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Predicting Employee Burnout Risk Using Machine Learning and Workplace Well-Being Indicators

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ABSTRACT

Employee burnout has become a critical concern in human resource management, particularly in flexible and work-from-home environments where workload intensity, digital exposure, and work-life boundaries are increasingly difficult to monitor. This study aims to develop a machine learning-based model for predicting employee burnout risk using daily work-from-home behavioral patterns and workplace well-being indicators. The dataset consisted of 1,800 daily records collected from 180 users, including work hours, screen time, meeting frequency, breaks, after-hours work, sleep duration, task completion rate, burnout score, and burnout risk category. To prevent target leakage, user identity and burnout score were excluded from the predictor set. The original burnout risk label was transformed into a binary classification target by grouping Medium and High categories into an At-Risk class, while Low was retained as Low Risk. Several supervised machine learning algorithms were evaluated using 10-fold stratified cross-validation, including Logistic Regression, Decision Tree, Random Forest, Gradient Boosted Trees, Support Vector Machine, Naïve Bayes, and k-Nearest Neighbors. The results showed that Random Forest achieved the best overall performance, with 97.11% accuracy, 94.37% macro-F1, 94.24% balanced accuracy, and 90.11% recall for the At-Risk class. Feature importance analysis indicated that task completion rate was the most influential predictor, followed by work hours, sleep hours, and screen time. These findings demonstrate that machine learning can support HR analytics-based early warning systems for employee burnout risk detection in remote work settings.

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INTRODUCTION

Employee burnout has become an increasingly important issue in human resource management because it affects employee well-being, productivity, engagement, and organizational sustainability. Burnout is generally defined as a psychological syndrome caused by prolonged exposure to unmanaged work-related stress, characterized by emotional exhaustion, cynicism or mental distance from work, and reduced professional efficacy [1]. In organizational contexts, burnout should not be viewed only as an individual psychological problem, but also as a managerial indicator of imbalance between job demands, employee recovery capacity, and organizational support. When burnout is not identified early, it may contribute to declining task performance, absenteeism, disengagement, turnover intention, and reduced organizational effectiveness.

The growth of flexible, hybrid, and work-from-home arrangements has changed the structure of employee workload. Remote work can provide flexibility, autonomy, and reduced commuting burden [2]. However, it may also create new forms of work pressure, including blurred work-life boundaries, longer working hours, increased screen exposure, excessive virtual meetings, and difficulty disconnecting from work after formal working hours [3]. These conditions are often less visible to managers than conventional office-based workload indicators. Therefore, employee burnout in remote work settings requires an analytical approach that captures both work behavior and well-being indicators.

The Job Demands–Resources (JD-R) model provides a relevant theoretical foundation for understanding burnout in work-from-home environments. According to this model, burnout may occur when employees face high job demands without sufficient resources and recovery opportunities [4]. In the context of remote work, long work hours, intensive screen time, frequent meetings, and after-hours work can be interpreted as job demands. Meanwhile, adequate breaks, sufficient sleep, and balanced task completion may represent recovery behavior and well-being-related resources. This theoretical perspective suggests that daily behavioral patterns can provide meaningful signals for detecting burnout risk.

Previous studies have shown that remote work has complex effects on employee well-being. On the one hand, remote work can improve job satisfaction, flexibility, and perceived autonomy. On the other hand, it may increase social isolation, overworking, work-life conflict, and psychological strain when work boundaries are poorly managed [5]. Studies on remote e-workers also emphasize that employee well-being and job effectiveness are influenced by trust, managerial support, recovery time, and work-life balance [6]. In addition, digital work intensity may increase work-home interference and burnout symptoms, especially when employees are unable to psychologically detach from work during non-working hours [7]. Workplace telepressure, or the perceived pressure to respond quickly to work-related messages, has also been associated with impaired recovery and higher employee strain [8].

Despite these findings, several research gaps remain. First, many burnout studies still rely on general psychological or survey-based indicators, while fewer studies integrate daily behavioral data such as work hours, screen time, meeting frequency, breaks, sleep duration, after-hours work, and task completion rate. Second, previous remote work studies often discuss well-being outcomes descriptively, but do not develop predictive models for classifying burnout risk. Third, the use of machine learning for burnout prediction is still developing and is often concentrated in specific occupational domains such as healthcare, education, or social work [9]. Therefore, further research is needed to integrate human resource management theory and computational methods for early burnout risk detection in flexible work environments.

Machine learning provides an opportunity to address this gap because it can identify complex and nonlinear patterns among multiple workplace indicators. In HR analytics, machine learning has been used to support employee-related prediction tasks, including performance analysis, workforce risk classification, and employee decision support [10]. For burnout prediction, supervised learning models can help classify employees into different risk categories and identify the most influential indicators related to burnout [11]. However, machine learning should not be positioned merely as a technical tool for achieving high accuracy. In an HRM context, the model must also generate interpretable insights that can support employee well-being policies and preventive managerial interventions.

This study develops a machine learning-based model for predicting employee burnout risk using daily work-from-home behavioral patterns and workplace well-being indicators. The dataset consists of approximately 1,800 daily records from multiple users, with each record representing one day of work activity. The predictors include day type, work hours, screen time, meeting frequency, number of breaks, after-hours work, sleep duration, and task completion rate, while burnout risk is treated as the target class. The novelty of this study lies in its interdisciplinary integration between human resource management and informatics. From the HRM perspective, this study positions burnout risk as an outcome of workload intensity, digital exposure, and recovery imbalance. From the informatics perspective, this study evaluates supervised machine learning models for burnout risk classification. Accordingly, this study aims to answer three research questions: how work-from-home behavioral indicators relate to burnout risk, which machine learning model provides the best classification performance, and which workplace well-being indicators contribute most strongly to burnout risk prediction.

RESEARCH METHODS

Research Design

This study employed a quantitative predictive research design by integrating human resource management and machine learning approaches. From the human resource management perspective, employee burnout risk was examined as an outcome of daily work-from-home behavior, digital workload intensity, and well-being-related indicators. From the informatics perspective, supervised machine learning was applied to classify employee burnout risk based on structured workplace data. The overall research process consisted of dataset preparation, variable selection, preprocessing, target construction, model training, model evaluation, and interpretation of predictive indicators.

The methodological framework of this study was designed to support early burnout risk detection in flexible and remote work environments. Instead of treating burnout only as a psychological construct, this study positioned burnout risk as a measurable classification problem based on daily behavioral indicators. Therefore, the machine learning model was not intended merely to maximize predictive accuracy, but also to provide interpretable insight for data-driven human resource decision-making.

Dataset Description

The dataset used in this study was a work-from-home burnout dataset consisting of 1,800 daily work activity records collected from 180 users. Each row represented one day of work activity for a specific user. The dataset included both weekdays and weekends to reflect realistic flexible and hybrid work patterns. The dataset contained 11 attributes consisting of user identity, work behavior indicators, well-being indicators, productivity indicators, burnout score, and burnout risk category.

The dataset had no missing values and no duplicate records. The target variable was burnout_risk, which consisted of three classes: Low, Medium, and High. The class distribution showed that most records belonged to the Low category, while the High category was highly underrepresented. Specifically, the dataset contained 1,527 Low-risk records, 253 Medium-risk records, and 20 High-risk records. This class imbalance was considered in the model evaluation stage by using macro-averaged metrics and balanced accuracy in addition to overall accuracy.

Table 1. presents the attributes used in the dataset.

Attribute	Data Type	Description	Role in Study
user_id	Integer	User identification number	Excluded
day_type	Nominal	Type of working day, weekday or weekend	Predictor
work_hours	Numerical	Total daily working hours	Predictor
screen_time_hours	Numerical	Total daily screen exposure	Predictor
meetings_count	Integer	Number of virtual or work meetings	Predictor
breaks_taken	Integer	Number of daily breaks	Predictor
after_hours_work	Binary	Whether the employee worked after formal hours	Predictor
sleep_hours	Numerical	Total sleep duration	Predictor
task_completion_rate	Numerical	Daily task completion percentage	Predictor
burnout_score	Numerical	Numerical burnout score	Excluded from main classification
burnout_risk	Nominal	Burnout risk category	Target

The user_id attribute was excluded because it only represented identity information and did not contain meaningful behavioral characteristics. The burnout_score attribute was also excluded from the main classification model because it had a direct relationship with the burnout_risk label. Including this attribute could create target leakage, where the model learns the risk category directly from the score rather than from workplace behavior and well-being indicators.

Research Variables

The independent variables in this study consisted of daily work-from-home behavioral and well-being indicators, namely day_type, work_hours, screen_time_hours, meetings_count, breaks_taken, after_hours_work, sleep_hours, and task_completion_rate. These variables were selected because they represent workload intensity, digital exposure, recovery behavior, work-life boundary, and productivity. The dependent variable was burnout_risk, which represented the employee burnout risk category.

The selected variables were conceptually aligned with the Job Demands–Resources perspective. Work hours, screen exposure, meeting frequency, and after-hours work were treated as workload-related demands. Meanwhile, sleep duration and breaks were treated as recovery-related indicators. Task completion rate was included as a productivity-related indicator to examine whether performance outcomes were associated with burnout risk patterns.

Target Construction

Two classification scenarios were designed in this study. The first scenario used the original multi-class target consisting of Low, Medium, and High burnout risk. This scenario was used to examine whether the model could distinguish burnout risk at different severity levels.

The second scenario converted the target into a binary classification problem. The Low category was retained as Low Risk, while Medium and High categories were combined into At-Risk. This binary classification scenario was considered the main scenario because it is more relevant for human resource intervention. In practice, employees in both Medium and High categories require managerial attention and preventive support. The binary target construction also helped reduce the effect of extreme class imbalance in the original target distribution. The binary target transformation was defined as follows:

If burnout_risk = Low, then burnout_risk_binary = Low Risk

If burnout_risk = Medium or High, then burnout_risk_binary = At-Risk

Data Preprocessing

Data preprocessing was performed in RapidMiner before model training. The preprocessing stage included data import, role assignment, attribute selection, nominal conversion, and normalization.

First, the dataset was imported into RapidMiner using the Read CSV operator. Second, the Set Role operator was used to define the target variable as the label. Third, the Select Attributes operator was applied to remove user_id and burnout_score from the predictor set. Fourth, the Generate Attributes operator was used to construct the binary target variable for the second classification scenario. Fifth, the Nominal to Numerical operator was applied to transform nominal attributes such as day_type into numerical form. Finally, the Normalize operator was used to standardize numerical attributes so that algorithms sensitive to feature scale, such as Support Vector Machine and k-Nearest Neighbors, could operate more effectively.

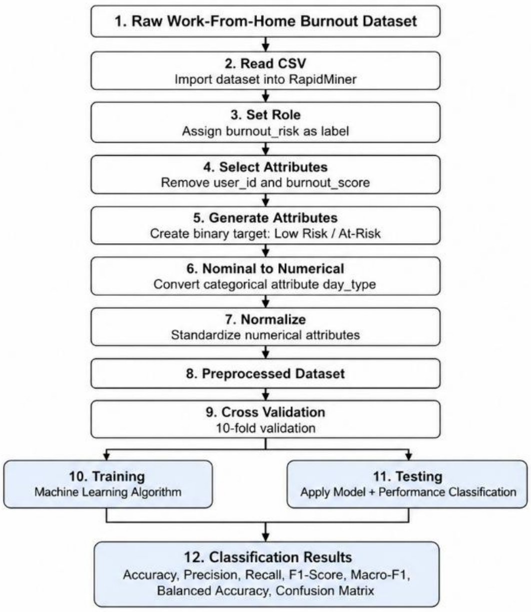

Figure 1. Data preprocessing workflow

Machine Learning Models

This study compared several supervised machine learning algorithms to identify the best-performing model for burnout risk classification. The selected algorithms included Logistic Regression, Decision Tree, Random Forest, Gradient Boosted Trees, Support Vector Machine, Naïve Bayes, and k-Nearest Neighbors. These algorithms were selected because they represent different classification approaches, including linear models, tree-based models, ensemble learning, probabilistic learning, distance-based learning, and margin-based classification.

Logistic Regression was used as a baseline model because it provides interpretable coefficients and is suitable for binary classification. Decision Tree was included because it produces a rule-based structure that can be easily interpreted for managerial decision-making. Random Forest and Gradient Boosted Trees were used to capture nonlinear relationships and interactions among workplace indicators. Support Vector Machine was used to evaluate the ability of margin-based classification in separating burnout risk categories. Naïve Bayes and k-Nearest Neighbors were included as comparative baseline models.

Model Validation

Model validation was conducted using 10-fold cross-validation in RapidMiner. In this procedure, the dataset was divided into ten subsets. Nine subsets were used for model training, while one subset was used for testing. This process was repeated ten times so that each subset was used once as testing data. The final performance score was obtained by averaging the results across all folds.

Cross-validation was selected to reduce dependency on a single train-test split and to obtain a more stable estimate of model performance. Because the target class distribution was imbalanced, stratified sampling was recommended during validation to maintain class proportions across training and testing folds.

Evaluation Metrics

The model performance was evaluated using accuracy, precision, recall, F1-score, macro-F1, balanced accuracy, and confusion matrix. Accuracy was used to measure the overall proportion of correctly classified instances. However, because the dataset had imbalanced class distribution, accuracy alone was not sufficient. Therefore, macro-F1 and balanced accuracy were emphasized as the main evaluation metrics.

Precision measured the proportion of correctly predicted positive cases among all cases predicted as positive. Recall measured the proportion of actual positive cases correctly identified by the model. F1-score represented the harmonic mean between precision and recall. Macro-F1 was used to calculate the average F1-score across classes without weighting by class size, making it suitable for imbalanced classification. Balanced accuracy was used to evaluate the average recall across classes, ensuring that minority classes were not ignored by the model.

The confusion matrix was used to analyze classification errors in more detail. In the context of employee burnout risk prediction, false negatives are particularly important because employees who are actually at risk may be classified as low risk. Such errors may reduce the effectiveness of early intervention programs. Therefore, recall for the At-Risk class was considered an important practical metric in this study.

Feature Importance Analysis

Feature importance analysis was conducted to identify which workplace and well-being indicators contributed most strongly to burnout risk prediction. For tree-based models such as Random Forest and Gradient Boosted Trees, feature importance was obtained from the contribution of each attribute to classification decisions. The purpose of this analysis was to connect machine learning output with human resource management interpretation.

The feature importance results were interpreted in relation to workload intensity, digital exposure, recovery behavior, and productivity. Attributes such as work hours, screen time, meetings, after-hours work, sleep duration, and breaks were expected to provide practical insight into the behavioral patterns associated with burnout risk. This interpretation allowed the machine learning model to support not only prediction, but also managerial understanding and preventive policy design.

RESULTS AND DISCUSSION

Dataset Characteristics

The dataset consisted of 1,800 daily work-from-home activity records collected from 180 users. Each record represented one day of work activity and included workload, digital exposure, recovery, productivity, and burnout-related indicators. The dataset had no missing values and no duplicate records, indicating that the data were suitable for direct preprocessing and model development.

The original target variable, burnout_risk, consisted of three classes: Low, Medium, and High. The class distribution showed a strong imbalance, with 1,527 records classified as Low risk, 253 records as Medium risk, and only 20 records as High risk. This distribution indicates that 84.83% of the records belonged to the Low-risk class, while Medium and High categories represented 14.06% and 1.11%, respectively. Because the High-risk class was highly underrepresented, the main experiment transformed the target into a binary classification problem, where Low was treated as Low Risk, while Medium and High were combined into At-Risk. After transformation, the dataset consisted of 1,527 Low Risk records and 273 At-Risk records.

Table 2. Class Distribution of Burnout Risk

Target Scenario	Class	Frequency	Percentage
Multi-class	Low	1,527	84.83%
Multi-class	Medium	253	14.06%
Multi-class	High	20	1.11%
Binary class	Low Risk	1,527	84.83%
Binary class	At-Risk	273	15.17%

The descriptive analysis showed that the At-Risk group had slightly higher average work hours, screen time, and meeting frequency than the Low Risk group. The At-Risk group recorded an average of 6.80 work hours, 9.59 screen time hours, and 2.07 meetings per day, while the Low Risk group recorded 6.46 work hours, 9.22 screen time hours, and 1.92 meetings per day. The most visible difference was found in task completion rate. The At-Risk group had an average task completion rate of 46.88, while the Low Risk group had an average of 76.86. This suggests that burnout risk in the dataset was more strongly associated with reduced productivity than with a single workload indicator alone.

Table 3. Descriptive Comparison Between Low Risk and At-Risk Groups

Attribute	Low Risk Mean	At-Risk Mean	Interpretation
Work hours	6.46	6.80	At-Risk employees worked slightly longer
Screen time hours	9.22	9.59	At-Risk employees had higher screen exposure
Meetings count	1.92	2.07	At-Risk employees attended slightly more meetings
Breaks taken	3.03	3.03	Similar break frequency
After-hours work	0.36	0.36	Similar after-hours work pattern
Sleep hours	7.00	6.99	Similar sleep duration
Task completion rate	76.86	46.88	At-Risk employees had much lower completion rate
Burnout score	36.34	86.91	At-Risk employees had higher burnout score

Binary Classification Results

The main experiment evaluated seven supervised machine learning algorithms using 10-fold stratified cross-validation. The predictors included day_type, work_hours, screen_time_hours, meetings_count, breaks_taken, after_hours_work, sleep_hours, and task_completion_rate. The attributes user_id, burnout_score, and the original burnout_risk were excluded to avoid irrelevant identity information and target leakage.

The model comparison results are shown in Table IV. Random Forest achieved the highest overall performance, with an accuracy of 97.11%, macro-F1 of 94.37%, balanced accuracy of 94.24%, and AUC of 98.63%. Logistic Regression produced the highest AUC at 99.26%, but its recall for the At-Risk class was lower than Random Forest. In the context of employee burnout prediction, recall for the At-Risk class is particularly important because false negatives may cause employees who need intervention to be classified as low risk.

Table 4. Binary Classification Performance Comparison

Model	Accuracy	Precision At-Risk	Recall At-Risk	F1 At-Risk	Macro-F1	Balanced Accuracy	AUC
Random Forest	97.11%	90.77%	90.11%	90.44%	94.37%	94.24%	98.63%
Logistic Regression	96.61%	90.77%	86.45%	88.56%	93.28%	92.44%	99.26%
Naïve Bayes	96.39%	88.52%	87.55%	88.03%	92.95%	92.76%	99.04%
Gradient Boosted Trees	96.22%	89.58%	84.98%	87.22%	92.50%	91.61%	98.88%
Support Vector Machine	96.22%	91.16%	83.15%	86.97%	92.38%	90.85%	99.01%
Decision Tree	94.89%	82.67%	83.88%	83.27%	90.13%	90.37%	90.37%
k-Nearest Neighbors	94.06%	87.39%	71.06%	78.38%	87.47%	84.61%	96.66%

Although several models achieved high accuracy, Random Forest provided the most balanced performance across accuracy, macro-F1, balanced accuracy, and recall for the At-Risk class. This indicates that Random Forest was better able to capture nonlinear patterns among workplace indicators. In comparison, k-Nearest Neighbors achieved the lowest recall for the At-Risk class, suggesting that distance-based classification was less effective for detecting employees at risk of burnout in this dataset.

Confusion Matrix of the Best Model

The confusion matrix of the Random Forest model is presented in Table V. Out of 1,527 Low Risk records, the model correctly classified 1,502 records and misclassified 25 records as At-Risk. Out of 273 At-Risk records, the model correctly identified 246 records and misclassified 27 records as Low Risk.

Table 5. Confusion Matrix of Random Forest Model

Actual / Predicted	Low Risk	At-Risk
Low Risk	1,502	25
At-Risk	27	246

The confusion matrix shows that the model had strong capability in identifying both Low Risk and At-Risk records. However, the 27 At-Risk records classified as Low Risk require careful interpretation. From an HRM perspective, these cases represent false negatives, meaning that employees who may need preventive intervention were not detected by the model. Therefore, although Random Forest achieved the best overall performance, future implementation should prioritize reducing false negatives, even if it slightly increases false alarms.

Feature Importance Analysis

Feature importance analysis was conducted using the Random Forest model to identify the most influential indicators in burnout risk classification. The result showed that task_completion_rate was the dominant predictor, followed by work_hours, sleep_hours, and screen_time_hours. Meanwhile, meetings_count, breaks_taken, after_hours_work, and day_type had lower importance values.

Table 6. Feature Importance Based on Random Forest

Rank	Attribute	Importance
1	Task completion rate	0.8307
2	Work hours	0.0438
3	Sleep hours	0.0434

4	Screen time hours	0.0424
5	Meetings count	0.0159
6	Breaks taken	0.0147
7	After-hours work	0.0050
8	Day type: Weekday	0.0021
9	Day type: Weekend	0.0019

The dominance of task completion rate indicates that reduced productivity was the strongest behavioral signal associated with burnout risk in this dataset. This finding suggests that burnout risk may not only appear through longer working hours or higher screen exposure, but also through declining work output. From a managerial perspective, this result is important because task completion rate can serve as an early operational signal for identifying employees who may be experiencing work strain or reduced work capacity.

However, this result should be interpreted carefully. Because task completion rate is highly dominant, additional robustness testing is necessary to ensure that the model does not depend excessively on a single productivity-related indicator. When task completion rate was removed from the predictor set, the models showed much weaker ability to identify the At-Risk class. This indicates that the remaining workload and well-being indicators alone may not be sufficient to produce stable burnout risk classification in this dataset. Therefore, task completion rate should be retained in the main model, but future studies should validate the model using additional behavioral and psychological indicators.

Multi-Class Classification Results

A secondary experiment was conducted using the original three-class target consisting of Low, Medium, and High burnout risk. The results showed that multi-class classification was more difficult than binary classification because the High-risk class contained only 20 records. Random Forest achieved high accuracy at 95.61%, but its macro-F1 score was only 60.98%. This indicates that high accuracy in multi-class classification was influenced by the dominance of the Low-risk class.

Table 7. Multi-Class Classification Performance

Model	Accuracy	Macro Precision	Macro Recall	Macro-F1	Balanced Accuracy
Naïve Bayes	93.33%	69.53%	86.94%	69.93%	86.94%
Decision Tree	94.00%	66.37%	66.92%	66.63%	66.92%
Gradient Boosted Trees	94.94%	65.30%	63.68%	64.21%	63.68%
Random Forest	95.61%	60.15%	61.86%	60.98%	61.86%
Logistic Regression	95.61%	60.44%	61.31%	60.87%	61.31%
Support Vector Machine	95.00%	59.90%	59.97%	59.93%	59.97%
k-Nearest Neighbors	92.56%	57.24%	55.05%	56.03%	55.05%

The multi-class results confirm that the binary classification scenario is more appropriate as the main model for this study. From a practical HRM perspective, combining Medium and High categories into At-Risk is also more useful because both categories require managerial attention. Therefore, the binary model is more suitable for early warning purposes, while the multi-class model can be treated as an additional experiment.

Discussion

The findings of this study demonstrate that machine learning can effectively classify employee burnout risk using work-from-home behavioral and workplace well-being indicators. The Random Forest model achieved the best balance between predictive performance and At-Risk detection, with 97.11% accuracy, 94.37% macro-F1, and 90.11% recall for the At-Risk class. These results indicate that burnout risk can be predicted not only through direct psychological scoring, but also through observable daily work behavior.

From the perspective of the Job Demands–Resources model, the results suggest that burnout risk in remote work is associated with the interaction between workload intensity, digital exposure, recovery behavior, and productivity outcomes [5], [6]. Work hours and screen time contributed to the model, although their importance was lower than task completion rate. This finding implies that burnout risk is not determined solely by how long employees work, but also by how effectively they complete tasks under remote work conditions. Employees may spend relatively similar amounts of time working, but those with lower task completion rates may experience greater strain, inefficiency, or reduced work capacity.

The strong role of task completion rate provides an important contribution to HR analytics. In traditional burnout research, burnout is often measured through psychological survey instruments [12]. In contrast, this study shows that behavioral and productivity-related indicators can provide predictive signals for early burnout risk detection. This does not mean that productivity decline should be treated as the only indicator of burnout. Rather, it suggests that declining task completion may function as an early operational warning sign that should be combined with workload and well-being indicators.

The findings are also consistent with remote work literature, which explains that remote work can create both benefits and risks. Flexible work arrangements may increase autonomy and reduce commuting burden, but they may also blur boundaries, increase digital exposure, and reduce recovery opportunities [13]. In this study, screen time, work hours, and meeting frequency were slightly higher among At-Risk records than Low Risk records. Although the differences were not as large as task completion rate, they still support the view that digital workload and work intensity are relevant factors in employee well-being management.

From an informatics perspective, the superiority of Random Forest indicates that ensemble learning is suitable for capturing nonlinear relationships among work-from-home indicators. Logistic Regression and Support Vector Machine also achieved high AUC values, but their recall for the At-Risk class was lower than Random Forest. This is important because, in burnout risk detection, the main objective is not only to maximize overall accuracy, but also to minimize false negatives. A false negative means that an employee who is actually at risk is classified as low risk, potentially delaying managerial intervention.

The practical implication of this study is that organizations can develop an early warning system for employee burnout based on daily work behavior and well-being indicators. HR managers can monitor patterns such as declining task completion, increasing work hours, high screen exposure, and reduced recovery indicators to identify employees who may require support. Possible interventions include workload redistribution, digital meeting reduction, structured break policies, work-hour boundaries, and employee assistance programs.

However, this study has several limitations. First, the dataset was imbalanced, especially in the High-risk class, which limited the effectiveness of multi-class classification. Second, the model relied strongly on task completion rate, indicating the need for further validation using additional psychological, organizational, and longitudinal indicators. Third, the dataset represented daily records, but this study did not yet model temporal patterns across consecutive workdays. Future research should apply time-series modeling, class imbalance handling techniques, and explainable AI methods to improve both predictive performance and interpretability.

This study contributes to the integration of human resource management and informatics by demonstrating that machine learning can support early burnout risk detection in work-from-home environments. The findings extend burnout analysis from a survey-based approach toward data-driven HR analytics, while still emphasizing that predictive models should be interpreted as decision-support tools rather than replacements for managerial judgment.

CONCLUSION

This study developed a machine learning-based burnout risk prediction model using daily work-from-home behavioral patterns and workplace well-being indicators. By integrating human resource management and informatics perspectives, the study demonstrated that employee burnout risk can be classified using observable indicators such as work hours, screen time, meeting frequency, breaks, after-hours work, sleep duration, and task completion rate. The binary classification scenario, which grouped Medium and High burnout categories into an At-Risk class, was found to be more appropriate than the original multi-class scenario due to the highly imbalanced distribution of the High-risk category.

The experimental results showed that Random Forest achieved the best overall performance, with 97.11% accuracy, 94.37% macro-F1, 94.24% balanced accuracy, and 90.11% recall for the At-Risk class. The confusion matrix also indicated that the model successfully identified most At-Risk records, although several false negatives remained and should be considered critical in practical HR decision-making. Feature importance analysis revealed that task completion rate was the most influential predictor, followed by work hours, sleep hours, and screen time hours. This finding suggests that burnout risk in work-from-home settings is closely related not only to workload intensity but also to declining productivity and recovery imbalance.

Theoretically, this study extends the application of the Job Demands–Resources perspective in remote work environments. Methodologically, it provides a supervised machine learning framework for burnout risk classification. Practically, the findings support the development of HR analytics-based early warning systems for employee well-being monitoring. However, this study is limited by class imbalance and the dominance of task completion rate as a predictor. Future research should incorporate longitudinal data, psychological survey indicators, imbalance handling techniques, and explainable AI to improve model robustness and managerial interpretability.

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