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Development and innovation of enterprise knowledge management strategies using big data neural networks technology

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ABSTRACT

To strengthen the development of enterprises and optimize knowledge management strategies, the current situation of enterprise knowledge management (EKM) is investigated and the evaluation indicators of EKM strategies are analyzed. The specific structure and principles of neural network algorithms are studied using big data. Finally, neural networks (NNs) technology is used to evaluate EKM strategies and calculate the specific weight and strategy application of EKM using big data. The results show that with the support of big data, the use of NNs technology can analyze not only the knowledge management strategies, but also the different strategies of knowledge management used by different enterprises. When analyzing EKM strategies, enterprises indicators collected by big data vary greatly. The highest and lowest values are approximately 0.94 and 0.28, respectively. It indicates that NNs technology can be used to study different knowledge management strategies. Using this technology, the knowledge management strategies of different enterprises are calculated and optimized. The error between the final calculation and the actual result is relatively small, with a maximum and minimum of approximately 0.197 and 0.012, respectively. With the support of big data, the innovation and development of EKM strategy using NNs technology provides technical support for EKM and a reference.

Introduction

Development is the most important task for an enterprise, and management strategies are important for promoting an enterprise's development (Chui et al., 2020; Nakayama et al., 2021). As a management center for experience and innovative knowledge in enterprise development, the optimization and application of management strategies are crucial (Plageras et al., 2018; Ruel et al., 2019). Although the optimization of enterprise knowledge management (EKM) strategies is not perfect at present, many studies have provided technical support.

Tomlinson (2020) pointed out that with the rapid development of the economy and technology and accelerated market globalization, enterprises are now facing an increasingly complex competitive environment. The traditional enterprise model can no longer adapt to this unpredictable competitive environment; therefore, virtual enterprises have emerged as the times require (Cai et al., 2022; Zheng et al., 2021a, 2021b). Knowledge management can be regarded as a magic weapon for competitive advantage of virtual enterprises (Li et al., 2019; Tomlinson, 2020). Marabelli & Newell (2019) showed that the exponential growth of data and emerging technical tools in the era of big data have put forward new requirements for EKM, thus the innovation and exploration of EKM is significant for improving the core competitiveness of enterprises based on big data (Marabelli & Newell, 2019; Zheng et al., 2021c). Chatterjee et al. (2021) indicated that innovation is the first driving force for development. This indicates that innovation-driven high quality economic development is an inherent requirement for realizing the transformation of development momentum and improving the quality of development. To accelerate the growth of an innovative country, implementing an innovation-driven development strategy and highlighting technological innovations that lead to all-round innovation are necessary (Fan et al., 2022; Zhang et al., 2021; Zhou et al., 2022). The capacity and

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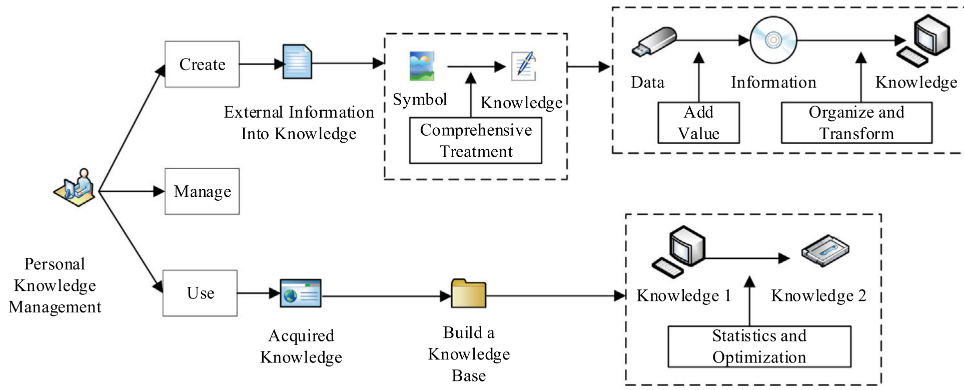

Fig. 1. Personal knowledge management framework.

level of the main body of technological innovation determines the success or failure of the growth of an innovative country. Knowledge management is a key driver of technological innovation. On the one hand, the implementation of knowledge management can tap the potential of enterprise innovation; on the other hand, it can reduce innovation risks. Knowledge management effectively promotes the continuous development of enterprises' technological innovation. Therefore, how to use knowledge management methods to efficiently integrate and promote technological innovation has become the primary issue for improving enterprises market competitiveness (Chatterjee et al., 2021; Chopra et al., 2022). Sorokin et al. (2020) demonstrated that with the continuous improvement of the economy and technology, technical means and artificial intelligence, particularly, artificial neural network (ANN) technology, have gradually attracted attention. ANN technology can imitate the relevant system structure and process the dynamic technology of the model using an Internet platform to achieve the actual goal of Internet management and control. With the maturity and improvement of relevant technologies, ANN technology has been widely used (Kumar et al., 2021; Sorokin et al., 2020). Gui & Xu (2021) suggested that in enterprises, the risk of knowledge sharing is a direct factor affecting the success or failure of EKM activities. Effective risk prediction of enterprise knowledge sharing leads to assessment of possible risks and help the enterprise to control them before occurrence. Timely adaptation to changes in the external environment is extremely important for enterprise development. Neural networks (NNs) technology can provide reliable risk prediction for the enterprise through calculation and management thus promoting effective enterprise development (Al-Qerem et al., 2020; Gui & Xu, 2021).

The summary of this paper is as follows: the current situation of EKM is understood, and its strategies are analyzed. Second, specific algorithms and applications of NNs technology are elaborated. Finally, NNs technology is applied to EKM strategies research, and the evaluation and optimization of EKM are analyzed. It not only provides technical support for the optimization of EKM strategies but also contributes to the development of enterprises.

EKM strategies and innovative development

Theory of EKM

EKM is divided into three parts: personal knowledge management, knowledge value management, and knowledge creation. Personal knowledge management refers to employee management of their own problem-solving skills and methods. There are four steps to personal knowledge management. First, employees can formulate methods and strategies to acquire knowledge according to their needs. Second, employees can filter the knowledge or information they acquire according to their conditions of use. Third, they formulate a specific usage strategy for filtered usage data. Finally, they can build their own databases based on the large data they have obtained and make adjustments at any time according to specific needs (Elgendy et al., 2021; Oliva et al., 2019). The specific requirement of personal knowledge management is that the enterprise's employees use of information and data ensures they can quickly obtain the required work data, thus improving the quality and efficiency of their work (Cvitić et al., 2021; Friedrich et al., 2019). The framework of personal knowledge management is illustrated in Fig. 1.

From Fig. 1, individuals should first collect the data needed in the work process of the enterprise in personal knowledge management and convert the collected data into their own knowledge. All knowledge statistics are then built into their own independent knowledge base through accumulation, such that they can timely obtain what they need in the process of work (Bouncken et al., 2022; Gou et al., 2019).

Knowledge value management refers to the use of knowledge by enterprises, which includes the acquisition, adjustment, and utilization of knowledge (Bouarara, 2021; Orenga-Roglá & Chalmeta, 2019; Singh & Sachan, 2021). In the process of acquisition, the enterprise needs to obtain information from external sources based on its needs and process this information into knowledge that meets the enterprise's needs. Finally, the obtained knowledge is managed and used through building a knowledge base (Lv et al., 2022; Mohd Selamat et al., 2020). The specific process of enterprise knowledge value management is shown in Fig. 2.

From Fig. 2, Enterprises manage the value of knowledge through various processes, such as processing, expansion, innovation, and reconstruction. The resulting knowledge statistics are sorted and built into a knowledge base used in the process of operation to improve the value of the enterprise (Gacanin et al., 2019; Sheng et al., 2022). Knowledge creation is significant in the development of enterprises, as through acquiring external knowledge according to its own development experience, the enterprise aggregates and sorts out the knowledge to obtain knowledge that can eventually be directly used (Chen et al., 2021; Mullins & Cronan, 2021). The acquisition of potential knowledge should be explored through new activities and converted into directly available knowledge. The acquisition of obvious external knowledge requires enterprises to strengthen external contact in the conducting new activities and then acquire useful knowledge (Lei et al., 2022; Skobelev et al., 2019). Ultimately, the enterprise needs to process the acquired knowledge into useful knowledge, which should be updated and improved in real time, for future development process (Sardi et al., 2019). The process of enterprise knowledge creation is shown in Fig. 3.

As shown in Fig. 3, Enterprises should first create different types and scales of activity. In the course of the activities, promptly exploring the required internal potential knowledge and external knowledge is necessary. Then, aggregating all the knowledge and internalizing it into the enterprise's own knowledge through processing is needed (Evans & Price, 2020; Wu & Zhu, 2021). The acquisition

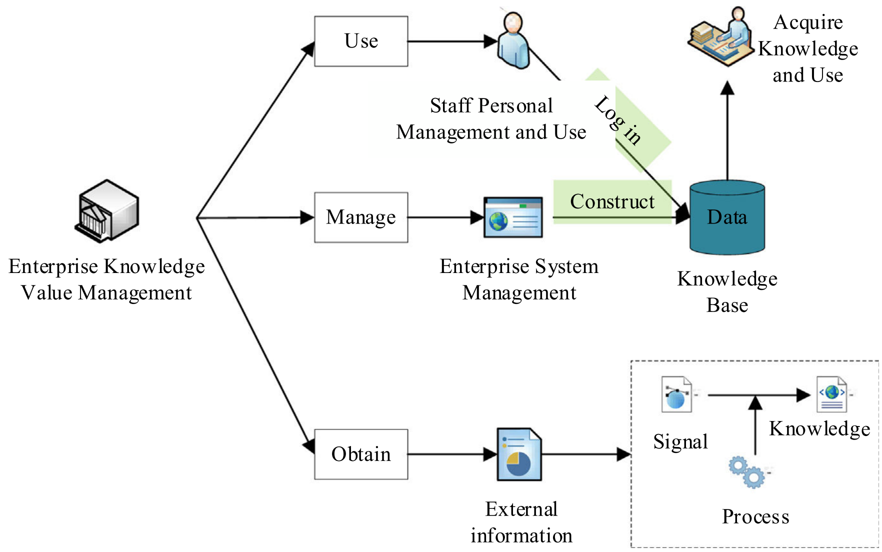

Fig. 2. Enterprise management of knowledge value.

and use of knowledge is critical in the process of enterprise development. Therefore, enterprises should strengthen their knowledge management strategies from two aspects. On the one hand, in terms of knowledge acquisition, participating in more activities to obtain useful external and internal information and converting this information into knowledge used timely by the enterprise is necessary. Therefore, building sufficient knowledge systems for effective knowledge management is essential. It can not only provide a knowledge storage environment for the enterprise but also improve the efficiency of knowledge usage. On the other hand, systematically managing knowledge usage process and to recording the usage and usage trends in real time is important. Knowledge management is the internal driving force of enterprise development; therefore, the optimization of knowledge management strategies is also crucial. To provide a reference for the optimization of EKM strategies, different knowledge management strategies for different enterprises will be studied.

Theory of NNs technology

NNs are used to build a data-processing model composed of many neurons and adaptive systems by simulating the neural network of the human brain. This model is similar to that of the biological nervous system. It can self-adjust, learn quickly, and store the data that needs to be processed; thus, it can process large data and store it in real-time. The structure of NNs mainly includes the input, hidden, and output layers. Each layer is composed of numerous neurons. Neurons in the same layer are not connected to each other, but are connected to neurons in other layers. The main function of the input layer is to support the input of data. The function of the implicit layer is to analyze the characteristics of the input data and transmit the characteristics to the output layer. The output layer summarizes and analyzes the data characteristics and outputs them to the user device (Anagnostopoulos & Rizeq, 2019; Chen & Sivakumar, 2021). The working and structural principles of the NNs are shown in Fig. 4.

In Fig. 4, when NNs process data, they first input the data into the structure of NNs through the input layer, then, they analyze the data and transmit features through the hidden layer. Finally, the characteristics of the data are output to the user device. Meanwhile, NNs carry out a reverse error analysis of the data through which data can be adjusted and improved and more accurate results can be obtained for data research.

Algorithms of NNs

The NNs are studied and calculated layer by layer, the eigenvalues of the data are obtained through forward calculation, and the errors of the results are analyzed through reverse calculation. Therefore, in the process of NNs calculation, the weight of the data calculation results should be adjusted first, as shown in Eq. (1)

$$w(t+1) = w(t) + \Delta w(t) \tag{1}$$

$w(t)$ represents the weight of the neurons in the calculation process, and $\Delta w(t)$ represents the adjustment direction of the neuron weights. There is an adjustment value for each adjustment, and the value satisfies Eq. (2):

$$F(w(t+1)) < F(w(t)) \tag{2}$$

The calculation equation of $F\Big(w(t+1)\Big)$ is shown in (3):

$$F(w(t+1)) = F\big(w(t) + \Delta w(t)\big) \approx F(w(t)) + g^T(t)\Delta w(t) \tag{3}$$

$g(t)$ represents the layer direction of the neuron adjustment value, as shown in Eq. (4)

$$g(t) = \nabla F(w)|_{w=w(t)} \tag{4}$$

The relationship between the layer direction and the direction of the neuron weight adjustment is shown in Eq. (5).

$$\Delta w(t) = -cg(t) \tag{5}$$

c represents the learning rate of the neurons. Through this, the error of the data calculation can be analyzed, as shown in Eq. (6)

$$E = \frac{1}{2}(d-y)^2 = \frac{1}{2}\sum_{k=1}^{l}\Big(d_k - f(w^T x)\Big)^2 \tag{6}$$

d indicates the expected output result value, x is the actual input data, and y shows the actual output result. The input vector of the input layer of the NNs is shown in Eq. (7).

$$X = (\, x_2 \quad x_2 \quad \ldots, \quad x_n\,)^T \tag{7}$$

The output vector of the hidden layer is shown in Eq. (8):

$$Y = (y_1 y_2 \ldots y_w)^T \tag{8}$$

The output vector of the output layer is shown in Eq. (9):

$$O = (O_2, O_2, \ldots, O_k \ldots, O_l)^T \tag{9}$$

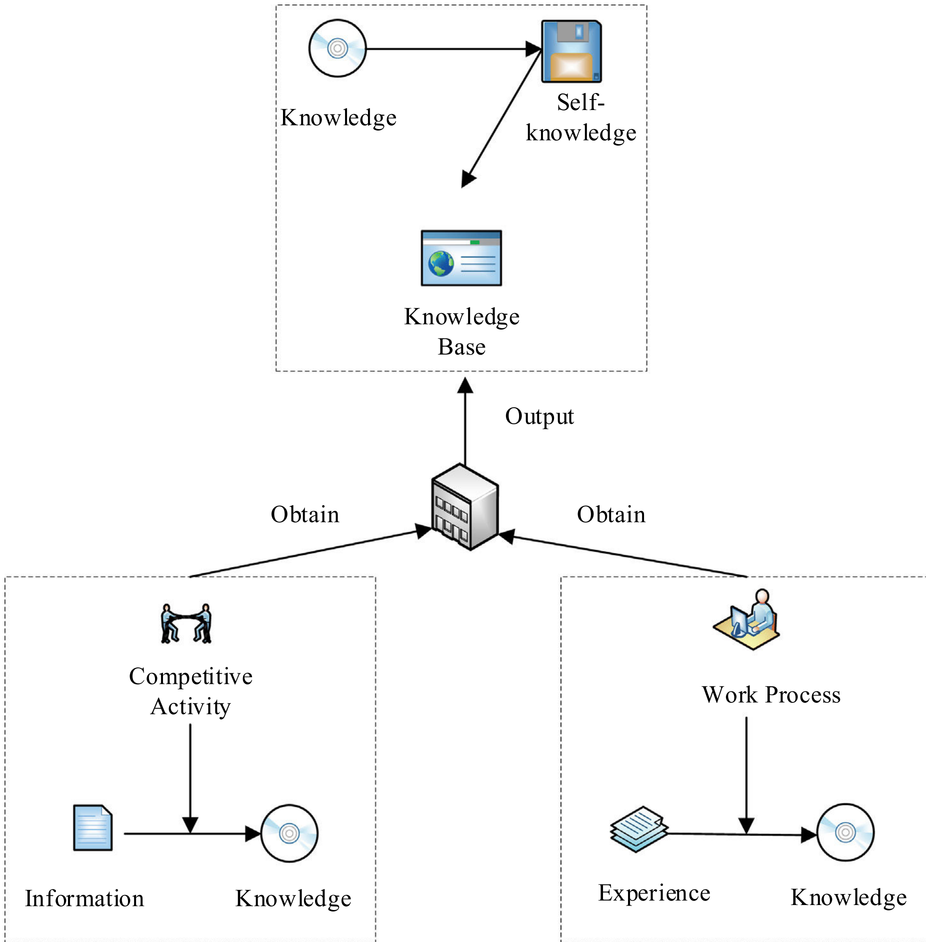

Fig. 3. Creation of enterprise knowledge.

During the calculation process, the vector of the user's expected output is given by Eq. (10).

$$d = (d_l d_2 \ldots, d_k \ldots, d_l)^T \tag{10}$$

The weight matrix between the input layer and hidden layer is given by Eq. (11).

$$V = (v_1, v_2 \ldots, v_m) \tag{11}$$

The weight matrix between the hidden layer and output layer is given by Eq. (12).

$$W = (w_l w_2 \ldots, w_l) \tag{12}$$

n, w, and l represent the calculated amounts of each factor in the calculation data. The calculation equation for the excitation function of the NNs is shown in Eq. (13).

$$f(x) = \frac{1}{1+e^{-x}} \tag{13}$$

The minimum error value can also be calculated using the error equation of the NNs. The specific adjustment direction of the weight should change, as shown in Eq. (14)

$$\Delta w_{jk} \propto -\frac{\partial E}{\partial w_{jk}} \tag{14}$$

$\frac{\partial E}{\partial w_{jk}}$ represents the rate of change of the error value; when the change value of w_{jk} is negative, the error is relatively reduced. Therefore, if the error value is reduced, you can change the amount of w_{jk} to a negative value. The equation for the direction of weight adjustment is shown in (15).

$$\Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}} \tag{15}$$

The equation for calculating the change of the weight matrix is shown in (16):

$$\Delta v_{ij} = -\eta \frac{\partial E}{\partial v_{lj}} \tag{16}$$

η is a constant and represents proportions. Each layer can be calculated based on a one-line equation, and the equation of the output layer is shown in (17).

$$net_k = \sum_{j=0}^{m} w_{jk} y_j (k = 1, 2, ..., l) \tag{17}$$

η is a constant and represents the ordinal number of each layer, as shown in Eq. (18)

$$d_k = f(net_k)(k = 1, 2, \ldots, l) \tag{18}$$

The equation for calculating the hidden layer is given by (19) and (20) as follows:

$$net_k = \sum_{j=0}^{m} v_{ij} x_i (j = 1, 2, ..., l) \tag{19}$$

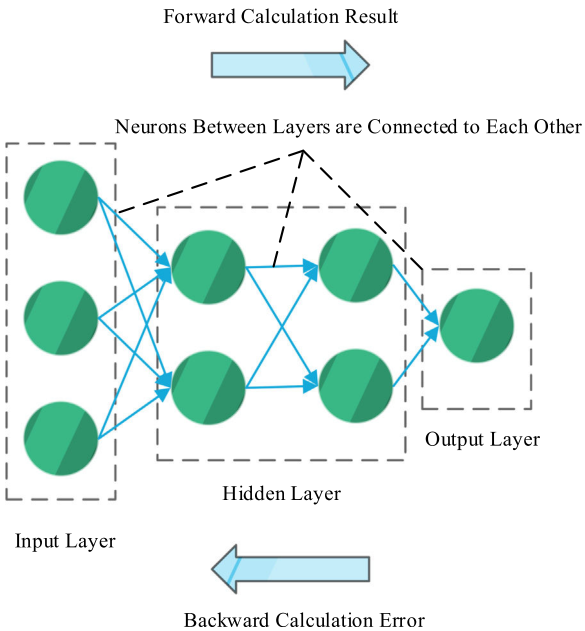

Fig. 4. Working principles of NNs technology.

$$y_j = f(net_j)(j = 1, 2, \ldots, m) \tag{20}$$

The equation for error values is shown in (21).

$$\frac{\partial E}{\partial d_k} = -(d_k - d_{k+1}) \tag{21}$$

The equation for the error values after the expansion of the hidden layer is given by Eqs. (22) and (23) as follows:

$$E = \frac{1}{2}\sum_{k=1}^{l}[d_k - f(net_k)]^2 = \frac{1}{2}\sum_{k=1}^{l}\left[d_k - f\left(\sum_{j=0}^{m} w_{jk}y_j\right)\right]^2 \tag{22}$$

$$\frac{\partial E}{\partial y_j} = \sum_{k=1}^{l}(d_k - d_{k+1})f'(net_k)w_{jk} \tag{23}$$

The equation for error values after expanding the input layer is shown in (24).

$$E = \frac{1}{2}\sum_{k=1}^{l}\left[d_k - f\left(\sum_{j=0}^{m} w_{jk}f(net_k)\right)\right]^2 \tag{24}$$

Further refinement produces Eq. (25):

$$E = \frac{1}{2}\sum_{k=1}^{l}\left[d_k - f\left(\sum_{j=0}^{m} w_{jk}f\left(\sum_{i=0}^{n} v_{ij}x_i\right)\right)\right]^2 \tag{25}$$

Eqs. (15) and (16) can be transformed into Eqs. (26) and (27), respectively:

$$\Delta w_{jk} = -\eta\frac{\partial E}{\partial w_{jk}} = -\eta\frac{\partial E}{\partial net_k}\frac{\partial net_k}{\partial w_{jk}} = \eta\delta_j^{\circ}y_j \tag{26}$$

$$\Delta v_{ij} = -\eta\frac{\partial E}{\partial v_{ij}} = -\eta\frac{\partial E}{\partial net}\frac{\partial net_j}{\partial v_{lj}} = \eta\delta_j^{y}x_i \tag{27}$$

Subsequently, the weight adjustment of each layer can be calculated. The derivation of the output layer is shown in Eq. (28):

$$\begin{aligned}\delta_i^{\circ} &= -\frac{\partial E}{\partial net_k} = \& - \frac{\partial E}{\partial d_{k+1}}\frac{\partial d_{k+1}}{\partial net_k} = -\frac{\partial E}{\partial d_{k+1}}f'(net_k)\\ &= (d_k - d_{k+1})d_{k+1}(1 - d_{k+1})\end{aligned} \tag{28}$$

The derivation of the hidden layer is shown in Eq. (29).

$$\delta_j^{'} = -\frac{\partial E}{\partial net_j} = -\frac{\partial E}{\partial y_j}\frac{\partial y_i}{\partial net_j} = -\frac{\partial E}{\partial y_j}f'(net_j) \tag{29}$$

Further refinement produces Eq. (30).

$$\delta'_j = \sum_{k=1}^{l}(d_k - d_{k+1})f'(net_k)w_{jk}f'(net_j) = \sum_{k=1}^{l}\delta_j^0 w_{jk}y_j(1 - y_j) \tag{30}$$

Combining δ_i° and $\delta_j^{'}$ with Eqs. (26) and (27), the direction of the weight adjustment of NNs is shown in Eqs. (31) and (32).

$$\Delta w_{jk} = \eta\delta_i^{\circ}y_j = \eta(d_k - o_k)o_k(1 - o_k) \tag{31}$$

$$\Delta v_{ij} = \eta\delta'_j x_i = \eta\left(\sum_{k=1}^{l}\delta_j^{\circ}w_{jk}\right)y_j(1 - y_j)x_i \tag{32}$$

All parameters are universal. NNs technology can obtain the results of the overall data through forward calculation as well as analyze the errors of the overall data through reverse calculation. Therefore, it not only obtains data in EKM but also timely adjusts the knowledge base to help enterprises improve the management of enterprise knowledge (Haghighat & Li, 2021).

Model construction

EKM requires not only the overall self-management by the enterprise but also the self-management by individual employees. In the EKM evaluation standard, enterprise employees are evaluated based on the frequency with which they log into the EKM system and the size of knowledge base built and data storage (Diederich et al., 2020; Gao et al., 2021; Pan et al., 2021). Enterprises are assessed based on the stability of the internal environment, adaptability to the external environment, competitiveness, and innovation ability of the enterprise (Bakar et al., 2019; Wu et al., 2021; Zhao et al., 2021). The evaluation basis for the EKM is shown in Fig. 5.

The external environment, internal environment, innovation ability, and competitiveness of enterprises are all crucial for enterprises. Therefore, these five aspects of data are used to evaluate EKM strategy and enterprise innovation development. To provide a guarantee for improving the efficiency and quality of EKM, the specific role of NNs technology in this application is evaluated and analyzed. The external environment is the situation in which the enterprise competes or cooperates with external enterprises. In this state, enterprises can analyze the management model or corporate culture of external enterprises, absorb information that is useful to the enterprise, and transform it for their own management and use. Internal environment refers to the internal working state of an enterprise, where the enterprise can regularly summarize and analyze its own performance, from which it obtains experience and information, and translates these into knowledge for their own management and use. Knowledge can be obtained from innovation capabilities through innovative activities within and outside the enterprise and can then be translated into enterprise knowledge. Acquiring knowledge in competitiveness refers to obtaining useful information from the internal and external competition and converting it into knowledge for management and use. Finally, the enterprise should evaluate its performance at all times, determine its various environments, obtain useful information from it, and translate it into useful knowledge for

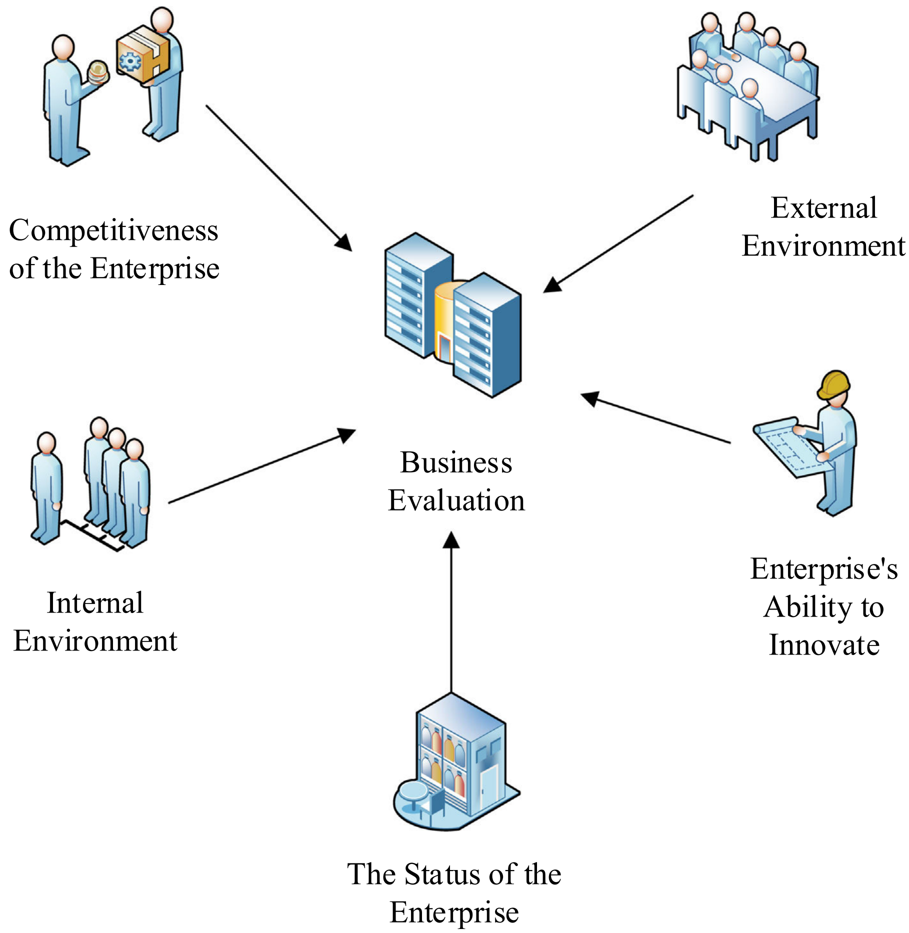

Fig. 5. The basis for enterprise evaluation.

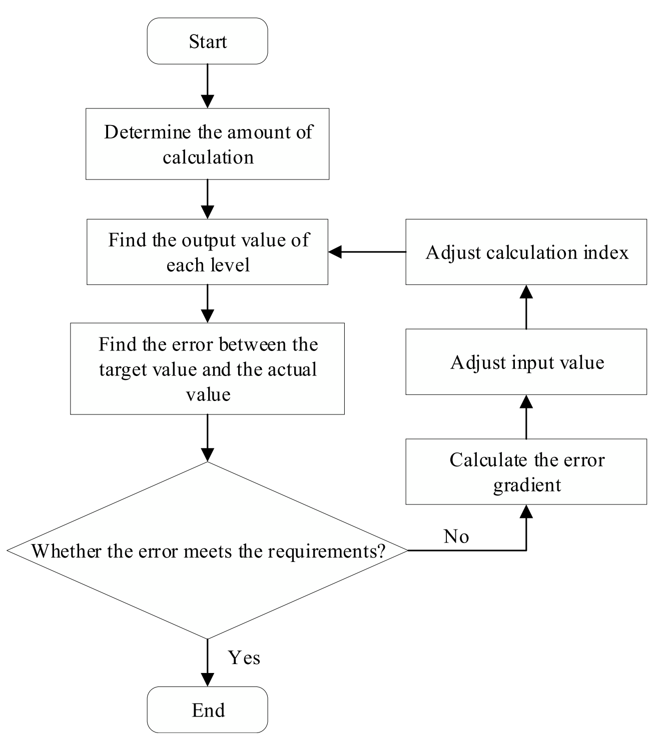

Fig. 6. NNs Calculation flowchart.

management and use. The process of evaluating EKM using NNs technology is shown in Fig. 6.

As shown in Fig. 6, when using NNs technology to calculate and evaluate EKM, the amount of input value and specific input data must be determined first, and then the output value of each layer must be calculated. The error value between the calculated results and the target must be determined through the output value of each layer, and the error value is used to determine whether it meets the estimate. Otherwise, the gradient of the error value must be calculated, and then the input value and calculation conditions are adjusted according to the error gradient. Finally, the error value between the actual and target results meets the estimated error value.

Results

Analysis results of evaluation indicators of EKM

The evaluation indicators of EKM include the external environment, internal environment, innovation ability, competitiveness, and the current situation of the enterprise. By testing these indicators, the enterprise's focus on knowledge management can be clearly understood. The results of the knowledge management evaluations of the six enterprises are shown in Fig. 7.

As shown in Fig. 7, the six enterprises have different performance in knowledge management evaluation. In the evaluation bidding of EKM, IE represents the internal environment of the enterprise, EE represents the external environment, IA represents creativity, C represents competitiveness, and ES indicates the current situation.

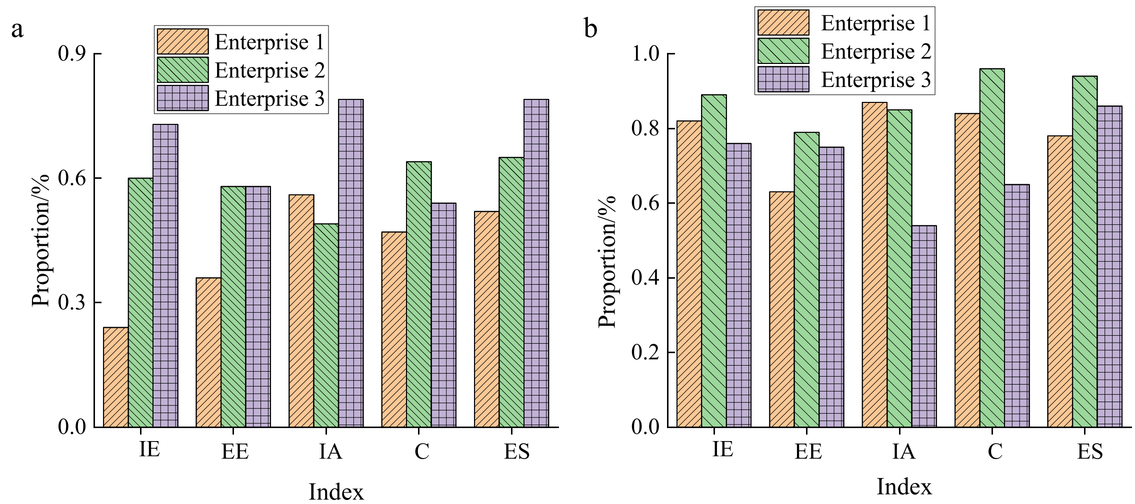

Fig. 7. EKM Evaluation indicators (a: Group I evaluation indicators; b: Group II evaluation indicators).

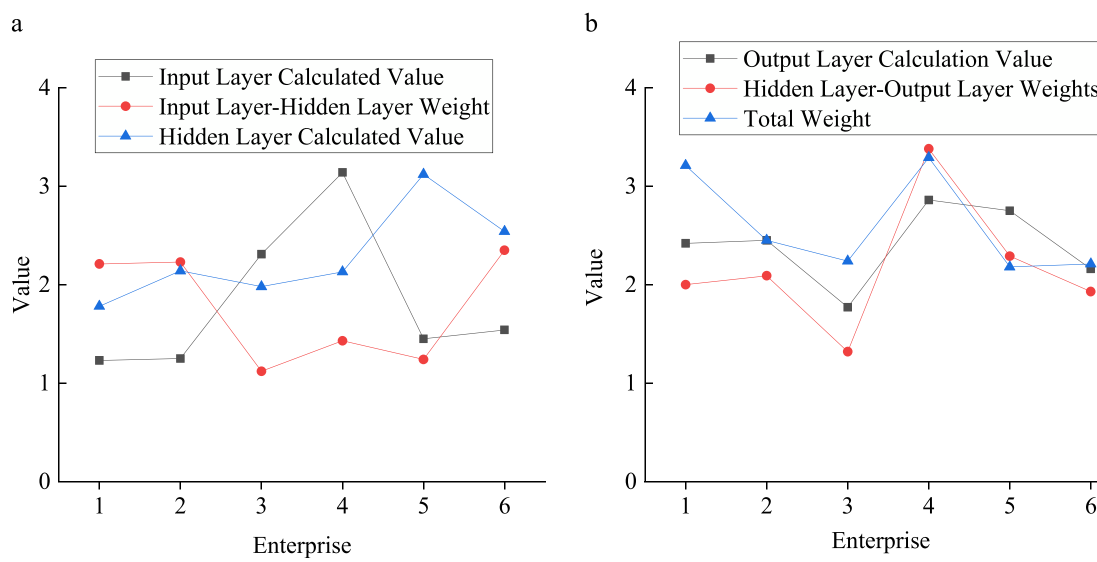

Fig. 8. Calculation results of EKM of six enterprises (a: results of input layer and hidden layer, b: results of output layer and hidden layer.).

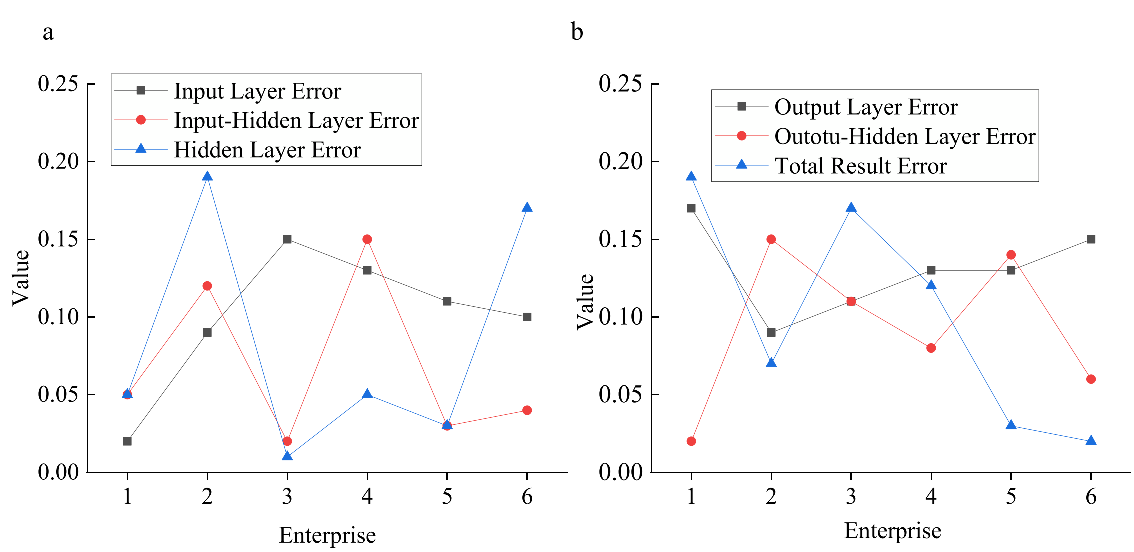

Fig. 9. Calculation error of EKM strategies (a: input layer and hidden layer errors, b: hidden layer, output layer, and total result errors.).

Through the different evaluation values of the enterprises for these indicators, it can be inferred that each enterprise has a different degree of emphasis on knowledge management. The values of Enterprises 1 and 2 in the second group are relatively high for the five indicators. It can be determined that these two enterprises focus more on knowledge management than others.

Optimization of NNs for EKM

NNs technology is used for the optimization of EKM through both forward and reverse calculations, and data results can not only be obtained quickly but also the data selection can be adjusted in time through data errors. The analysis of knowledge management in the six enterprises using NNs technology is shown in Fig. 8, where we elaborate on the optimization process.

The knowledge management of the six enterprises is investigated and analyzed using big data, and the data can be calculated and analyzed step by step through the calculation of NNs technology. Fig. 8 shows that the investments of the six enterprises in knowledge management are very different. Therefore, the requirements for calculation methods are relatively high, and different enterprises should perform different degrees of calculation. From the calculation results, the comprehensive value of Enterprise 4 is relatively high, with a maximum of approximately 3.2, thus the knowledge management strategy of Enterprise 4 is relatively perfect compared with other enterprises. The NN technology can not only calculate the data results forward but also analyze the errors of the calculation results in reverse, providing users with more comprehensive data support. The calculation errors are obtained by analyzing the knowledge management strategies of six enterprises using NNs technology, as shown in Fig. 9.

As shown in Fig. 9, through the error between the reverse calculation and actual results, it is found that the error of all calculation results is relatively small, with a maximum of approximately 0.197 and a minimum of approximately 0.012. This indicates that it is very reliable to optimize the EKM using the NNs technology. By comparing six enterprises, NNs can analyze EKM strategies for enterprises with different conditions and management systems. The analysis can provide technical support and important references for the innovation and development of EKM.

Discussion

EKM is crucial to the growth and development of enterprises because EKM can provide data support for enterprises, summarize experience, and guide the direction for the development of enterprises. Modern enterprises are paying increasing attention to knowledge management, and the study of EKM is also becoming increasingly significant. However, related technology is lacking. Therefore, EKM is researched and analyzed using NNs technology through big data. In the process of enterprise development, NNs technology analyzes and obtains data for enterprises in a timely manner and provides relatively complete knowledge through forward and reverse error calculations. This helps enterprises build an independent knowledge base, evaluate it in real time during the application of the knowledge base, and improve stored knowledge. In other words, using NNs technology can not only create new knowledge for enterprises, but also provide technical support for the development and improvement of EKM. In addition, if enterprises want to strengthen the optimization of knowledge management strategies, they should obtain relevant information from external sources, convert useful information into their own knowledge through exploration, combine knowledge to build a knowledge base to improve the depth of EKM, and extract useful information through development. They should also transform information into their own useful timely knowledge to fill gaps in the knowledge base and improve EKM strategies. In terms of evaluation, enterprises need to strengthen their adaptability to the external environment, improve the vitality of the environment, increase competitiveness and creativity, and comprehensively improve their management ability.

Conclusion

With the support of big data, NNs technology is used to study and analyze EKM strategies and provide data through step-by-step analysis to enable formulation of relative strategies for EKM. Optimizing EKM should start with improving the adaptability to the external environment of the enterprise, vitality of the internal environment, competitiveness and creativity, and real-time analysis of the current situation of the enterprise. Meanwhile, the management model of the enterprise should be adjusted in a timely manner according to the collection and analysis. Using NNs technology to analyze EKM strategies can not only analyze different enterprises but also calculate the knowledge management indicators of different strategies. The final calculation results reflect the knowledge management indicators and provide calculation errors for the enterprise. Enterprises can adjust their own knowledge management strategies according to the calculated indicators and can also analyze the practicality of the calculation based on the errors provided in the calculation process and adjust the calculation items. The calculation of NNs technology provides technical support for EKM strategies and guarantees optimization. Although the EKM method is relatively comprehensive, it is not ideal for practical application. In the future, this part will be strengthened to improve the application of NNs technology in the optimization of EKM strategies.

Declaration of Competing Interest

The authors declare that there's no conflict of interest.

Data availability

The simulation experiment data used to support the findings of this study are available from the corresponding author upon request.

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