Eng Int Syst (2025) 5: 535–544

Engineering
Intelligent Systems

Dynamic Panel Data Estimation of the Impact of Digital Finance on Technological Innovation Performance of Chinese Enterprises Based on BP Neural Network Analysis

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Given the rapidly evolving field of digital finance, this study used a combination of back propagation (BP) network analysis and dynamic panel data estimation to investigate the impact of digital finance on the performance of Chinese enterprises in regard to scientific and technological innovation. The data was sourced from two open datasets: Quandl and Crunchbase. After cleaning and standardizing the data, a dynamic panel data model was constructed and analyzed using a BP neural network (BPNN). Through an evaluation of the BPNN model's dynamic adaptability index, characteristic importance consistency index, and innovation contribution index, this study determined the relationship between digital finance and enterprise's scientific and technical innovation performance. The results showed that for the two datasets, the dynamic adaptability indexes of BPNN model were above 82% and 83% respectively, indicating that the model has strong adaptability to data changes in different time periods. The consistency index of feature importance was above 86%, indicating the stability of the model when judging the importance of different input features. The findings demonstrate that the BPNN model has clear advantages when analyzing the relationship between digital finance and the scientific and technological innovation performance of enterprises. It can accurately capture the complex relationship between them and provide a reference for enterprises and policy makers. However, there are several limitations such as limited data set selection and incomplete evaluation indicators. Overall, the innovation contribution index is above 81% and 86%, which highlights the unique contribution of digital finance-related characteristics to the performance prediction of scientific and technological innovation of enterprises. By means of innovative evaluation indicators, the study also comprehensively analyzes the effect of applying the BPNN model in this field, thereby providing a valuable reference for subsequent research and practice.

Keywords: digital finance; scientific and technological innovation; back propagation network; dynamic adaptability; consistency of feature importance

1. INTRODUCTION

The strong integration of technology and finance in the current digital era is changing the world economy landscape. With its benefits of great efficiency, affordability, and ease of use, digital finance, as a new format in the financial industry, offers organizations new opportunities as well as challenges in terms of scientific and technological innovation [1]. China, a significant player in the global digital economy, has made impressive strides in the growth of digital finance, and its impact on the success of businesses' technological and

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scientific innovation has grown [2]. The ability of businesses to innovate in science and technology is what drives high-quality economic development, and finance, which is at the center of the modern economy, is essential to this process [3]. Many of the problems associated with the traditional financial system, such as information asymmetry, difficulties assessing risk, and a lack of financing channels, make it difficult for businesses to innovate in science and technology. The emergence of digital money (finance) offers fresh approaches to, and solutions for, these issues [4]. Digital finance can increase the effectiveness and precision of financial services, reduce transaction costs, expand financing channels, and offer more convenient and all-encompassing financial support for businesses' technological innovation using digital technologies like big data, blockchain, and artificial intelligence (AI) [5].

The way that digital finance influences an organization's success in terms of scientific and technical innovation is still quite unclear [6]. By reducing financial barriers, increasing the effectiveness of resource allocation, and fostering information sharing, digital finance can, on the one hand, directly support businesses' efforts to innovate in science and technology. However, there is a chance that digital banking may also bring with it new risks and difficulties, such as problems with data security, more onerous financial monitoring, etc., which could hamper businesses' ability to innovate in science and technology [7]. Furthermore, a multitude of factors, including the macroeconomic environment, rules, and regulations, impact the growth of digital finance. These factors can also have a complicated and dynamic effect on an enterprise's success in scientific and technical innovation [8].

This study uses the dynamic panel data estimation method and backpropagation neural network (BPNN) analysis to determine the influence that the digital financing mechanism has on the scientific and technological innovation performance of Chinese firms. As a powerful machine learning algorithm, BPNN has good nonlinear mapping ability and adaptive learning ability, and can effectively deal with complex economic data and relationships. This study provides theoretical support and policy recommendations for the coordinated development of digital finance and enterprise technological innovation in China by building a dynamic panel data model of digital finance and enterprise technological innovation performance, and using BPNN to estimate and analyze it. The current study presents an in-depth discussion of the mechanism of digital finance and its influence on the performance of enterprises in terms of enterprise technological innovation.

2. LITERATURE REVIEW

The relationship between digital finance and the technological innovation performance of businesses has gained a lot of attention in academic circles in recent years. In their research, Gao and Su stressed that digital finance, with its distinct benefits, might effectively increase the financing channels available to businesses, lower financing costs, and offer dependable financial support for technology innovation in businesses [9], the subsequent investigation was made possible by this perspective. Further investigation by Natanelov et al. revealed that digital finance could enhance the effectiveness of financial resources allocation, encourage businesses to invest more in technological and scientific innovation, and ultimately lead to a notable improvement in the performance of these initiatives [10]. Bayram et al. highlighted that the emergence of digital finance helped mitigate the issue of information asymmetry, lower the risk associated with enterprise innovation, and foster a favorable environment for enterprise scientific and technological innovation [11]. Empirical research conducted by Daraojimba et al. revealed a strong positive correlation between enterprise technological innovation and digital finance, with the latter's innovative service mode better suited to meeting the financial demands of the former [12]. Small and medium-sized businesses were the focus of the study conducted by Doukidis et al., who noted that digital financing was particularly evident as a factor that encouraged small and medium-sized businesses to innovate in science and technology. It can assist them to overcome financial obstacles, improve their capacity for innovation, and revive their development [13]. In regard to technological innovation, Eckert and Osterrieder conducted empirical research and concluded that technological innovation in digital finance could offer new instruments and techniques for technological innovation in businesses, and significantly boost innovation productivity [14]. According to Matsuoka et al., the growth of digital finance has helped to foster competition in the financial markets, raising the standard of financial services and creating an environment that is favorable to business technological innovation [15]. However, Gorkhali and Chowdhury astutely noted that, in addition to encouraging scientific and technological innovation within enterprises, digital finance also inroduced new risks, including increased supervision challenges and data security risks, which raised concerns for the industry's healthy development [16]. According to Liu 's research, combining digital and traditional finance could result in more comprehensive financial support for enterprise technological innovation, achieve complementary benefits, and foster enterprise technological innovation in tandem [17]. Ma et al. emphasized that the government should strengthen its oversight and direction of digital finance, and fully capitalize on the sector's contribution to business innovation in the fields of science and technology [18].

The literature demonstrates that a great deal of research has already been conducted to determine the various ways that technological innovation performance of businesses and digital finance are related. For this study, which aims to thoroughly examine the dynamic panel data assessment of the impact of digital finance on the technical innovation performance of Chinese firms, previous research offers a strong theoretical foundation and a valuable source of reference. Nonetheless, there are still certain gaps in the current body of knowledge. For example, there is a dearth of research on the dynamic mechanism of digital finance and how it influences the performance of scientific and technological innovation in businesses, as well as a lack of analysis regarding the different characteristics of various industries and geographical areas. Thus, building on previous research, this study delves deeper into the internal mechanisms underlying digital finance's impact on Chinese enterprises' scientific and technological innovation performance. The

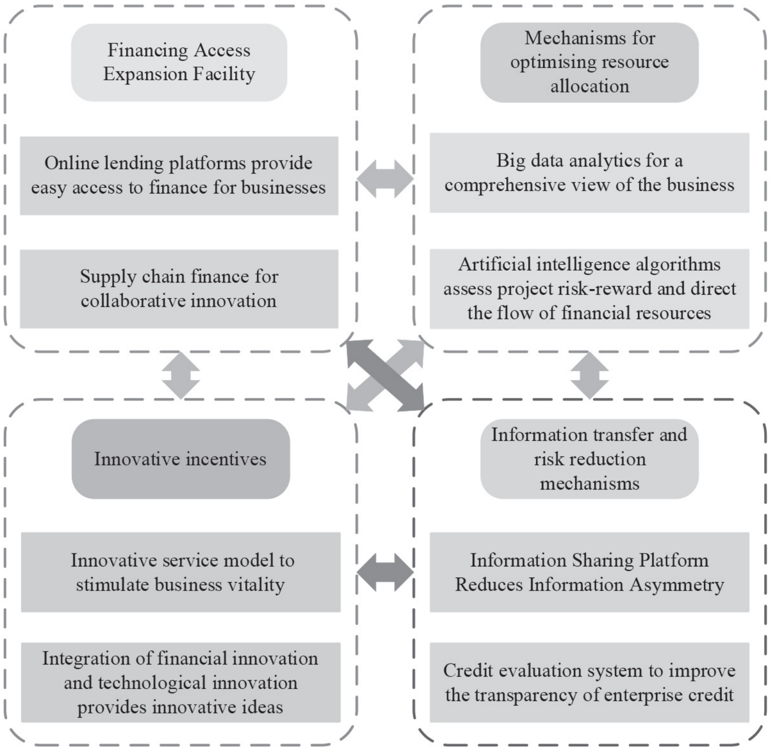

Figure 1 The influence mechanism of digital finance on technological innovation of enterprises.

study also offers more insightful policy recommendations for the synergistic growth of digital finance and enterprise-level innovation.

3. DIGITAL FINANCE AND TECHNOLOGICAL INNOVATION OF ENTERPRISES

3.1 Influence Mechanism of Digital Finance on Enterprise's Scientific and Technological Innovation

The following methods are the major ways that digital finance influences businesses' technological innovation:

(1) Financing channel expansion mechanism

Digital finance broadens financing channels for enterprises. Peer-to-peer lending platforms provide convenient financing for enterprises. For example, small technology enterprises can get start-up capital through a peer-to-peer network lending platform [19]. Supply chain finance can be acquired via digital finance, providing accurate financial services for core enterprises and supporting enterprises, and promoting collaborative innovation [20].

(2) Optimization mechanism of resource allocation

Digital finance determines the best way to allocate resources by precisely assessing the risk and value of businesses using big data, artificial intelligence (AI), and other technologies. Big data analysis shows the situation of enterprises, and AI algorithms evaluate the risks and benefits of scientific and technological innovation projects, so that financial resources can flow to enterprises and projects with innovative value [21].

(3) Information transmission and risk reduction mechanism

Digital finance reduces information asymmetry and innovation risk by establishing an information-sharing platform and credit-evaluation system. The credit-evaluation system reduces risks for financial institutions and enhances the credit transparency of businesses, while the information-sharing platform offers market and technical information [22].

(4) Innovative incentive mechanism

The digital finance industry's creative service model fosters the innovation vitality of businesses. For instance, the equity crowdfunding platform helps businesses to acquire capital and attract creative talent. Businesses can benefit from innovative ideas and approaches that come from the fusion of technical and financial innovation [23]. The impact of digital finance on company technology innovation is shown in Figure 1.

Figure 1 clearly illustrates how digital finance influences businesses' technological innovation. Peer-to-peer lending platforms and supply chain finance assist businesses to obtain cash as part of the financing channel growth process [24]. The resource allocation optimization mechanism uses big data and AI to allocate resources more accurately. Information transmission and risk reduction mechanism reduce innovation risk, while innovation incentive mechanism stimulates enterprise vitality [25].

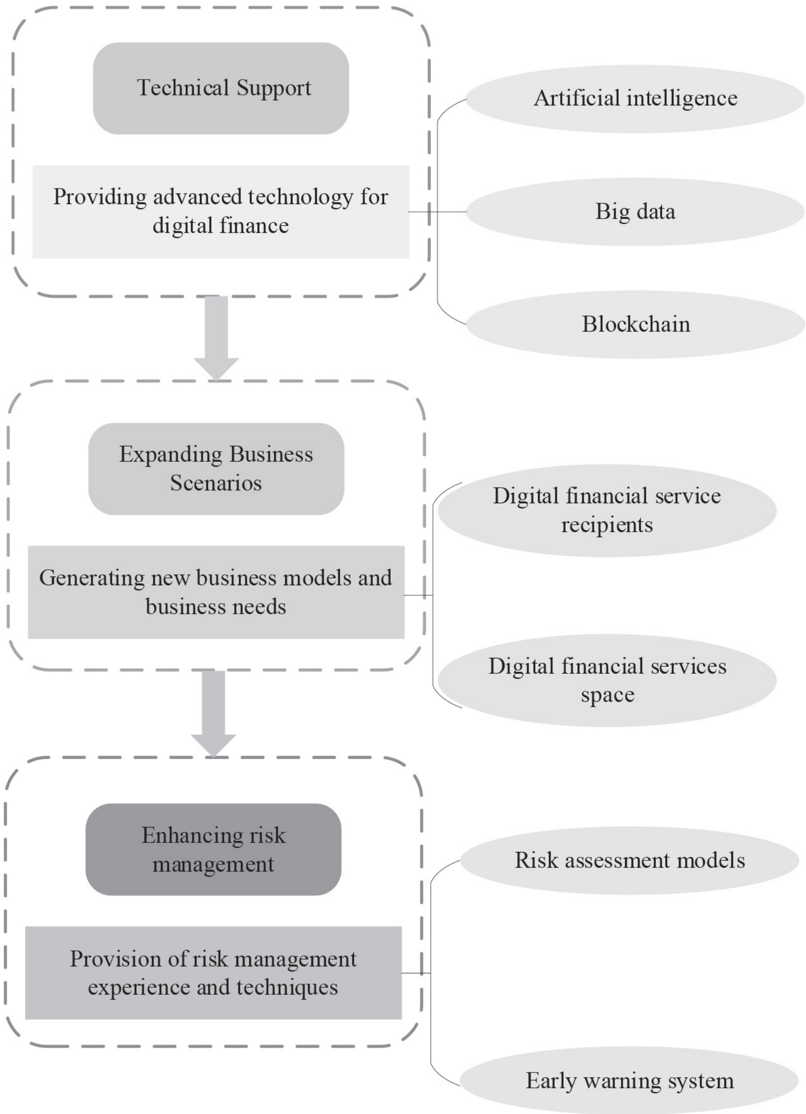

Figure 2 The feedback effect of enterprise technological innovation on digital finance.

3.2 The Feedback Function of Enterprise's Scientific and Technological Innovation to Digital Finance

Digital finance is developing because of significant feedback from enterprise scientific and technology innovation [26]. First, businesses can offer more sophisticated technical assistance for digital finance through technology innovation. The field of digital finance can also use these cutting-edge technologies as a means of increasing the effectiveness and security of digital financial services, given the ongoing scientific and technological advancements made by businesses [27]. Examples of these advancements include the creative applications of big data analysis, blockchain, AI, and other technologies [28, 29].

Secondly, enterprise technological innovation can expand the business scenarios of digital finance. Enterprises generate new business models and business requirements when they engage in technological innovation, which provides new service targets and development space for digital finance. For example, emerging technology companies may need more personalized and customized financial services, and digital financial institutions can create new financial products and service models according to these needs [30].

Lastly, enterprise technology innovation helps to raise the standard of digital financial risk management. Digital financial institutions can benefit from the risk management expertise and technology amassed by businesses in scientific and technological innovation, such as risk assessment models and early risk-warning systems. These resources can aid in the identification, assessment, and management of risks more effectively, as well as guarantee the steady operation of the digital financial market [31]. Figure 2 shows the feedback effect of enterprise technological innovation on digital finance.

In Figure 2, the feedback effect of enterprise technological innovation on digital finance is significant [32]. In terms of technical support, the innovative achievements of enterprises in the fields of AI, big data analysis and blockchain can be used for reference by digital finance to improve service efficiency and security [33]. With the expansion of enterprises, technological innovation has spawned new business models and demands, and opened new service areas for digital finance, such as providing customized financial services for emerging technology enterprises. In terms of risk management, the experience and technology, such as risk assessment models and early warning systems, accumulated by enterprises help digital financial institutions to better manage risks and ensure the stable operation of the market [34].

4. RESEARCH METHODS AND DATA SOURCES

4.1 Research Method

Error backpropagation is the foundation of the BP network's learning mechanism. Basically, the error that exists between the expected and actual network outputs is computed, and then gradually transmitted from the output layer to the input layer. To reduce the error and enhance network performance, the connection weight between neurons in each layer is modified in this process based on the error. Neurons are the fundamental processing units in a BP network. After undergoing nonlinear transformation via an activation function, each neuron outputs the input signal that it received from the preceding neuron. Tanh, Rectified Linear Unit (ReLU), and Sigmoid functions are examples of common activation functions.

The expression of the Sigmoid function is shown as Equation (1):

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

It maps the input value between 0 and 1, has a smooth curve and differentiability, and is widely used in early BP networks. However, the gradient is close to 0 when the Sigmoid function's input value is high or small, which can easily result in the problem of gradient disappearance and have an impact on the network's training efficiency. The ReLU function is is shown as Equation (2):

$$f(x) = \max(0, x) \tag{2}$$

The gradient is always 1 when the input is positive, which effectively fixes the gradient disappearance issue and accelerates the network's training rate. However, when the input of ReLU function is negative, the output is 0, which may cause some neurons to "die". The Tanh function expression is shown as Equation (3):

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{3}$$

It maps the input value between -1 and 1, which has nonlinear characteristics similar to the Sigmoid function, but to some extent it alleviates the problem of gradient disappearance. The following key steps comprise the BP network's training process:

(1) Initialization: The connection weights between neurons are randomly initialized at all levels in the network.

(2) Forward propagation: This involves feeding inputs into the network and using each layer's neuronal computation to determine the output layer's outcome.

(3) Error calculation: The output result is compared with the expected output and the error is calculated.

(4) Back propagation: The connection weight between neurons in each layer is modified in accordance with the error, which is backpropagated from the output layer to the input layer.

(5) Steps 2 to 4 are repeated until the error meets the predetermined accuracy requirement or reaches the maximum number of iterations.

The introduction of BPNN is the main topic of this study, which also examines supply chain financing methods and virtual economy risk management. This study investigates the risk control approach under the supply chain financing mode by building a thorough research model. It then builds a model to forecast and assess the virtual economic risk in supply chain financing based on BPNN. The following is the result of model construction: suppose there are n input features $(x_1, x_2, \ldots, x_n)$, m hidden layer neurons $(h_1, h_2, \ldots, h_m)$, and k output neurons $(y_1, y_2, \ldots, y_k)$.

(1) Transfer from input layer to hidden layer:

For each hidden layer neuron hj, the input zj is calculated with Equation (4):

$$zj = \Sigma(wij * xj) + bj \tag{4}$$

(2) The hidden layer uses the activation function to map the input to obtain the output aj, as shown in Equation (5):

$$aj = f(zj) \tag{5}$$

(3) Transmission from hidden layer to output layer:

For each output neuron yk, the input zk is calculated with Equation (6):

$$zk = \Sigma(vkj * aj) + ck \tag{6}$$

(4) The output layer uses the activation function to map the input to obtain the final output yk_{hat}, as shown in Equation (7):

$$yk_{hat} = g(zk) \tag{7}$$

(5) Cost function:

According to the types and objectives of specific problems, the corresponding cost function is selected, as shown in Equations (8)–(9):

$$\text{Loss} = \Sigma(1/2 * (yk - yk_{hat})^2) \tag{8}$$

$$\text{Loss} = \Sigma(-yk * log(yk_{hat})) \tag{9}$$

Figure 3 shows the model structure of BPNN.

As shown in Figure 3, the BPNN model has a distinct structure. It consists of three layers: input, hidden and output. Data is received by the input layer and sent to the hidden layer. Using many neurons, the hidden layer processes the data nonlinearly in order to extract features. The ultimate prediction result is generated by the output

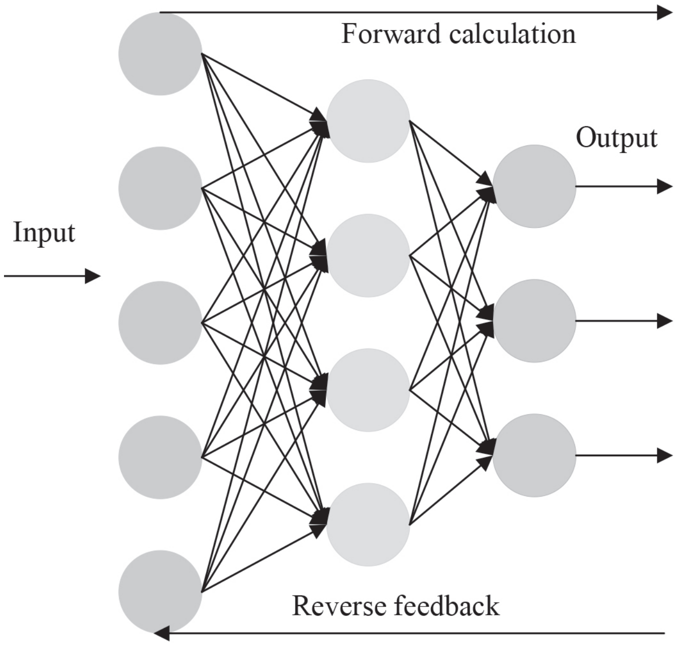

Figure 3 Structure of the BPNN model

layer. Weights are used to connect each layer and, during the training process, the weights and thresholds are continuously changed to maximize the performance of the model. The multilayer structure of BPNN enables it to deal with complex nonlinear relations and adapt to different types of data and problems. Its powerful learning ability and generalization ability make it widely used in many fields.

4.2 Data Source and Processing

(1) Quandl financial and economic dataset

Quandl offers a wealth of financial and economic data, encompassing information on enterprise technological innovation and digital finance. For example, people can find financial data about enterprises in different regions, financial market data and some scientific and technological innovation index data. This dataset can be used to assess how well BPNN performs in forecasting how digital finance will affect businesses' technical innovation performance.

Processing method: The information is sorted, and the variables pertaining to digital finance (e.g., the amount of digital loans and the frequency of electronic payments) are extracted, as well as the performance of businesses in terms of scientific and technological innovation (e.g., the percentage of investment in R&D and the growth in patents). To make it easier to enter data and compare models, any anomalous or missing numbers are attended to, and then the data is normalized.

(2) Crunchbase enterprise dataset

Crunchbase contains information on many enterprises, including their financing situation and technological innovation achievements. This dataset can be used to investigate the impact of digital finance on the technological innovation performance of businesses. It includes information on the financing sources of businesses at different stages of their development, including digital finance, as well as enterprise innovation accomplishments such as new product releases and technological breakthroughs.

Processing method: From the dataset, fields are chosen that are most directly connected to digital finance and the technological innovation performance of enterprises. Then, the data is cleaned to guarantee its quality and integrity. The data is then standardized so that the different indicators are comparable in value to ensure a more accurate evaluation of the model.

5. EMPIRICAL ANALYSIS

5.1 BPNN model evaluation

The BPNN model is a crucial analytical tool and its evaluation is crucial in the research on the impact of digital financing on the performance of scientific and technical innovation of Chinese firms. People can acquire a better understanding of the intricate relationship between digital finance and an enterprise's scientific and technological innovation performance by evaluating this model, which also serves as a solid foundation for future discussions of the dynamic changes in these relationships. With its powerful nonlinear mapping ability and adaptive learning characteristics, BPNN has unique advantages in dealing with such complex problems, which will be explained in detail below.

(1) Dynamic adaptability index of the model

This index measures the model's adaptability to changes in the data distribution. For instance, differences in the

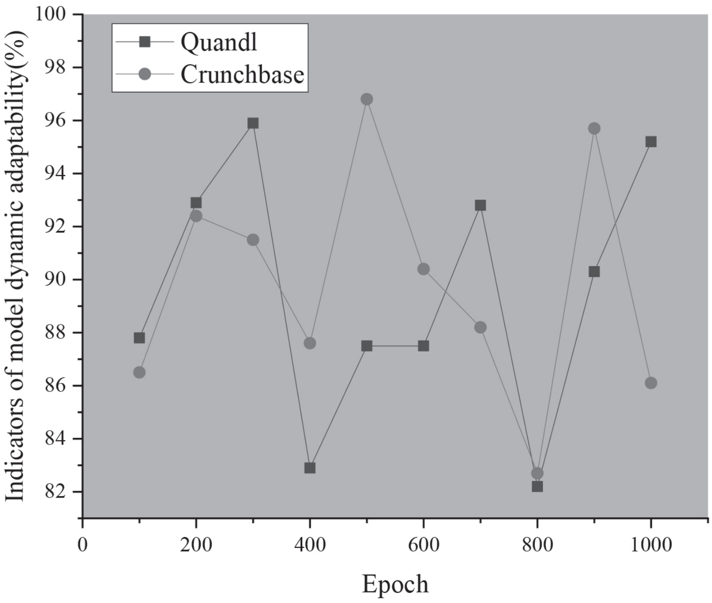

Figure 4 Evaluation results for dynamic adaptability index of the BPNN model.

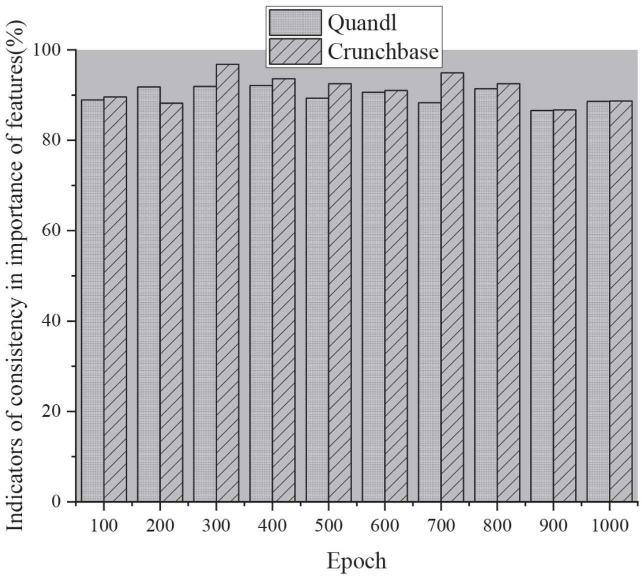

Figure 5 Evaluation results for feature importance consistency index of the BPNN model.

model's performance are determined by using data that is gathered across several time periods. The model's capacity to adapt to the dynamic changes in data is stronger when the difference is smaller. The change rate of prediction accuracy on data over several time periods can be used to express it. The evaluation findings of the BPNN model's dynamic adaptability index are displayed in Figure 4.

Figure 4 shows the results obtained by evaluating the BPNN model using two different datasets. The model's dynamic adaptability index for the Quandl dataset is outstanding and consistently above 82%. This means that the model can adapt to the change of data distribution and shows strong robustness regarding the data collected from the Quandl dataset in different time periods. For the Crunchbase dataset, the dynamic adaptability index of the model is more than 83%. This demonstrates that the model can maintain high adaptability in different time periods whether it be for the Quandl dataset or the Crunchbase dataset, which provides a reliable guarantee that the complex relationship between digital finance and enterprise's technological innovation performance will be determined accurately.

(2) Consistency index of feature importance

The consistency index of feature importance is highly significant when evaluating the BPNN model. It can reflect the stability of the model in judging the importance of different input features and provide a strong basis for the reliability of the model. Figure 5 displays the evaluation results for the feature importance consistency index of the BPNN model.

In Figure 5, the evaluation results for the feature importance consistency index of the BPNN model are

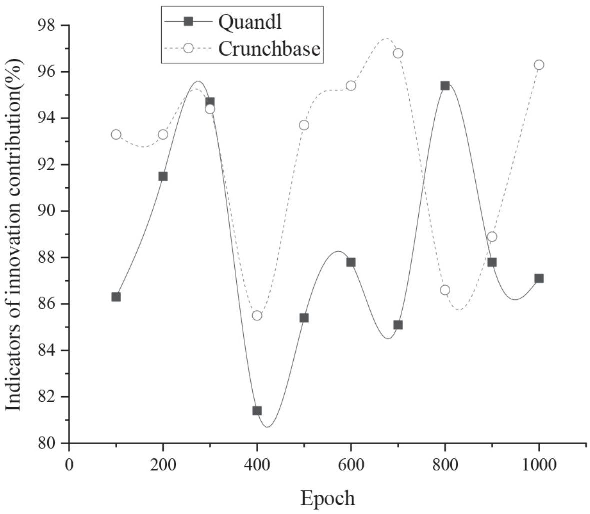

Figure 6 Evaluation results for innovation contribution index of the BP model.

clearly presented. For two different datasets, the evaluation index results of this model are all above 86%. This shows that the model has high stability in judging the importance of different input features. Regardless of which dataset, the model can identify key features consistently, which provides a reliable guarantee that the relationship between digital finance and enterprise's technological innovation performance can be accurately determined, and fully demonstrates the advantages and value of the model in practical application.

(3) Innovation contribution index

An important consideration when assessing the BPNN model is the innovation contribution index. It can clearly demonstrate the distinct contribution of the features of digital finance to the companies' performance forecast of scientific and technological innovation, and it can also confirm the model's usefulness. The evaluation results for the BP model's innovation contribution index are shown in Figure 6.

In Figure 6, the results obtained by evaluating the BPNN model using two different datasets are presented intuitively. In the Quandl dataset, the innovation contribution index of the model is remarkable, as it remains above 81%. This clearly demonstrates that, when the Quandl dataset is analyzed, the associated features of digital finance are highly significant in predicting the performance of the enterprise's technical and scientific innovation within the model. In the Crunchbase dataset, the innovation contribution index of the model is as high as 86% or more. This further demonstrates the great significance of digital finance features in the model when compared to the Quandl dataset, and it makes a big difference in predicting how well businesses will innovate in in terms of science and technology. Strong evidence for a deeper understanding of the relationship between them can be found in the Quandl and Crunchbase datasets, which both fully validate the efficacy and reliability of the BPNN model in measuring the impact of digital finance on enterprise's scientific and technological innovation performance.

5.2 BPNN Analysis of the Influence of Digital Finance on the Scientific and Technological Innovation Performance of Chinese Enterprises

Enterprise technical innovation is significantly impacted by the growth of digital finance. This study describes how to investigate this influence in depth and shows how to use BPNN, a powerful tool for studying this relationship. The evaluation findings are displayed in Table 1.

The data results presented in Table 1 demonstrate how several variables affect an enterprise's capacity for scientific and technical innovation. Such innovation is significantly influenced by elements such as the scale of the enterprise, the intensity of R&D investment, and the development level of digital finance. The emergence of digital finance fosters scientific and technological innovation while offering businesses more convenient financial services. As the scale of an enterprise increases, more resources can be invested in research and development. The intensity of R&D investment directly determines the innovation ability of enterprises. Industry competition can stimulate innovation power, and a high level of regional economic development provides a better environment for innovation. Enterprise management level, talent reserve and policy support are also indispensable factors. Although the stability of the financial market has a relatively small impact, it also provides a guarantee for scientific and technological innovation. Overall, these variables work together to improve the performance of scientific and technological innovation within the enterprise.

6. CONCLUSION

The impact of digital finance on businesses' scientific and technological innovation is becoming more and more noticeable due to the rapid expansion of digitalization. The aim of this study was to investigate the ways in which digital finance influences the performance of Chinese businesses in terms of their scientific and technical innovation. For

Table 1 BPNN analysis of the impact of digital finance on the scientific and technological innovation performance of Chinese enterprises.

Variable	Coefficient	Standard error	T value	P value	Lower limit of 95% confidence interval	Upper limit of 95% confidence interval
Development level of digital finance	0.45	0.08	5.62	0.0001	0.29	0.61
Scale	0.22	0.06	3.67	0.0003	0.10	0.34
R&D investment intensity	0.38	0.07	5.43	0.0001	0.24	0.52
Degree of industry competition	0.15	0.05	3.00	0.003	0.05	0.25
Regional economic development level	0.28	0.07	4.00	0.0002	0.14	0.42
éEnterprise management level	0.18	0.06	3.00	0.003	0.06	0.30
Talent reserve level	0.25	0.07	3.57	0.0004	0.11	0.39
Policy support	0.20	0.06	3.33	0.001	0.08	0.32
Financial market stability	0.12	0.05	2.40	0.017	0.02	0.22

this research, the BPNN model was adopted and combined with the dynamic panel data estimation method, and was evaluated from multiple perspectives. By collecting data from Quandl and Crunchbase datasets, the dynamic adaptability index, feature importance consistency index and innovation contribution index of the model were analyzed in detail. The research focused on the relationship between digital finance and performance of enterprises in terms of technological innovation. The evaluation results for different indicators revealed the advantages of the BPNN model when dealing with this complex problem. The research results show that the BPNN model demonstrated high performance on two datasets. The dynamic adaptability index of the model was above 82% and 83%, indicating its strong adaptability to the changes of data in different time periods. The consistency index of feature importance was above 86%, indicating the stability of the model in judging the importance of different input features. The innovation contribution index is above 81% and 86%, highlighting the special contribution of features in the digital finance model to the performance forecast of technical and scientific innovation in businesses. The findings demonstrated the clear benefits of using the BPNN model to determine how digital finance affects an enterprise's capacity for scientific and technical innovation. It can accurately capture the complex relationship between them and provide a valuable reference for enterprises and policy makers. However, this study also has several limitations. Firstly, the selection of datasets may have some limitations and cannot fully represent the situation of all enterprises. Secondly, the evaluation index of the model may not be comprehensive enough; hence, a better evaluation system needs to be developed. Future research can further expand the scope of datasets and improve the generalizability of the research findings.

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