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Retraction

Retracted: Research on Job Burnout Evaluation and Turnover Tendency Prediction of Knowledge Workers Based on BP Neural Network

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

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Research Article

Research on Job Burnout Evaluation and Turnover Tendency Prediction of Knowledge Workers Based on BP Neural Network

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The traditional dimission prediction method for knowledge workers does not take into account the impact of job burnout on employees' dimission tendency, resulting in low accuracy of dimission prediction. In view of the above problems, this paper introduces the employee burnout evaluation and researches the knowledge employee burnout evaluation and turnover tendency prediction method based on BP neural network. After analyzing the influencing factors of job burnout of knowledge workers, the evaluation index system of job burnout is established. The weight of the job burnout evaluation index was determined by fuzzy hierarchy, and BP neural network model was established. Boosting method added the fusion layer of the correlation analysis of job burnout and turnover intention to the neural network model to predict the turnover intention of employees. In the method test, the accuracy rate of employee turnover tendency prediction is higher than 90%, the reliability of employee burnout evaluation is higher, and it is more helpful for human resource management.

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1. Introduction

With the accelerating pace of world integration and economic globalization and the rapid development of information technology, the focus of global competition has tended to shift from material resources to soft resources such as talents, science and technology, information, and capital. The shortage of high-tech knowledge-based talents has long been a common problem in the world today, so how to strengthen the development of talent resources and create a good environment for talents to start their own business, so as to attract and retain talents is a top priority for any enterprise. At present, the competition for talents is becoming more and more fierce, and the enterprises hope to recruit talents, train talents, use talents, and retain talents in various ways, so as to maximize the role of talents. In several industries, the phenomenon of talent loss shows an increasingly serious trend, and the abnormal high-frequency flow of enterprise employees usually destroys the originally more stable industrial and worker teams, significantly increasing various explicit and implicit operating costs of enterprises, and the departure of key talents will have a great impact on the development of enterprises [1]. Preventing talent loss and reducing recruitment costs has become an urgent task for many companies. This study defines the propensity to leave as a behavioral tendency of employees to plan to give up their current jobs or leave their jobs and organizations, and it is also an important basis for weighing whether an individual will really leave or not. Due to the changes in the work processes and environment of employees, it is difficult for some organizations and employees to adapt, and subsequently, the work pressure keeps increasing, week after week, leading to a sudden sense of burnout, which is present in every employee to some extent. Although there is no way to directly prevent employees from leaving, companies can try different measures to make

employees change their decision to leave as much as possible. By anticipating and taking action before talent leaves, companies can greatly reduce the damage caused by talent loss. While economists were the first to study employee turnover, psychologists have also been conducting research on employee turnover, and are gradually moving away from single-factor turnover research to multifactor turnover research.

Knowledge-based workers' work is a complicated cerebral thinking process that is not confined by time or place, has no specific steps or processes, is implicit, autonomous, and self-contained, and is difficult to gaze into and monitor. Employee departures result in a loss of human resources and an increase in management expenses, both of which have a significant impact on a company's future growth and are issues that companies must confront and address. The elements that influence the departure of knowledge-based talent are many, and in order to provide an accurate forecast, all parts of talent data must be considered. Data mining technology is frequently utilised in human resource management, with an emphasis on turnover prediction, reasons for turnover, and remedial strategies. Single classifier algorithms such as KNN, SVM, and decision tree have helped enterprises predict the risk of talent turnover to some extent with the development of machine learning, but the talent turnover prediction models thus constructed have problems such as low prediction accuracy and poor generalisation, making it difficult to meet the actual requirements of enterprises [2–5]. Employee turnover has long been a subject of human resource management research, and numerous experts both at home and abroad have studied the link between work satisfaction and turnover tendency. However, research on the association between turnover tendency and burnout is confined to certain groups, and research on the influence of each component of burnout on turnover tendency is insufficiently precise and in-depth. To enrich the theory of turnover tendency, it is of excellent theoretical value to expand the research on the link between burnout and turnover tendency and investigate the association between burnout and turnover tendency of the knowledge personnel.

Some scholars have started to use neural networks to predict employee turnover tendency, which has improved the accuracy of prediction to a certain extent [6]. However, there are too many factors affecting employee turnover in modern society, and the traditional prediction methods have certain limitations, which make it difficult to meet the demand for knowledge-based talent management. In order to identify and control the impact and risk brought by their knowledge-based employee behaviors to enterprises and effectively dissect the reasons for knowledge-based employee departures, this paper will purposefully introduce burnout as an important indicator to measure employees' work emotions and study the BP neural network-based burnout assessment and departure tendency prediction method for knowledge-based employees in order to provide talent management in future enterprise HRM work management suggestions, reduce the proportion of knowledge-based talents leaving the enterprise, and reduce the enterprise's investment in knowledge-based talents leaving management.

2. Research on Job Burnout Evaluation and Turnover Tendency Prediction of Knowledge Workers Based on BP Neural Network

2.1. Factors Influencing Burnout among Knowledge Workers. The increase of diversified demand for talents, the rise of uncertainty in career development, the accelerated pace of work and life, and the increase in cost of living aggravate the emotional exhaustion of employees, the increasing complexity of the interpersonal network, the increase of work saturation, and the imbalance between the organisational system and the work environment and the match of individual knowledge employees, and other factors lead to the overload of physical functions of knowledge employees and produce a state of exhaustion or physiological discomfort, that is, individual fatigue. Work fatigue not only adversely affects the physical and mental health of individuals but also restricts the labor efficiency and performance of knowledge-based employees, and affects the positive competitive posture of enterprises.

Employee job tiredness caused by knowledge-based tasks is an essential aspect of human capital management and an important notion for the long-term success of modern businesses in the knowledge-based economy. The knowledge economy is based on the efficient development and investment of human capital. Individual efficiency cannot remain efficient for a long time in the context of established time constants, and there are fluctuations, according to the human capital investment aspect of labour economics theory, and the study of work fatigue contributes to the longevity and high rate of return of human capital. Employee burnout is becoming increasingly widespread as a primary source of competition for the success of firms with knowledge-based staff [7]. As a consequence, burnout occurs, and its antecedent variables are many and complicated. When knowledge-based workers of businesses experience burnout, they are more prone to lose motivation, which leads to a vicious cycle in which employees are more inclined to abandon their positions.

The formation of burnout among knowledge employees cannot be separated from individual, professional, organisational, and social reasons, and once burnout is formed, it will in turn have direct or indirect effects on these aspects. The factors affecting burnout of knowledge-based employees can be divided into individual and external dimensions in general, among which the individual dimension is mainly the demographic characteristics of individuals, covering age, position, education, working years, and other factors, respectively. Usually, young people under 30 years of age, who have just taken up their jobs, are full of enthusiasm and thus have a relatively low sense of burnout, while the older they get, the more their enthusiasm decreases with the boring

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work week after week, leading to an increase in burnout. At the same time, burnout is higher in women than in men, which is due to the fact that usually women are engaged in more repetitive labor positions, boring and tedious work, and increasing family pressure, leading to higher burnout in women than in men [8]. Employees' sense of psychological control, personality traits, emotions at work, career expectations lifestyle, and interpersonal relationships can also influence burnout. In addition, education, position, and marital status are correlated with burnout.

External variables that impact knowledge workers' burnout may be separated into occupational, organisational, and social aspects. Occupational factors include occupational type, role, and workload; organisational factors include organisational culture, motivation, and equity; and social factors include national industrial policy adjustments, social manpower competition pressure, regional labour market characteristics, and social support, among others [9]. The factors that can be used to assess the burnout of knowledge-based employees are selected as assessment indexes based on the above analysis of the factors affecting employee burnout, and a burnout assessment index system is established to predict employees' tendency to leave with the results of burnout assessment.

2.2. Construction of Employee Burnout Assessment Index System. Knowledge-based employees usually have strong learning ability and creativity, strong demand for self-development, high mobility in career choice, generally high education level, low loyalty to the company, heavy workload and overtime, and generally high life stress, etc. All dimensions of work stressors and burnout are positively correlated, and previous studies considered satisfaction as an influencing factor of employee burnout. In addition to supporting this view, this study also found that satisfaction is the most important factor influencing burnout of knowledge-based employees. Based on the analysis of the factors influencing the burnout of knowledge-based employees in the above paper, this paper establishes the burnout assessment index system for knowledge-based employees as shown in Table 1 below [10].

When the workload is low or high, human performance is poorer and burnout is greater, according to the employee burnout evaluation index presented in Table 1 China. The key variables impacting employee burnout, according to the characteristics and job aspects of knowledge-based workers, are psychological strain generated by occupation, work pressure, and changes in the quality of life of employees, in addition to employee contentment with their profession. The weights of the aforementioned primary components' assessment indexes are set relatively high, and the index weights are derived using hierarchical analysis to create a neural network model for assessing employee burnout.

2.3. Establish the Neural Network Model of Employee Job Burnout Evaluation. Since there are differences between the main and secondary factors affecting job burnout of knowledge workers engaged in different fields, fuzzy hierarchy theory is adopted in this paper to calculate the weight of each evaluation index in Table 1. Different evaluation indexes have different evaluation grades. This study is set as an evaluation set $P = \{p_1, p_2, \ldots, p_m\}$, where p_i represents the evaluation grade corresponding to the indexes. Evaluation indexes consist of the evaluation factor subset $U = \{u_1, u_2, \ldots, u_n\}$, and u_j is the evaluation index of knowledge workers' job burnout [11]. The fuzzy subset $W = \{w_1, w_2, \ldots, w_k\}$ on the evaluation factor subset is the weight assignment, and w_k is the weight considered by the evaluation factor w_k. The vector $R(u_i)$ of a fuzzy mapping R from the evaluation factor subset to the comment set is a single factor evaluation, and it is a fuzzy subset of the comment set, where r_{ij} represents the membership degree that this index can be rated as p_i considering factor u_i. The transformation matrix R of comprehensive evaluation is obtained by combining all the vectors of fuzzy mapping.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}. \tag{1}$$

When analyzing the job burnout of knowledge workers, the weight of each assessment index is shown in the matrix above. To create the employee job burnout assessment neural network, the weight is used as the connection weight of each layer of the BP neural network.

The number of nodes in the knowledge worker burnout assessment neural network's input layer matches the number of indicators in the criteria layer, and the number of nodes in the hidden layer matches the indicator layer's number of indicators. Because the output of the BP neural network node number is 2, the output of the BP neural network node number is job burnout evaluation for employees and employee turnover intention. To analyze the association between knowledge workers' job fatigue and turnover intention, a fusion layer is added to the traditional three-layer BP neural network to predict employees' turnover intention [12]. When evaluating job burnout of knowledge workers, the input function of the hidden layer is as follows [13]:

$$H_j = \sum_{j=1}^{n} r_{ji} x_i + q_{j0}, \tag{2}$$

where H_j is the input of the hidden layer; r_{ji} is the weight of evaluation index calculated by fuzzy hierarchy; x_i is the i th input node of the hidden layer; q_{j0} is the calculation threshold of the hidden layer. The activation function of the BP neural network for employee burnout assessment is defined as follows:

$$F(x) = \left[1 + e^{-x}\right]^{-1}. \tag{3}$$

The error function between the output of BP neural network assessment results and the expected output of job burnout assessment is defined as follows [14]:

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Table 1: Employee burnout assessment index system.

Target layer	Guideline layer	Indicator layer	Indicator definition
Burnout assessment for knowledge workers	Individual factors	Demographic characteristics	Gender, age, years of service, income, education, job rank, marital status, maternity status
		Personality traits	Psychometric personality types
		Mental health (subjective well-being)	Employees' subjective feelings
		Career aspirations (career aptitude)	Attitudinal tendencies of employees who wish they were in a particular career
		Lifestyle	Regular health checkups, quality of diet, quality of sleep, personal preferences
		Interpersonal stress	Including interpersonal stress with customers, colleagues and superiors
		Interpersonal skills	Employee's ability to handle interpersonal relationships
	Work factors	Job pleasure	Can employees enjoy their work
		Work regularity	The degree of regularity with which employees perform their jobs
		Professional tension	Mental tension of employee job work
		Working environment	Employee's work environment impact
		Workload	Whether the workload of the employees is acceptable
		Work-life balance	The impact of work on employees' lives
		Size of responsibility	The amount of responsibility employees assume
		Salary satisfaction	Employee satisfaction with compensation
	Organizational factors	Social status of the occupation	Social identity of the occupation
		Basic characteristics of the organization	The nature of the organization, level
		Job satisfaction	Employee satisfaction with their jobs
		Sense of belonging to the organization	The organization gives members a sense of belonging
		Interpersonal atmosphere	Whether there is an atmosphere of mutual trust, mutual understanding, mutual motivation, mutual concern, and mutual cooperation in the organization
	Social factors	Social support	Difficult help given to employees in different dimensions of society

$$E(\vec{r}) = \frac{\|\vec{e} - \vec{z}\|^2}{2}, \tag{4}$$

where $\vec{e}$ is the expected output of the evaluation network output node; $\vec{z}$ is the actual output of the evaluation network output node; $\vec{r}$ is the weight threshold vector of job burnout evaluation. After establishing the BP neural network model of job burnout evaluation for knowledge workers, the correlation between job burnout and turnover intention is analyzed, and the prediction result of turnover intention is obtained by perfecting the BP neural network model.

2.4. Realize the Prediction of Turnover Tendency of Knowledge Workers. To achieve the prediction result of the turnover tendency of knowledge workers, the boosting technique is used to establish the association between job burnout and the turnover tendency of knowledge employees, and the weak learner of the boosting method is used to categorise them. Boosting works at fitting many weak learners consecutively in a very flexible way: each model in the series provides more weight to observations in the sequence that were poorly handled by prior models.

The based model is often used to enhance the low variance high bias model since it focuses on reducing bias. Both classification and regression may benefit from boosting. Boosting the principles behind is as follows: each step creates a weak learning, learns by repeatedly applying the weak of the weighted sum to the whole model, and ultimately gets a strong prediction model. The following is the fundamental formula [15]:

$$B_t(x) = \sum_{i=1}^{t} \xi_i b_i(x), \tag{5}$$

where t is the number of base learners, ξ is the coefficient, b is the base learners, and B is the total predictive classification learners. Boosting method's training objective is to minimize the loss function as much as possible, while the total predictive classification learner is weighted by multiple base learners, so it is impossible to solve simultaneously. Therefore, gradient lifting uses a greedy algorithm to improve B's performance step by step by predicting the classification learner B as a constant function at the beginning and solving the base learner and its coefficients one at a time. Each time I make this term equal to the negative gradient of the loss function, I minimize the loss function the fastest. Boosting method was used to analyse the correlation between knowledge employees' job burnout evaluation results and turnover intention, and then it was used as the fusion

Table 2: Experimental results of the method.

Company number	Method based on BP neural network		Method based on decision tree		Method based on data mining	
	Deviation of evaluation	Turnover prediction accuracy (%)	Deviation of evaluation	Turnover prediction accuracy (%)	Deviation of evaluation	Turnover prediction accuracy (%)
1	2.2	93.8	8.2	85.1	6.7	89.2
2	4.5	92.2	6.6	87.8	7.0	86.8
3	4.1	90.1	7.9	89.2	7.1	87.9
4	4.7	92.9	6.5	86.6	7.3	87.4
5	4.2	93.3	6.7	88.9	5.4	86.3
6	3.9	92.5	7.8	86.3	6.3	87.8
7	4.1	91.7	5.4	86.5	6.9	89.5
8	4.3	90.1	6.5	86.4	7.7	89.1
9	3.9	92.4	9.0	84.2	6.9	89.6
10	4.5	93.6	7.3	86.7	7.5	88.9

layer of the BP neural network to process the employees' job burnout evaluation results of the hidden layer, and the final prediction result was obtained. The data related to job burnout and turnover intention of knowledge workers are selected to form a sample set to train the BP neural network and determine the connection weights of each layer of a network [16]. The above is to complete the job burnout assessment and turnover tendency prediction research of knowledge workers based on the BP neural network. The BP neural network can be used to judge the specific situation of employees in advance so that the human resource management department can take various measures to weaken the turnover tendency and enhance the stability of employees.

3. Experimental Research and Analysis

Above studies the knowledge staff job burnout assessment based on BP neural network and turnover tendency forecasting method, this section will evaluate the reliability of the method and the test and analysis of prediction accuracy.

3.1. Experiment Content. This article examined and contrasted work burnout and turnover intention prediction methods based on data mining and prediction methods of job burnout and turnover intention, job burnout evaluation based on the decision tree, and turnover forecast technique. The training set consisted of 65 percent of the dimission data of knowledge workers from various industries, while the test set consisted of 35 percent of the data set, and the test set was utilised as the reference for the experimental outcomes. Following the application of three procedures to the experimental data set, the output was compared to the test set, and the measurement's reliability and accuracy were assessed.

3.2. Experimental Results. Table 2 compares the reliability of job burnout assessment and the accuracy of turnover intention prediction of knowledge workers using three different methods. In this experiment, the deviation between the proportion of burnout and the real proportion was used to characterize the reliability of evaluation results, and the accuracy of turnover prediction was used to characterize the accuracy of turnover tendency prediction.

By analyzing the data in Table 2, it can be seen that the prediction accuracy of the method in this paper for employee dimission is higher than 90%, and the prediction accuracy is far superior to the other two methods. In terms of the resulting bias of the method for knowledge workers' burnout evaluation, the method presented in this paper is not only numerically smaller than the other two methods but also has a smaller evaluation bias fluctuation range, indicating that the method presented in this paper is more reliable for employees' burnout evaluation. To sum up, this paper studies the knowledge staff job burnout assessment based on BP neural network and turnover tendency prediction method in practical application, to be able to accurately assess employees' job burnout and predict turnover intention; work for human resource management provides a reliable technical support.

4. Conclusion

In the era of the knowledge economy, knowledge and professional skills have become important resources to create wealth and become the most critical resources in economic development. The competition among enterprises for human resources is becoming increasingly fierce, which means that whoever has abundant human resources can seize the initiative in the era of the knowledge economy. The demand for various types of workers in the domestic and foreign markets has increased significantly, and the ability and physical and mental quality of workers also gradually put forward higher requirements, and the phenomenon of occupational stress is becoming increasingly prominent. Our country's economy is now in a stable state of growth, and talent flow is reasonably active; yet, our country's company confronts new challenges in terms of talent management. Employee turnover will always result in some losses for the company, with the negative effect of employee turnover in key roles being more visible. Staff work burnout has been more widespread in recent years as a result of increased competitive pressure. Maintaining the stability, cohesiveness, and inventiveness of employees is critical to the success of any business. Employees from all areas of life are being laid off at an alarming pace at the moment.

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Dimission tendency research has long been a source of controversy and difficulty in the area of human resource management. This research presents a technique for evaluating job exhaustion and predicting knowledge worker turnover based on BP neural networks. The reliability of the assessment outcomes of this approach, as well as the accuracy of employee turnover propensity prediction, are confirmed by an experimental investigation. That is, after modifying the necessary parameters, the approach may be used for the management of knowledge talent resources in various sectors.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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