare professionals. Logistic Regression, SVM, and XGBoost emerged as top performers, offering a balance of accuracy and practicality. These insights pave the way for more effective predictive modeling and strategic interventions, contributing to improved well-being and productivity within healthcare organizations. Future research should focus on refining complex models and integrating broader data sources to further enhance their clinical applicability and impact. This study systematically evaluated the predictive performance of various machine learning regression models in assessing burnout severity among healthcare professionals, applying a

comprehensive dataset and advanced preprocessing techniques. The findings underscore the potential of AI-driven predictive analytics in identifying burnout risk factors and facilitating early intervention strategies within occupational and clinical health settings [35;36].

Logistic Regression (LR) emerged as the most clinically reliable model, achieving the lowest error metrics (MAE: 0.0241, MSE: 0.0011, RMSE: 0.0325) and demonstrating strong explanatory power ( $R^2$ : 96.91%). Its simplicity and interpretability make it an ideal candidate for integration into healthcare systems, allowing for the continuous monitoring of burnout symptoms through electronic health records (EHRs) and periodic standardized assessments [37]. By enabling early detection, this model supports personalized interventions, such as counseling services, structured stress reduction programs, and workload optimization strategies, thereby mitigating burnout's impact on both healthcare professionals and patient care outcomes.

Support Vector Machines (SVM) and XGBoost (XGB) also demonstrated strong predictive capabilities, effectively balancing prediction accuracy and variance explanation. These models are particularly valuable in high-demand clinical environments, where early recognition of burnout symptoms can inform resource allocation and prevent workforce attrition. Their application in occupational health monitoring enables the identification of high-risk departments and individuals, allowing hospital administrators to proactively deploy targeted support teams and implement wellness initiatives tailored to the needs of specific healthcare units [38].

The study also revealed a strong correlation between burnout and key stress-related indicators, particularly PrimaryStressScore and PsychologicalDistressScore, reinforcing the well-documented association between chronic occupational stress and adverse health outcomes. These include an increased risk of cardiovascular diseases, hypertension, depression, and anxiety disorders [3]. The integration of machine learning-based burnout risk assessment into occupational health protocols presents an opportunity to proactively address these risks, improving employee well-being while simultaneously reducing long-term healthcare costs and absenteeism rates [39].

Beyond individual health monitoring, machine learning models can optimize resource allocation within hospitals and clinics. By leveraging SVM and XGBoost, healthcare organizations can prioritize interventions for departments or roles that exhibit higher burnout risk, ensuring that support structures—such as mental health programs, peer-support networks, and resilience training workshops—are implemented where they are most needed. This data-driven approach enhances workforce sustainability and promotes a healthier, more resilient healthcare system [4].

Advanced models such as Artificial Neural Networks (ANN) and CatBoost (CB) demonstrated high explanatory power, despite exhibiting higher prediction errors. Their capacity to capture complex, nonlinear interactions suggest promising applications for future research, particularly when paired with wearable technology or real-time physiological monitoring systems. The integration of biometric stress markers, including heart rate variability, cortisol levels, and sleep patterns, could refine predictive models by providing a more holistic understanding of burnout's physiological impact. Additionally, embedding these models within telemedicine platforms may improve remote mental health assessments, enabling more precise and individualized burnout management strategies [40].

Moving forward, ensemble learning techniques that combine the strengths of multiple models could enhance predictive accuracy and robustness. By leveraging the transparency of Logistic Regression alongside the deep learning capabilities of ANN and the efficiency of gradient boosting models like XGBoost and CatBoost, hybrid AI frameworks may further improve burnout prediction and intervention efficacy [38].

This study underscores the transformative potential of machine learning in occupational health by demonstrating the feasibility of AI-driven burnout risk assessment. Logistic Regression, SVM, and XGBoost emerged as top-performing models, offering a balance between predictive accuracy, interpretability, and practical implementation. These findings highlight the importance of AI in facilitating early identification of burnout symptoms, enabling proactive intervention measures that

enhance healthcare workforce resilience [39]. Future research should focus on refining complex models such as ANN and CatBoost through advanced hyperparameter tuning, optimization of neural network architectures, and regularization techniques to enhance predictive precision and reduce variance errors. Furthermore, expanding the dataset to include multimodal inputs—such as wearable sensor data, longitudinal EHR records, and subjective well-being measures—could significantly improve model generalizability and foster real-time burnout detection systems.

Additionally, integrating AI-powered burnout risk assessments into hospital management systems and mobile health applications could facilitate real-time monitoring, supporting personalized mental health interventions tailored to individual risk profiles [40,41]. A multidisciplinary approach combining AI, behavioral psychology, and occupational medicine will be essential in developing scalable, evidence-based solutions to mitigate burnout in high-stress work environments.

## Abbreviations

|                |                                                         |
|----------------|---------------------------------------------------------|
| AMD            | Advanced Micro Devices                                  |
| ANN            | Artificial Neural Network                               |
| AUC            | Area Under the Curve                                    |
| AUROC          | Area Under the Receiver Operating Characteristic Curve  |
| BATEREP        | Burnout Assessment Tool                                 |
| BM             | Burnout Measure                                         |
| CB             | CatBoost                                                |
| CBI            | Copenhagen Burnout Inventory                            |
| CCDSS          | Center for Social Research and Development 'Solidarity' |
| CNN            | Convolutional Neural Networks                           |
| COVID          | Corona Virus Disease                                    |
| EHR            | Electronic Health Record                                |
| GridSearchCV   | Grid Search with Cross-Validation                       |
| HDD            | Hard Disk Drive                                         |
| IDE            | Integrated Development Environment                      |
| IQR            | Interquartile Range                                     |
| LR             | Logistic Regression                                     |
| MAE            | Mean Absolute Error                                     |
| MBI            | Maslach Burnout Inventory                               |
| MBI-HSS        | Maslach Burnout Inventory–Human Services Survey         |
| ML             | Machine Learning                                        |
| MLP            | Multilayer Perceptron                                   |
| MSE            | Mean Squared Error                                      |
| PES-NWI        | Practice Environment Scale of the Nursing Work Index    |
| PQLMS          | Professional Quality of Life Monitoring System          |
| R <sup>2</sup> | R-squared                                               |
| RAM            | Random Access Memory                                    |
| ReLU           | Rectified Linear Unit                                   |
| RF             | Random Forests                                          |
| RMSE           | Root Mean Squared Error                                 |
| SVM            | Support Vector Machines                                 |
| XGB            | XGBoost                                                 |

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