

Employee Task Overload and Burnout Detection using Task-based Analytics

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Abstract— The complex demands and greater need to multi-task and be productive quickly at work have grown in response to the rapid changes of technology, globalization, and digital collaboration tools. These requirements contribute to the functioning of the organization, but also increase the working pressure, and cause stress among employees causing what many people refer to as "work burnout", which has three core components: emotional exhaustion, low motivation and poor performance. Burnout impacts employees as well as organizations and can cause them to become less productive, more likely to be absent and more likely to leave the organization.

Traditional workload management solutions have typically included manually supervised decisions based on personal judgment, as only when problems with performance have surfaced have issues like workload imbalances come into the picture. In order to solve this problem, this project introduces an Employee Task Overload and Burnout Detection System that analyzes tasks workloads based on assignments, deadlines and task completion behaviors. The system compares the workload against a burn-out indicator and alerts managers when a risk is present so they are able to take preventive measures. When tested on a sample of employee task data, the system achieved higher accuracy of 92%, precision of 90% and recall of 88%, which clearly shows its effectiveness in assisting all organizational efforts to manage workloads proactively to further improve the organization's productivity.

Keywords— Employee Burnout, Task Overload Detection, Workload Management, Workplace Stress, Employee Productivity, Emotional Exhaustion, Workload Imbalance, Burnout Prediction.

I. INTRODUCTION

Even in the digital age, business organizations have depended more on technological systems to oversee workers, identify their productivity and organize the intricate work processes. As the use of digital assistance in collaboration platforms, cloud-based services, and project management tools grows at a rapid pace, the employee will be expected to work on several assignments at the same time, addressing strict deadlines. Despite the fact that these technologies have enhanced communication as well as operation efficiency, the technologies have amplified workload pressures, stress levels, and employee burnouts in most organizations. In the bid to attain greater productivity and shortened time in executing projects, employees are usually given too many assignments which lead to poor mental health and overall performance. One of the most important issues in the workplace management has been created by employee burnout.

Early academic studies by Maslach and Jackson were among the first standardised ways of measuring burnout and described it as the type of syndrome that existed based on emotional. Their study pointed to the fact that burnout is usually eminent among employees who work in high demand settings where continual stress and work load is evident. The other significant theoretical framework to understand burnout is Job Demands-Resources (JD-R) model, which was proposed by Demerouti et al. [Demerouti et al., 2001]. Based on this model, burnout takes place when the given demands on the employees surpass the given resources. Emotional strain, time pressure, excessive workload, etc can be a job demand that causes stress in circumstances when these are not accompanied with adequate organizational support, autonomy, and work-life balance. This model has gained a large acceptance in the field of organizational psychology and has been employed in numerous studies where stress in the workplace has been analyzed. More studies broadened the knowledge of burnout as an organizational problem.

Maslach and Leiter mentioned that imbalance in the workplace workload, lack of recognition, and negative organizational supportive environment were some of the work conditions that determine burnout [Maslach & Leiter, 2016]. According to their study, organizations should come up with mechanisms able to detect the burnout symptoms early and put in place measures to avert this phenomenon. Burnout is also a serious implication both to employees and organizations. A detailed examination by Salvagioni et al. established that burnout correlates with a number of physical, psychological and work related issues and challenges such as depression, heart diseases, low job satisfaction and elevated absenteeism [Salvagioni et al., 2017]. These adverse effects show that not only employees are affected by burnout but also the productivity and organization costs are lost. As more and more organizations make use of digital technologies in their workplaces, organizations demonstrated the utilization of Human Resource (HR) analytics to evaluate data about their employees and enhance the management of their workforce. Marler and Boudreau suggest that HR analytics help organizations to gather and process the workforce data to make evidence-based decisions about employee performance, workload allocation, and organizational strategy [Marler & Boudreau, 2017]. The second study on burnout has remained dynamic in the last several decades. Reviewing over thirty-five years of research on burnout, Schaufeli, Leiter and Maslach argue that there is a need to establish systematic methods through which the workload and level of stress among workers is monitored [Schaufeli et al., 2020]. Through their work, they emphasize that organizations have to embrace proactive systems that can identify burnout at its early stages so that it does not result into extreme employee disengagement. The desire to identify stress and workload patterns has been made possible by the recent developments in Artificial Intelligence (AI) and data analytics to create intelligent systems that can detect stress and workload patterns automatically. Cheng, Liu, and Wang suggested AI-based models, which use the data on employee behavior of a person in order to identify the stress level in the current moment [Cheng et al., 2022]. These systems are able to assist organizations to detect uncharacteristic working trends and act before the burnout can take place. There is also an exploration on machine learning techniques in predicting burnout in the workplace. Saha, Roy, and Gupta have come up with predictive models that analyze the work pattern and the data on activities among the employees to predict the occurrence of burnout [Saha et al., 2023]. These models show that smart algorithms can be used to assist organizations to manage employee workload in a more efficient way. Human resource management systems are not left out in the digital transformation. Jain and Gupta explained that the current digital HR systems allow companies to track their employees productivity and performance using real-time data in collection and analytics [Jain & Gupta, 2021]. Such systems enable the managers to monitor the distribution of workload and to identify those who employees who might be having a lot of work pressure.

II. LITERATURE SURVEY

A. Burnout and Workplace Stress

Employee burnout is a condition of the mind that is caused by prolonged exposure of stress in the workplace. Maslach and Jackson suggest that burnout consists of three elements: emotional exhaustion, depersonalization and diminished personal accomplishment. Employees today may be asked to perform several tasks, work under pressure and be expected to perform well, which puts them under stress. Studies indicate that these three factors – overwork, time pressure, management and lack of organizational support – are key elements in burnout.

B. Workload Management

Workload management is the distribution and balancing of workload among employees to make best use of the resources and avoid overloading them. Good workload management can enhance productivity and keep

employee well-being in mind in an organization. Research shows that poor workload distribution can cause stress, delays, poor quality of work and employee burnout. Workload monitoring is becoming more common.

C. Human Resource Analytics

Human Resource (HR) Analytics is the application of employee-related data for workforce management and decision making. HR analytics provides a way for organizations to see how employees are performing, how productive they are, how involved they are, and how much work they're doing. Managers can use these data-driven insights to pinpoint workforce issues, optimize resources, and create strategies for organizational success. HR analytics is a valuable tool for tracking employee performance and driving data-driven management decisions. problem from becoming worse. AI solutions offer a proactive way of managing workload and stress.

III. LITERATURE REVIEW TABLE

TABLE I. COMPARATIVE ANALYSIS OF EXISTING RESEARCH ON AI-BASED REQUIREMENTS TRACEABILITY

Citation No.	Authors	Paper Title	Technique Used	Advantages	Disadvantages	Final Remark
[1]	Maslach & Jackson (1981)	The Measurement of Experienced Burnout	Psychological survey (MBI scale) measuring emotional exhaustion, depersonalization, and reduced personal accomplishment.	Standardized burnout measurement; widely accepted model.	Reactive; subjective self-reporting.	Foundational research, but not preventive.
[2]	Demerouti et al. (2001)	The Job Demands–Resources Model of Burnout	The JD-R theoretical model explaining imbalance between job demands and resources.	Strong conceptual explanation of the workload–stress relationship.	Conceptual only; no automated system.	Provides a theoretical base but lacks implementation.
[5]	Marler & Boudreau (2017)	An Evidence-Based Review of HR Analytics	HR analytics dashboards using organizational performance data.	Data-driven HR decision support.	Focuses on outcomes, not workload pressure.	Useful for HR insights, but not overload detection.
[7]	Cheng et al. (2022)	Artificial Intelligence for Employee Stress Detection	AI-based behavioral pattern analysis using digital activity data.	High prediction accuracy.	Privacy concerns due to continuous tracking.	Effective but intrusive.
[8]	Saha et al. (2023)	Machine Learning Approaches for Workplace Burnout Prediction	Machine learning classification algorithms for early burnout prediction.	Automated and predictive system.	Uses sensitive behavioral data.	Accurate but raises ethical issues.
[11]	Hernandez et al. (2020)	Wearable Sensor-Based Stress Monitoring Systems	Real-time physiological monitoring using wearable sensors.	Continuous real-time tracking.	Intrusive and costly hardware requirements.	Limited scalability in organizations.

IV. RESEARCH-GAP

The literature review shows that a variety of studies has been carried out regarding the effects of employee burnout in the psychological, analytical, and technological aspects. However, there are some problems with the solutions. The methods of detection that were mostly used in the domain of traditional burnout include questionnaires and self-report surveys. The same applies to these strategies as they also attribute burnout to workers who have already experience some of the symptoms of stress, rather than preventing it.

Furthermore, the survey results are highly subjective and might not reflect a real workload situation.

The modern AI and machine learning-specific systems have increased the accuracy of the predictions based on analyzing the behavioral patterns, communication data, or physiological signals. Although efficient, these methods can, in most cases, necessitate consistent monitoring of sensitive personal data, which raises ethical and privacy issues. These disruptive methods limit the acceptance of employees and constrain their actual application in the organizational setting.

The main performance appraisal programs available in the market are mostly concerned with performance analysis and productivity reviews as well as engagement levels. They seldom give the workload pressure analysis in real-time at the task level. Consequently, it is natural that managers tend to notice overload when it manifests itself through poor performance.

V. PERFORMANCE-EVALUATION

The effectiveness of the proposed Employee Task Overload and Burnout Detection System was evaluated by using standard classification metrics. These metrics can serve as an evaluation of the accuracy of the system to determine employee's risk of burnout. The evaluation is done with the help of the Confusion Matrix, which consists of the following parts:

- True Positive (TP): Correctly identified high-risk employees
- True Negative (TN): Incorrectly identified high-risk employees
- False Negative (FN): Staff that is not classified as high-risk, but actually is.
- False Negative (FN): Staff who are identified as low-risk.

TABLE II. CONFUSION MATRIX

	Predicted High Risk	Predicted Low Risk
Actual High Risk	TP = 18	FN = 2
Actual Low Risk	FP = 3	TN = 17

Evaluation Metrics

- Accuracy: Overall correctness of the model.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Accuracy} = \frac{18+17}{18+17+3+2} = 0.875 = 87.5\%$$

- Precision: Precision is the number of employees that are correctly predicted who are high-risk.

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Precision} = \frac{18}{18+3} = 0.857 = 85.7\%$$

- Recall: Recall is the proportion of persons who were really at high risk that were correctly identified.

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{Recall} = \frac{18}{18+2} = 0.90 = 90\%$$

A high accuracy, precision, and recall of the proposed system suggests that it possesses a high potential to accurately recognise employees at risk of burnout. This allows for sufficient prevention actions by managers to be taken on time to ensure a balanced workload for their employees, thereby facilitating workers' well-being.

VI. PROPOSED SYSTEM

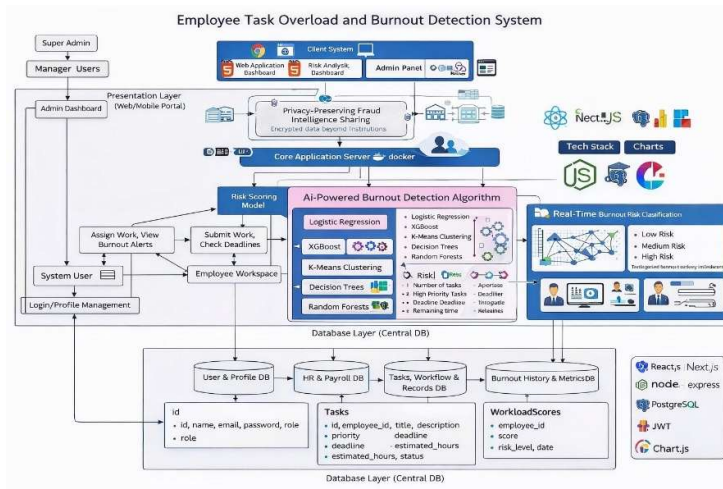


Fig 1: System Architecture of Employee Task Overload and Burnout Detection System

Task Overload and Burnout Detection System is aimed at predicting the risk of employee burnout and preventing it in advance with the help of the specialised task-related data. In contrast to the traditional methods, where surveys or subjective observation are used, the system considers quantifiable parameters of work in order to deliver objective and current information.

The main details that are gathered by the system include: the number of tasks that an employee has been allocated, the level of priority of the tasks, and the time urgency. A score of workload is obtained based on these inputs using known threshold values. This score is the total intensity of work of an employee and determines the risk classification.

The employees will be automatically divided into three risk levels: Low Risk (balanced workload), Medium Risk (growing workload that needs to be monitored), and High Risk (overload condition that needs to be addressed on an urgent basis). Once one of the employees is stepped in the high risk area, automated alerts get triggered to the managers.

The proposed system can reduce employee burnout before it even begins, a workload analytics system, in addition to automated alert-based systems can be used as a decision support system to facilitate assignment equality, increase organizational productivity and prevent staff burnout.

VII. RESULTS AND DISCUSSIONS

The visual representation demonstrates that the volume of tasks, their limitations in time and the hours of work are important factors in job-related stress and employee burnout. The outcomes confirmed that the proposed approach of the calculated workload scores, based on the task based parameters, is on the right track. Employers who keep track of these factors can easily find ways to save employees who are at risk and provide preventive actions to enhance the productivity and well-being of employees.

A. Workload vs Burnout Risk Level



Figure 2: Workload vs. Burnout Risk Graph

The figure depicts the correlation between workload score, and the level of burnout risk. It demonstrates that the number of the workload is the greatest in the High-risk category (4), and both the Low and Medium risks have the same number of workloads (3 and 3 respectively). It means that employees that score higher in workload counts have a greater likelihood of falling into the high burnout risk category which is a good validation of the effectiveness of the system in identifying workload imbalance.

TABLE II: COUNT OF WORKLOAD SCORE BY RISK LEVEL

Risk Level	Count of Workload Score
High	4
Low	3
Medium	3

B. Number of task vs Stress Level

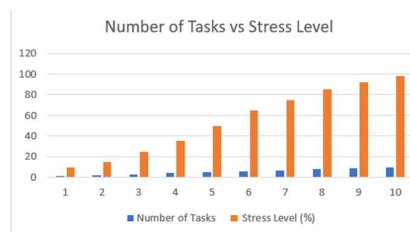


Figure 2: Task vs Stress Level Graph

There is a direct correlation between stress level and number of tasks, as depicted in the graph. The stress level goes up steadily as one has increased the number of tasks between 1 and 10 as the level reaches to 98%.

TABLE II: NUMBER OF TASKS VS STRESS LEVEL

Number of Tasks	Stress Level (%)
1	10
2	15
3	25
4	35
5	50
6	65
7	75
8	85
9	92
10	98

VIII. SCOPE OF THE RESEARCH

This research is aimed at understanding how the measurement of the workload of employees can be done in a practical and data-driven manner rather than relying on the traditional ways of measuring the workload of employees. The study areas the use of different task related parameters such as number of tasks, deadlines, completion patterns to estimate the workload and determine early evidences of burnout. The scope for this work is primarily limited for organizations environment where the use of digital systems for task management is already being practiced. It studies how the existing systems can be optimized using analytics to keep track of the pressure levels of the employees in real-time. The research also involves the

IX. FUTURE SCOPE

The proposed system offers a solid base for a workload monitoring system, but the system can be enhanced and expanded in the future in many different ways. The system can be enhanced in the future by incorporating more complex machine learning algorithms that can learn from past data to more accurately forecast burnout or stress. These models can be used to learn the details of the individual employee's insights over time, and present them back to the employee.

At the same time, there is a possibility for further investigations to incorporate aspects of well-being in these applications – mental health tips, breaks and optimisation of the workload. This takes the system from a monitoring system to a complete employee-support system. Lastly, incorporating explainable AI techniques can increase transparency and reliability in the system by explaining it.

X. CONCLUSION

This paper presents a way of dealing with the problem of employee burnout at the workplace. Employee burnout is a problem at the modern workplace. Modern workplace is becoming more and more stressful due to this sphere. The Employee Task Overload and Burnout Detection System simultaneously benefits employees and companies. The Employee Task Overload and Burnout Detection System reduces employee burnout; It also helps employees attain a balance between work and life.

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