Eng Int Syst (2025) 5: 597–606

Engineering
Intelligent Systems

The Impact of Employees' Mental Health Status on Performance Based on Data Mining

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With the intensification of global competition, employee mental health issues have increasingly become a key factor affecting corporate performance. A large multinational technology company A has more than 20,000 employees worldwide. It was found that about 40% of employees had experienced varying degrees of mental health challenges, such as anxiety and depression, in the past year. To meet this challenge, Company A launched the "Psychological Capital Improvement Program", which aims to evaluate and improve employees' mental health through data mining technology and psychological models, and improve job satisfaction and performance. The project team first conducted demand research and technology selection, chose suitable data mining tools, and established a multi-source data collection platform, integrating information such as mental health questionnaires, behavioral logs, and physiological signals. Through multiple linear regression, LSTM model and cluster analysis, the complex relationship between mental health status and performance was revealed. Based on these analysis results, personalized management strategies were formulated, such as interventions to stimulate work motivation and support mental health. Ultimately, through continuous monitoring and optimization of processes, Company A significantly improved the mental health level and work efficiency of its employees, while also promoting the growth of innovation capabilities. The success of this project not only brought significant economic benefits and social value to Company A, but also provided valuable experience for other companies in terms of mental health management.

Keywords: mental health management, data mining, personalized intervention, performance improvement, LSTM

1. INTRODUCTION

Employees are the core resource for enterprise development, and their mental health is directly related to the production efficiency and sustainable development capabilities of enterprises. With the rapid development of the social economy, the increase in work pressure and the accelerated pace of life, the mental health problems of employees are becoming increasingly prominent. According to statistics from the World Health Organization (WHO), about one-third of employees worldwide have suffered from mental health problems such as anxiety and depression in their careers. These psychological problems not only affect the physical and mental health of individuals, but may also lead to problems such as reduced productivity, poor team collaboration and even high turnover rates [1, 2]. How to effectively manage and improve the mental health of employees has become an important issue that cannot be ignored in the human resource management of modern enterprises [3].

In corporate management practice, the significance of mental health management is that it can improve employees' happiness and job satisfaction as well as work efficiency, and reduce the risk of accidents caused by psychological problems. As an important part of the sustainable development of enterprises, mental health management can help enterprises maintain their competitive advantages. Therefore, in-depth research on the relationship between employee mental health and performance, and the exploration of effective management strategies, are of great theoretical and practical significance for corporate management [4, 5].

The impact of mental health on employee job performance has broad theoretical and practical support. Employees with

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good mental health usually have stronger work concentration, creativity and teamwork ability, which enables them to complete work tasks better. Conversely, poor mental health may lead to lack of concentration, reduced work efficiency and increasing conflicts with colleagues or customers, which will have an adverse impact on individual performance and overall team performance. Academic research shows that there is a complex two-way relationship between mental health and performance. On the one hand, mental health has a direct impact on performance; for example, increased anxiety levels may lead to decreased productivity. On the other hand, in turn, the level of work performance may also affect mental health [6, 7]; for instance, long-term high-performance pressure may place a psychological burden on employees. Therefore, a comprehensive analysis of the potential relationship between mental health and performance requires not only considering the direct impact of mental health on performance, but also exploring potential mediating factors and path mechanisms, such as job satisfaction, organizational support and team relationships [8].

The aim of this study is to explore the impact of mental health status on employee performance, focusing on the main factors influencing employees' mental health status, its impact on work performance through direct or indirect paths, and whether there are significant differences in performance among specific mental health status groups. The study uses data mining technology to analyze the data collected by the company regarding employee mental health and performance, to reveal the correlation between the two, and construct a mental health management model that companies can use to achieve effective monitoring and management of employee mental health. In terms of theory, this study introduces data-driven analysis methods to fill the gap in the research involving analysis of data pertaining to employee's mental health and performance, and provide a new research perspective. In regard to practical application, the research results can be transformed into management tools such as mental health status prediction models and performance risk early warning systems to help companies achieve early intervention and personalized management of mental health, improve employee satisfaction and overall performance, and provide data support for corporate human resource management.

2. LITERATURE REVIEW

2.1 Current Status of Research on Mental Health and Performance

Mental health is one of the core driving forces of employee work efficiency and innovation. Studies have shown that employees with good mental health usually demonstrate greater enthusiasm for work, and stronger adaptability, thus having an advantage in productivity and innovation. Mental health has a significant positive impact on employees' positive behaviors (such as initiative and creativity). This positive impact is not only reflected at the individual level, but also extends to the overall performance of the organization through the strengthening of teamwork [9]. In addition, mental health damage, such as anxiety and depression, is often associated with low efficiency, increased error rates and increased employee turnover rates [10]. In the study of mental health and performance, psychology and management theory provide important theoretical frameworks. The hierarchy of needs theory proposes that mental health is a prerequisite for self-realization [11]. Employees with poor mental health cannot meet their basic security needs, let alone achieve self-realization, which has a negative impact on performance. Another key theory is the stress-performance curve [12], which points out that the relationship between stress and performance is an inverted U-shaped: moderate psychological stress may stimulate employee potential, but excessive psychological stress will lead to decreased performance. Therefore, maintaining a balanced state of employee mental health is an important goal of corporate management.

2.1.1 Application of Data Mining Technology in Mental Health Research

With the development of data science, data mining technology has been widely used in mental health research to reveal hidden patterns and laws. Common data mining methods include cluster analysis, association rule mining, and regression analysis. In addition, machine learning methods such as support vector machines and random forests have been used to predict employees' mental health status and its impact on performance. In terms of software tools, Python, R, SPSS, etc. have become important auxiliary tools in research, especially libraries such as Scikit-learn and TensorFlow in Python, which provide powerful algorithm implementation capabilities. Although data mining technology is widely used, the collection and analysis of mental health data still faces many challenges. On the one hand, mental health data involves privacy and ethical issues, and the legality and security of data acquisition need to be strictly managed. On the other hand, mental health data are usually highly subjective and heterogeneous. For example, the relationship between psychological questionnaire scores, work performance evaluations, and biological signals (such as heart rate and brain waves) is relatively complex and difficult to compare directly [13, 14]. In addition, the processing of missing data and the multicollinearity between variables are also technical difficulties in analysis.

2.1.2 Research Gaps and Improvement Directions

Although existing studies have revealed the relationship between mental health and performance, there are still some shortcomings. First, most studies rely on cross-sectional data and find it difficult to capture dynamic causal relationships. For example, short-term fluctuations in mental health may have an immediate impact on performance, but the long-term cumulative effect has not been fully studied [15, 16]. Second, many studies use self-report questionnaire data, which is susceptible to social desirability bias, thus affecting the reliability of the results. In addition, the relationship between mental health and performance of employees in different companies and industry backgrounds is heterogeneous, but existing studies mostly use a single background as a research sample and lack universality. To make up for the shortcomings of existing research, this study proposes several innovations. First, using time series analysis and dynamic regression models, it explores the dynamic relationship between mental health and performance and captures the temporal variation characteristics of the impact of mental health on performance. Second, mental health questionnaires, behavioral data (such as work logs) and biological data are integrated to achieve multi-source data fusion and improve the dimensionality and reliability of data [17]. Third, based on cluster analysis and personalized recommendation algorithms, personalized management strategies are formulated for employees with different mental health issues [18, 19]. Fourth, LSTM is used to analyze the long-term impact of temporal changes in mental health on performance.

3. RESEARCH METHODS AND TECHNICAL FRAMEWORK

This study aims to reveal the dynamic impact of employees' mental health status on performance. To this end, a technical framework based on data mining and deep learning is constructed. It comprises dynamic data analysis, multi-source data fusion, personalized analysis, and LSTM-based time series prediction model. The following sections discuss the research model design, data sources and preprocessing, and evaluation indicators and technical tools.

3.1 Research Model and Innovations

This study uses dynamic data analysis methods to capture the temporal correlation between mental health status and performance. Mental health status is a variable that changes over time, and changes in performance may also be affected by multiple temporal factors. Based on time series analysis and dynamic regression models, the study assumes that Y_t there is a significant temporal correlation between performance indicators and mental health status. Its mathematical expression is as follows H_t, as shown in Equation (1) [20, 21].

$$Y_t = \beta_0 + \beta_1 H_t + \beta_2 X_t + \epsilon_t \tag{1}$$

where them, Y_t represents the performance level at time t, H_t is the mental health score, X_t represents other control variables (such as working hours, task difficulty, etc.), and ϵ_t is the random error term. Through the dynamic regression model, the immediate and lagged effects of mental health on performance can be clarified, and a reference can be provided for corporate decision-making [22].

Multi-source data fusion is one of the core innovations of this study. The mental health status of employees can be quantitatively analyzed through questionnaire scores (such as depression scores and anxiety scores), and by extracting key features from behavioral data (such as work logs and attendance records) and biological data (such as heart rate variability and sleep quality). Based on the Bayesian inference formula, we integrate multi-source data into a unified probability distribution framework to ensure the complementarity of various types of data, as shown in Equation (2).

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)} \tag{2}$$

where, D represents data sets from different sources, and H represents mental health status. The fusion of multi-source data can effectively improve the accuracy and robustness of mental health status prediction.

In order to meet the management needs of employees with different mental health status, this study also designed a personalized analysis module. By means of cluster analysis methods (such as K-Means clustering and hierarchical clustering), employees are divided into different groups with different mental health status and performance characteristics. On this basis, combined with personalized recommendation algorithms, corresponding mental health intervention and management strategies are proposed for each type of employee. For example, for the “high health and low performance” group, the focus should be on improving work motivation; while for the “low health and low performance” group, psychological support and stress relief intervention should be strengthened [23].

Finally, the deep learning model (LSTM) is an important technical tool adopted for this study. Both mental health and performance indicators have time series characteristics, and it is difficult to capture long-term dependencies using traditional regression methods. LSTM (Long Short-Term Memory Network) can effectively handle the dynamic changes of long time series through the memory gating mechanism. The relevant equations are shown in Equations (3)-(7).

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{3}$$
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{4}$$
$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{5}$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{6}$$
$$h_t = o_t \odot \tanh(c_t) \tag{7}$$

By training the LSTM model, we can capture the long-term impact trend of mental health on performance and provide companies with dynamic prediction and intervention references.

3.2 Data Source and Preprocessing

The data sources of this study cover multiple dimensions, mainly including mental health questionnaires, employee behavior logs, key performance indicators (KPIs), and biological data. The mental health questionnaire mainly uses internationally recognized scales, such as depression scores (PHQ-9) and anxiety scores (GAD-7); the behavior log records employees' working hours, task completion, and rest periods; biological data are collected through portable sensors, covering indicators such as heart rate, blood pressure, and sleep duration. These data can reflect employees' mental state and performance level from different perspectives [24].

Data preprocessing is required before modeling. First, for the processing of missing values, this study used the KNN (K-Nearest Neighbors) interpolation algorithm to preserve the temporal consistency of the data. Second, to avoid the problem of inconsistent scales between different data sources, all variables were standardized, as shown in Equation (8) [25].

$$z = \frac{x - \mu}{\sigma} \tag{8}$$

where x is the original value, μ is the mean, σ The standardized data is suitable for machine learning algorithms and also improves the training effect of deep learning models.

In addition, for time series data, this study performed time window segmentation. For example, the mental health and performance data for a consecutive year were divided into windows by week, and each window contained multiple feature vectors, which were convenient for the input of the LSTM model. The sliding window technology improved both the data utilization rate and the model's ability to capture time dependence.

3.3 Evaluation Indicators and Technical Tools

This study used multidimensional evaluation indicators to measure the effectiveness and predictive ability of the model. Mental health indicators include depression scores, anxiety scores, and resilience scores (Resilience Scale); performance indicators include KPI completion rate, task efficiency, and innovation contribution. Together, these indicators provide the basis for the analysis of the correlation between mental health and performance.

The model performance is evaluated using the following indicators:

(1) Mean Square Error (MSE) measures the deviation between the predicted value and the true value, as shown in Equation (9).

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{9}$$

(2) Mean absolute error (MAE): The absolute value of the deviation is averaged to reduce the impact of extreme values, as shown in Equation (10).

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{10}$$

(3) Coefficient of determination (R^2) is used to measure the goodness of fit of the model, and its value range is from 0 to 1, as shown in Equation (11).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{11}$$

Regarding technical tools, this study used Python and TensorFlow for data analysis and modeling. Pandas is used for data cleaning and feature engineering, Scikit-learn is used for clustering analysis and regression modeling, and TensorFlow is used for the construction and training of LSTM networks. The entire research process was completed based on an open-source framework to ensure the reproducibility and versatility of the research.

4. EMPIRICAL ANALYSIS

4.1 Case Background

A large multinational technology company, A, (hereinafter referred to as "Company A") has more than 20,000 employees worldwide, and its business scope covers software development, hardware manufacturing, technical services and other fields. In recent years, with the intensification of market competition and the acceleration of work pace, the management of Company A has gradually realized that the mental health problems of employees have had a significant impact on the company's overall performance. According to internal surveys, about 40% of employees have experienced varying degrees of mental health challenges in the past year, such as anxiety and depression. These problems not only affect individual work efficiency, but also have a negative impact on team collaboration and corporate innovation. In order to meet this challenge, Company A decided to launch a project called "Psychological Capital Improvement Plan", which aims to evaluate and improve the mental health status of employees through scientific methods, thereby improving employees' job satisfaction and personal performance. To this end, Company A cooperated with many well-known universities and research institutions, introduced advanced data mining technology and psychological theoretical models, and built a comprehensive mental health monitoring and intervention system. The establishment of this system was based on a large number of empirical studies including, but not limited to, multi-source data fusion such as employee mental health questionnaires, daily behavior data analysis, and physiological index collection. At the same time, in order to ensure the scientific rigor and effectiveness of the project, Company A also hired a team of professional psychological counselors to provide personalized mental health counseling and support services for employees. In addition, taking into account the differences between different departments and job levels, the project team formulated a hierarchical and classified mental health management strategy to meet diverse needs.

In the implementation process, Company A adopted a dynamic data analysis method to capture the changing trend of employees' mental health status and its impact on performance; cluster analysis technology was used to divide employees into different mental health status groups, and customized management plans were designed for each group; deep learning algorithms such as LSTM (Long Short-Term Memory Network) were used to predict long-term changes in mental health status, providing strong data support for corporate decision-making. Together, these measures constitute a comprehensive and systematic mental health management system, enabling Company A to maintain its competitive advantage in a fierce market environment.

4.2 Implementation Process

When implementing the "Psychological Capital Enhancement Plan", Company A strictly followed certain steps to ensure the smooth progress of the project and the achievement of

Table 1 Distribution of employees' mental health status.

Mental health status	Frequency	Percentage (%)
Healthy	1200	60.0
Mild anxiety/depression	400	20.0
Moderate anxiety/depression	300	15.0
Severe anxiety/depression	100	5.0

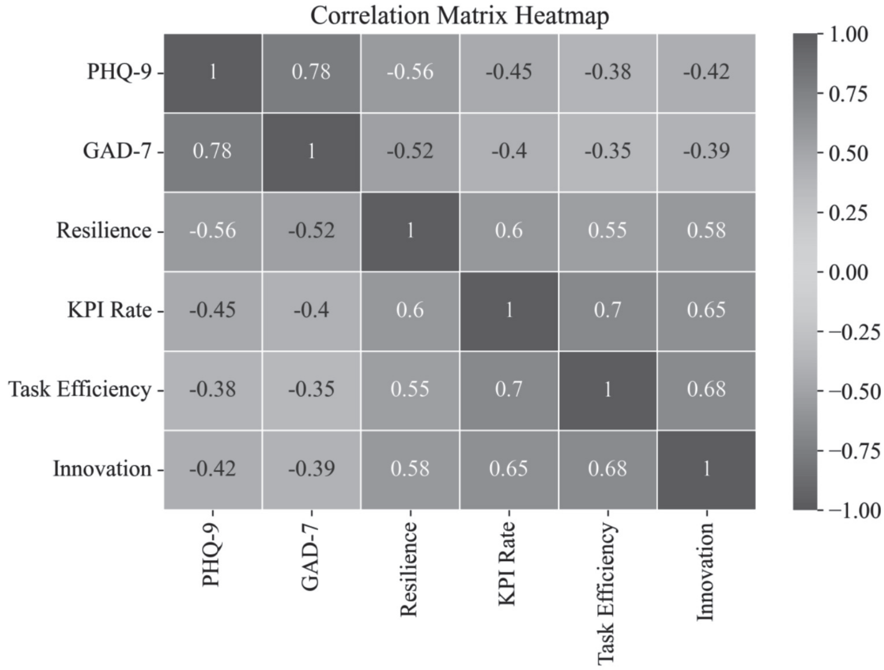

Figure 1 Correlation matrix between mental health status and performance indicators.

expected goals. First, the project team conducted a detailed demand survey and technology selection, and selected data mining tools and analysis frameworks that were appropriate given the characteristics of the enterprise. On this basis, a special data collection platform was established to integrate information from multiple channels, including employees' self-reported mental health, daily work behavior records, and physiological signals provided by wearable devices. The project team used the KNN interpolation method to fill missing values to ensure the integrity of the data; all variables were standardized to facilitate comparison between data of different scales; and used sliding window technology to segment time series data to enhance the model's ability to capture future trends. After a series of meticulous data cleaning and feature engineering processes, a high-quality data set was formed, providing a good foundation for the next step of modeling and analysis. The project team applied a variety of machine learning algorithms, such as linear regression, random forest, and support vector machine, to explore the relationship between mental health status and performance. In particular, in order to capture the characteristics of mental health status changing over time, the team built an LSTM model, which can effectively handle complex dependencies in long time series data, thereby improving prediction accuracy. In addition, through cluster analysis methods, employees were divided into several groups with similar characteristics according to their mental health status, which helped to identify the factors that most affected the performance of specific groups.

4.3 Experimental Results

Table 1 shows the overall distribution of mental health status of employees in Company A. A mental health questionnaire survey of 2,000 employees showed that 60% of employees are in a healthy mental state, able to effectively cope with work pressure and maintain high work efficiency; 20% of employees show mild anxiety or depression symptoms. This group of people may feel emotional fluctuations in certain situations, but it has not yet affected their daily work; 15% of employees have moderate anxiety or depression problems. These employees may encounter more challenges at work and need additional support and attention; the remaining 5% of employees are assessed as being severely anxious or depressed. The mental health of these employees has had a significant impact on their work and personal life, and they are in urgent need of professional psychological intervention and support.

Figure 1 shows the results of the correlation between mental health status (including depression score, anxiety score and resilience score) and performance indicators (KPI completion rate, task efficiency and innovation contribution). By calculating the Pearson correlation coefficient, we found that there is a significant correlation between mental health status and performance. For example, depression score and anxiety score are negatively correlated with KPI completion rate, task efficiency and innovation contribution, indicating that employees with poor mental health often have lower work

Table 2 Regression analysis results of the impact of mental health status on performance.

variable	Regression coefficient	Standard error	t-value	p-value	95% CI lower limit	95% CI upper limit
Intercept	0.80	0.15	5.33	<0.001	0.50	1.10
Depression score	−0.30	0.05	−6.00	<0.001	−0.40	−0.20
Anxiety score	−0.25	0.04	−6.25	<0.001	−0.33	−0.17
Resilience score	0.40	0.06	6.67	<0.001	0.28	0.52
Control variables	0.15	0.03	5.00	<0.001	0.09	0.21

Table 3 Characteristics of mental health status groups based on cluster analysis.

Group number	Mean depression score	Average anxiety score	Average resilience score	KPI completion rate	Task efficiency	Innovation Contribution
Group 1	3.2	2.8	4.5	85.0	88.0	87.0
Group 2	6.5	5.9	3.2	70.0	72.0	71.0
Group 3	9.1	8.6	2.0	55.0	58.0	56.0

Figure 2 Cluster analysis.

efficiency and innovation ability; on the contrary, resilience score is positively correlated with various performance indicators, which means that employees with strong resilience are more likely to achieve excellent performance at work.

Table 2 reports the statistical results of the impact of psychological traits on performance obtained through the multivariate linear regression model. The study shows that depression scores, anxiety scores, and resilience scores are all important factors affecting employee performance. Specifically, for every unit increase in depression scores, the KPI completion rate decreases by an average of 0.30 standard deviations; for every unit increase in anxiety scores, the KPI completion rate decreases by an average of 0.25 standard deviations; and for every unit increase in resilience scores, the KPI completion rate increases by an average of 0.40 standard deviations. Control variables (such as work experience, position level, etc.) are also included in the model to ensure the accuracy of the estimated values.

Table 3 uses cluster analysis technology to divide employees into three different mental health status groups. The results are shown in Figure 2, and the performance of each group in multiple dimensions is compared. As can be seen from the table, employees in group 1 have lower depression and anxiety scores and higher psychological resilience scores. They perform well in KPI completion rate, task efficiency and contribution to innovation. In contrast, although the mental health of employees in group 2 is slightly worse, they can still maintain a relatively good performance level; while employees in group 3 show the worst mental health and the lowest performance.

Figure 3 uses cluster analysis technology to divide employees into three different mental health status groups, and compares the performance of each group in multiple dimensions. As can be seen from Figure 3, employees in group 1 have lower depression and anxiety scores and higher psychological resilience scores, and they perform

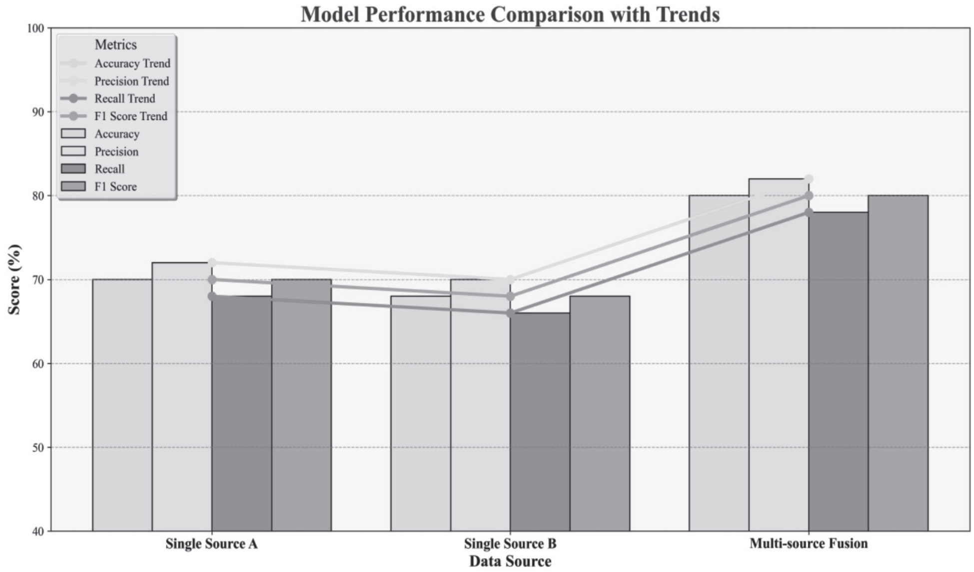

Figure 3 Prediction accuracy of psychological traits after multi-source data fusion.

Table 4 Evaluation of the effectiveness of personalized management strategies.

Management policy type	Average performance before implementation	Average performance after implementation	Improvement (%)	Significance test p value
Strategy 1	75.0	82.0	9.3	<0.001
Strategy 2	68.0	78.0	14.7	<0.001
Strategy 3	80.0	86.0	7.5	<0.001

Table 5 LSTM model predicts the performance of time series changes in mental health.

Time window length	MSE	MAE	R2R2	Training set accuracy (%)	Test set accuracy (%)
One week	0.05	0.20	0.88	90.0	85.0
Two weeks	0.07	0.25	0.85	88.0	83.0
Three weeks	0.09	0.30	0.82	86.0	81.0

well in KPI completion rate, task efficiency and contribution to innovation; conversely, although the mental health of employees in group 2 is slightly worse, they can still maintain a relatively good performance level; while employees in group 3 show the worst mental health and the lowest performance.

Table 4 summarizes the performance changes of three different personalized management strategies before and after implementation. Strategy 1 is aimed at employees with good mental health but low performance, and stimulates work motivation through incentives and goal setting; Strategy 2 provides psychological support and stress relief intervention for employees with poor mental health and low performance; Strategy 3 focuses on cultivating employees' psychological resilience and improving their ability to cope with complex work tasks. As can be seen from the table, all strategies have achieved significant results, among which Strategy 2 has the largest improvement, reaching 14.7%; followed by Strategy 1, with an improvement of 9.3%; and finally, Strategy 3 has an improvement of 7.5%.

Table 5 shows the prediction performance of the LSTM (Long Short-Term Memory Network) model for future mental health status and performance change trends under different time window lengths. As the time window length increases, the MSE (mean square error) and MAE (mean absolute error) gradually increase, while the determination coefficient decreases, indicating that a longer time window may lead to a slight loss in prediction accuracy. However, even under a three-week time window, the LSTM model still maintains a high accuracy rate for the training set and test set (86% and 81% respectively), showing its strong long-term prediction ability.

Table 6 tracks the mental health status and performance trends of employees at different time points after the implementation of the comprehensive intervention measures. The data shows that in the first month after the implementation of the intervention measures, the average KPI completion rate, task efficiency and innovation contribution of employees all increased significantly, while the average depression and anxiety scores began to decline; over time, this positive trend continued and reached its highest point in the 12th month - the KPI completion rate, task efficiency and innovation contribution increased to 88%, 91% and 89% respectively, while the average depression and anxiety scores dropped to 3.5 and 3.0. The changes in KPI completion rate are shown in Figure 4.

4.4 Personalized Management Strategy

Based on the results of the model analysis, the project team developed personalized management strategies for employees with different mental health conditions, aiming to accurately

Table 6 Long-term performance trends after implementation of comprehensive intervention measures.

Time point (month)	Average KPI completion rate	Average task efficiency	Average innovation contribution	Mean depression score	Average anxiety score
Month 0	75.0	78.0	76.0	5.5	5.0
Month 1	78.0	81.0	79.0	5.0	4.5
Month 3	82.0	85.0	83.0	4.5	4.0
Month 6	85.0	88.0	86.0	4.0	3.5
Month 12	88.0	91.0	89.0	3.5	3.0

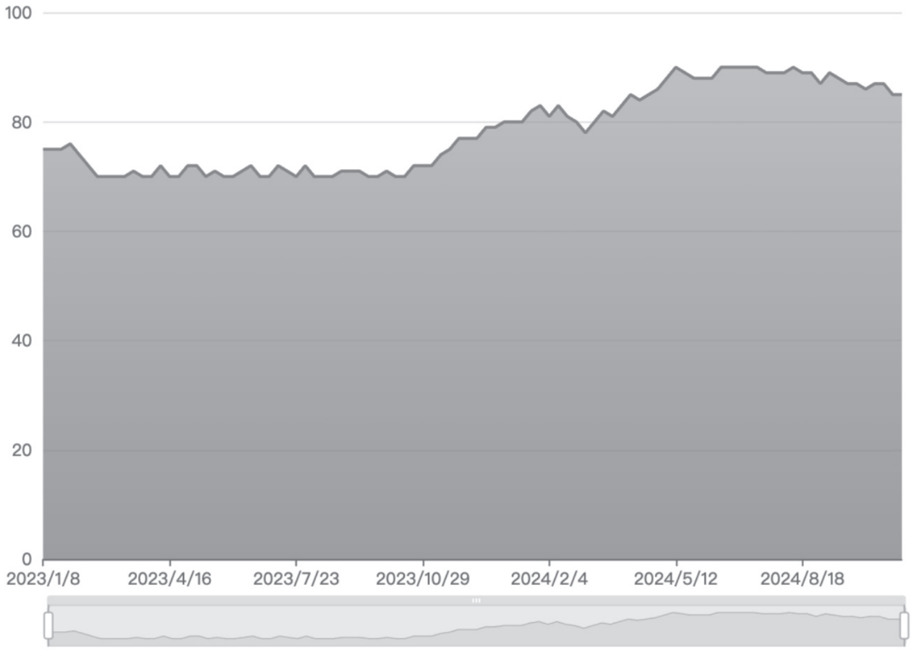

Figure 4 KPI completion rate changes.

respond to the specific needs of each employee. For those employees who showed good mental health but low performance, the project team focused on stimulating their work motivation and career development momentum. Specific measures included setting clear career development goals, providing more promotion opportunities, and implementing an incentive compensation system. These measures not only improved employees' work enthusiasm, but also strengthened their sense of belonging and loyalty to the company.

For employees with poor mental health and low performance, the project team focuses on providing psychological support and stress relief intervention. First, the company set up a mental health counseling hotline and service platform to ensure that every employee has timely access to professional psychological counseling and support services. In addition, mental health lectures and group activities are regularly organized to help employees improve their psychological adjustment ability and skills in coping with stress. Through these activities, employees can learn effective stress relief methods, and also enhance the communication and cooperation among colleagues in a relaxed and pleasant atmosphere, thereby creating a more harmonious working environment.

In order to further improve the intervention effect, Company A also introduced customized training courses and personalized counseling plans. For example, for employees who are under long-term high pressure, special mental health experts are arranged to provide one-on-one in-depth counseling; for employees who have specific skill needs or are confused about career planning, targeted career development guidance is provided. This multi-level and multi-dimensional support system not only solves the psychological problems currently faced by employees, but also lays a solid foundation for their long-term development.

Throughout the project cycle, Company A continuously monitored changes in various indicators to ensure the effectiveness and adaptability of management strategies. By regularly evaluating the effectiveness of mental health interventions and continuously optimizing processes and technical means, the overall mental health level of employees was ultimately improved, while also promoting the growth of work efficiency and innovation capabilities. For example, by introducing advanced data mining technology and machine learning algorithms, Company A was able to predict the mental health trends of employees and take preventive measures in advance to avoid potential problems more accurately. In addition, based on the real-time feedback mechanism, management can quickly adjust strategies to ensure that all interventions are in line with actual conditions and achieve the best results.

Figure 5 shows the changes in key performance indicators of Company A before and after the implementation of

Figure 5 Comparison of KPIs before and after implementation.

the mental health management project, demonstrating the significant positive impact of the project on employee mental health and work efficiency. The mental health score increased from 65 to 80 points. By setting up an internal mental health counseling hotline, organizing regular mental health lectures and providing one-on-one psychological counseling, the mental health level of employees has been significantly improved. At the same time, the performance score increased from 70 to 85 points, thanks to the development of personalized management strategies for employees with different mental health conditions, especially for those with good mental health but low performance, setting clear career development goals, and providing promotion opportunities and incentive compensation systems. The work motivation score increased from 60 to 80 points, and the career development motivation score increased from 55 to 75 points, indicating that through the introduction of customized training courses and personalized counseling plans, employees' career planning has become clearer, their work enthusiasm has been significantly enhanced, and their confidence in future development has also been greatly improved. The sense of belonging and loyalty score jumped from 65 to 85 points, thanks to the improvement of the working environment and the strengthening of teamwork and support measures, which has enabled employees to have a stronger sense of identity and loyalty to the company, and reduced staff turnover. The team collaboration score increased from 70 points to 85 points. Regular team building activities not only improved employees' ability to cope with stress, but also promoted communication and cooperation among colleagues, creating a more harmonious working environment. Finally, the social value score (CSR index) increased from 60 points to 85 points. The success of the project not only brought significant economic benefits, established a good corporate image and social responsibility, became a benchmark case in the industry, but also provided a valuable experience reference for other companies. In summary, through systematic mental health management and personalized employee care, Company A not only improved the overall happiness and satisfaction of employees, but also maintained strong competitiveness and sustainable development capabilities in the fierce market competition. In the future, as more companies recognize the importance of mental health management, Company A's successful model is expected to be widely promoted, and will make a positive contribution to the building of a healthier and more harmonious corporate culture.

5. CONCLUSION

The successful implementation of the "Psychological Capital Enhancement Program" confirms the important role of systematic mental health management and personalized intervention measures in corporate performance. By introducing advanced data mining technology and psychological theoretical models, Company A not only effectively assessed the mental health of employees, but also accurately identified the characteristics of employees in different mental health states, enabling the formulation of targeted management strategies. Studies have shown that multi-source data fusion enhances the robustness and reliability of the prediction model, while the LSTM model improves the ability to predict future trends. Personalized management strategies, such as incentives and psychological support, significantly improve employees' mental health and enthusiasm for work tasks, In addition, regular mental health lectures and group activities help employees improve their psychological adjustment ability and coping skills. Throughout the project cycle, Company A achieved an overall improvement in the mental health level of employees through continuous monitoring and optimization of processes, while increasing employees' work efficiency and innovation capabilities. The successful experience of the project not only brought significant economic benefits and social value to Company A, but also provided a valuable reference case for other companies, emphasizing the importance of mental health management in modern enterprises.

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