Hindawi
Wireless Communications and Mobile Computing
Volume 2023, Article ID 9803768, 1 page
https://doi.org/10.1155/2023/9803768

Retraction

Retracted: Enterprise Management Model Innovation and Performance Index Evaluation Based on the Era of Big Data

Wireless Communications and Mobile Computing

Received 13 September 2023; Accepted 13 September 2023; Published 14 September 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

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

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

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

References

[1] Y. Xie, "Enterprise Management Model Innovation and Performance Index Evaluation Based on the Era of Big Data," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 2714892, 12 pages, 2022.

Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 2714892, 12 pages
https://doi.org/10.1155/2022/2714892

Research Article

Enterprise Management Model Innovation and Performance Index Evaluation Based on the Era of Big Data

Yun Xie

Huaxin Gas Group Co., Ltd., Taiyuan, Shanxi 030000, China

Correspondence should be addressed to Yun Xie; 2016922@tyust.edu.cn

Received 19 May 2022; Revised 24 June 2022; Accepted 28 June 2022; Published 9 July 2022

Academic Editor: Kalidoss Rajakani

The innovation of enterprise management model has increasingly become one of the important sources of competitive advantage for enterprises. At present, the market environment is changing rapidly, and information technology is changing the nature and structure of enterprise competition. In the competitive landscape of enterprises under the background of network economy, only relying on technological innovation can no longer meet the needs of enterprise development. In recent years, the successful practice of a large number of enterprises has shown that the innovation of enterprise management mode is also an indispensable and important factor to promote the sustainable development of enterprises. In the new format of competition among enterprises, the innovation of enterprise management mode is playing an important role. Scholars have very rich research contents on the innovation of enterprise management model. First, they focus on the research between the innovation of enterprise management model and the value creation of enterprises. They believe that determining the structure of new business and innovation of enterprise management model can create value for enterprises. The innovation of enterprise management model can effectively explain the differences in enterprise performance; secondly, the research of enterprise management model innovation has been extended to its classification research; that is, different types of enterprise management model innovation have different effects on performance; finally, in the existing research, in this paper, some progress has been made in the exploration of the mediating variables between enterprise management model innovation and performance. The example verification shows that the performance of the momentum-adaptive algorithm is the best. Using the BP network model can effectively evaluate the innovation of enterprise management mode and performance indicators, so as to guide the implementation of enterprise management mode innovation activities. Although this paper has made some innovative achievements, there are still many limitations and deficiencies in the research. The depth of literature search, the breadth of data measurement collection, and the subjectivity of questionnaires will affect the accuracy of the results. The practicality of the research results needs to be further improved in the follow-up research.

1. Introduction

Dataization and informatization integrate various types of things such as equipment, people, and enterprises, thus forming the operating form and framework of the network economy [1]. In the context of the new economy, there is both cooperation and competition among enterprises, and the competition form has gradually evolved from individual competition to competition in the entire transaction network. The process of value creation also shows that the behavior of a single enterprise evolves into a network of enterprise members and collaborative activities [2].

With the rapid development of big data and the Internet of Things, along with the gradual integration of the consumer Internet and the industrial Internet, the traditional enterprise management model will be completely subverted, and the industry competition rules will be completely changed [3]. Therefore, under the new economy, the continuous innovation of enterprise management model has become an important rule to obtain sustainable competitive advantage [4].

The long-term goal of an enterprise should be to maximize enterprise value, and the process of value creation in the traditional economy is entirely from the efforts of the enterprise itself [5]. The rapid development of information technology

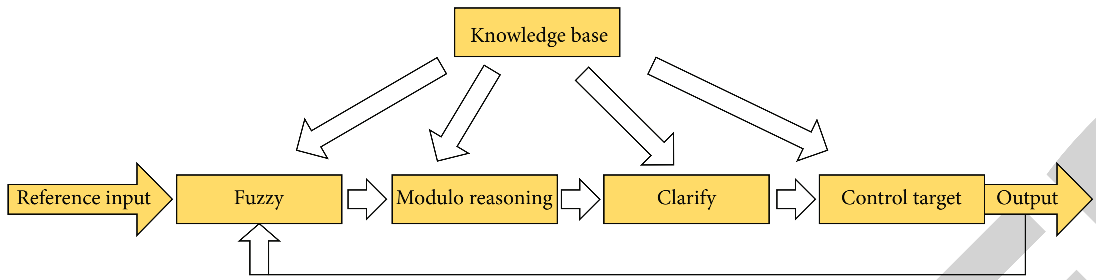

Figure 1: Fuzzy controller.

and network has brought about profound changes in the process of enterprise value creation and realization. There are three aspects to the concept of network value creation: first, the enterprise value creation originates from the internal; secondly, the competitors backlash against the value and the value creation assisted by the partners; and thirdly, the value creation will be affected by the supplier's assistance and the customer's bargaining [6]. Obviously, this is a cross-border operation system, including the collaborative activities of the enterprise itself, partners, and customers. Information technology and the Internet economy make the above-mentioned value creation process possible [7].

New communication and computing technologies and the establishment of an open global trading system mean that customers have more choices and diverse customer needs can find diverse expressions and provide more transparent alternatives [8].

The store model is the initial form of the enterprise management model, that is, opening stores in places where consumers are concentrated [9]. Fedex's "centralized network operation mode" and Dell's "customized + direct" enterprise management mode. However, fundamentally speaking, its profit model still does not deviate from the essence of the traditional model [10].

The traditional enterprise management has been developed for hundreds of years, and the enterprise management mode of production-agent-retail-customer has been maintained [11]. Businesses are profitable and profitable, and their value creation process can continue. As shown in Figure 1, what followed was a backlog of products, an increase in inventory, and an increase in storage costs, which eventually led to a break in the company's cash flow, making it unsustainable for the company to operate [12].

The innovation of enterprise management model in various industries is showing diversification, appearing one after another in various forms [13]. Since the innovation of enterprise management mode provides new paths and possibilities for enterprise development, new enterprise management modes will inevitably emerge one after another in the future enterprise competition [14].

The accelerating process of globalization has made market competition ruthless. With the continuous emergence of innovative products, there are many examples of corporate management giants failing miserably, resulting in the disappearance of their former glory. But as the changes continue to accelerate, some dazzling superstars have been born [15]. These business miracles have sparked a lot of thinking from practitioners and scholars [16]. The innovation of enterprise management mode can effectively improve the consumption and purchase experience of customers and then bring greater benefits to the enterprise itself [17]. The development of technology always precedes the birth of enterprise management model innovation, because the enterprise management model innovation needs to conform to the development situation of society, economy, and culture in order to play its due role [18].

The enterprise management model has gradually stabilized, and its position in the entire transaction network and the way of interaction with other transaction parties are also gradually fixed [19]. Customer preferences, market orientation, and policy changes are changing all the time, and even the entire ecological structure of the enterprise will change. If incumbent companies are greedy for the existing success and inherent stable model, they will be overtaken by latecomers and lose their former glory [20].

Even if there are good products and technologies, they have not found a suitable enterprise management model innovation. Therefore, the innovation of enterprise management mode and the rapid replication of successful enterprise management mode will be a normal state of enterprise competition. In order to gain the recognition of customers and create value for customers continuously, an enterprise must continuously innovate its management model [21].

2. State of the Art

2.1. Research Status of Enterprise Management Model Innovation. Generally speaking, compared to other businesses, the capital required to operate a service in a service enterprise is relatively low. Platform companies license their technology to other pharmaceutical or biotech-advanced companies. The advantage of this type of business is that the nature of their development is very stable and cumulative. This means that most of these techniques have broad applicability, and the number of application areas can be extended over time. Enterprises that adopt the product enterprise management model innovation take drug development as their main activity, and such enterprises can be divided into early and late-stage drug development enterprises, mainly depending on the stage of their product development. The products of early-stage development companies have reached clinical trial stage I/II, and the products of late-stage drug development have reached at least stage III clinical trials. Therefore, there are three

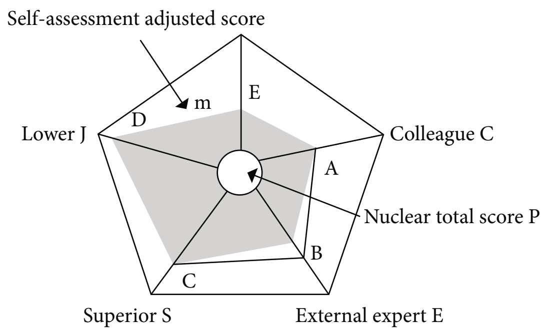

Figure 2: Five-star chart of performance appraisal.

possible modes: hybrid service and product mode, hybrid platform and product mode, and hybrid service and platform mode.

Yuan Lei (2007) proposed the "3-4-8" composition system of enterprise management model innovation. Yuan Lei (2009) proposed that the innovation of enterprise management mode of retail enterprises can be divided into three types: enterprise management mode that seeks profit from customer value, enterprise management mode that seeks profit from partner value, and enterprise management mode that seeks profit from enterprise value. Wikström et al. (2009) took product-driven, innovation and technology-driven, profit-driven, and service-driven as the basic types of enterprise management model innovation.

Morris, Shirokova, and Shatalow (2013) took Russian food service enterprises as a sample, identified seven innovations in enterprise management models in this industry, and pointed out the relationship between them and performance.

Saeb and Foss (2014) divided enterprise management model innovation into four categories: efficiency-oriented, user-centric, cooperation-oriented, and open platform. Rasmussen and Foss (2014) took the pharmaceutical industry as a sample and distinguished three types of enterprise management modes: traditional mode, service mode, and intermediate mode.

After sorting out and analyzing the literature, this study found that the classification and characterization of the innovation classification of enterprise management model by researchers are related to the business model of the enterprise and different economic environments and situations. Among all the classifications, two types of enterprise management model innovations, efficiency and novelty (Zott & Amit, 2007), can best reflect the structure of enterprise management models. The nature of the elements.

2.2. Research Status of Enterprise Performance Evaluation. The domestic research on enterprise performance evaluation started relatively late, and two research trajectories have formed: one is the construction of a government-led state-owned enterprise performance evaluation system. The five-star relationship table of the performance assessment of enterprises is shown in Figure 2.

The Chinese government has successively The enterprise performance evaluation system has been revised and improved several times, and the evaluation idea has also developed from the initial evaluation of "growth rate" and "economic benefits" to evaluation of "operational performance" and "comprehensive performance." There are 4 items of operation status, solvency status, and development capacity status. These 4 items are composed of 3 levels of basic indicators, revised indicators and expert evaluation indicators, and a total of 32 indicators. Improve the level of return on capital, and correctly guide the business behavior of enterprises.

The research on enterprise performance evaluation conducted by scholars has mostly introduced and borrowed foreign evaluation theories, and on this basis, they have carried out research innovations in theory and application, such as Shi Jiafang, Liu Qiaoqin, Yan Mei, and Yan Zhigang, and many other scholars have published relevant academic research results.

The fuzzy neural network structure can be used in the enterprise performance evaluation aspect, and the operation diagram of this structure is shown in Figure 3. On the whole, domestic research on enterprise performance evaluation has made certain achievements, but there are still some deficiencies: (1) In terms of timeliness, the existing enterprise performance evaluation system is past-oriented and single, mainly for enterprises that have already The economic business that has occurred is confirmed after the fact. (2) In terms of index setting, the evaluation index is still mainly based on financial indicators, and there is a lack of non-financial performance indicators such as customer satisfaction, market share, basic management level, development strategy, social impact, and ecological environment impact. (3) In terms of analysis methods, there is no original evaluation method, which is mostly limited to the improvement of foreign performance evaluation methods, and has not formed an overall performance evaluation theoretical system.

3. Methodology

3.1. Additional Momentum Term Algorithm. The standard BP algorithm only adjusts according to the gradient descent direction of the error at a certain moment and lacks the consideration of the gradient direction before this moment. Therefore, fluctuations often occur in the process of weight adjustment, and the convergence speed is slow. The additional momentum term takes into account the weights after the last correction, and has a damping effect on the weight adjustment at this time, preventing the network from falling into a local minimum point. On the basis of the weight change formula, add a factor proportional to the last weight change, namely:

$$\Delta\omega_{jk}(n) = \alpha\Delta\omega_{jk}(n-1) + \eta\delta_k^o(n)y_j(n) = \alpha\Delta\omega_{jk}(n-1) - \eta\frac{\partial E(n)}{\partial\omega_{jk}(n)}, \quad (1)$$

where α is the momentum term, which is generally a positive number, which determines the impact of the last weight change on the current weight change.

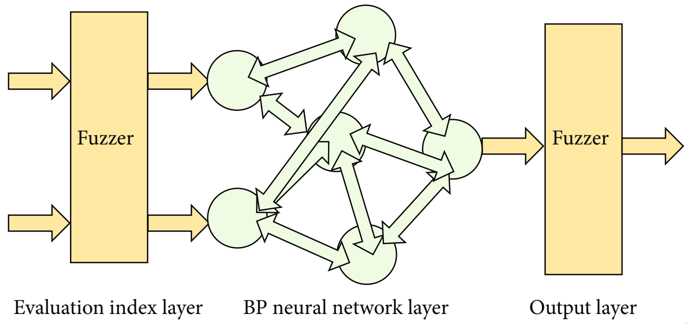

FIGURE 3: Fuzzy neural network structure.

3.2. Adaptive Learning Rate Algorithm. The inappropriate learning rate is one of the important reasons for the slow convergence of the standard BP algorithm. Due to the complexity and randomness of the network error, the error surface corresponding to the weight change will have different characteristics in different intervals. Some places are relatively flat, and the gradient of the error changes is small. If the step size is chosen to be a definite constant, it cannot be the optimal learning rate all the time. If the learning rate is too large, the network is prone to oscillation or even divergence during the training process, and the system is unstable. At this time, the learning rate is required to be small enough; if the learning rate is too small, the convergence process will be very slow, and it is required to increase the learning rate. This problem can be solved by the adaptive learning rate method. The basic idea is to increase η and shorten the learning time when learning converges, and reduce η in time when η is too large to converge. The rules for adaptive learning rate are as follows:

On the entire training set of the neural network, if the error function E increases after the weight adjustment and exceeds a predetermined percentage μ (generally 1% to 5%), the weight adjustment is cancelled, and the learning rate η is multiplied by with the factor ρ ($0 < \rho < 1$), and the additional momentum term (i.e., $\alpha = 0$) is cancelled at the same time. Usually $\mu = 4\%$, $\rho = 0.7$. If the error function E decreases after the weight adjustment, the adjusted weight is accepted, the learning rate η is multiplied by the factor ρ ($\rho > 1$), and the accessory momentum term is restored (i.e., $\alpha \neq 0$); if the error function$E$increases less thanμ, the learning rateηremains unchanged and the additional momentum term ($\alpha \neq 0$) is restored. The above rule can be expressed by the following equation:

$$\eta(k+1) = \begin{cases} a\eta(k) & E(k+1) < E(k) \\ \eta(k) & E(k) < E(k+1) < E(k) \times 1.04, \\ b\eta(k) & E(k+1) > E(k) \times 1.04 \end{cases} \quad (2)$$

where η is the learning rate, k is the number of training times, and E is the error function. Generally, take $a = 1.05$, $b = 0.7$. The selection range of the initial learning rate $\eta(0)$ can be more arbitrary. The adaptive learning rate method can enable the network to learn at an acceptable maximum rate, so that the convergence speed of the network can be effectively improved.

3.3. Levenberg-Marquardt (LM) Algorithm. The most prominent problem of the BP algorithm is the problem of convergence speed. The convergence speed of standard BP algorithm is too slow and even loses practical value. The LM algorithm is a standard nonlinear least squares optimization algorithm, which converges 10-100 times faster than the ordinary BP algorithm. Its basic idea is to allow each iteration of the error to search in the direction of deterioration, rather than along a single negative gradient direction, while making the weights of the network adaptively adjusted between the gradient descent method and the Gauss-Newton method, improving the convergence speed of the network. Let the error function be:

$$E(\omega) = \frac{1}{2}\sum_{i=1}^{n} e_i^2(\omega) = \frac{1}{2} e^T(\omega) e(\omega). \quad (3)$$

Among them,

$$e^T(\omega) = [e_1, e_2, \cdots, e_n], \quad (4)$$

where $w(k)$ represents the weight and threshold vector of the k-th iteration, then:

$$\omega(k+1) = \omega(k) + \Delta\omega. \quad (5)$$

Newton's algorithm adjusts the size of the weights according to the second-order derivative information and expands the error function $E(w)$ according to the second-order Taylor formula to obtain:

$$E(\omega(k+1)) \approx E(\omega(k)) + g^T(k)\Delta\omega(k) + \frac{1}{2}\Delta\omega^T(k)A(k)\Delta\omega(k), \quad (6)$$

where $gT(k)$ is the gradient vector of $E(w)$, $A(k)$ is the Hessian matrix of $E(w)$, and its element value is the second derivative of $E(w)$ to each weight; that is, $A(k) = \partial^2 E(w)/\partial$

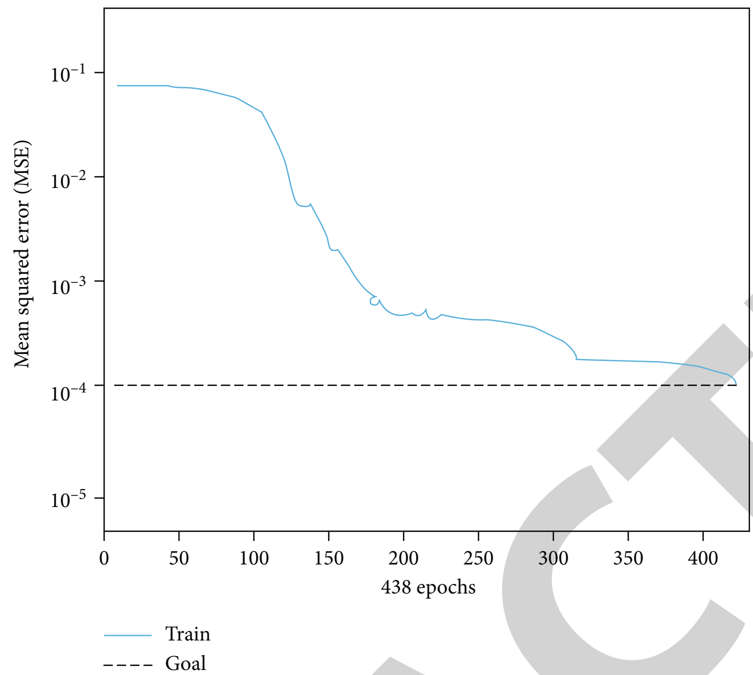

Figure 4: Training error performance curve of momentum-adaptive algorithm.

$w_i \partial w_j$, the weight. The corrected error function change is:

$$\Delta E(k) = g^T(k)\Delta\omega(k) + \frac{1}{2}\Delta\omega^T(k)A(k)\Delta\omega(k). \tag{7}$$

In order to obtain the minimum value of the above formula $\Delta E(k)$, it is necessary to satisfy:

$$\Delta\omega(k) = -A^{-1}(k)g(k). \tag{8}$$

This is the basic principle of Newton's method, namely:

$$\Delta\omega(k) = \left[-\nabla^2 E(\omega)\right]^{-1} \cdot \nabla E(\omega), \tag{9}$$

where $\nabla E(w)$ represents the gradient vector and $\nabla 2E(w)$ represents the Hessian matrix of the error function $E(w)$.

The gradient of $E(w)$ is:

$$\nabla E(\omega) = \sum_{i=1}^{n} e_i(\omega)\frac{\partial e_i(\omega)}{\partial \omega} = J^T(\omega)e(\omega). \tag{10}$$

In the formula,

$$J^T(\omega) = \begin{bmatrix} \frac{\partial e_1(\omega)}{\partial \omega_1} & \frac{\partial e_1(\omega)}{\partial \omega_2} & \cdots & \frac{\partial e_1(\omega)}{\partial \omega_n} \\ \frac{\partial e_2(\omega)}{\partial \omega_1} & \frac{\partial e_2(\omega)}{\partial \omega_2} & \cdots & \frac{\partial e_2(\omega)}{\partial \omega_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial e_n(\omega)}{\partial \omega_1} & \frac{\partial e_n(\omega)}{\partial \omega_2} & \cdots & \frac{\partial e_n(\omega)}{\partial \omega_n} \end{bmatrix}, \tag{11}$$

is the Jacobian matrix.

$$\nabla^2 E(\omega) = J^T(\omega) \cdot J(\omega) + S(\omega), \tag{12}$$

where $S(\omega) = \sum_{i=1}^{n} e_i(\omega) \cdot \nabla^2 e_i(\omega)$, $\nabla^2 e_i(\omega)$ is the Hessian matrix of $e_i(w)$.

When $S(w) \approx 0$ near the extreme point, it can be modified to Gauss-Newton method:

$$\Delta\omega = -\left[J^T(\omega) \cdot J(\omega)\right]^{-1} \cdot J(\omega) \cdot E(\omega). \tag{13}$$

The LM algorithm adjusts the Gauss-Newton method again, and the adjusted weight rules are:

$$\Delta\omega = -\left[J^T(\omega) \cdot J(\omega) + \mu I\right]^{-1} \cdot J(\omega) \cdot E(\omega), \tag{14}$$

where w is the adjustment increment of the weight and threshold vector, e is the error vector, J is the Jacobian matrix of the error to the weight threshold, μ is a scalar, and I is the identity matrix. During the learning process, the value of μ determines the properties of the learning algorithm. If the value of μ increases, the learning process is mainly based on the gradient descent method with a small learning rate; if the value of μ decreases to 0, the learning algorithm becomes the Gauss-Newton method. Since the matrix$[J^T J + \mu I]$is positive definite equation (14).The solution always exists. The LM algorithm smoothly reconciles between the gradient descent method and the Gauss-Newton method. If the expected error is met, the maximum number of training times is reached, or if the μ reaches the maximum value, the network stops training. The LM method requires approximate calculation of the Hessian

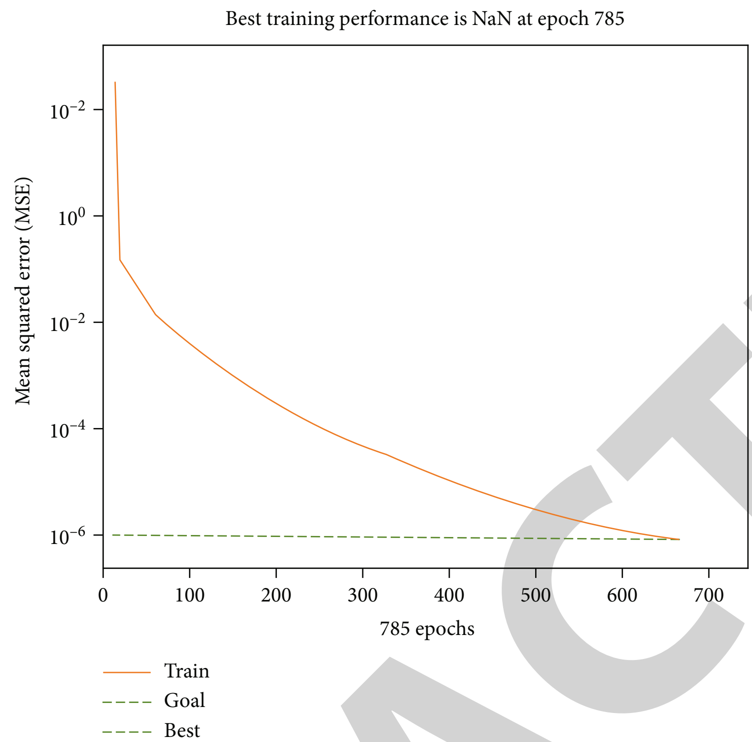

Figure 5: Graph of network training change.

matrix, which requires a large amount of computation and storage, and is suitable for smaller networks.

4. Result Analysis and Discussion

It can be seen from the results of the 7 experiments that the mean square error of the first training is the smallest, and the average absolute error and relative error of the second training are small, but the step size is too large. Therefore, the BP neural network of this enterprise knowledge management performance evaluation adopts the network of the first training. The training error performance curve of the network is shown in Figure 4. It can be seen that after 438 times of learning, the network has converged.

The topology of the network is 20-8-1 with 785 iterations per training. The requirement of error target goal = 0.001 is reached. The network training change curve is shown in Figure 5.

The prediction model output by the neural network training sample model after the index data reduction is shown in Figure 6.

4.1. Reliability and Validity Test Results

4.1.1. Enterprise Management Model Innovation Scale. The enterprise management model innovation scale contains two dimensions: the efficient enterprise management model innovation and the novel enterprise management model innovation. There are 16 items on the scale of enterprise management model innovation. This paper uses the Likert 5-level score as the scoring standard for the scale assignment. The scale is composed of a group of statements. Each statement has five responses, namely, "strongly agree," "agree," "not necessarily," "disagree," and "strongly disagree," which are recorded as 5, 4, 3, 2, and 1, respectively. The total score of each respondent's attitude is the sum of his answers to each question. This total score can explain his attitude or his different status on the scale. The degree of matching with the real situation of the enterprise is expressed in order from 1 to 5, as shown in Table 1.

This method can find out a few key indicators among a large number of indicators, so that researchers can understand and analyze the data more accurately, and can also understand the relationship between variables and factors more clearly and clearly, so this method has been obtained, which has been unanimously favored by the majority of researchers.

Since the factor loading results of the 16 items of enterprise management model innovation are all higher than the value of 0.5, the items A1-A16 in the scale are all suitable for measuring enterprise management model innovation. Through the test, the KMO value is 0.820, which is above 0.7, which meets the requirements of factor analysis, and the Bartlett sphericity test shows significance. The reason why the cumulative contribution rate of the factor variance is 62.221% is that all measurement items can reach the benchmark value above 0.5 to correspond to the load on the factor. Two factors are identified, as shown in Table 2:

This paper finds that the corrected correlation coefficient of a single project of enterprise management model innovation to all projects is greater than 0.35, and the *a* value of the excluded index is smaller than the "a value of the overall

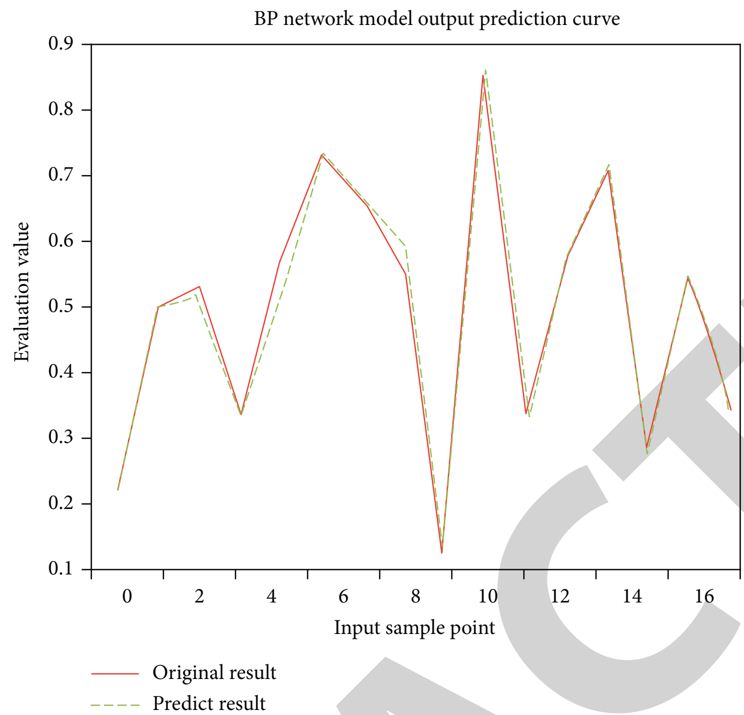

Figure 6: The output prediction curve of the network model.

Table 1: Descriptive statistics and correlation analysis of enterprise management model innovation.

Independent variable	Dimension	Item	Score	Standard deviation
Business model innovation	The efficient enterprise management model innovation	A1	2.85	0.917
		A2	3.05	0.809
		A3	3.17	0.985
		A4	2.56	0.873
		A5	2.79	0.861
		A6	3.12	1.015
		A7	3.17	1.101
		A8	3.01	0.813
	Novel enterprise management model innovation	A9	2.73	0.923
		A10	3.37	0.926
		A11	3.31	0.810
		A12	3.03	0.901
		A13	2.81	0.892
		A14	3.07	0.814
		A15	3.26	0.961
		A16	2.98	0.911

factor" and all projects The Cronbach's value of Cronbach's is greater than 0.7. Therefore, the items of the scale of enterprise management model innovation meet the requirements, no need to delete any items, and the validity of the reliability of the scale is proved. Accordingly, the reliability of the scale of enterprise management model innovation is good, and the items involved can be retained (see Table 3 for details).

According to the combination of measurement items in the scale and the tendency of its prediction range, it can be concluded that the two factors should be named as the innovation of efficient enterprise management mode and the innovation of novel enterprise management mode. Validity analysis shows that the validity of the scale of enterprise management model innovation is satisfactory.

We take the first 16 groups of data as training samples, the last 4 groups of data as test samples for the system, and the expected error of the network is 0.001. After 785 times of training, input the 4 sets of data as test samples into

Table 2: Analysis of innovation factors of enterprise management model.

Independent variable	Dimension	Item	Factor loadings 2
		A1	0.585
		A2	0.765
		A3	0.651
	The efficient enterprise management model innovation	A4	0.705
		A5	0.672
		A6	0.718
		A7	0.573
Business model innovation		A8	0.523
		A9	0.751
		A10	0.565
		A11	0.702
	Novel enterprise management model innovation	A12	0.742
		A13	0.758
		A14	0.742
		A15	0.505
		A16	0.577

Table 3: Reliability analysis of enterprise management model innovation.

Independent variable	Dimension	Item	Item-to-item corrected correlation coefficient	Delete this	Overall project
		A1	0.465	0.710	
		A2	0.537	0.596	
		A3	0.642	0.637	
	The efficient enterprise management model innovation	A4	0.648	0.689	0.798
		A5	0.557	0.584	
		A6	0.586	0.700	
		A7	0.600	0.631	
Business model innovation		A8	0.521	0.685	
		A9	0.601	0.703	
		A10	0.624	0.618	
		A11	0.599	0.580	
	Novel enterprise management model innovation	A12	0.205	0.568	0.715
		A13	0.574	0.610	
		A14	0.201	0.528	
		A15	0.596	0.620	
		A16	0.658	0.699	

the trained network, and get the training results, the actual evaluation value, and the error. The comparison chart between the test results and the expert evaluation value is drawn as shown in Figure 7.

4.1.2. Enterprise Performance Scale. The items of the enterprise performance scale include short-term financial performance and long-term market performance. Considering the time lag in the implementation effect of enterprise management model innovation, this study divides enterprise performance into two dimensions: short-term financial performance and long-term market performance. In this paper, the Likert 5-level scoring method is used in the assignment of measurement items. D1-D11 implies short-term financial performance and long-term market performance. The conclusions of factor analysis can show whether the expected design results can be verified. The scale of enterprise performance, the minimum value of the questionnaire respondents' evaluation is 1, and the maximum value is 5 (see Table 4 for details).

The factor analysis of the enterprise performance scale shows that the KMO value is higher than 0.7, and the Bartlett sphericity test is required to show significance to meet the requirements of factor analysis. The reason why the

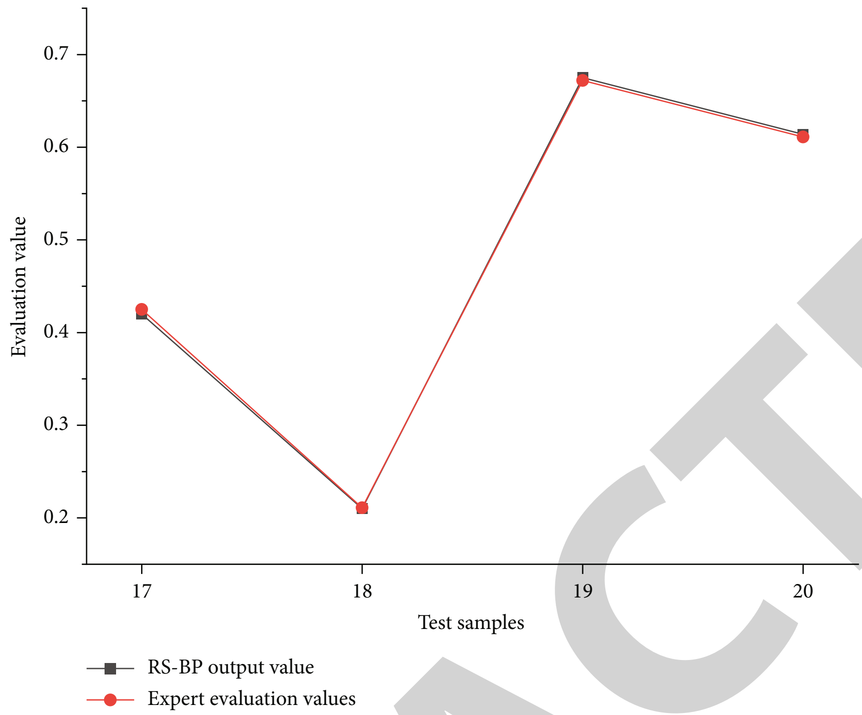

FIGURE 7: Comparison of RS-BP test results and expert evaluation values.

TABLE 4: Descriptive statistics and correlation analysis of enterprise performance.

Independent variable	Dimension	Item	Score	Standard deviation
Business performance	Short-term financial performance	D1	2.55	0.894
		D2	2.79	0.901
		D3	2.99	0.789
		D4	3.54	0.903
		D5	3.32	0.888
	Long-term market performance	D6	3.57	1.055
		D7	3.17	0.894
		D8	3.05	0.964
		D9	3.02	0.843
		D10	3.21	0.900
		D11	2.35	0.793

cumulative contribution rate of factor variance can be 61.545% is that all measurement items can reach the benchmark of 0.5 to correspond to the load on the factor. Factors were identified (see Table 5 for details).

This paper finds that the corrected correlation coefficient of a single item of the institutional environment to all items is greater than 0.35, and the index is excluded. "a value" should be small, and the Cronbach's a value of all items is greater than 0.7. Therefore, the items of the enterprise performance scale meet the requirements, and there is no need to delete any items, and the validity of the reliability of the scale is proved. Accordingly, the reliability of the enterprise performance scale is good, and the items involved can be retained (see Table 6 for details).

Through the analysis of the above data, it is found that the two dimensions of enterprise performance can be clearly reflected under the retained enterprise performance items and can accurately represent their meanings. It can be seen that the evaluation results of the RS-BP network neural model and the unknown-AHM model are basically the same, but the difference between the two errors for each test sample is obvious. The fitting effect of the unconfirmed training samples is shown in Figure 8. It can be seen that although the unconfirmed-AHM has reached a high training accuracy, the test error of the unconfirmed-AHM is significantly higher than that of the RS-BP. It shows that the unsure AHM cannot guarantee a good generalization ability even if the training achieves a high accuracy; that is, the phenomenon of overlearning occurs.

Table 5: Analysis of enterprise performance factors.

Independent variable	Dimension	Item	Factor loadings 2
Business performance	Short-term financial performance	D1	0.724
		D2	0.730
		D3	0.506
		D4	0.598
		D5	0.555
	Long-term market performance	D6	0.665
		D7	0.508
		D8	0.507
		D9	0.755
		D10	0.598
		D11	0.605

Table 6: Reliability analysis of enterprise performance.

Independent variable	Dimension	Item	Item-to-item corrected correlation coefficient	Delete this	Overall project
Business performance	Short-term financial performance	D1	0.561	0.678	0.765
		D2	0.501	0.690	
		D3	0.491	0.641	
		D4	0.678	0.701	
	Long-term market performance	D5	0.642	0.704	0.721
		D6	0.666	0.711	
		D7	0.680	0.707	
		D8	0.569	0.666	
		D9	0.540	0.670	
		D10	0.571	0.681	
		D11	0.555	0.700	

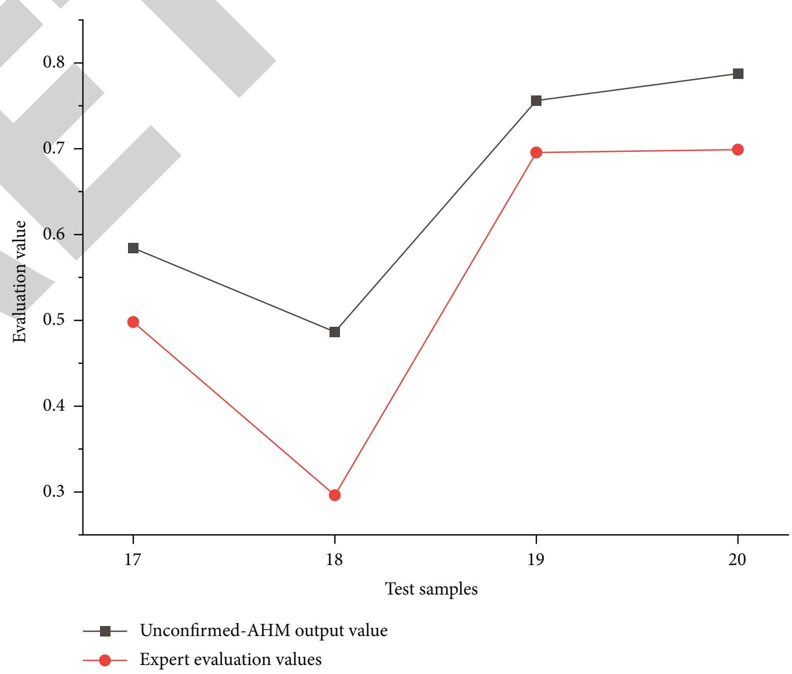

Figure 8: Comparison of unconfirmed-AHM test results and expert evaluation values.

5. Conclusion

Through empirical research, it can be considered that a successful enterprise is bound to have a set of suitable and effective enterprise management models or innovations of enterprise management models that are constantly adjusted according to the needs of enterprise development, so as to improve the competitive advantage of the enterprise and improve the enterprise and performance. For enterprises of different types and levels of development, their emphasis on the choice of enterprise management model innovation will be different. In order to study which kind of enterprise management model innovation is most suitable for the development of enterprises, it is necessary to classify the types of enterprise management model innovation. The effects produced are relatively obvious, and they are all core designs that enterprises pay attention to. However, for different types of enterprises, according to themselves and the market conditions they face, the focus on the choice of enterprise management model innovation will be different. The innovation of the novel enterprise management model is to include the transaction parties that have not participated before and then to connect the transaction parties in a new way to form a new transaction mechanism. The innovation of novel enterprise management mode is mainly centered on brand-new service concepts and innovative operation methods, which stimulates customers' willingness to purchase and expand the market share of the enterprise itself.

Only by innovating management models and promoting knowledge acquisition, dissemination, sharing, and innovation can enterprises improve their competitiveness in the knowledge age. The performance index evaluation of management mode innovation. By evaluating the status quo of innovation and finding out its deficiencies, a reasonable allocation of enterprise resources can be achieved, thereby maximizing enterprise profits. The primary problem in implementing performance evaluation is the construction of an index system, and a scientific and reasonable index system can produce scientific and reasonable evaluation results. This paper designs a two-level evaluation index system by reading the relevant literature and according to the enterprise practice and uses the analytic hierarchy process to select 8 important indexes as evaluation indexes.

Then, the method of BP neural network is used to evaluate the innovation and performance indicators of the enterprise's management model. After the model parameters are selected, we first use the standard BP algorithm to train the network, but the training effect is not very good, and sometimes even the training fails, which is caused by the inherent defects in the standard BP neural network algorithm; that is, there are local minimum point, slow convergence speed, and poor generalization ability. In response to these problems, it is proposed to use the momentum-adaptive learning rate algorithm, LM algorithm, and genetic neural network algorithm to train the network. The momentum-adaptive learning rate algorithm combines the advantages of the adaptive learning rate and the additional momentum term algorithm, not only improving the network The convergence performance is suppressed, and the convergence speed is significantly accelerated; the LM algorithm is converted between the standard algorithm and the Gauss-Newton method, which greatly improves the convergence speed; the genetic neural network algorithm uses the genetic method to search for the optimal weight threshold. The convergence accuracy and convergence speed are also greatly improved. The example verification shows that the performance of the momentum-adaptive algorithm is the best. Using the BP network model can effectively evaluate the innovation of enterprise management mode and performance indicators, so as to guide the implementation of enterprise management mode innovation activities.

Data Availability

The figures and tables used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The authors would like to show sincere thanks to those techniques who have contributed to this research.

References

[1] T. T. Lasisi, A. Ozturen, K. K. Eluwole, and T. Avci, "Explicating innovation-based human resource management's influence on employee satisfaction and performance," *Employee Relations*, vol. 42, no. 6, pp. 1181–1203, 2020.

[2] P. A. Danarahmanto, I. Primiana, Y. Azis, and U. Kaltum, "Sustainable performance of digital startups based on customer engagement, innovation, and business model," *Verslas Teorija ir Praktika*, vol. 21, no. 1, pp. 115–124, 2020.

[3] P. Antosz, W. Jager, G. Polhill, and D. Salt, "Informing agent-based models of social innovation uptake," in *International Work-Conference on Artificial Neural Networks*, pp. 19–26, Cham, 2021.

[4] F. Li and S. Zhang, "Policy orientation, knowledge dynamic ability and green innovation: a mediation model based on China provincial panel data," *Zbornik radova Ekonomskog fakulteta u Rijeci/Proceedings of Rijeka Faculty of Economics*, vol. 39, no. 7, pp. 55–63, 2021.

[5] L. A. Benz and M. S. Li, "Critical success factors for circular business model innovation from the perspective of the sustainable development goals," *Sustainability*, vol. 14, no. 6, pp. 1–8, 2022.

[6] A. Borsato and A. Lorentz, "Data production and the coevolving AI trajectories: an attempted evolutionary model," *BETA*, vol. 56, no. 9, pp. 104–110, 2022.

[7] F. Ciampi, S. Demi, A. Magrini, G. Marzi, and A. Papa, "Exploring the impact of big data analytics capabilities on business model innovation: the mediating role of entrepreneurial orientation," *Journal of Business Research*, vol. 191, no. 2, pp. 123–130, 2020.

[8] P. Dec, R. Cottereau, and B. Faure, "Identification of a randomly-fluctuating continuous model of the ballasted track based on measurements at the pass-by of high-speed trains," *Noise and Vibration Mitigation for Rail Transportation Systems*, vol. 15, no. 3, pp. 78–84, 2021.

[9] E. Tamassia, S. Hähnel, F. Pini, T. Grunwald, T. Bergs, and F. Leali, "An analytical model for robot-based grinding of axisymmetric mold inserts using a rotary unit," in *International Conference on Design, Simulation, Manufacturing: The Innovation Exchange*, pp. 101–109, Cham, 2022.

[10] M. Z. U. Haq, M. Gu, and B. Huo, "Enhancing supply chain learning and innovation performance through human resource management," *Journal of Business & Industrial Marketing*, vol. 5, no. 2, pp. 112–118, 2020.

[11] H. Arabshahi and H. Fazlollahtabar, "Supply chain innovation performance evaluation based on cross efficiency concept: case study of supply chain innovation awards winners, runner-ups and finalists," *International Journal of Logistics Systems and Management*, vol. 35, no. 1, pp. 1–9, 2020.

[12] H. Yang, L. Li, and Y. Liu, "The effect of manufacturing intelligence on green innovation performance in China," *Technological Forecasting and Social Change*, vol. 178, no. 6, article 121569, 2022.

[13] G. Roberts, L. Reevell, R. Pleace, A. L. Kor, and C. Gorse, "Strategic management of assets and compliance through the application of bim and digital twins: a platform for innovation in building management," *Climate Emergency–Managing, Building, and Delivering the Sustainable Development Goals*, vol. 14, no. 6, pp. 78–86, 2022.

[14] B. Prusak, S. Morawska, M. Łukowski, and P. Banasik, "The impact of bankruptcy regimes on entrepreneurship and innovation. Is there any relationship?," *International Entrepreneurship and Management Journal*, vol. 18, no. 3, pp. 133–141, 2022.

[15] W. Cetera, W. Gogołek, A. Żołnierski, and D. Jaruga, "Potential for the use of large unstructured data resources by public innovation support institutions," *Journal of Big Data*, vol. 9, no. 1, pp. 781–788, 2022.

[16] C. Torre, G. M. Guazzo, V. Çekani, and V. Bacco, "The relationship between big data and decision making. A systematic literature review," *Journal of Service Science and Management*, vol. 15, no. 2, p. 19, 2022.

[17] T. Heubeck and R. Meckl, "Antecedents to cognitive business model evaluation: a dynamic managerial capabilities perspective," *Review of Managerial Science*, vol. 155, no. 20, pp. 1436–1440, 2021.

[18] J. Tan, "Information analysis of advanced mathematics education-adaptive algorithm based on big data," *Mathematical Problems in Engineering*, vol. 2022, Article ID 7796681, 9 pages, 2022.

[19] V. K. Tuan, "The role of human resources practices and the mediating effect of innovative capacity on the growth of Vietnamese enterprises," *Journal of Human Resource Management*, vol. 24, no. 6, pp. 112–119, 2021.

[20] X. Lv and M. Li, "Application and research of the intelligent management system based on internet of things technology in the era of big data," *Mobile Information Systems*, vol. 2021, Article ID 6515792, 6 pages, 2021.

[21] Z. K. Hou, H. L. Cheng, S. W. Sun, J. Chen, D. Q. Qi, and Z. B. Liu, "Crack propagation and hydraulic fracturing in different lithologies," *Applied Geophysics*, vol. 16, no. 2, pp. 243–251, 2019.