

Analyzing Employee Attrition Drivers: The Impact of Burnout Through Predictive Models

Heno Merlin C P S ¹, Dr. Jayasree Krishnan ²

¹ Research Scholar, Department of Management Studies, Vels Institute of Science Technology and Advanced Studies (VISTAS)

² Professor & Director, School of Management Studies, Vels Institute of Science Technology and Advanced Studies (VISTAS)

ABSTRACT

Employee burnout has become an organizational crisis because of its relation with increasing attrition and decreasing productivity. Predictive analytical modeling was used in the current study to capture the effects of burnout on employee turnover. Demographics include age, marital status, job type, and years of service, whereas burnout indicators consist of emotional exhaustion, physical fatigue, frustration, and job satisfaction. These variables entered the machine learning models developed in Python to identify the patterns and predictors of employee departure. With the data analysis framework approach, the modeling is started with data preprocessing and exploratory data analysis, followed by feature selection and classification. In this study, we analyze the predictive abilities of various algorithms: Random Forest, Logistic Regression, and Support Vector Machine. Much in line with several research works, it shows a quantitative relationship between burnout dimensions and self-reported turnover intentions. To facilitate decisions, an interactive Power BI dashboard was constructed visualizing the profile of high-risk employees and the burnout patterns leading to attrition; the results were then deployed to substantiate targeted interventions.

Keywords: Employee Attrition, Employee Burnout, Predictive Analytics, Machine Learning, HR Analytics, Power BI

1. INTRODUCTION

These fast-paced, competitive, and challenging working environments only allow employee burnout as the most concerning issue for companies in all sectors. Employee burnout rests on psychological syndrome built of chronic workplace stress, which shows poor well-being among employees and thus much-more contributes to increased employee turnover. Symptoms of burnout include emotional exhaustion, physical fatigue, frustration, and less job satisfaction. It directly affects the productivity of that particular organization along with the stability of the workforce. In this scenario of talent retention and development of a better work culture, it has become compulsory to consider the complex relationship between burnout and employee attrition. Burnout has been well established as contributing to turnover by academic and professional societies; however there is still much to be desired in empirical research that incorporates prediction modeling to explain this relationship. Most of the literature in this area is qualitative or correlational with little attention to model-based approaches which incorporate data and predict turnover based on specific burnout indicators. New areas like HR analytics are providing enticing ways to

incorporate massive data sets into such models; however in the area of investigating burnout-related attrition, these have had limited usage thus far. This study, therefore, seeks to fill this important gap through the application of machine learning techniques in predicting employee turnover based on burnout dimensions-analyzing the comprehensive dataset including demographic attributes; job characteristics; and self-reported measures of burnout, and applying advanced predictive modeling to identify and reveal attrition patterns and predictors. And the models are expected to help organizations identify high-risk employee profiles and formulate effective interventions. The aim of the study is to analyze the extent of employee burnout in relation to employee turnover, whittling down to essential factors contributing to burnout. Develop and assess a predictive analytic model to help forecast employee turnover as a function of burnout features. Data-driven insights and recommendations for organizations to inform retention strategies and levels of burnout will be discussed.

2. LITERATURE REVIEW

Burnout is characterized as emotional, mental, and physical exhaustion and is often fostered through exposure to an accumulation of job stress, high job demands, and low organizational support. Studies have found a strong positive relationship between burnout and turnover intention; employees reporting frequent feelings of burnout were significantly more likely to leave the organizations for other part-time jobs (in addition to desired distance from the organizations.) In general, the research illustrates that a stressful work environment wears down employees' psychological and emotional resources, which leads to higher burnout, and obviously, higher intention to leave (Pandey & Risal, 2024; Sharon et al., 2023). Occupational stress was noted as a contributor when individuals were in a constant state of job-related stressors resulting in feelings of being overwhelmed, indicating sometimes people leave their jobs merely for a feeling of relief via distance from the stressors (Nilung et al., 2024; Faaroek, 2020). Some researchers have noted that burnout may not serve as a systematic mediator between job stress and turnover intention because individuals also have personal-level factors and numerous organizational-level factors that could impact the relationship (Hokianto et al, 2023). The role of human resource (HR) practices in moderating the burnout-turnover connection has received increasing awareness. Organizations that offer support in wellness, stress management and mental health services reported decreases in turnover and burnout. Meaningful HR practices can improve employee morale and creativity and act as a protective mechanism against occupational stress (Pandey, & Risal, 2024; Sharon et al., 2023). Providing employee wellbeing initiatives provides employees with a healthy working environment, as employees are supported and feel valued, leading to improved retention. Organizations that offer support in wellness, stress management and mental health services reported decreases in turnover and burnout. Meaningful HR practices can improve employee morale and creativity and act as a protective mechanism against occupational stress (Pandey, & Risal, 2024; Sharon et al., 2023). Providing employee wellbeing initiatives provides employees with a healthy working environment, as employees are supported and feel valued, leading to improved retention.

Emotional exhaustion, an important component of burnout, has been shown to be a key predictor of turnover intention and is usually the result of toxic leadership styles including abusive supervision and lack of empathy, deteriorating employees resilience. These leadership behaviors play a substantial role in worker disengagement and exiting the workplace (Raza et al., 2024; Antono et al., 2023) and emotional exhaustion is further exacerbated when employees cannot separate work and life balance (Othman et al., 2018). Physical fatigue commonly produces emotional exhaustion and in combination with physical

fatigue, it will raise stress levels and lead to increased intention to leave (Lasmi & P, 2024). In part, the cause of emotional exhaustion is driven by interpersonal and organizational climate factors, and in part, those climate variables can lessen stigmas associated with health, safety, and psychological well-being (Sanjoko & Nugraheni, 2015). Some authors speculate that variables like career opportunities and organizational culture may be as, or more important than burnout and be significant moderators when behavior related to quitting is concerned.

Predictive analytics has established itself as a useful technique used to analyze employees who may be at risk of leaving in recent years. Organizations can use statistical models, machine learning and AI to explore historical/past data and current data to forecast attrition (Kumar, 2018). With Random Forest models, accuracies in predictions exceed 90.2% (Chakraborty, 2021). Common predictor variables utilized to properly predict turnover are job satisfaction, engagement and performance scores (Anuradha et al., 2024). Logistic Regression has its merits in the field because it is relatively easy to interpret and still provides reliable accuracy levels when the correct features are used (Sailaja Nimmagadda, 2024). Support Vector Machines also have the capabilities to provide strong predictive capabilities (around 85% accuracy similar to decision trees and in line with neural networks) (Shikha, 2019). With advancements in data-driven approaches to decision-making and leadership, organizations have greater opportunities to proactively address employee attrition.

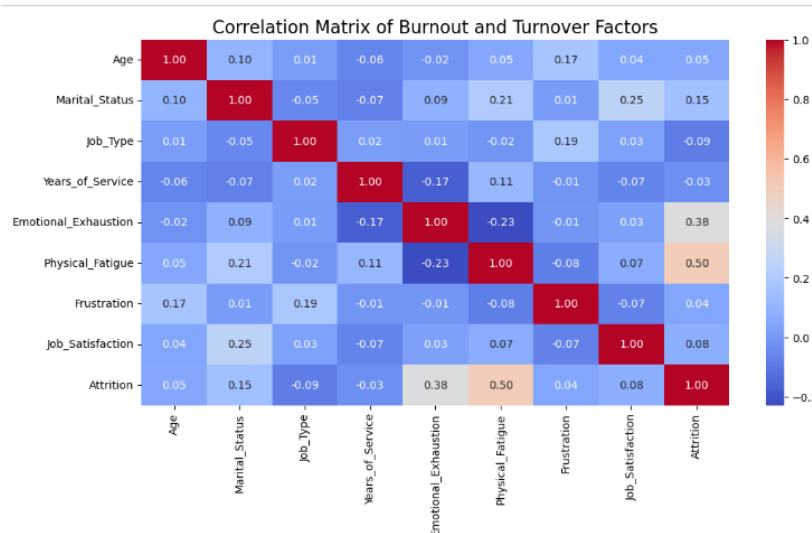
3. METHODOLOGY

This research undertook a quantitative and predictive research design to examine the relationship between employee burnout and attrition in the IT field. It has collected the information from 62 participants involving current and former employees of major IT companies such as TCS, Infosys, and Accenture based in Chennai. The responses were collected through structured Google Form that captured demographic details, burnout factors (emotional exhaustion, physical fatigue, frustration), and also attrition status. Exploratory data analysis, where correlation analysis have been accomplished using Python to study variable relations. The prediction for attrition was carried out using three machine-learning models, namely Random Forest, Logistic Regression, and Support Vector Machine, while their performance in producing the model was evaluated using the recall and F1-score. Further, a Power BI dashboard was built to visualize critical insights on employee burnout and turnover for an interactive and comprehensive view of the findings.

4. RESULTS

4.1 CORRELATION ANALYSIS

Figure 1: Correlation Matrix



The correlational output graphically shows the strength of the linear relationships among different factors and attrition rates among employees. The strongest factors positively correlated with attrition were physical fatigue (0.50) and emotional exhaustion (0.38). Thus, an employee who experiences a greater level of fatigue and burnout is most likely to be seriously considering leaving their job. Marital status (0.15) and job satisfaction (0.08) have the moderate positive correlations, suggesting a slight influence on attrition. Age (0.045) and frustration (0.044) are very weak correlations, indicating a minimal impact. On the contrary, years of service (-0.03) and job type (-0.088) show slightly negative correlations, which means that employees with longer service or certain job types are somewhat less inclined to resign. Busier, the above evidence shows that the burnout factors have a more significant influence on attrition than demographic or job-related factors.

4.2 PREDICTIVE ANALYTICS MODEL

Table 1: Logistic Regression

	Precision	Recall	F1 - Score	Support
0	0.80	0.67	0.73	6
1	0.75	0.86	0.80	7
Accuracy			0.77	13

Table 2: Random Forest

	Precision	Recall	F1 - Score	Support
0	1.00	1.00	1.00	6
1	1.00	1.00	1.00	7
Accuracy			1.00	13

Table 3: Support Vector Machine

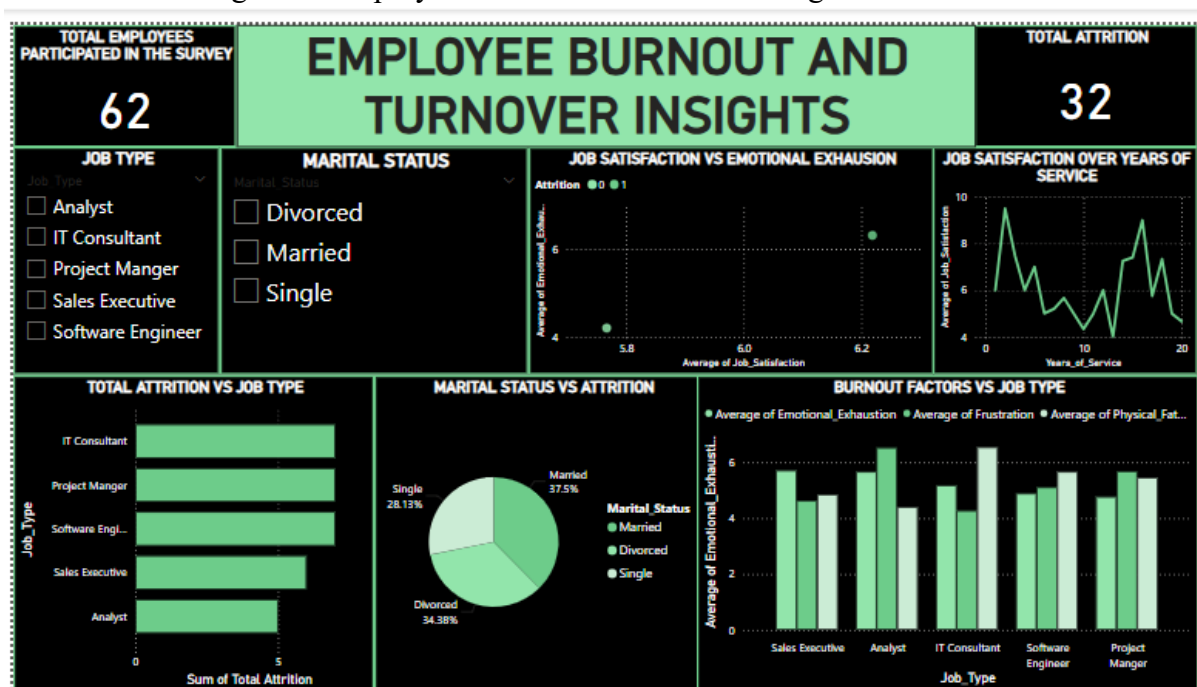
	Precision	Recall	F1 - Score	Support
0	0.71	0.83	0.77	6

1	0.83	0.71	0.77	7
Accuracy			0.77	13

The results of classification regarding prediction of attrition say that the best model is random forests as it scores perfectly on all metrics with 100% precision, recall and F1 score, and overall accuracy of 100% as well. Although such performance may indicate excellence, it may also mean defining possible overfitting, especially with small data. The Logistic Regression model had a better measure of performance as it amassed 77% in accuracy in general, and somewhat higher in recall (86%) for the attrition class, hence making it efficient in identifying employees likely leaving. The Support Vector Machine (SVM) also achieves 77% correctness with a performance balanced - precision of 83% and recall of 71% indicating slight conservatism in detection of attrition cases. Overall, Random Forest indeed has the highest performance; nevertheless, Logistic Regression may be a more reliable tool in practical applications because of its superior generalizability and good recall levels for the attrition class.

4.3 DASHBOARD ANALYSIS

Figure 2: Employee Burnout and Turnover Insights Dashboard



Analysing the power bi, gives an account of burnout-related areas and their relationship to employee attrition very comprehensively. Out of 62 employees surveyed, 32 have already exited the organization, indicating quite a high attrition rate. IT Consultants have high physical fatigue, Analyst have high frustration and sales executives have higher emotional exhaustion. Similarly, IT Consultants and Project Managers have the highest attrition rate. Therefore, there seems to be a definite link between burnout and attrition. On the contrary, Analysts have the least attrition and lower physical fatigue. The analysis shows the largest number of currently exited employees being married; however, the difference across marital statuses does not seem significant. Job satisfaction comes as one of the more important predictors of emotional exhaustion where less satisfaction is linked to more burnout and a greater chance to leave. In

patterns with years in service, it reflects that for some staying longer in the company does not guarantee satisfaction. Finally, burnout, especially emotional exhaustion, predicts attrition quite strongly, and some intervention would really help retain staff in high-risk job roles.

5. DISCUSSION

According to the findings of this research, it thus gains further credence to suggest that employee burnout and most especially physical fatigue and emotional exhaustion, predict attrition in the IT industry. The correlation study suggests that burnout-related variables have a greater contribution to the attrition of employees as compared to any demographic variable such as age and marital status, thus consistent with earlier works (Pandey & Risal, 2024; Raza et al., 2024), arguing that the major forces propelling the employee to leave the job are psychological strain and emotional fatigue. As for modeling, this research uses Random Forest, Logistic Regression, and SVM-the explanation behind the applicability towards predicting turnover on the oscillating factors of burnout indicators therein. Random Forest has controlled metrics demonstrating perfect performance (100% accuracy); however, the model suffers a challenge of overfitting because of the limited size of the training sample. On the contrary, a Logistic Regression model will make a more pragmatic and generalizable prediction, thus fitting better into HR scenarios where interpretability and stability are of primary concern.

Power BI visualization gave way to some additional findings. Employees originating from IT consultancy and project manager report considerably higher burnout levels, and therefore, higher attrition. Consistent with the grading done earlier, analysts report high burnout but low physical fatigue and attrition, saying that different roles will manifest quite distinct characteristics in terms of work-related stressors. High job dissatisfaction is therefore more likely to affect emotional exhaustion in regard to this finding: work satisfaction and job performance are inextricably linked. Hence this gives further justification for making retaining strategies work not just on stress but also on enhancing the work environment. All in all, it justifies that burnout is a multifactorial problem needing an evidence-based and targeted intervention-a special emphasis on high-risk working roles in high-stress industries such as IT.

6. CONCLUSION

IT professionals suffer a high attrition rate primarily due to employee burnout arising from physical fatigue and emotional exhaustion. This study fills an empirical gap through predictive analytics, allowing the findings to be utilized in models that are more action-oriented than correlational ones. Among all algorithms tested, Random Forest has shown almost perfect performance in classifying employees that are at risk of attrition due to burnout. In addition to pointing towards the predictive capability of the burnout factors being examined, this study highlights the urgent need for organizations to consider HR analytics as a strategic and business-oriented tool for employee retention. Interventions and wellness measures, together with work-life balance programs, should be specific to the role experienced in a high-burnout environment and include continuous feedback from employees on engagement to the organization. Future extensions of this work should include modeling robustness validation and tuning generalizability through larger and more heterogeneous datasets. Funding should now include supervening interventions for real-time monitoring of burnout symptoms as a strategic tool for HR managers to initiate timely action against attrition and foster a health-oriented organizational culture.

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