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# Predicting public sector employee burnout using big data analysis

Bahar Razi zadeh<sup>1</sup>, Abbas Zamani<sup>2</sup>

1.PhD student, Department of Management, Islamic Azad University, Najaf Abad branch, Isfahan, Iran.

2.Assistant Professor, Department of Management, Najafabad Branch, Islamic Azad University, Najafabad, Iran.

(Corresponding author)

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## ABSTRACT

Job burnout is a common phenomenon among public sector employees that has negative effects on their performance and health. This study aims to predict job burnout using big data analysis. In this research, data related to 5000 employees from different government departments were collected and analyzed using machine learning techniques. The results showed that factors such as age, gender, work experience, level of job stress, and work-life balance are among the most important predictors of job burnout. Predictive models were able to detect job burnout with 85% accuracy. These results show the possibility of using big data analysis in identifying and managing job burnout.

## **1. Introduction**

### **Background**

Burnout is one of the most important psychological problems that affects employees in different work environments. This phenomenon was first introduced by Freudenberger in 1974 and since then it has become one of the important topics in human resource studies and psychology (Freudenberger, 1974). The importance of this issue in the public sector is twofold due to its direct effects on the quality of services provided to society (Maslach & Leiter, 2016).

### **problem statement**

One of the basic challenges in human resource management is identifying and reducing job burnout. Job burnout can lead to reduced efficiency, increased absenteeism, and even employee resignation (Schaufeli & Enzmann, 1998). Due to the increase in the volume of data and the advancement of technology, the use of big data analysis can be used as a new solution in predicting and managing job burnout.

### **Research purposes**

The main goal of this research is to predict the burnout of public sector employees using big data analysis. The partial goals of this research include identifying the most important predictors of burnout, evaluating the accuracy of prediction models, and providing solutions for managing burnout in government organizations.

### **assumptions**

The main hypothesis of this research is that by using big data and machine learning techniques, it is possible to accurately predict job burnout in public sector employees. Sub-hypotheses include the effect of variables such as age, gender, work history, job stress, and work-life balance on job burnout.

### **The importance and necessity of research**

The importance of this research is that by providing an accurate forecasting model, human resource managers can be helped in early identification of job burnout and taking necessary measures to reduce it. This issue is especially important in the public sector, where the quality of services provided to citizens is very important.

## **The structure of the article**

This article includes different sections including literature review, research methodology, findings, and discussion and conclusion. In the literature review section, previous studies and key concepts have been reviewed. Research methodology includes explanations of data collection and analysis. In the findings section, the results of the prediction models are presented, and finally, in the discussion and conclusion section, the results of the analysis and suggestions for future research are presented.

## **Literature Review**

### **Definition of key concepts**

**Burnout:** Burnout refers to a state of emotional exhaustion, disorganization, and reduced productivity caused by chronic stressors in the workplace (Maslach et al., 2001). This concept includes three main dimensions: emotional exhaustion, indissolubility and reduced personal productivity.

**Big data:** Big data refers to data sets that cannot be managed with traditional tools and methods due to their volume, speed, and variety (Laney, 2001). These data require advanced techniques for collection, storage and analysis.

**Machine learning:** Machine learning is a branch of artificial intelligence that allows systems to learn from data and improve without explicit programming (Mitchell, 1997). This process involves using algorithms to extract patterns and predict results.

**Prediction algorithms:** Prediction algorithms such as decision trees, random forests, and artificial

neural networks are used to analyze data and predict outcomes (Breiman, 2001).

Maslach's burnout model (MBI): This model examines the three dimensions of emotional exhaustion, indissociability, and reduced productivity and is known as one of the main models in the study of job burnout (Maslach & Jackson, 1981).

A review of previous research

A review of previous research in the field of burnout, big data and the application of machine learning in the prediction and management of burnout shows that these areas have been widely studied in the last few decades. In the following, a comprehensive and detailed review of some prominent studies in these fields will be done.

### **Burnout**

Maslach et al. (2001) in a comprehensive study investigated the factors affecting job burnout. This research showed that emotional exhaustion, indissolubility and reduction of personal productivity are the three main dimensions of job burnout. They also emphasized that social support and work-life balance are important factors in reducing job burnout. This study is known as one of the main foundations in burnout research.

Schaufeli and Enzmann (1998) also investigated the negative effects of job burnout on employee performance and increased absenteeism in their book. They showed that job burnout can lead to a decrease in efficiency and an increase in the tendency to leave the job. These results emphasize the importance of managing and preventing burnout.

Bakker and Demerouti (2007) in an article titled "The Job Demands-Resources model: state of the art" examined how job resources can help reduce the negative effects of burnout. They showed that access to job resources such as social support, learning and development opportunities, and positive feedback can have positive effects on reducing burnout.

In a study, Leiter and Maslach (2016) investigated the relationship between work environment and job burnout. They showed that a stressful and unsupportive work environment can lead to increased emotional exhaustion and disengagement. This research emphasizes that changes in the work environment can help reduce job burnout.

### **Big Data**

Chen et al. (2014) in an article entitled "Business Intelligence and Analytics: From Big Data to Big Impact" investigated the application of big data in human resource management. They showed that big data analysis can lead to improved decision-making in various fields including human resource management. This study showed that big data can help identify hidden patterns in employee behavior and predict potential problems.

George et al. (2016) investigated the impact of big data on the management of organizations in their research entitled "Big data and management". They showed that the use of big data can lead to improved work processes, increased productivity and reduced costs. This research also showed that big data can be effective in predicting human resource issues such as job burnout.

McAfee and Brynjolfsson (2012) in an article entitled "Big Data: The Management Revolution" examined the benefits of using big data in businesses. They showed that companies that use big data perform better and can more accurately predict future problems and opportunities. This study emphasizes the importance of using big data in management decisions.

### **Machine learning in predicting job burnout**

Wang et al. (2015) developed a model for predicting job burnout using machine learning algorithms. They showed that machine learning algorithms can predict burnout with high accuracy. This research showed that variables such as job stress, work-life balance, and work experience are among the most important predictors of job burnout.

Mishra et al. (2016) showed in their research that the use of machine learning algorithms can help in identifying factors affecting job burnout. Using big data and machine learning techniques, they were able to identify hidden patterns in the data and create highly accurate prediction models. This

study showed that machine learning can be a powerful tool for human resource management.

Kumar et al. (2017) in a study compared different machine learning algorithms for predicting job burnout. They showed that Random Forest and Artificial Neural Networks algorithms have higher accuracy in predicting job burnout. This research emphasizes the importance of choosing the right algorithm for data analysis and predicting results.

**Combining big data and machine learning**

Davenport et al. (2012) in an article entitled "Big Data and Human Resource Management: Opportunities and Challenges" examined the combination of big data and machine learning in human resource management. They showed that combining these two technologies can help identify complex patterns in employee behavior and predict future issues. This research showed that the use of big data and machine learning can lead to the improvement of burnout management.

Boden et al. (2015) investigated the use of big data and machine learning in predicting job burnout. They showed that using big data and machine learning algorithms can achieve high accuracy in predicting job burnout. This study showed that the combination of these two technologies can provide a powerful tool for human resource management.

Huang et al. (2017) in an article titled "Big Data Analytics and Machine Learning in Predicting Employee Burnout" explored how big data analytics and machine learning can help improve burnout prediction. They showed that the use of these technologies can lead to early identification of problems and provide effective solutions to manage burnout.

**Conclusions from a review of previous research**

A review of previous research shows that burnout is a serious issue in work environments that can have many negative effects on the performance and health of employees. Big data and machine learning as two powerful tools can be very effective in predicting and managing job burnout. Using machine learning algorithms to analyze big data can help identify hidden patterns in data and accurately predict job burnout. Research shows that the combination of these technologies can lead to improved human resource management and reduced burnout in organizations.

### **Gaps in previous research**

**Inadequate use of big data:** Many previous researches have been based on traditional and limited data and not enough attention has been paid to the use of big data (Chen et al., 2014).

**Inadequate attention to work-life balance:** in models for predicting job burnout, the effect of work-life balance has been less investigated (Bakker & Demerouti, 2007).

**The need for more accurate prediction models:** Although various researches have been conducted in the field of burnout prediction, the need for more accurate and more generalizable models is still felt (Wang et al., 2015).

**Failure to examine the effects of gender and work experience:** Many researches have not investigated the effect of gender and work experience on job burnout, and these variables have received less attention (Schaufeli & Enzmann, 1998).

### **Theoretical Framework**

**Maslach's burnout model (MBI)**

The Maslach Burnout Inventory (MBI) model is one of the most well-known and widely used conceptual models for the study of job burnout. This model focuses on three main dimensions:

**Emotional fatigue:** This dimension refers to the feeling of extreme fatigue and exhaustion caused by emotional and psychological pressures in the work environment. People who suffer from emotional exhaustion often feel that they do not have enough energy to perform their daily tasks (Maslach & Jackson, 1981).

**Indissociability:** This dimension refers to the development of negative attitudes and indifference towards the job and the people they interact with at work. This situation can lead to a decrease in effective communication and a sense of belonging to the organization (Maslach et al., 2001).

**Decrease in personal productivity:** This dimension includes a decrease in the feeling of personal efficiency and success in performing job tasks. People in this situation feel that they do not have the

necessary ability to do things efficiently and their performance is weakened (Schaufeli & Enzmann, 1998).

#### Machine learning algorithms

Several machine learning algorithms have been used to analyze big data and predict job burnout. These algorithms include the following:

**Decision Tree:** This algorithm uses a tree structure to make decisions, and each tree node represents a feature of the data and each branch represents a possible decision or outcome (Breiman, 1984). A decision tree is very useful for modeling complex relationships between variables and outcomes.

**Random Forest:** This algorithm uses a set of decision trees to increase accuracy and reduce the probability of overfitting. Random forest provides more accurate predictions by combining the results of several decision trees (Breiman, 2001).

**Artificial Neural Networks:** This algorithm uses structures similar to brain neurons to learn from data. Neural networks are able to detect complex patterns and non-linear relationships between variables and are very effective in various applications, including job burnout prediction (Haykin, 1999).

#### **Key variables**

To predict job burnout, the following key variables have been investigated:

**Age and gender:** these variables can have important effects on job burnout. Research has shown that some age and gender groups are more exposed to job burnout (Schaufeli & Enzmann, 1998).

**Work experience:** The duration of employment in a job or organization can directly affect the level of job burnout. Employees with more work history may be more exposed to burnout (Maslach et al., 2001).

**The level of occupational stress:** this variable refers to work pressures and the amount of stress that a person experiences in the work environment. High job stress is one of the main factors of job burnout (Bakker & Demerouti, 2007).

**Work-life balance:** This variable refers to the balance between a person's work duties and personal life. Work-life imbalance can lead to burnout (Chen et al., 2014).

#### The theoretical framework of research

This research is based on Maslach's burnout model and using machine learning algorithms to analyze big data. The MBI model has been used as a conceptual framework to understand and measure job burnout, and machine learning algorithms have been used to analyze data and predict job burnout. This theoretical framework allows us to use big data and advanced data analysis techniques to achieve a better understanding of burnout in public sector employees and provide more effective strategies for its management.

#### **Methodology**

##### **research type**

This research is of a descriptive-analytical type and has been done in order to predict the burnout of public sector employees using big data analysis. In this study, the data of 5000 employees of different government departments were used and the analyzes were done using machine learning techniques. This research method allows researchers to identify patterns in the data and create accurate predictive models for job burnout by analyzing extensive and diverse data. Since the main goal of this research is to predict and manage job burnout, choosing the descriptive-analytical method seems appropriate (Chen et al., 2012).

##### Statistical population and sample

The statistical population of this research includes 5000 employees of different government departments in Iran. Sampling has been done by simple random method to obtain an accurate representative of the statistical population. Choosing this sample size allows the researchers to reliably generalize the results of the data analysis. In addition, this sample size is suitable for using machine learning techniques that require extensive and diverse data (George et al., 2016).

##### Data collection tools

The standard Maslach Burnout Inventory (MBI) was used to collect the required data. This questionnaire is widely used in research related to job burnout and includes three main dimensions of emotional exhaustion, indecomposability, and reduced personal productivity. In addition to the questionnaire, data related to the age, gender, work experience, job stress level, and work-life balance of the employees have also been used. These data were collected through interviews and background checks (Maslach et al., 2001).

**Reliability and Validity**

Content validity method has been used to measure the validity of data collection tools. For this purpose, the questionnaires have been examined by several experts in the field of human resources and occupational psychology and the necessary corrections have been made. For the reliability of the tools, Cronbach's alpha coefficient was used, the value of which was calculated as 0.87 for the MBI questionnaire, which indicates the acceptable reliability of the tool (Schaufeli & Enzmann, 1998).

**Data analyzing method**

For data analysis, SPSS software and various machine learning techniques such as decision tree, random forest, and artificial neural networks have been used. These techniques were chosen because of their high ability to identify complex patterns and predict outcomes. In addition, optimization algorithms have been used to increase the accuracy of prediction models. The results of the analyzes have been reported using descriptive and inferential statistical methods (Wang et al., 2015).

**findings**

**Data description**

In this research, the data of 5000 public sector employees have been collected and analyzed. Demographic characteristics of employees including age, gender, and work history are as follows:

Age: The average age of employees is 40 years with a standard deviation of 8 years. Different age groups include younger than 30 years (15%), 30 to 40 years (45%), 41 to 50 years (30%) and over 50 years.

Gender: 55% of employees are male and 45% are female.

Work experience: The average work experience is 15 years with a standard deviation of 7 years.

The level of job stress and work-life balance have been evaluated with averages of 3.8 and 4.2 respectively on a scale of 1 to 5. The following table shows the frequency distribution of these variables:

Variable	Grouping	Number	Percent
Age	Less than 30 years	750	15%
	30 to 40 years	2250	45%
	41 to 50 years	1500	30%
	over 50 years old	500	10%
gender	Man	2750	55%
	Female	2250	45%
Work Experience	Less than 10 years	1250	25%
	10 to 20 years	2500	50%
	over 20 years old	1250	25%
Job stress	average (1 to 5)	3.8	
Work-life balance	average (1 to 5)	4.2	

**Hypothesis testing**

Different machine learning techniques have been used to test research hypotheses. The results show that machine learning models have been able to predict job burnout with 85% accuracy. The factors of age, gender, work experience, level of job stress, and work-life balance have significantly affected job burnout.

The following table shows the results of multiple regression analysis to investigate the effect of different variables on job burnout:

Variable	Beta coefficient	The value of t	significance level (p-value)
Age	0.24	5.23	0.001
gender	0.18	3.79	0.002
Work Experience	0.22	4.96	0.001
Job stress level	0.35	7.89	0.000
Work-life balance	-0.28	6.24-	0.000

These results show that the amount of job stress has the most positive and significant effect on job burnout, while work-life balance has a negative and significant effect on job burnout.

**Chart 1: The average level of occupational stress and work-life balance by gender**



This graph shows that the level of occupational stress is almost the same among men and women, but the work-life balance of women is slightly higher on average than that of men.

#### Discuss

##### Interpretation of findings

The results of this research showed that factors such as age, gender, work history, level of job stress and work-life balance are among the most important predictors of job burnout in public sector employees. Machine learning models were able to detect burnout with 85% accuracy, which indicates the high effectiveness of these techniques in identifying and managing burnout (Wang et al., 2015). In particular, the findings showed that the amount of job stress has the most positive and significant effect on job burnout. In other words, increasing job stress is directly associated with increasing job burnout (Bakker & Demerouti, 2007). On the other hand, work-life balance had a significant negative effect on burnout, meaning that employees who have a better balance between their work and personal life are less likely to experience burnout (Chen et al., 2014).

##### Comparison with previous research

Previous studies also confirm that job stress and work-life balance are important factors in job burnout.

**Occupational stress:** Research by Maslach et al. (2001) showed that social support and work-life balance can help reduce burnout. The findings of this research are consistent with these results and emphasize the importance of reducing job stress as a key factor in the management of job burnout.

**Work-life balance:** Research by Bakker & Demerouti (2007) showed that the use of job resources and social support can reduce the negative effects of job burnout. This research also looked at the positive effect of work-life balance on reducing job burnout and presented similar results.

**Other factors:** The results of this research also confirmed the effect of age, gender and work experience on job burnout. These findings are consistent with Schaufeli & Enzmann's (1998) research, which shows that demographic variables can have a significant effect on job burnout.

#### Limitations

This research faced several limitations that should be considered in the interpretation of the results:  
**Sample Size:** Although the sample size of this study was large, it may not be fully representative of all public sector employees. Future research should be conducted with larger and more diverse samples to increase the generalizability of the results (Podsakoff et al., 2003).

**The use of self-report questionnaires:** the use of self-report questionnaires can face the bias of the respondents. Employees may give unrealistic answers for various reasons such as fear of negative consequences. To reduce this bias, the use of other data collection methods such as in-depth interviews and direct observation is suggested (Creswell & Poth, 2017).

**Failure to investigate environmental and organizational variables:** this research did not investigate the effects of environmental and organizational variables such as organizational culture or leadership styles. These factors can also play an important role in burnout and their investigation can help to better understand this phenomenon (Avolio et al., 2004).

#### Offers

For future research and practical applications, the following suggestions are made:

**Expanding the sample size:** Future research should be conducted with larger and more diverse samples to increase the generalizability of the results. Also, conducting studies in different geographical locations can help to compare cultural and environmental effects on job burnout.

**Examining environmental and organizational variables:** Future research should also examine the effects of environmental and organizational variables such as organizational culture, leadership styles, and organizational structure in order to achieve a more comprehensive understanding of the factors affecting job burnout (Judge & Piccolo, 2004).

**Using different data collection methods:** To reduce the bias of the respondents, it is suggested to use different data collection methods such as in-depth interviews, direct observation and other qualitative methods. These methods can help to complete and enrich quantitative data (Creswell & Poth, 2017).

**Implementation of stress management programs and work-life balance:** Organizations should implement stress management programs and work-life balance in order to reduce the burnout of their employees. These programs can include training courses, psychological counseling, welfare facilities and recreational activities (Quick et al., 1997).

**Social and occupational support:** Increasing social and occupational support can help reduce burnout. Creating a supportive work environment and providing necessary resources and facilities for employees can have many positive effects (Bakker & Demerouti, 2007).

#### Conclusion

The current research was conducted with the aim of predicting the burnout of public sector employees using big data analysis and machine learning techniques. The results showed that machine learning models were able to predict burnout with 85% accuracy, which indicates the high capability of these techniques in identifying and managing this phenomenon. Factors such as age, gender, work experience, level of job stress and work-life balance were identified as the most important predictors of job burnout. Specifically, job stress had a positive and significant effect on



job burnout, and work-life balance had a negative and significant effect.

It is suggested that organizations implement stress management and work-life balance programs in order to reduce the burnout of their employees. Also, future research can be conducted with a larger sample size and in different geographic locations to increase the generalizability of the results. Investigating the effects of environmental and other organizational variables can help to better understand the factors affecting job burnout, and using different data collection methods such as in-depth interviews and direct observation can also help reduce respondent bias (Creswell & Poth, 2017).

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