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Research Article

Human Capital Digital Incentive Mechanism Construction Based on Deep Learning

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The introduction of human capital can be traced back to the ancient Greek period, emphasizing the important role of knowledge and skills in the production and life process. Human capital reward mechanism promotes modern social and economic development and is an important part of social and economic growth. The core management of the enterprise is the management of human capital, and the central work of human capital management is the incentive of human capital. Many enterprises are now facing difficulties in industrial operation, serious brain drain, and lack of core competitiveness in the market. As a result, enterprises cannot adapt to the speed and requirements of today's social and economic development. One of the important reasons is that the enterprise lacks attention to the value of the human capital incentive system, or the human capital incentive system of the enterprise is unreasonable, which leads to a series of problems such as poor employee enthusiasm and low enterprise performance. How to establish a reasonable and effective incentive mechanism to mobilize the enthusiasm and creativity of employees has become a problem that enterprises must pay attention to. Taking the technical managers and general technicians of a high-tech enterprise as an example, combined with the deep learning method, the article made a detailed analysis of the four major incentive factors of enterprise human capital. It made employees' satisfaction with corporate cultural incentives reaching 56.1%, which showed that emotional motivation was also one of the key factors for employees to be satisfied with the corporate incentive system.

1. Introduction

With the rapid development of science and technology and the advent of the digital age, the human capital incentive mechanism closely follows the pace of the times and changes the original traditional model. At the same time, deep learning has achieved great success in a series of fields such as computer vision, image processing, natural language processing, and semantic recognition in recent years. However, the application of deep learning in the construction of human capital incentive mechanism is still limited. In the digital age, applying deep learning to the human resources incentive mechanism can create a new creative method for enterprises, which can improve the effectiveness of the incentive mechanism. The construction of a reasonable and effective corporate incentive mechanism is based on a fair and just, employee-centered principle and center. It must meet the differentiated needs of employees and pay attention to the material and spiritual needs of employees, and can arouse the enthusiasm of employees with long-term generous material rewards, a good working environment, and corporate organizational culture. While retaining talents for the enterprise, it can also bring the economic development of the enterprise.

This paper conducted a systematic analysis and research on deep learning algorithms and explored the role of deep learning methods in the establishment of human capital incentive mechanisms, and on this basis, it found out what digital incentives mean for businesses and employees. From the analysis of the four motivational factors of human capital, it was found that material incentives and spiritual incentives were more valued in the hearts of employees.

Employees needed not only real salary incentives to meet material needs but also respect and care to meet certain spiritual needs. This finding had guiding significance for mobilizing employees' enthusiasm and creativity. In addition, a good corporate culture and corporate environment were also an effective way to retain talents.

With the wide application of deep learning, there are more and more research studies on deep learning in the construction of human capital incentive mechanism. Shen et al. provided an overview of computer-aided image analysis in the field of medical imaging. Recent advances in machine learning, particularly deep learning, facilitate the recognition, classification, and quantification of patterns in medical images. Central to these advances is the provision of hierarchical feature representations learned only from data rather than artificially designed features based on domain-specific knowledge. Deep learning is rapidly becoming a state-of-the-art technique that improves the performance of a wide range of medical applications and so on. Finally, research questions were discussed and future directions for further improvements were proposed [1]. Dong and Li summarized recent advances in deep learning-based acoustic models and examined the motivations and insights behind these techniques [2]. Ravi et al. provided a comprehensive and up-to-date review of research on the adoption of deep learning in health informatics, critically analyzing the relative merits, potential pitfalls, and future prospects of this technology [3]. In the study of Schirrmeister et al., convolutional neural networks (ConvNets) were applied to the EEG anomaly corpus at Temple University Hospital for the task of differentiating pathological from normal EEG recordings. Two basic architectures, surface and deep convNets, and algorithms developed for this purpose were used to decode task-relevant information from the EEG. When decoding EEG pathology, both ConvNets achieved much higher accuracy than the only published results on this dataset (85% and 79% improvement in accuracy, respectively, compared to 6% accuracy). In addition, both ConvNets maintained high accuracy when trained on one-minute recordings and when tested on six-second recordings. An automatic method was then used to optimize the hyperparameters of the architectures, and interestingly, different ConvNet architectures were found. After viewing additional features using spectral power variations in the delta (0–4 Hz) and theta (4–8 Hz) bands, the visualization of ConvNet decoding behavior was consistent with that expected from the spectral analysis of EEG and textual diagnostic data. The text analysis of diagnostic reports also showed that accuracy could be improved by including background information (e.g., subject's age) [4]. Hou et al. investigated the visual quality of images assessed blindly by learning the rules of linguistic descriptions and proposed several learning-based IQA models by analyzing the mappings from images to numerical scores. However, the accuracy of the learned mappings is not sufficient because some information is lost due to the irreversible transformation from linguistic descriptions to numerical scores. Therefore, we propose a blind IQA model that learns qualitative scores directly and outputs numerical scores for general use and fair comparison. Images are represented by statistical features of natural scenes. Images are represented by statistical features of natural scenes, and a discriminative depth model is trained to classify these features into five levels corresponding to five explicit psychological concepts: excellent, good, fair, poor, and very poor. These qualitative labels were then converted into scores by applying a newly designed quality library. This classification framework is not only more natural than the regression-based model but also more robust to small batch problems. To validate the effectiveness, efficiency, and robustness of the model, exhaustive experiments were conducted on a common database [5]. The study of Grimpe et al. concluded that the ability of innovative firms to create and capture values depends on the rapid and widespread adoption of innovations. However, stakeholder concerns may be a significant barrier to diffusion; Grimpe et al. examined the human capital challenge and investigated whether innovative firms pay a wage premium to new employees who have worked for advocacy organizations such as Transparency International. Human capital and stakeholder theory are also combined to discuss the experience of advocacy groups and their transfer of innovation from the perspective of stakeholder knowledge. Valuable human capital signals were created in terms of legitimacy transfer. Using matched data from 3,562 Danish employees, it is found that new recruits with advocacy team experience enjoy higher wage premiums in technologically superior companies, in occupations with direct stakeholder interaction, and in the top management of advocacy teams [6]. Saeed et al. found that the success of an organization's program for environmental sustainability depended on employees' environmental behavior. One of the important contemporary challenges faced by HR professionals was ensuring that environmental sustainability was properly integrated into HR policies. Green HRM was developed from organizations working on issues related to environmental protection and maintaining ecological balance. The purpose of their study is to examine the effects of green HRM practices (green recruitment and selection, green training and development, green performance management and evaluation, green rewards and compensation, and green empowerment) on employees' green behaviors. In addition, the mediating effects of pre-environmental psychological capital and environmental knowledge on the pre-environmental behavior of green HRM practices will be examined. The results show that green HRM practices positively influence employees' pro-environmental behaviors, and pro-environmental psychological capital mediates this association. The moderating role of employees' environmental knowledge on the effect of green HRM practices on pro-environmental behavior [7]. These literatures were very detailed in the introduction of deep learning and human resource theory incentive system and had a constructive role in the research of this article.

Based on the restricted Boltzmann machine, autoencoder, and multilabel classification method of convolutional neural networks and recurrent neural networks in deep learning, this paper analyzed and compared the satisfaction degree of an enterprise's technical management personnel and general technical personnel to the enterprise's incentive mechanism. It found out the psychological tendency characteristics of these employees in the incentive mechanism, summarized these characteristics, and then constructed a reasonable and effective incentive mechanism based on these characteristics.

2. Human Capital Digital Incentive Mechanism Construction Method Based on Deep Learning

2.1. Restricted Boltzmann Machine. Restricted Boltzmann Machine (RBM) is developed from the Boltzmann machine, which is a two-layer undirected graph model [8, 9]. Figure 1 is a structural model diagram of a restricted Boltzmann machine. According to different tasks, the restricted Boltzmann machine can be trained by supervised learning or unsupervised learning.

The energy function $F(w, b)$ of a restricted Boltzmann machine can be expressed as

$$F(w, b) = -\sum i w_i h_i - \sum j b_j c_j - \sum i, j w_i b_j L_{ij}. \tag{1}$$

Both i and j represent nodes, w and b represent the value and bias of the node, and L_{ij} represents the connection weight between the visible layer and the hidden layer.

In 2007, some experts used the restricted Boltzmann machine model for the first time to construct the digital incentive mechanism of human capital, as shown in Figure 2 [10]. The restricted Boltzmann machine model made two changes on the traditional model. The first was that the visible layer used a 0-1 vector unit of length K to represent employee performance data. Second, because employees generally could not be rewarded every day, employees without reward records were represented by a special unit (No reward), and the special unit and the hidden layer unit were not connected. In the restricted Boltzmann machine, the visible layer usually represents the original input data, while the hidden layer represents the data generated through learning, expressing the implicit characteristics of the original data. Each rewarded employee was represented by a separate restricted Boltzmann machine, all of which corresponded to a common hidden layer. The weight and bias parameters were shared between all RBMs, so if two employees had the same reward record and were rewarded at the same time, the same weight was used for the calculation [11].

Compared with the traditional restricted Boltzmann machine model, the weight value between the hidden layer and the visible layer of the changed model is S times that of the previous model. v represents the reward matrix, which is a multidimensional matrix; Z_i is a normalized item, which is used to ensure that the sum of the probabilities of all user scores on item I is 1; and the updated energy function is obtained:

$$\begin{aligned} F = (w, b) = &-\sum i, s v_i^s h_i^s - \sum j b_j c_j - \sum i, j, s v_i^s b_j L_{ij}^s \\ &+ \sum i \log Z_i. \end{aligned} \tag{2}$$

After the above training is completed, set the known employee reward as T, and the reward corresponding to the employee reward record according to the employee's work performance data is

$$\chi = F\left(w_y\right) = \sum s * P\left(w_y^s = \frac{1}{T}\right). \tag{3}$$

When the restricted Boltzmann machine model is applied to the employee reward mechanism, the employee reward mechanism is effectively improved and optimized, and the reward algorithm process is simplified [12, 13]. The restricted Boltzmann machine model has been successfully applied to collaborative filtering, classification, dimensionality reduction, image retrieval, information retrieval, language processing, automatic speech recognition, time series modeling, document classification, nonlinear embedding learning, transient data model learning, and signal and information processing.

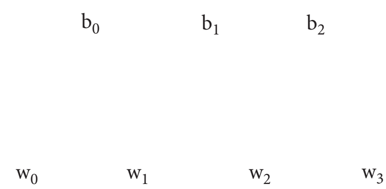

Figure 1: Structure model diagram of the restricted Boltzmann machine.

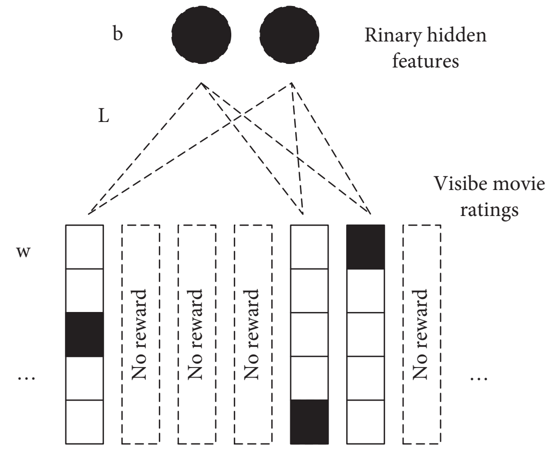

Figure 2: RMB collaborative filtering model.

2.2. Autoencoder. Autoencoder is a kind of neural network related to deep learning. The main role of an autoencoder is to train between input values and output values, also known as unsupervised learning models [14]. The structure of the autoencoder is shown in Figure 3. This model includes three parts: encoder, decoder, and hidden layer. The working process of the automatic encoder includes two parts: encoding and decoding. In the encoding stage, the input data is mapped to the feature space, while in the decoding stage, the encoded data is mapped back to the original sample space.

When the decoder activation function is an identity function, the resulting even variance formula is

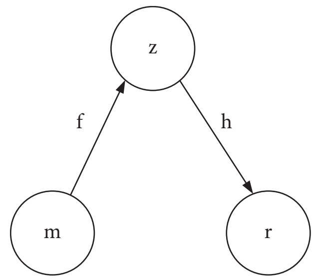

Figure 3: Schematic diagram of the structure of the autoencoder.

$$L(m,n) = m - n^2. \quad (4)$$

When the decoder activation function is a sigmoid function, the cross entropy function is obtained:

$$L(m,n) = -\sum_{i=1}^{x}\left[m_i \log(n_i) + (1-m_i)\log(1-n_i)\right]. \quad (5)$$

According to the reconstruction error function, the overall loss function is obtained:

$$Y_{AE}(\partial) = \sum_{m\in} L(m, h(f(m))). \quad (6)$$

S is the training set, and minimizing the function can get the required parameters.

In an autoencoder, the hidden layer represents the input, and the goal of the hidden layer is to keep the information of the input layer stable [15]. In order to improve the availability of the data, the original data cannot be completely copied. Some experts propose denoising autoencoders to better represent features, improving the ability of the autoencoder to capture key information features by adding robustness and noise to the original input data to destruct the original input data [16, 17]. The calculation process of the denoising autoencoder is as shown in Figure 4.

Assuming that the input data is w, and the randomly corrupted input data is w', this mapping process is represented by function $f_\theta(w)$:

$$h = f_\theta(w) = s(Pw' + b). \quad (7)$$

$\theta = \{P, b\}$ represents the entire set of maps, s represents a nonlinear function like sigmoid, and b represents the bias vector.

When $\theta = \{P', b'\}$ represents the set of reconstructed mappings, the decoder remaps the implicit feature m to the reconstructed data n, the value range of implicit feature m is $m \in [0, 1]^{\text{d}}$, and we obtain the formula

$$n = k_\theta(m) = s(P'm + b'). \quad (8)$$

When the input data in the denoising autoencoder represents $w^{(i)}$, the hidden layer feature represents $m^{(i)}$, and the reconstructed original data represents $n^{(i)}$, the minimum reconstruction error is obtained by continuously adjusting and optimizing the parameters in the model:

$$L(m,n) = \|m - z\|^2. \quad (9)$$

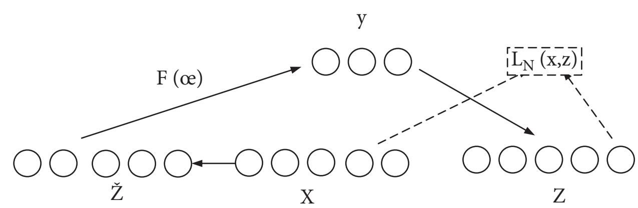

Figure 4: Calculation process of denoising autoencoder.

At the same time, in order to prevent the model from overfitting due to too much weights, it is necessary to set a weight decay term for the model

$$D == \frac{1}{2}\|P\|^2. \quad (10)$$

We get the objective function:

$$z = \frac{1}{2v}\sum_{i=1}^{v} L\left(m^{(i)}, n^{(i)}\right) + \beta D. \quad (11)$$

β is the weight parameter after decay. Z is the optimization parameter. The denoising autoencoder will get a low-dimensional representation of the input data.

2.3. Multilabel Classification Method of Convolutional Neural Network. To build a mature human capital incentive mechanism, it is inseparable from the classification of the characteristics of each employee's work performance. It is crucial for an enterprise to establish a more accurate reward system based on the classification of each characteristic of employees' work performance [18]. The convolutional neural network is a relatively simple deep learning structure with excellent classification and recognition capabilities. It is mainly composed of four layers: convolution layer, pooling layer, fully connected layer, and output layer. Each layer has the same weight as the previous layer, which can simplify the training parameters and accurately extract key data features [19].

A method commonly used in convolutional neural networks for multiclassification tasks is the Softmax regression model. The Softmax function is often used as the final classifier, which is an extension of the logical classifier only applicable to binary classification problems. Softmax maps the outputs of multiple neurons to the (0, 1) interval, and the sum of all output values is 1. In the classification process, each performance feature is classified, and each feature is classified into a class and represented by a label. After completing the training, multilabel classification can automatically assign one or more category labels to the samples, which can better adapt. In addition, compared with the single label learning framework in which each sample is only associated with one category label, each sample in the multilabel learning framework can be associated with multiple category labels. Its purpose is to effectively predict the label set of unknown samples by learning a given multilabel training set. In addition, multilabel classification faces problems such as higher algorithm complexity and uncertain number of related labels.

Suppose there is a training set $\{(m^{(1)}, n^{(2)}), \ldots, (m^{(s)}, n^{(s)})\}$ of s samples, and the feature vector m is $t+1$ dimension. Therefore, for the input m samples, the probability $r(w = k|m)$ of each category of work data category k is obtained. The number of class labels v in Softmax regression is greater than 2, and the probability formula for outputting a v-dimensional vector representing each class is

$$h_\alpha\left(m^{(i)}\right) = \begin{bmatrix} r\left(w^{(i)} = 1|m^{(i)}; \alpha\right) \\ r\left(w^{(i)} = 2|m^{(i)}; \alpha\right) \\ \vdots \\ r\left(w^{(i)} = v|m^{(i)}; \alpha\right) \end{bmatrix} = 1, \sum_{j=1}^{v} e^{\alpha_j^P m^{(i)}} \begin{bmatrix} e^{\alpha_1^P m^{(i)}} \\ e^{\alpha_2^P m^{(i)}} \\ e^{\alpha_v^P m^{(i)}}_v \end{bmatrix}, \tag{12}$$

$\alpha_1, \alpha_2, \ldots, \alpha_v$ is the model parameter [20], and then the cost function definition formula is

$$\nabla_{\alpha_j} K(\alpha) = -\frac{1}{x} \sum_{i=1}^{x} \left[m^{(i)}\left(1\left\{w^{(i)} = k\right\} - r\left(w^{(i)} = k|m^{(i)}; \alpha\right)\right)\right]. \tag{13}$$

Using iterative optimization such as gradient descent, the solution parameters need to be minimized to $K(\alpha)$, and the gradient formula after derivation is

$$K_{(\alpha)} = -\frac{1}{x}\left[\sum_{i=1}^{x}\sum_{j=1}^{v} 1\left\{w^{(i)} = k\right\} \log \frac{e^{\alpha_j^P m^{(i)}}}{\sum_{l=1}^{v} e^{\alpha_l^P m^{(i)}}}\right]. \tag{14}$$

After the gradient is calculated, it is brought into the gradient descent algorithm and the parameters are updated iteratively. After the parameter training is completed, the output feature m is classified as the probability of category k, and the formula used is

$$r\left(w^{(i)} = k|m^{(i)}; \alpha\right) = \frac{e^{\alpha_j^P m^{(i)}}}{\sum_{l=1}^{v} e^{\alpha_l^P m^{(i)}}}. \tag{15}$$

2.4. Recurrent Neural Network. Recurrent Neural Network (RNN) solves the problem of knowledge reserve to a certain extent and is a kind of neural network with memory function. The memory function is mainly realized by the feedback neural network between the input data and output data of the regret layer, which is the biggest difference from the traditional neural network. The shared weights of all recurrent neural networks can be expanded according to time nodes, and it is a deep feedforward neural network with the weight shared by all layers, which feeds back the output of the hidden layer to the input of the hidden layer. The connection structure of this feedback neural network makes RNN have the corresponding memory ability, as shown in Figure 5.

The parameters of the recurrent neural network mainly include three parts. At each time point, the same parameters were used for the calculation of the input information. Input the information in chronological order and get an output and hidden state information at each moment, and input the hidden state information together with the next time point

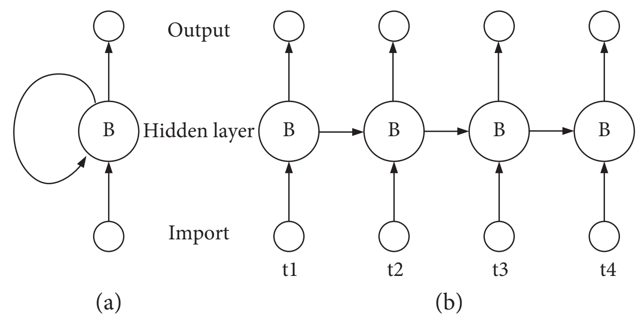

Figure 5: Schematic diagram of the recurrent neural network mechanism. (a) Single layer recurrent neural network and (b) recurrent neural network expanded by time nodes.

into the network for the calculation of the next time point [20, 21].

Like traditional neural networks, RNN can be trained using the backpropagation algorithm, which is also known as backpropagation through time [22]. In the forward propagation, the information is calculated in sequence according to the experimental order. Similarly, the backpropagation is to define a loss function and then transfer the accumulated residual at each time point from the last time point to the first time point. The traditional recurrent neural network has memory function but also has some drawbacks. Since some information is lost with each feedback, the initial memory will gradually fade or even disappear over time. Each iteration of the derivative is a multiplicative relationship since backpropagation needs to be accumulated over time points. If the conduction value is less than 1, the residual transmitted to the first time point after multiple multiplication tends to be close to 0, resulting in the disappearance of the gradient, so that the network cannot converge. On the contrary, if the conduction value is greater than 0, a large number will be obtained after multiple multiplication, which will also lead to nonconvergence and become gradient explosion [23]. In response to these problems, an improved recurrent neural network, called Long Short-Term Memory (LSTM), was first proposed in 1997, which has been continuously improved and developed. This kind of long and short memory recurrent neural network can solve the problem of nonconvergence very well so that the nervous system can preserve long-term "memory."

Figure 6 is a schematic diagram of the basic functional unit gate structure of the long-short-term memory model. The gate structure diagram of the long-short memory model includes four parts: the input gate, the cellular memory unit, the forgetting gate, and the output gate. The gate structure is a vector with an operation output value between 0 and 1 that allows information to selectively pass through. Its main function is to record, add, or erase memories. The proportion of information passing through the model is determined by the Sigmoid function. When other parts of the model are discarded, the calculation formula is obtained:

$$h_t = \varepsilon\left(m_h \cdot \left[x_{t-1}, r_t\right] + n_h\right). \tag{16}$$

Among them, h_t represents the proportion of information retention, t represents the variable of the time node,

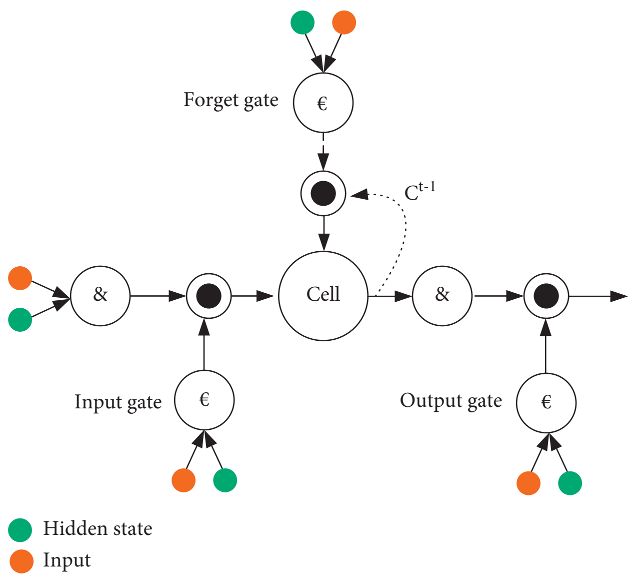

Figure 6: Schematic diagram of the basic functional unit gate structure of the long-short-term memory model.

m_h represents the parameters of each gate, and r_t represents the hidden state of the cell.

When the calculation determines that the cell should retain information, the input gate information and the input cell information are used for calculation, and the formula is obtained:

$$i_t = \varepsilon\left(m_h \cdot \left[x_{t-1}, r_t\right] + n_h\right). \tag{17}$$

Multiply the state value of the cell at the previous time point by the forget gate, and add it to the new candidate value vector generated by the tanh function to obtain the new cell state. The updated formula is

$$\begin{aligned}\widetilde{e}_t &= \tanh\left(m_e \cdot \left[x_{t-1}, r_t\right] + n_e\right),\\ e_t &= h_t \times e_{t-1} + i_t \times \widetilde{e}_t.\end{aligned} \tag{18}$$

Finally, the output of the cell is determined by the state of the cell, and the formula can be obtained:

$$\begin{aligned}y_t &= \varepsilon\left(m_y \cdot \left[x_{t-1}, r_t\right] + n_y\right),\\ x_t &= y_t \times \tanh\left(e_t\right).\end{aligned} \tag{19}$$

3. Human Capital Digital Incentive Mechanism Experiment

The so-called incentive mechanism is a way to reflect the interaction between the incentive subject and incentive object through a set of rational systems. It is also the sum of the internal operation structure and development and evolution law of enterprise incentive employees. It is an institutional system established and implemented to make the personal behavior of enterprise employees consistent with the enterprise objectives, realize the win-win strategy of enterprise and employees, and give full play to the personal ability of each employee [24]. The establishment of the incentive mechanism is inseparable from the interpretation of incentive theory. The traditional motivation theory is mainly divided into two categories: process type and content type. Content type includes Maslow's hierarchy of needs theory, two-factor theory, ERG theory, etc. They focus on researching the starting point and source basis of incentives, meeting the basic needs of employees, and mobilizing the enthusiasm of employees through incentive systems. Process motivation theory mainly includes Locke's goal setting theory, Froome expectation theory, etc. They impress the psychology of employees through the incentive process, including what kind of goal needs to be achieved and what kind of reward can be obtained after a big wish, both material rewards and spiritual rewards, and then stimulate the enthusiasm of employees and strength. This paper took a high-tech enterprise as an example to discuss the current situation and problems of human capital in the company.

3.1. The Status Quo of the Company's Human Capital. The current situation of the human capital of the company is shown in Figure 7 and Table 1, which is the company's personnel distribution in 2021 and the distribution of employees' technical grades and educational levels. With the development of the company, the number of employees continues to grow. The company's front-line employees account for 64% of the company's employees, and the technical employees account for 26%. From the technical level and educational level of the company's employees, it can be seen that the educational level is 32.4% of technical secondary school and high school staff, 52.98% of junior high school and below employees, and 86.8% of the total number of people without professional titles, indicating that in the company, general technical personnel account for a large number of the total number, and the proportion is unbalanced.

Although the company had achieved some operating results, there were still many problems in human capital incentives. The unreasonable salary structure of employees and the low salary level led to a serious loss of manpower in the company. The company's incentive mechanism did not play an effective role, the salary level did not meet the expectations of employees, and some excellent technical talents chose to change jobs.

Table 2 shows the company's technical talent loss in 2018. Over a four-year period, the attrition rate of technical managers was greater than that of general technical personnel. From 2018 to 2021, the company lost one technical manager per year, with a maximum turnover rate of 50%. The turnover rate of general technicians had increased year by year, rising from 12% in 2018 to 17% in 2019, as high as 21% in 2020, and 25% in 2021. It can be seen from the data that the ratio of technical personnel turnover has reached a quarter in the past four years. There are many reasons for general employees to leave, but salary is a very important factor. Coupled with the increase of external competitive pressure, many employees will choose rival companies with more reasonable salary structure and in line with their expectations. Therefore, establishing a reasonable and perfect salary system is the basic method to retain talents.

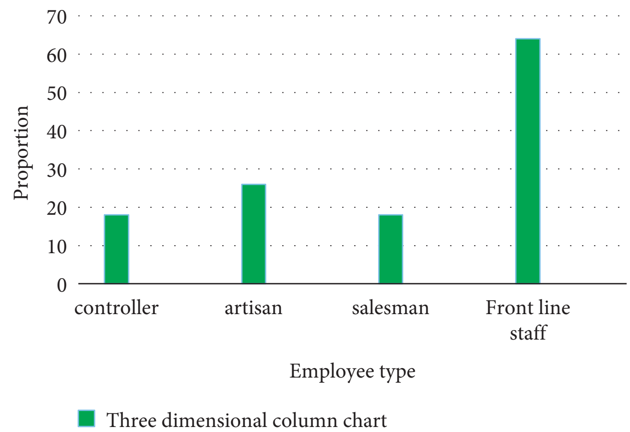

Figure 7: Company personnel distribution in 2021.

Table 1: Distribution of technical grades and educational levels of employees in 2021.

Educational level	Number of people	Proportion in total (%)	Technical grade	Number of people	Proportion in total (%)
Graduate student	4	2	Senior title	3	1.4
Undergraduate	24	5.68	Intermediate title	8	3.4
Specialty	36	8.32	Primary title	36	8.4
Technical secondary school and senior high school	64	32.4	No title	155	86.8
Junior high school and below	72	52.98			

Table 2: Technical staff turnover from 2018 to 2021.

Loss type number of people lost	2018		2019		2020		2021	
	Loss number	Loss rate (%)	Loss number	Loss rate (%)	Loss number	Loss rate (%)	Loss number	Loss rate (%)
Supervisory engineering staff	1	25	2	50	2	50	1	25
General technical personnel	11	12	14	17	17	21	20	25

3.2. Comparative Analysis of the Weights of Human Capital Incentives. As shown in Figure 8, it is the vertical plane coordinate axis of the analysis of the combined characteristics of human capital material and spiritual incentives. The points on the coordinate axis correspond to the corresponding combination of excitation types, including the indifference curve and the ability growth curve. The indifference curve represents the combined preference for the two incentives, and the ability growth curve represents the preference for a certain incentive. It is found that whether it is material incentive or spiritual incentive, the two complement each other and form the characteristics of mixed cross-demand. Material incentives provide material conditions for employees to survive and develop, followed by spiritual needs.

Starting from the four factors of human capital's material incentive, emotional incentive, cultural incentive, and work incentive, the satisfaction performance of the company's incentive system on the four levels of technical managers and general technical personnel is obtained by collecting the satisfaction of the company's employees.

Material incentive is the basis of the incentive mechanism. Its core is to link the interests of the enterprise with the personal interests of employees so that the objectives of the enterprise can become the consistent objectives of employees' work. As can be seen from Figure 9, technical managers are more satisfied with the company's material incentive system than the general technical staff. The satisfaction of general technicians is relatively low, and the satisfaction with the proportion of various incentive elements is also relatively low. For general technicians, the satisfaction of vocational training at the beginning of entry is higher. It reflects the unreasonable salary structure of technical management personnel and general technical personnel, and the proportion of performance appraisal elements is relatively large. Therefore, when establishing a digital incentive

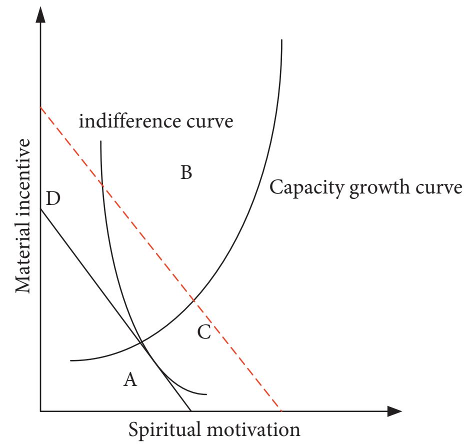

FIGURE 8: The combination of the human capital material and spiritual incentives.

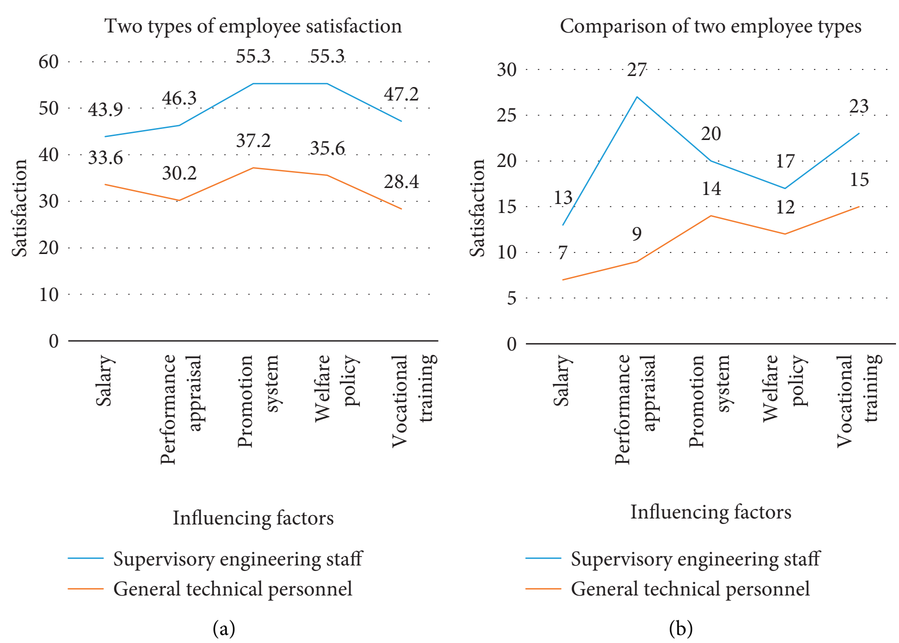

FIGURE 9: Employee satisfaction with material incentives. (a) Two types of employee satisfaction and (b) comparison of two employee types.

system, it is necessary to strengthen the optimal combination of salary treatment and performance appraisal and take into account other factors.

The most commonly used incentive methods in enterprise emotional incentive are integration incentive, questioning incentive, authorization incentive, participation incentive, and tolerance incentive. From Figure 10, it can be seen that emotional incentive satisfaction and paying attention to employees' emotional needs are also key parts of establishing a mature incentive system. The above data shows that the two types of employees are less satisfied with caring for employees and honoring them, and the emotional needs of employees are not met. Therefore, when establishing a digital incentive system, it is necessary to focus on the concern and praise of employees in terms of emotional incentive factors and to take into account other emotional factors.

Cultural incentives are an invisible force emanating from an enterprise's corporate culture. According to Figure 11, the two groups of technicians are highly satisfied with the communication rapport, especially the technical management staff's satisfaction with the communication rapport reaches 56.1%. Two groups of employees are less satisfied with the organizational culture and work environment. Therefore, when building a new digital incentive system, more consideration should be given to enhancing the fun of organizational activities, relieving employees' pressure, and at the same time creating a good working environment and atmosphere so that employees can work better.

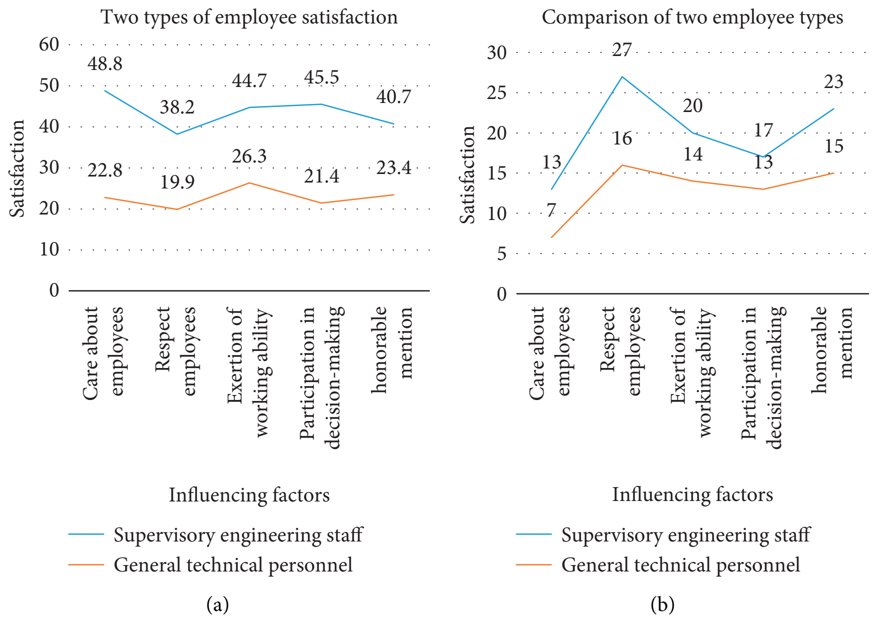

Figure 10: Employee satisfaction with emotional motivators. (a) Two types of employee satisfaction and (b) comparison of two employee types.

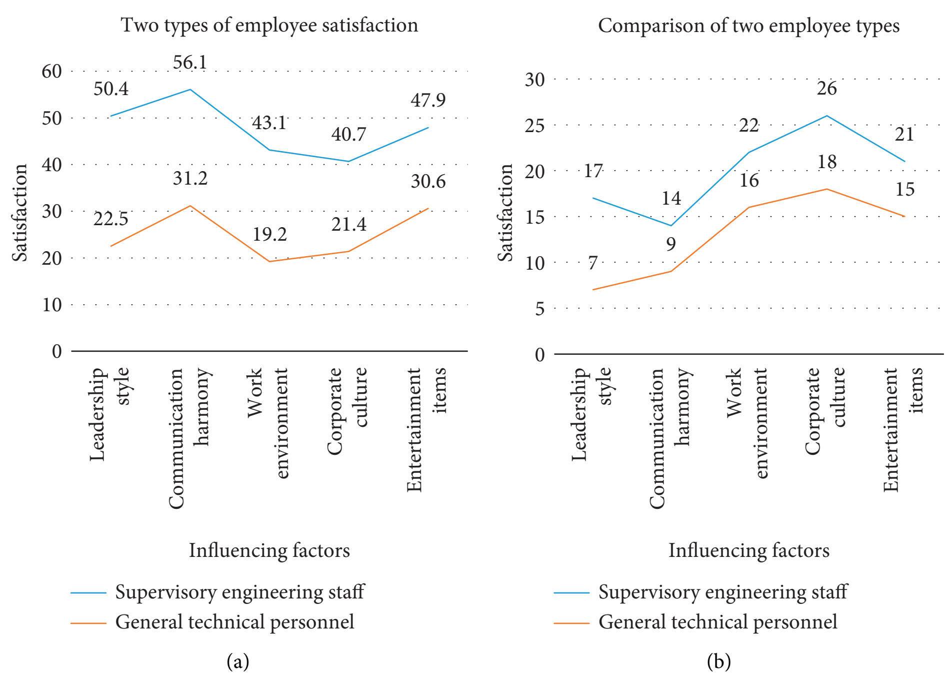

Figure 11: Employee satisfaction with cultural incentives. (a) Two types of employee satisfaction and (b) comparison of two employee types.

From Figure 12, technical managers and general technical staff have the highest satisfaction with technical collaboration among members. The data results show that it is necessary to improve the challenge and autonomy of employees in their work. The low satisfaction of employees in this area also indicates that employees have higher requirements for themselves. Therefore, in the design of the digital incentive system, the challenge and autonomy of work should be strengthened so that employees can realize their maximum value.

As can be seen from Table 3, a mature and effective incentive system can be constructed according to the proportion of each element. Material incentives are the foundation of all incentives, and spiritual incentives are the core. Only by combining the two can achieve the effectiveness of the incentive system.

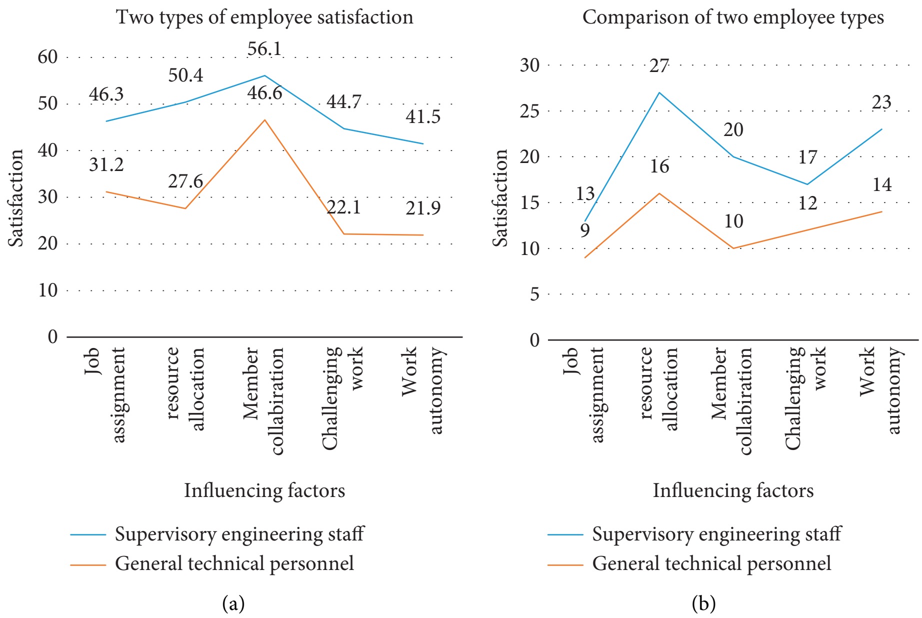

Figure 12: Employee satisfaction with job motivators. (a) Two types of employee satisfaction and (b) comparison of two employee types.

Table 3: Analysis of the four motivating factors of human capital.

Factor satisfaction	Very satisfied	Satisfied	Commonly	Dissatisfied	Very dissatisfied	Satisfaction (%)	Proportion of each factor
Material incentive factors	10	40	51	12	10	40.7	0.21
Emotional incentives	8	38	60	9	8	37.4	0.34
Cultural incentives	9	40	59	9	6	39.8	0.24
Job incentives	8	42	55	10	8	40.7	0.21

3.3. Incentive Mechanism Model Construction. The establishment of a reasonable incentive system for enterprises is conducive to the common development of enterprises and employees. In the incentive mechanism model in Figure 13, the company provides employees with a favorable working environment and a good corporate culture. By striving to achieve goals at work, the material and spiritual needs of employees are met. Increasing the challenge and innovation of work can stimulate the internal potential of employees. At the same time, a reasonable and effective incentive system can retain excellent talents for enterprises, create a benign competitive environment for employees, mobilize employees' enthusiasm, and attract excellent talents for the company to a certain extent.

4. Discussion

In this paper, various deep learning algorithms were applied to the human capital incentive system, and the characteristics of employees' satisfaction with the incentive mechanism were summarized and analyzed, and then an incentive mechanism that meets the needs of most employees was constructed according to the satisfaction characteristics. From the comparative analysis of the weights of human capital incentive factors, it could be seen that the company's technical personnel strongly required the company to meet their needs in material and spiritual rewards among the four categories of incentive factors. Under these circumstances, the company's incentive mechanism should be optimized and integrated to maximize the interests of the company and employees.

5. Conclusions

The success of an enterprise is inseparable from the reasonable human resources incentives of the enterprise. Building a reasonable and effective incentive mechanism and using effective incentives to maximize corporate profits and enable enterprises and employees to obtain the most optimal and most satisfactory benefits are the result of their joint efforts. Based on various methods of deep learning, in order to protect the basic needs and rights of employees at work, the company must establish basic incentive methods, incentive directions, and incentive time, and adjust the salary structure. The company must optimize the combination of company systems, improve the market structure, provide employees with a better working environment and organizational culture, and enhance their enthusiasm based on the principles of fairness, justice, and efficiency [25].

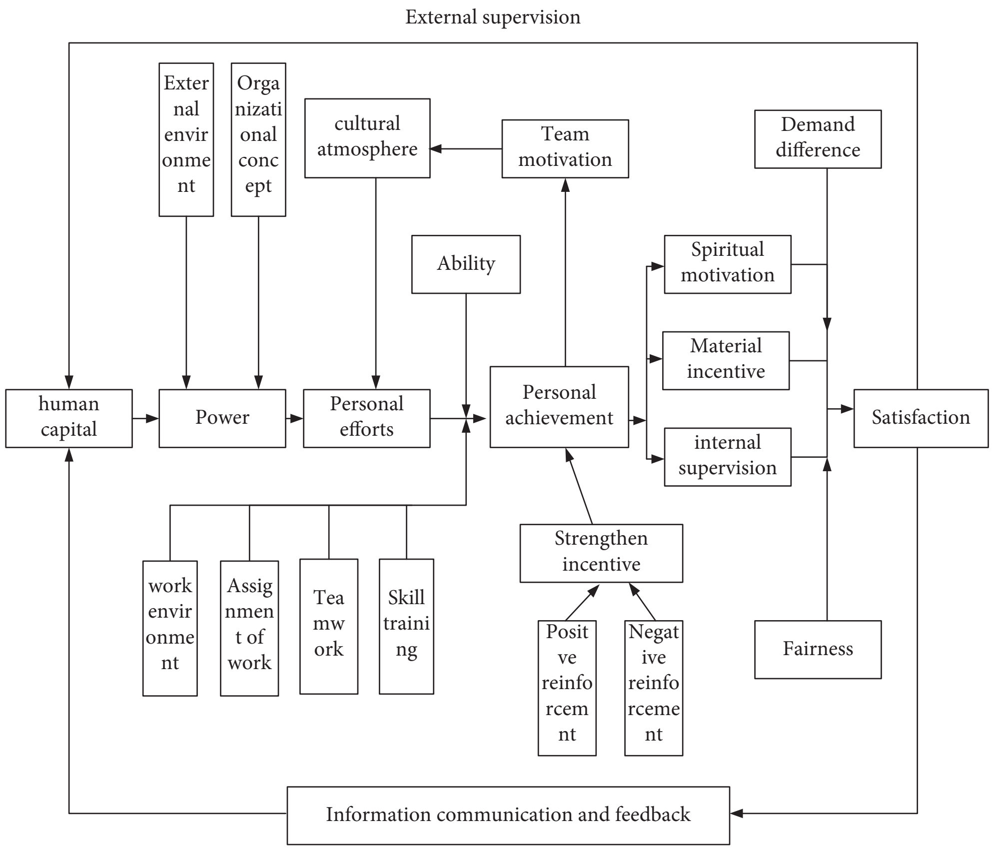

Figure 13: Incentive mechanism model.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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