Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 6815255, 8 pages
https://doi.org/10.1155/2022/6815255

Research Article

Risk Prediction of E-Payment by Big Data Management Technology

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Received 12 April 2022; Revised 17 May 2022; Accepted 18 May 2022; Published 2 June 2022

Academic Editor: Wen-Tsao Pan

E-payment has penetrated every aspect of people's daily life, and the development and application of E-payment technology have made life more convenient. Besides, the process of E-payment has endless hidden dangers, posing a great threat to payment security. In this context, risk assessment and prediction of E-payment are particularly important. Therefore, this paper mainly studies the E-payment analysis and prediction method based on big data technology. Specifically, this paper uses the BP neural network to extract E-payment data feature and compare and analyze the characteristic of different methods; finally, the payment risks are predicted based on the features, the simulation experiments show that the best result is obtained by the method proposed in this paper, and thus the effectiveness of the new method is verified.

1. Introduction

With the development of Internet technology in China, especially under the explosive development of e-commerce business, there is a demand for guaranteed payment, and third-party payment is born in such a context at the same time, causing great threats to online payment security [1, 2]. Risk assessment of the E-payment system becomes more and more important. At present, the risk assessment of the E-payment system is mainly based on the standards and schemes of information security risk assessment [3]. Information security risk assessment is to use the most advanced technical means to analyze E-payment risks, find out the certainty of payment system, and provide a comprehensive description of system security for management, so as to better understand and improve the system [4]. The following will illustrate the necessity of payment risk prediction with specific payment software.

Take Alipay as an example, in its development process, it has accumulated a large number of users relying on Taobao, a large platform. By mining the financial needs of users, it has derived a new financial form, namely, Internet finance. The development of Internet financial enterprises represented by Ant Financial has driven the development of the whole market, and due to its important market position, it has a strong demonstration role for other enterprises, that is, the one who wins the entrance wins the world, and payment is the entrance. Therefore, many enterprises began to pour resources into payment, so many third-party payment companies mushroomed [5, 6]. According to the latest data, in the mobile payment market, the mainstream third-party payment companies include Alipay, Tenpay, Jingdong Pay, Baidu Pay, Shunpaypay, and so on. Security threats in the field of third-party mobile payment in Internet finance are gradually increasing [2]. Meanwhile, there has been more than one risk and security accident in the media in the last two years, and each accident has affected users' transaction and use for a long time. The risk and security problems of third-party payment companies are highlighted, and the payment risk control system needs to be strengthened urgently [7]. The management measures for online payment business of nonbank payment institutions issued by the People's Bank of China in 2016 require third-party payment companies to have a complete set of payment risk control system [8, 9]. Generally speaking, the risk prediction of payment systems is different from that of other systems.

However, the E-payment system is also different from the ordinary information system [10]. The government also pays much attention to the development of third-party E-payment. China's third-party E-payment enterprises are seen as nonfinancial institutions, which are supervised by the central bank. In addition, under the push of the People's Bank of China, China's payment and settlement industry association was established in May 2011, and all payment enterprises should join together for security of economic market, which marks that the new regulatory framework of the combination of government coercion and industry self-discipline for third-party E-payment in China been used. In order to better control the third-party E-payment risk, China mainly develops laws and regulations from the following aspects, including the third-party E-payment enterprise customers and antimoney laundering, in a series of results, and at the same time, it also has many drawbacks [11, 12]. Therefore, it is necessary for us to study the development of E-payment and its risk management of the third-party [13]. It is because the third-party E-payment institutions have safe and reliable platform technology and are independent from the legitimate status. Hence, they are trusted by both parties. Without these premises, trust is out of the question. However, in the development process of third-party E-payment, there are also many problems such as security credit supervision [14]. These problems are in urgent need of more specific regulations [15]. Section 2 of this work shows the related works, and then big data technology-based E-payment risk prediction is introduced in Section 3. After that, Section 4 gives the experimental results and analysis. Finally, Section 5 concludes the whole paper.

2. Related Work

Electronic payment is a new means of payment based on digital currency. It replaces the circulation and storage of currency with digital information to complete transaction payment [16]. Common E-payment tools include electronic check, electronic credit card, and electronic cash. Electronic check is an electronic document that electronizes real-life check and applies it to online payment. The original signature is replaced by electronic digital signature technology. Electronic credit card means that users directly input their credit card information when making online purchases [17]. The form of electronic cash is the electronic certificate after ciphertext. It uses cryptography to encrypt a series of payment vouchers and generate the corresponding ciphertext, which can be verified in the merchants supporting electronic cash.

The word "Risk Management" first appeared in Gallagher's [18] pioneering study of the new era of cost control—risk management. They divide risks into nontechnical risks and technical risks according to their characteristics. A systematic risk classification study was conducted from project risk sources to risk consequences. This is a process that mainly identifies the potential risks that may affect the subject and then carries out risk management so as to keep the risks within the subject's control and ensure the realization of the subject's goals. It is implemented by a company's top and middle and grassroots staff. At the same time, the papers [19, 20] also define the risk management framework, which is known and used in eight aspects, including risk identification, assessment, response, monitoring, control, internal environment, goal setting, information, and communication.

Electronic payment technology is developing rapidly. Given the potential challenges, many researchers are focusing on real-world applications to try to discern the possible payment risks [21]. It argues that new E-payment technologies have brought a lot of uncertainty, and these new technologies have made risk control more complicated. The author of [22] also pointed out that the existing network architecture and the rapid development of E-payment technology bring additional challenges to risk control [23]. The emergence of the Internet technology and the development of electronic commerce, this kind of role in weakening the emerging technology, have brought many uncertain factors, producing payment risk on multiple levels. The authors of [24] pointed out that with the convenience brought by computer technology to payment, we should also pay attention to the risks it brings, and these risks can be summarized to fraud risks, operational risks, and legal risks. The first two are more realistic in the absence of adverse selection and moral hazard. For payment risk, control risk, or containment risk, all stakeholders should take corresponding measures [25].

Reference [26] thought that the economy and the health of the Internet are inseparable, involving related parties, have various interest groups and regulators. The risk of third-party payment is the main risk at present. Corey et al. [27] believed that the innovation of Internet financial entities represented by ant financial in multiple fields of payment and settlement not only brings new challenges to traditional finance but also faces difficulties and risks of its own, mainly including business risks, technical risks, and legal risks [19, 28]. Reference [29] systematically analyzed the evolution of the existing concept of risk management, and the relationship between risk management and capital control, risk control management and enterprise value, as well as the strategic issues in risk management, and looked into the future of integrated risk management. The authors of [30] also analyzed and summarized the concept and nature of risk from the perspective of financial risk and pointed out the essence and characteristics of modern risk management and control. Park et al. [31] took WeChat as an example to give the contents involved in payment risks and preventive measures.

At present, the risk prediction of E-payment has formed relatively mature technologies and methods, such as analytic hierarchy process, fuzzy theory, grey theory neural network, Bayesian network, and rough set theory. In the security assessment of E-payment, the above classical methods have emerged. The authors of [32] took the perspective of sociology trade reputation. The decision on whether to trade is based on two factors: the probability of whether the counterparty will cooperate and whether the loss (the transaction amount) of the transaction failure is acceptable. In the practical application of electronic commerce, consumers pay mode diversification, along with the progress of the society and people life rhythm speeding up, mobile payment as a kind of important electronic commerce payment, affecting the confidence of the people to use mobile payment.

The unlearned risk prediction results of e-commerce mobile payment make the risk prediction error of e-commerce mobile payment large and cannot meet the security requirements of the e-commerce management system. The research results at home and abroad have laid a foundation for the research of this paper and provided valuable references. However, there are still deficiencies in existing research, mainly in the risk and management control of third-party payment, especially with the advent of the mobile Internet era, ubiquitous mobile payment and behind these payment behaviors. Risk control has brought great challenges to the existing risk control theory. Not only that, until now, the academic circle has not formed a theoretical system to study the risk control of third-party payment, which is seriously lagging behind the rapid development of third-party payment industry.

From what has been discussed above, the existing electronic payment based on expert experience risk index system is perfect, but each index did not consider the factor of human, only from the paid content level to evaluate transaction security; when faced with malicious traders (such as receiving shipments, goods wrong card), it is also a serious threat for the whole transaction security. However, the assessment system based on human factors does not consider the security risk of technology and system too much. Based on the above discussion, the contributions of this paper are shown as follows:

(1) The BP neural network is used to extract E-payment data feature
(2) The payment risks are predicted based on the extracted features by the BP neural networks
(3) The simulation experiments on different datasets have proved the effectiveness of the new method

3. Big Data Technology-Based E-Payment Risk Prediction

3.1. Big Data Technology. A certain data scale is the basis for big data to play its role. High speed means large amount of data, which determines the speed of data collection. Diversity is the diversity of data types and the extensiveness of source channels. Value refers to the use of big data can create high value at low cost.

3.2. BP Neural Networks. BP (back propagation) neural network is a highly complex nonlinear dynamic analysis system proposed by Rumelhart and McClelland et al. [33] in 1986. It is a network structure connected by various independent units. According to the error between the actual value and the expected value, from the output layer through the hidden layer to the input layer, the link weight between each layer is revised layer by layer, which is shown in Figure 1.

Through repeated weight modification, the difference between the actual value and the expected value is gradually reduced. When the error is less than a certain value, it indicates that the network training is completed.

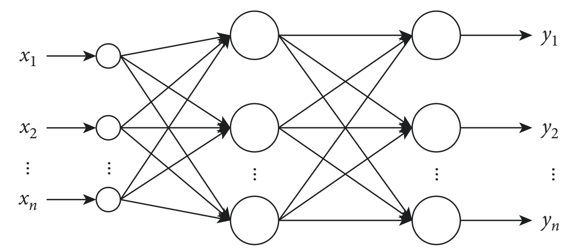

Figure 1: Schematic diagram of the BP neural network.

$$E = \sum_{i=1}^{m} \left(x_i - c_i\right)^2. \tag{1}$$

Then, expand the above error definition to the hidden layer:

$$E = \frac{1}{2}\sum_{\kappa=1}^{\ell} \left[d_\kappa - f\left(\mathrm{net}_\kappa\right)\right]^2 = \frac{1}{2}\sum_{\kappa=1}^{\ell} \left[d_\kappa - f\left(\sum_{j=0}^{m} \omega_{j\kappa} y_j\right)\right]^2. \tag{2}$$

Expanding further to the input layer, there is

$$\begin{aligned}
\Delta v_{ij} &= -\eta \frac{\partial E\, \partial}{v_{ij}}, \quad i = 0, 1, 2, \ldots, n;\ j = 1, 2, \ldots, m,\\
\Delta \omega_{j\kappa} &= -\eta \frac{\partial E}{\partial \omega_{j\kappa}}, \quad j = 0, 1, 2, \ldots, m;\ \kappa = 1, 2, \ldots, \ell,\\
E &= \frac{1}{2}\sum_{\kappa=1}^{\ell} d_\kappa - f\left[\sum_{j=0}^{m} \omega_{j\kappa} f\left(\mathrm{net}_j\right)\right]\\
&= \frac{1}{2}\sum_{\kappa=1}^{\ell} d_\kappa - f\left[\sum_{j=0}^{m} \omega_{j\kappa} f\left(\sum_{j=0}^{n} v_{ij}\chi_i\right)\right]^2.
\end{aligned} \tag{3}$$

Then, the weight adjustment formula of each layer is

$$\Delta \omega_{j\kappa}^{h+1} = \eta \delta_{h+1}^{\kappa} y_j^h = \eta \left(d_\kappa - o_\kappa\right) o_\kappa. \tag{4}$$

According to the above rule layer by layer analogy, the weight adjustment formula of the first hidden layer is

$$\Delta \omega_{pq}^{1} = \eta \delta_q^1 \chi_p = \eta \left(\sum_{r=1}^{m_2} \delta_r^2 \omega_{qr}^2\right) y_q^1. \tag{5}$$

There are some problems such as slow convergence speed, poor performance, uncertain learning rate, and easy to fall into local minimum, so optimization algorithm is usually introduced to improve it. In the traditional BP neural network, the local convergence rate is very slow and even oscillation and divergence are common problems. The optimization algorithm proposed in this paper is aimed at the shortcomings of the traditional BP neural network. The differential evolution algorithm (DE) is introduced into the neural network, which can make the neural network have better nonlinear mapping ability and improve its prediction

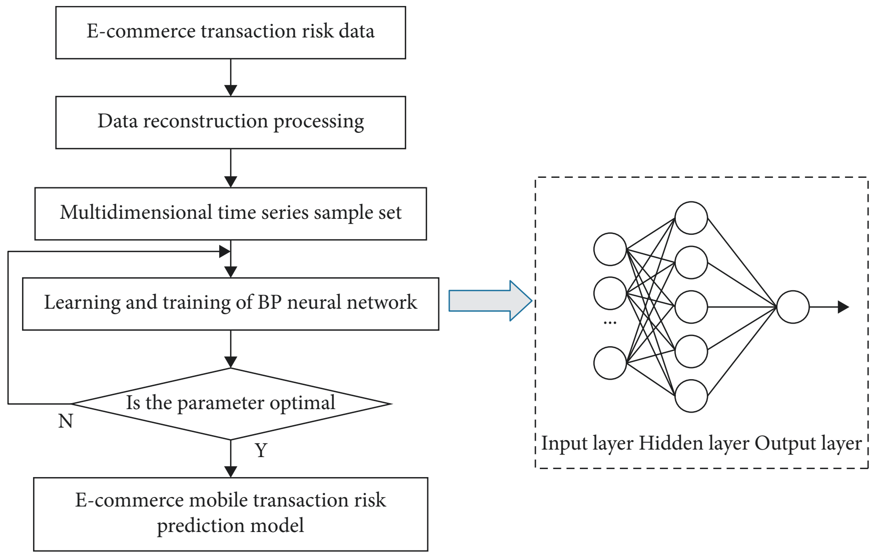

FIGURE 2: Schematic diagram of E-payment risk prediction based on the BP neural network.

accuracy. And, the population initialization in DE is as follows:

$$x_{i,1} = x_i^L + \text{rand}\left(x_i^U - x_i^L\right), \quad i = 1, 2, \ldots, NP. \tag{6}$$

The mutation operation formula is as follows:

$$v_{i,G+1} = x_{r1,G} + F\left(x_{r2,G} - x_{r3,G}\right). \tag{7}$$

Then, the interlace operation is

$$u_{ji,G+1} = \begin{cases} v_{ji,G+1} & r_j \leq CR \text{ or } j = \text{rand}(i), \\ x_{ji,G} & r_j \geq CR \text{ or } j \neq \text{rand}(\text{i}). \end{cases} \tag{8}$$

Accordingly, the selection operations are as follows:

$$x_{i,G+1} = \begin{cases} u_{i,G+1} & f\left(u_{i,G+1}\right) \leq f\left(x_{i,G}\right), \\ x_{i,G} & f\left(u_{i,G+1}\right) > f\left(x_{i,G}\right). \end{cases} \tag{9}$$

The fitness function is

$$f(X) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(Y_i^0 - Y_i\right)^2}. \tag{10}$$

Based on equations (1)–(10), Figure 2 gives BP technology-based E-payment risk prediction proposed in this paper. Specifically, the E-payment risk data is firstly input into the model, and all BP neural networks are used for model training. If the parameters reach the optimal, the model training is stopped; otherwise, the model will continue to train.

4. Experimental Results and Analysis

4.1. Experimental Data Set. The selection of data is also an innovation of this paper. Basel Agreement clearly stipulates that operational risk includes legal risk [21]. However, by referring to data, previous measurement data of operational risk of third-party E-payment by scholars are only limited to loss caused by system and personnel, but not including legal risk.

This paper adds data of legal losses caused by violations of third-party E-payment enterprises in recent years. Due to data availability, only public data are collected here. The data were obtained from the publicly disclosed data of the official website of the People's Bank of China and major financial websites (Yahoo one Finance), and a total of 125 lost data were collected. And, data amount is large, which spans the E-payment data from 2010 to 2020, and the data contain 125 E-payment data with dimensions ranging from tens of thousands to hundreds of thousand [34]. Hence, it is difficult to be processed by conventional machine learning methods, so this paper uses a more intelligent neural network model to handle the big data. Since the probability of such operational risks is very low and the data are very limited, extreme value theory has very low requirements on the amount of data, which is also one of the important reasons why extreme value theory is used to measure the risk. Considering the high homogeneity of the third-party E-payment market, it is analyzed as a whole.

In order to obtain better prediction results, it is necessary to normalize all data with the max-min method. In addition, it is necessary to remove outliers in the data to ensure data reliability. Figure 3 shows the outlier identification results based on the box graph.

4.2. Analysis of Experimental Results. In the test phase, 2000 default samples of the test data set are used to train the BP neural network model to verify the prediction effect. For the test data set, the error between the predicted value and the actual value corresponding to each sample is shown in Figure 4. It can be seen from the figure that the error of most risk data is less than 1%, and only a small number of samples near the 2000-th sample have an error value of more than 1%, but it does not reach 1.5%, which indicates that the proposed method has a good prediction performance.

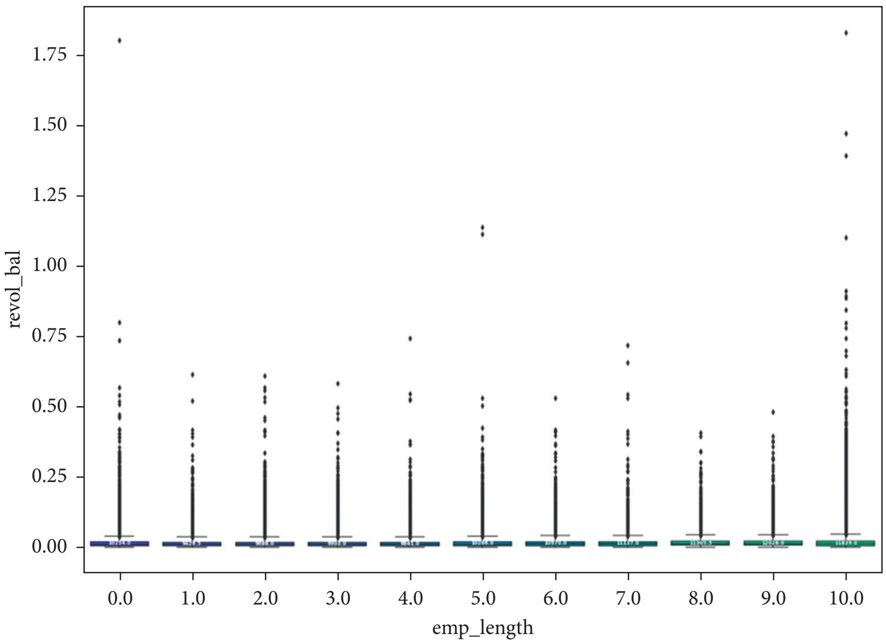

FIGURE 3: Outlier identification results by box graph.

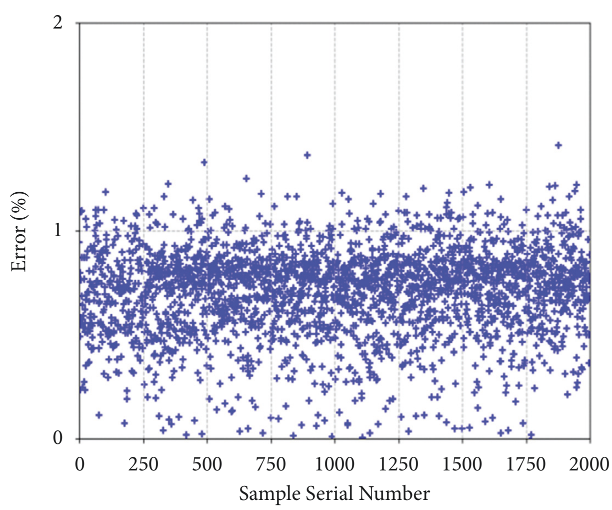

FIGURE 4: Error distribution for 2000 default test samples.

Because validation data is part of the training set, it can be used to detect payment risks in a timely manner after each epoch. However, with the increase of training times, the training accuracy and testing accuracy will be improved correspondingly with the increase of epoch if the overfitting or underfitting problems are not aggravated. As can be seen from Figure 5, when 20 epochs were iterations, the training results were relatively stable, and the training effect was better than that with less than 20 epochs. The stability and persistence of the proposed method are explained.

The prevention and control of prior risk is not the prevention and control of prior capital risk (at this time, the capital transaction has not happened). Therefore, its main risk points include the weak security awareness of customers and the risk of payment process. Therefore, it is necessary to predict the risk in advance, so as to better control it. In addition, from Figure 6, we know that traditional time series analysis method [28] has the worst prediction result of single-step payment risk, and the corresponding prediction error of payment risk is the largest. This is because this method cannot depict the nonlinear characteristics of risk data, but only describe the linear change law of payment risk, and cannot obtain ideal risk prediction results of e-commerce mobile payment. Similar results also appear in ART (adaptive resonance theory) neural network, and the BP algorithm in this paper can describe a variety of features of process data more comprehensively, so as to achieve the best prediction accuracy, and the prediction curve can well fit the real risk curve.

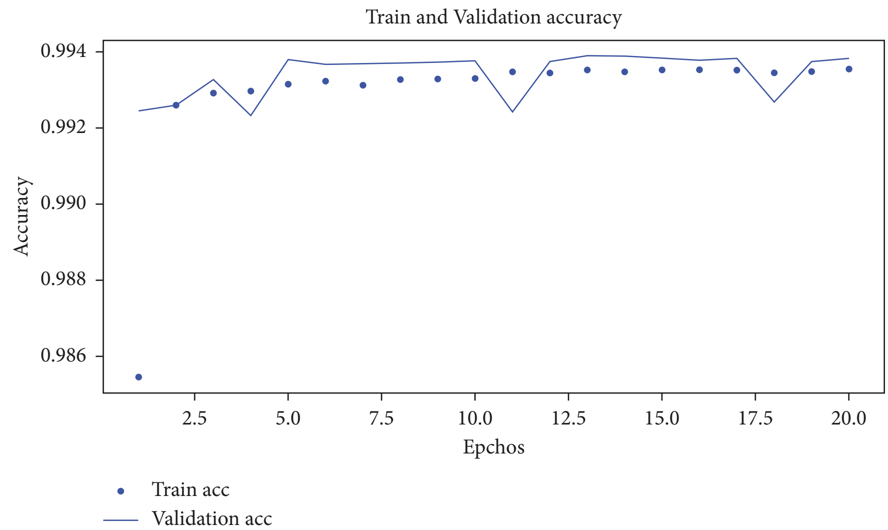

Figure 5: Comparison results of training accuracy and testing accuracy.

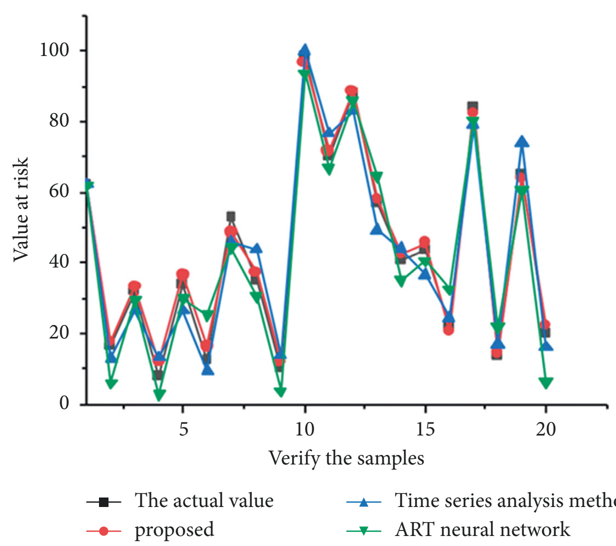

Figure 6: The results of single step prediction of payment risk by different methods.

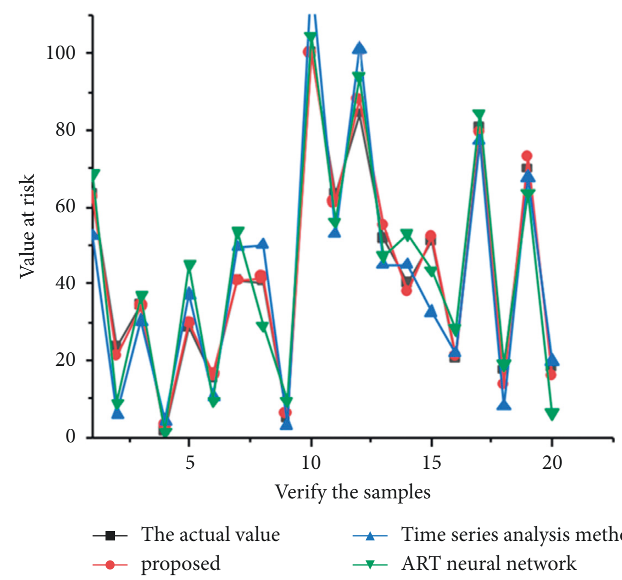

Figure 7: Multistep prediction results of payment risk by different methods.

Figure 7 shows the multistep prediction results of payment risk by different methods [31]. From the figure, we know that the risk prediction results of multistep E-payment are generally larger than that of single-step payment, which makes the prediction results worse, but the multistep payment risk prediction results can still meet the actual demand. At the same time, the prediction results of the proposed BP neural network model are superior to the traditional time series analysis and ART neural network, which proves the practicality and reliability of the proposed model again.

Based on the above research, it can be seen that payment risks have been successfully predicted, so that effective supervision and control can be carried out in order to curb the occurrence of payment risks from the source and improve the health of the market. Figure 8 gives the factors affecting payment risk rank; from the figure, we know that personal information disclosure risk and credit risk are the main factors affecting payment risk. And, the application of Internet finance is more and more extensive. This is largely due to the large amount of personal data provided by customers. Therefore, improving consumers' risk management ability and personal information protection ability is particularly important, which may be the main measure to eliminate payment analysis. In addition, imperfect market regulation makes opportunistic enterprises and individuals take advantage of this loophole to conduct illegal acts, thus further increasing the risk of payment.

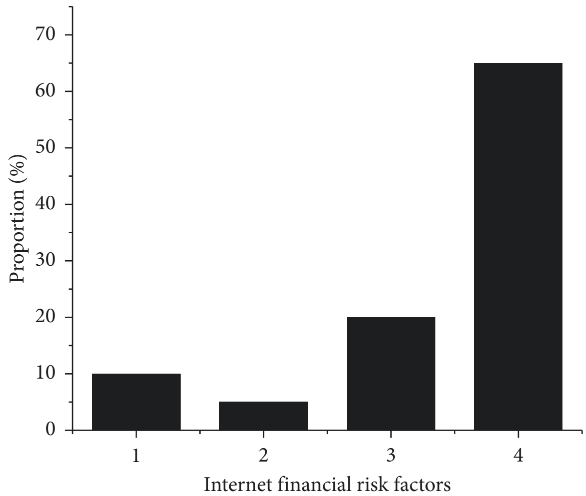

Figure 8: Factors affecting payment risk rank. (1) Imperfect market and legal regulation; (2) risk of Internet financial technology selection; (3) credit risk; (4) divulge personal information.

5. Conclusions

This paper first reviewed the research of E-payment risk under the risk management theory through literature review, especially the research on e-payment risk control. Through literature review, we summarized the main risks existing in E-payment, including fraud risk, moral hazard, and compliance risk. Furthermore, to better study the payment risk status, we made short-term and long-term prediction of possible payment analysis based on big data technology.

Therefore, one of the research directions of risk control and payment risk control in the future will be the application of big data risk control, artificial intelligence, block chain, and other emerging technologies in risk control and prevention. The availability of computing power provides capability guarantee for the realization of big data risk control and artificial intelligence risk control. Therefore, the major research direction in the future is how to use big data and artificial intelligence to improve the efficiency and accuracy of risk control and realize automation and intelligence.

Data Availability

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

Conflicts of Interest

The author declares no conflicts of interest.

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