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Research on the Innovation-driven Development Assessment Model Based on Artificial Intelligence Algorithms

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ABSTRACT

Innovation capability has become an essential indicator in assessing the competitiveness of a nation, a company, or an individual. However, traditional assessment methods are subjective and limited, making it difficult to comprehensively and accurately evaluate a region's innovation capability. By constructing an innovation-driven development assessment model based on artificial intelligence algorithms, this article provides an effective method for evaluating innovation capability. The model not only provides objective evidence for decision-makers but also promotes the implementation of innovation-driven development strategies. Taking the platform economy business model as an example, this paper explores how to assess and enhance the competitiveness of B2B ecommerce companies to promote the orderly and healthy development of the B2B ecommerce industry. This paper presents innovative research on the platform economy business model driven by the BP neural network and artificial intelligence technology.

Keywords: Artificial Intelligence Algorithm, BP Neural Network, Innovation-driven Development, Assessment Model, Platform Economy

1. Introduction

With the rapid development of the global economy, innovation has become a key factor in promoting social progress and enhancing national competitiveness [1]. The innovationdriven development strategy was born in this context. It emphasizes improving a nation or region's innovation capability through various means, such as technological innovation, institutional innovation, and industrial innovation, to achieve sustainable economic and social development [2]. However, how to evaluate a region or organization's innovation capability is an urgent problem in *implementing the innovation-driven development strategy. Traditional evaluation methods often rely on subjective indicators and fixed weights, making it difficult to reflect innovation-driven development's complex and changing situation [3]. Therefore, seeking a more objective and accurate evaluation method has become a focus of both academia and industry. With the rapid development of artificial intelligence technology, its application in various fields is becoming increasingly widespread. Artificial intelligence has powerful data processing and pattern recognition capabilities, extracting useful information from massive data and providing significant support for decision-making. Therefore, applying artificial intelligence to the research of innovation-driven development assessment models has important practical significance and theoretical value [4]. Artificial intelligence algorithms simulate problem-solving based on the principles inspired by the laws of nature. Artificial intelligence algorithms can be classified according to different principles and implementation methods. Common ones include artificial neural networks, genetic algorithms, simulated annealing algorithms, swarm intelligence, ant colony algorithms, particle swarm algorithms, etc. Artificial intelligence algorithms can automatically extract useful information from data, provide significant support for decision-making, and have broad applicability and scalability. The innovation-driven development evaluation model based on artificial intelligence algorithms can provide more objective and accurate results [5]. Subjective factors often influence traditional evaluation methods, while artificial intelligence algorithms can extract useful information automatically through data mining and analysis, reducing human interference and making the evaluation results more objective and fair.*

This model can provide important government, enterprise, and academic decision support. The innovation-driven development evaluation model based on artificial intelligence algorithms can formulate personalized innovation-driven development strategies according to the actual situation of the region, providing important support for the decision-making of the government, enterprises, and academia. The innovation-driven development evaluation model based on artificial intelligence algorithms has important theoretical significance and practical value. It can provide more objective and accurate evaluation results, improve the efficiency and accuracy of the evaluation, have broad applicability and scalability, and provide important decision support for the government, enterprises, and academia. At the same time, this model can also promote the implementation of an innovation-driven development strategy and sustainable economic and social development.

2. Related Work

Innovation has become an important driving force for social development and economic growth in today's era. As an essential part of innovation management, the innovation-driven development assessment model is of great significance for assessing the effectiveness of innovation-driven development and formulating targeted policies [6]. With the continuous development of artificial intelligence technology, the innovation-driven development assessment model based on artificial intelligence algorithms has gradually become a research hotspot. Nurmalasari and others proposed an innovation-driven development assessment model based on artificial intelligence algorithms. They used deep learning algorithms to learn and train historical data, constructing a multi-layer neural network model. This model can automatically extract features from data and classify and predict based on these features. Experimental verification with actual data provides decision support for formulating innovation-driven development strategies [7]. Sund and others proposed an innovation-driven development assessment model based on fuzzy cognitive maps and deep learning algorithms. Firstly, a fuzzy cognitive map model was constructed, expressing the relationship between innovation-driven development's influencing factors and goals as fuzzy logic and fuzzy rules. Using deep learning algorithms, they successfully converted a large amount of information into a complex multi-dimensional neural network model and significantly improved practical applications. This allowed for better guidance of enterprise innovation development [8], thus better-promoting business success. Winter and others proposed a brand-new evaluation model based on integrated learning and deep learning technologies to promote industry development. Firstly, an ensemble learning algorithm was used to combine multiple base models into a robust model to improve the model's predictive performance and robustness. Then, the authors used deep learning algorithms to learn and train data, constructing a multi-layer neural network model. Experimental verification provides decision support for formulating innovation-driven development strategies [9]. Ekawati proposed an innovation-driven development assessment model based on knowledge graphs and transfer learning algorithms. Firstly, a knowledge graph was used to model and represent the relationship between the influencing factors and goals of innovation-driven *development. Then, the author used transfer learning algorithms to analyze and process data, extracting valuable knowledge and information. Experimental verification provides decision support for formulating innovation-driven development strategies [10].*

3. Material and Method

3.1. BP Neural Network Algorithm and Transfer Learning Integration

Nowadays, with the breakthrough of neural network AI technology in computer vision, the feature representation built with CNN can further advance experimental results. Recent research shows that the feature representations learned through neural networks possess stronger discriminative capabilities compared to traditional, manually designed features. When the number of hidden layers exceeds a certain value, the performance of the hidden layers will decline. Generally speaking, a three-layer BP neural network can perform nonlinear mapping from n-dimensions to m-dimensions under any circumstances. The number of nodes in the input layer corresponds to the number of parameters presented to the network as input. Based on the B2B e-commerce enterprise competitiveness evaluation index system established above, the number of secondary indicators is the number of nodes in the input layer, i.e., 16. Since studying B2B e-commerce enterprise competitiveness ultimately requires calculating its competitive output, the output layer only has one value. Hence, the number of nodes in the output layer is 1. It is crucial to determine a reasonable number of nodes in the hidden layer to obtain efficient, accurate, and reasonable results within a limited time. There are no universal and appropriate methods to determine the number of neurons in the hidden layer. Formula 1 below could be chosen for reference.

$$C = -\frac{1}{n}\sum_{x}\left[y\,log\,(a) + (1\text{-}y)\,log\,(1\text{-}a)\right] \tag{1}$$

3.2. Model Activation Function

Generally, BP neural networks typically use linear functions (purely) and nonlinear sigmoid functions (S-shaped functions). S-shaped functions include logarithmic functions and tangent functions, with their respective value ranges within [0, 1] and [-1, 1]. When dealing with nonlinear issues, to ensure the range of output values, nonlinear functions are usually employed from the input layer to the hidden layer and linear functions from the hidden layer to the output layer. After data normalization, the input layer meets the value range requirement of the logarithmic S-shaped function mapping within [0, 1]. Therefore, this paper selects the logarithmic S-shaped function from the input layer to the hidden layer and the purelin function from the hidden layer to the output layer. For the s-th data, the input to the hidden neuron is as shown in formula 2.

$$loss = \sum_{s=1}^{s}\ \sum_{-m \le j \le m,\, j\neq 0} loogp\left(w^{(s+j)} \mid w^{sd}\right). \tag{2}$$

3.3. Expected Values of Network Samples

Generally, the expected value of a BP neural network is the quantified actual value. However, the competitiveness of B2B e-commerce enterprises is extensive and complex, and the value of competitiveness is unclear. Therefore, the combination weighting method is used to calculate the weights of each indicator in the evaluation index system, and then combined with standardized data, the weighted summation method is used to obtain the competitiveness value of B2B e-commerce enterprises. The expected value of BP neural network training samples is the weighted sum value. As for the determination of the weight of evaluation indicators, a scientific and reasonable method is needed. Scholars often use subjective methods such as Delphi and the analytic hierarchy process, and some scholars use the relatively objective entropy method to obtain indicator weights. The proportion of subjective factors is relatively high, and the result will produce a considerable degree of bias. Generally, it is difficult to meet the objective evaluation conditions and reflect the preferences of the evaluators, and sometimes, it may deviate from the evaluators' wishes. To avoid the above problems and calculate relatively objective and reasonable weight values, the evaluation model in this paper uses a combined weight coefficient method, as shown in Formula 3.

$$min\ z = \sum_{j=1}^{m} [(W_J - W^S{}_J)^2 + (W_J - W^{\circ}{}_J)] \quad (3)$$

3.4. Innovative Process Integration Model

As a mainstream business model, the creatively disruptive nature of the platform economy has changed the original business logic. This model can not only bring "win-win" situations to economic participants but also realize the value creation of the platform itself. Meanwhile, the phenomenon where winners take all is also rare in market competition. As the organizational carriers and value focus of platform economy development, platform companies aim to create a unique business ecosystem. This system provides channels for value realization for transaction subjects from different types of bilateral markets, promoting bilateral users' value exchange and interaction. Figure 1 shows the process integration diagram of the business model innovation process.

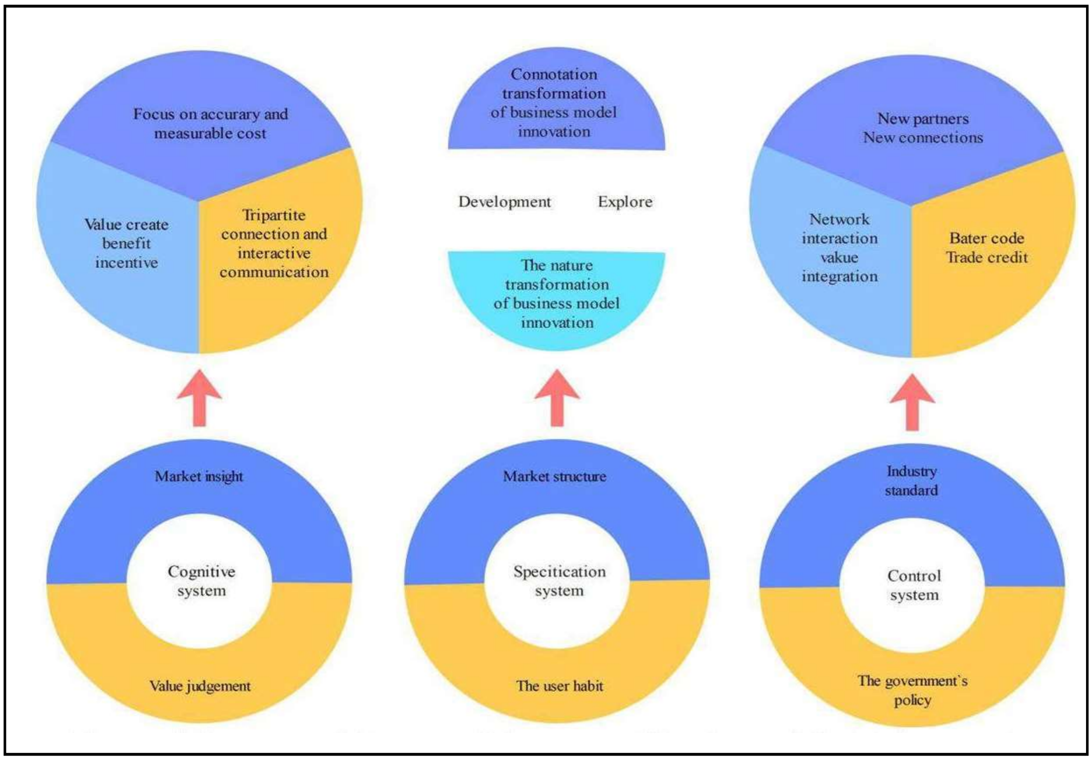

Figure 1. Integrated Process Diagram of Business Model Innovation

4. Results

4.1. Experiment Design

Data related to innovation-driven development, including indicators such as innovation input, talent introduction, and innovation capability, as well as background data such as regional economic level and policy environment, were collected from public datasets. The collected data underwent preprocessing, including data cleaning, missing value filling, feature selection, and feature engineering. The dataset was split into a training set and a test set, usually using 70% of the data as the training set and 30% as the test set. Models such as neural networks, support vector machines, random forests, and naive Bayes were constructed according to the algorithms mentioned in the experimental principles. For the neural network model, the network topology needs to be designed according to the characteristics and needs of the dataset, including the number of input layers, hidden layers, output layers, and the number of neurons. Metrics like prediction accuracy, F1 score, and recall rate were calculated to evaluate the model's classification performance. Comparisons between models were made, observing the strengths and weaknesses of different models and their performance on different indicators. Based on the current research, listed B2B ecommerce enterprises were chosen as the research objects, and their competitiveness evaluation index system was constructed. The research was carried out regarding evaluation indicator screening, indicator weight calculation, and sample research analysis. BP neural network was chosen to train the selected samples to achieve the desired simulation effect, and the simulation output results were used to evaluate the competitiveness of B2B ecommerce enterprises. Evaluating the competitiveness of e-commerce enterprises with the help of the BP neural network is feasible and can achieve correct evaluation effects; this method also has certain adaptability in evaluating the competitiveness of enterprises in other industries.

4.2. Experimental Results Analysis

The model pruning operation is carried out before the model in the artificial intelligence target domain branch migrates to the target domain. Its purpose is to alleviate model overfitting and further enhance the transfer effect. This operation is independent of other steps in the method and will not affect each other. Therefore, the above factors were divided into two groups for experimentation, namely the heterogeneous network model transfer experiment with model pruning operations and the experiment without model pruning operations. Using MSTAR10 class data as experimental data, we first gave the classification accuracy without expanding training data and without transfer operations. Compared with the VGG-16 model, the Mnet10, designed specifically for SAR, improved its classification accuracy by nearly 16 percentage points in the MSTAR decimal task due to its lightweight structure and good discrete feature extraction capability. For different tasks in the processing domain, vectors use different corpora. In-depth research has been done on vector models in different tasks of natural processing. The neural network was trained with the help of functions in the MATLAB neural network toolbox. This function includes parameters such as the maximum number of learning times and the maximum allowable error, i.e., the convergence accuracy target and the minimum allowable time. The longest learning time is set to 5000 times. Usually, the smaller the convergence accuracy target, the more accurate the network training can be ensured. Set it to a sufficiently small accuracy of 1x10−5; other parameters are set to default values. Twenty B2B e-commerce companies were randomly selected as training samples for neural network training. When the number of training sessions reached 3,297, the mean square error of the samples was 9.9869e−06, and the training network converged. The results are shown in Figure 2.

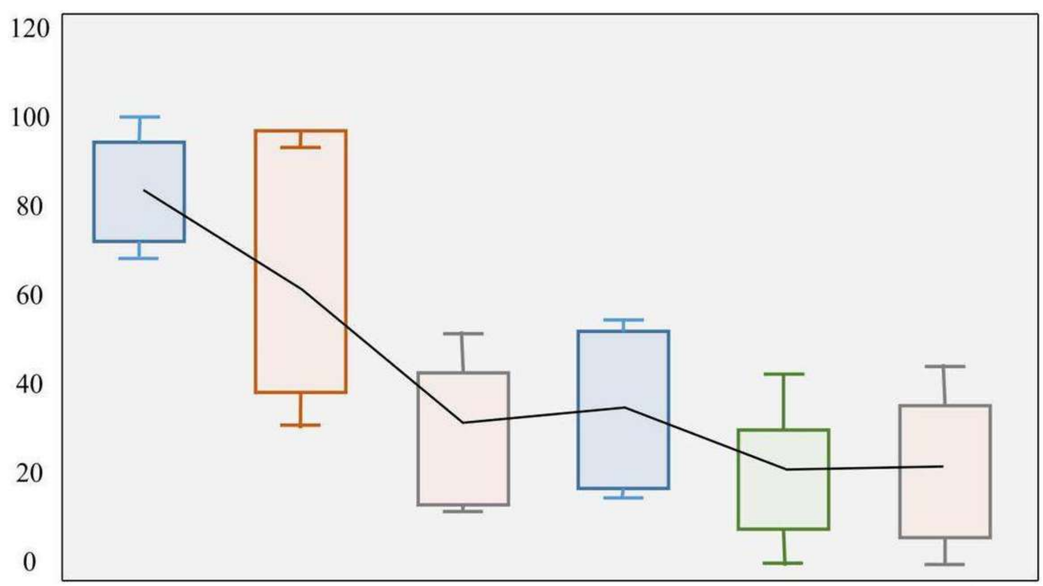

Figure 2. Convergence Precision of BP Neural Network Training Results

Among the 23 B2B e-commerce enterprises selected in this paper, Hikvision, Small Commodity City, Longping Hi-Tech, Haihong Holdings, etc. are included. As shown in Figure 3, these companies are more competitive, mainly reflected in company scale, operating income and profits, brand *value, and R&D investment. On the one hand, stateowned controlled enterprises have many assets and large enterprise sizes, occupying a natural advantage in capital and policies. On the other hand, state-owned-controlled enterprises pay more attention to comprehensive development, so they will invest capital and technology to improve and cultivate various elements, improving the overall competitiveness. Compared with this, the turnover rate of fixed assets of state-owned controlled enterprises is relatively low, the utilization efficiency of fixed assets is weak, and the utilization rate of enterprise assets is low, which restricts the company's profit potential to some extent.*

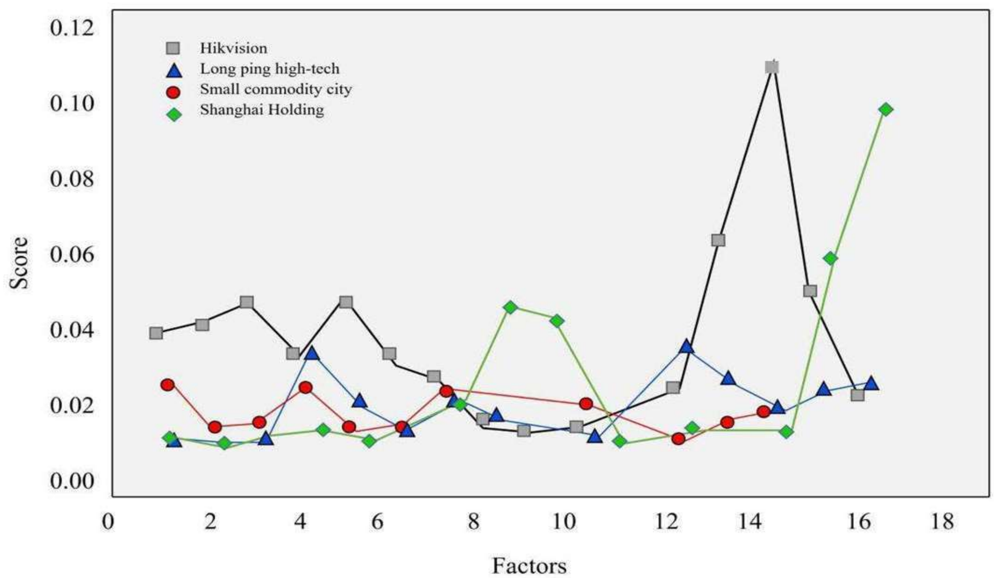

Figure 3. Competitive Factors of Enterprises

5. Conclusions

This paper has innovated a business evaluation system based on BP neural networks and artificial intelligence technology. This article takes 23 listed B2B e-commerce enterprises as analysis samples. It evaluates the competitiveness of B2B e-commerce enterprises with specific indicators such as total assets, total number of employees, total sales, the proportion of R&D staff, and the proportion of R&D investment to total sales. The neural network uses data from 23 companies for training and testing. Finally, the trained network will be used to obtain the competitive value of B2B e-commerce enterprises, analyse the evaluation results, point out the advantages and disadvantages of different types of enterprises, and provide related improvement suggestions. For specific enterprises, not collecting, sorting, and analyzing corporate data for many years in a row neglects the longitudinal analysis and excavation of corporate competitiveness. Therefore, future research work should take representative B2B e-commerce enterprises as research objects, study their competitive development routes, study and analyze the reasons for the increase or decrease in corporate competitiveness, and provide experience and reference for related enterprises in the B2B e-commerce industry. The evaluation model for innovation-driven development based on artificial intelligence algorithms has significant significance and application value in the innovation-driven development strategy. In the future, in-depth research and development can be carried out through improving algorithms, optimizing models, and integrating multimodal data, providing scientific and effective evaluation and decision-making support tools for innovation-driven development. Cross-disciplinary cooperation will also be one of the key directions for future research. Through the cooperation and exchange of experts in different fields, this field's development and application level can be further promoted.

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