Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 8606624, 10 pages
https://doi.org/10.1155/2022/8606624

Research Article

Internet Financial Risk Model Evaluation and Control Decision Based on Big Data

Liancheng Chen [1] and Rong Jiang [2]

[1] *Jose Rizal University, Mandaluyong City 1552, Philippines*
[2] *Northern University of Malaysia, Suntuk Town 06010, Malaysia*

Correspondence should be addressed to Liancheng Chen; chenliancheng@alu.scu.edu.cn

Received 10 June 2022; Revised 20 July 2022; Accepted 27 July 2022; Published 13 August 2022

Academic Editor: Chia-Huei Wu

Internet finance is the application of advanced information technology to traditional finance. Internet finance is accelerating its growth, and its performance is most obvious in the financial market. The Internet financial reduces costs of traditional financial, which makes it more civilian. The unstable factors of Internet finance, such as regulation, credit reporting, and network security, lead to a gradual increase in risks. The current Internet financial risk model is slow to deal with risks and cannot solve the financial risks that arise in time to ensure the safety of the platform. In order to solve this problem, the big data technology was applied to the Internet financial risk model to evaluate and control financial risks. The default rate, rate of return, risk control time, model performance score, and other aspects of the Internet financial risk model using big data were tested. It is found that by applying big data technology to the Internet financial risk model, the customer default rate decreased by 6.14%, the yield increased by 7.6%, the time to deal with risks was reduced by 0.46 minutes, and the model performance score was improved by 0.796 points. Big data technology can effectively control and avoid Internet financial risks and help investors avoid risks.

1. Introduction

Internet finance is a product of the continuous development of information technology. The Internet provides a platform for financial transactions to be used for transactions. Compared with traditional finance, Internet finance is safer and faster in transaction speed, and the cost of transactions between both parties is lower. Internet finance supports online transactions, which is not affected by time and place and is more in line with contemporary lifestyles. As the mainstream technology of the information age, big data technology can scientifically analyze large-scale and diverse data, so as to provide higher-quality data information and guidance for the development of the industry, which can significantly improve the ability of Internet finance to control and avoid credit risks.

The emergence of Internet finance has made people's life more convenient, but financial risks affect the development of Internet finance. More and more researchers are studying the risks of Internet finance. Li believed that Internet finance was a new financial model. Due to the lack of corresponding legal systems and mature technologies, there were many financial risks. It was the key for reducing Internet financial risks to improve Internet financial laws and regulations [1]. Based on traditional debt risk control, Wang et al. proposed a device-based Internet user credit risk management model. Its scheduling and risk forecasting capabilities provide ISPs with new ideas and insights for designing risk management strategies [2]. Wu and Chen conducted research and analysis on related risk early warning models. The next weighted KNN Internet financial risk control algorithm with variable precision rough set was proposed, which could directly judge the sample categories belonging to the positive area, and other areas could be judged by the KNN algorithm based on quantitative weighting. The experimental results verified the effectiveness of the above algorithm [3]. Ullrich proposed a credit rating model based on a speed measurement algorithm and developed a credit risk rating model for

Internet finance companies. By taking an internet lender as an example, the performance of the traditional credit card evaluation model and the proposed algorithm training model is compared. The results show that the prediction results of the ML algorithm are more accurate, and the data processing process is more flexible and reliable [4]. Yang et al. used the t-SNE training algorithm, the Internet business growth index data covering 31 regions, cities, and 335 regions was exported. Three major risks of the Internet financial system were proposed, and more localized targeted tips for Internet financial risks were provided [5]. Zhao used Garch-EVT-Copula to scale the market risk of these products. Through extreme value theory and Copula function VaR model, extreme market risk was quantified. Through examples, the risk of Internet structured financial products on the platform was measured, and a scientific decision-making basis was provided for the risk management of Internet financial products [6]. Yue analyzed and controlled how to participate in Internet financial risk management from how to develop Internet finance and reduce the occurrence of Internet financial risks. In response to the problems faced, corresponding improvement paths were proposed, which aimed to provide a reference for improving Internet financial supervision [7]. The above researches show that Internet finance can effectively reduce financial risks. But with the continuous improvement of technology, new problems have emerged.

As a mainstream technology in the new era, many scholars have cooperated to explore it. Based on big data analysis in a laptop environment, Wang et al. introduced a health information system (HIS). The process provides a high degree of integration, interaction, discovery, and sharing of health data among healthcare providers, patients, and staff to help fitness professionals make timely and important decisions [8]. Xu et al. proposed a large-scale competitive intelligence business model based on big data and analyzed the functions of intelligent data subsystem, intelligent data management system, intelligent data analysis subsystem, intelligent data service system, and intelligent integrated management system [9]. Wang et al. proposed a forecasting system by combined with big data technology, which could select appropriate forecasting models for different load processes. And by combining the forecasting results of a single load, the expected total load of the system was captured. The proposed new method could guarantee the accuracy of short-term load forecasting within the required scale [10]. Chen and Chi discussed the concept of building a medical big data platform and introduced the construction of clinical models. Medical data could be collected and integrated through distributed computing technology. Medical models could be established through analysis techniques such as artificial neural networks and gray models. A new model was established for joint clinical research in specialist and special disease clinics [11]. Ke et al. studied the short-term load capacity prediction method based on big data. Through the use of big data technology for data mining, it was found through experiments that it was completely suitable for the requirements of load forecasting and could greatly reduce the calculation time of load forecasting and improve the forecasting accuracy [12]. Zualkernan and Rashid designed an early warning system for power equipment based on big data from the perspective of time series analysis and unsupervised learning, which realized a new perspective of data association and data evolution. This method proposed an anomaly detection framework, which had a fast detection speed. When there was a problem with the power equipment, an early warning could be given at the first time to avoid errors [13]. Zapevalova and Chen conducted big data analysis of smart grids, proposed a system for calculating errors, and extended the results of previous data in space and time. A high-dimensional state estimation matrix was constructed, and the state estimation matrix was analyzed by multidimensional scaling and local abnormality factor, and the local abnormality factor of each node was calculated. According to the value of local anomaly factors and the relationship between nodes, fault detection and localization could be achieved [14]. The above researches show that big data technology has a role in promoting the development of various fields. Internet finance has played an important role in financial innovation and providing comprehensive financial services to customers. But there are also many problems in the development process. Internet finance includes legal and institutional risks, occupational risks, and technical security risks. Big data technology is applied to the Internet financial risk model, and data mining technology is used to classify financial information to ensure the safety of financial platforms. With the help of preset algorithms, Internet finance can accurately grasp the development trend of the market, understand the specific factors that lead to risk outbreaks, and identify the best measures to deal with possible outbreaks of risks, thereby helping Internet finance companies to adjust their own development strategies in a timely manner, and effectively avoid market risks.

2. Internet Financial Risk Model

2.1. Internet Financial Risk Management Platform. The construction of the Internet risk management model is based on the study and recognition of the OECD risk management strategy, and the existing system is improved by integrating big data technology. Based on risk management concepts, data management traditional business data, and big data (business data, process data, external data, and other data), the valuable big data rules are summarized [15]. And these rules are applied to financial data collection and management services. Different tests are carried out according to the risk level to eliminate financial risks and jointly build a comprehensive management framework based on risk management [16]. The financial risk management system in this paper is divided into two parts: “risk management platform” and “process management platform” for its scalability, ease of use, and portability [17], as shown in Figure 1.

The financial risk management platform is guided by risk management and supported by data mining technology. Dangerous data existing on financial platforms is mined, risk data is extracted and then analyzed, risk assessment is performed, and measures are summarized to deal with risks.

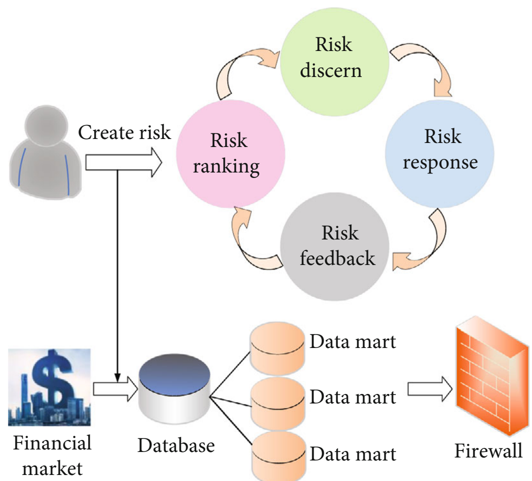


Figure 1: Internet financial risk management platform.

Risk feedback evaluation is carried out. According to different types of financial risks, the occurrence of risks can be avoided or prevented through reasonable services and management measures [18].

2.2. Risk Process Management Platform. The risk process management platform takes data sharing as the core; carries out the process of financial data search, identification, sharing, extraction, and maintenance; and transforms key management into data management. The risk process control platform can not only realize the risk management function of loading the risk management system but also realize the daily functions created by loading other systems. The tasks involved in the process management process are divided into risk tasks and daily tasks. The daily tasks control the running time and running process of the program according to the data control and timely control the risk factors in the running process. The system also has an automatic monitoring function, which monitors and manages the system in real time, improves internal management, and improves the performance of financial professionals [19]. In addition to distributing and delivering risk tasks from the risk management platform, the risk management system can also support the flow, feedback, monitoring, and calibration of tasks from the application platform, such as data quality management platform, financial risk tracking management, and financial monitoring management. The specific business process is shown in Figure 2.

2.3. Feature Design Based on Big Data. This paper uses the data mining CRISP-DM model to extract financial risk characteristics and combines the knowledge of system framework and information system to develop and design a new unit financial risk management mechanism, that is, response system programming [20]. This process treats the entire risk management process as a control system consisting of five main components: input, control system, execution system, project design, and data output. The design process emphasizes system feedback and power control, and system feedback is a key step in the design process. Asset valuations are assessed through financial and regulatory risk rules, people, costs, and organization. Primary data sources are collected as required by risk management. In each system, according to the scale of management, execution, feedback, and control, the expected effect is finally achieved: it can improve financial risk compliance, investor satisfaction, and the implementation process of control and reduce the appearance of risk data, as shown in Figure 3.

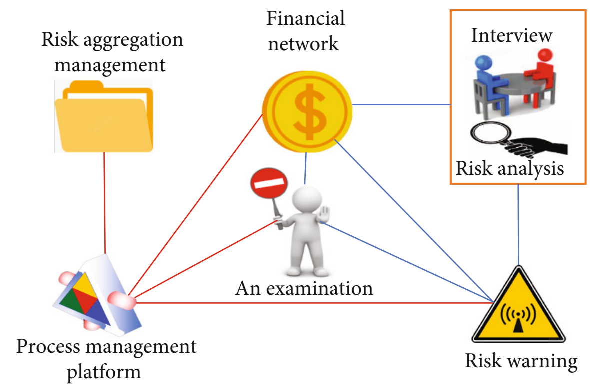


Figure 2: Risk process management platform.

Data mining risk methods can be divided into two categories. One is the indicator type, which develops an indicator system with financial risks based on traditional experience and implements preventive measures according to the risk level. Another data mining risk method is professional data analysis to create various risk libraries with the help of SAS, SPSS, S_PLUS, and other software. Through the customization of virtual network, C5.0, partition tree, accounting retrieval, and other methods and some loading algorithms, risk data is collected and appropriate risk management measures are implemented according to different loading systems [21].

2.4. System Physical Architecture. The physical architecture of the system is to form the physical environment in which the system software runs by selecting suitable physical devices and combining them according to a specific mode. In order to ensure the security of the system information, this paper uses the C/S system to decompose the computer application program and integrate it through multiple computers, that is, the principle of "service sharing" is used. The main function of the client is to process data, represent data, and understand the user interface, while the server is responsible for important functions such as data management [22]. The physical architecture of the financial risk management system is shown in Figure 4.

The physical structure diagram of the system is described as follows. First, the financial risk management system is accessed through the client, the system view is opened, and the user name and password that can use the program are entered. Then, the application server in the database and data processing functions is employed. On the one hand, it is responsible for responding to customers' requests for data processing and data transmission, and on

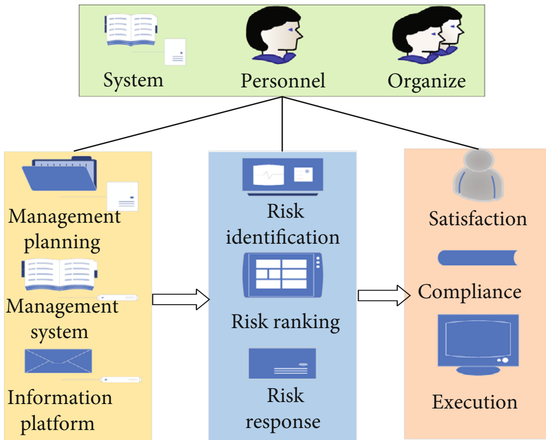


FIGURE 3: Feature design based on big data.

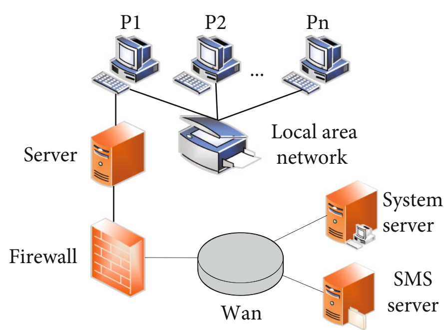


FIGURE 4: Physical architecture diagram of financial risk management system.

the other hand, it conducts data interaction, and the interaction process can use various mobile devices. Finally, the development programs below the system server and the SMS platform server are deployed, and the interface access software is used to transmit the data to the application server through the local area network.

2.5. Recommendation Algorithm

(1) Logistic regression model

The logistic regression model is a binary classification model that can be represented by a conditional probability distribution $p(y=1|x)=p$. The form is the parameterized logistic distribution, assuming that vector $x=(x_1, x_2, \cdots, x_n)$ has n independent variables, and the conditional rate $p(y=1|x)=p$ is the probability that the observed value occurs for x. Specifically as follows [23]:

$$p(y=1|x)=\pi(x)=\frac{1}{1+e^{-f(x)}}, \tag{1}$$

$$f(x)=w_0+w_1x_1+\cdots+w_nx_n. \tag{2}$$

Under this condition, the probability that y does not occur is

$$p(y=0|x)=1-p(y=1|x)=1-\frac{1}{1+e^{-f(x)}}=\frac{1}{1+e^{f(x)}}. \tag{3}$$

So the ratio of probabilities to occur is

$$\frac{p(y=1|x)}{p(y=0|x)}=\frac{p}{1-p}=e^{f(x)}. \tag{4}$$

This division is called event division of events and is recorded as odd. By taking the logarithm of odds, it can be obtained:

$$\ln\left(\frac{p}{1-p}\right)=f(x)=R_0+R_1x_1+\cdots+R_nx_n. \tag{5}$$

Generally, the maximum probability model is used to calculate the data of the classification model:

$$L(w)=\prod_{1}^{n}(\pi(x_i))^{y_i}(1-\pi(x_i))^{1-y_i}. \tag{6}$$

The maximum probability value is to outcrop the parameter $R_0, R_1, \cdots R_n$, so that to get the maximum value of $L(w)$.

The basic idea of using Logistic to evaluate personal financial risk using regression model is calculated. Given n groups of sample data $(X_{i1}, X_{i2}\cdots X_{\text{in}} : Y_i)(i=1,2,\cdots k)$ are indicator variables, $y_i=[0,1]$ is a 0-1 type variable, the representation of Y_i, X_{i1}, and $X_{i2}\cdots X_{\text{in}}$ is as follows:

$$E(Y_i)=P_i=g(\beta_0+\beta_1X_{i1}+\beta_2X_{i2}+\beta_nX_{\text{in}}). \tag{7}$$

Among them, $g(x)$ is the increasing monotonic activity at [0,1].

$$p_i=g(X)=\frac{e^x}{1+e^x}. \tag{8}$$

Y_i is a 0-1 distribution with mean $P_i=g(\beta_0+\beta_1X_{i1}+\beta_2X_{i2}+\beta_nX_{\text{in}})$, and the probability function is

$$\begin{cases} P(Y_i=1)=P_i, \\ P(Y_i=1)=1-P_i. \end{cases} \tag{9}$$

Then, the logistic regression formula is

$$P_i=\frac{\exp\left(\beta_0+\beta_1X_{i1}+\beta_2X_{i2}+\cdots+\beta_nX_{\text{in}}\right)}{1+\exp\left(\beta_0+\beta_1X_{i1}+\beta_2X_{i2}+\cdots+\beta_nX_{\text{in}}\right)}. \tag{10}$$

The above formula can be linearly transformed, so there is

$$\ln\left(\frac{p_i}{1-p_i}\right)=\beta_0+\beta_1X_{i1}+\beta_2X_{i2}+.\cdots+\beta_nX_{\text{in}}, i=1,2,\cdots n. \tag{11}$$

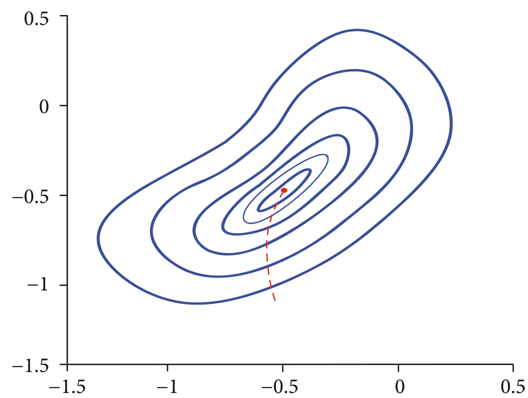


Figure 5: Schematic diagram of Newton's method and gradient descent method.

X_i and $X_2 \cdots X_n$ are independent binary variables, $\beta_i(X_i)$ represents the probability of $X_i = 1$ or 0. The likelihood function is

$$L(\beta) = g(Y_1, Y_2, \cdots Y_n) = \prod_1^n f_i(Y_i) = \prod_1^n (1 - P_i)^{1-Y_i}. \tag{12}$$

By taking the natural logarithm on both sides of formula (12) at the same time, there is

$$\begin{aligned} \ln g(Y_1, Y_2 \cdots Y_n) &= \sum_1^n [Y_i InP_i + (1 - Y_i)\text{In}(1 - P_i)] \\ &= \sum_1^n [Y_i InP_i - Y_i \text{In}(1 - P_i) + \text{In}(1 - P_i)] \\ &= \sum_1^n \left[Y_i \text{In}\left(\frac{p_i}{1 - P_i}\right)\right] + \sum_1^n [\text{In}(1 - P_i)]. \end{aligned} \tag{13}$$

By bringing formulas (10) into (14), there is

$$\begin{aligned} Ing(Y_1, Y_2 \cdots Y_n) = {} & \sum_1^n Y_i(\beta_0 + \beta_1 X_{i1} + \cdots + \beta_n X_{\text{in}}) \\ & - \sum_1^n \text{In}\left[1 + e^{(\beta_0 + \beta_1 X_{i1} + \cdots + \beta_n X_{\text{in}})}\right]. \end{aligned} \tag{14}$$

The gradient descent method updates the parameters as follows: the slope value of a square field function under the current parameter value is calculated, there is a data control α parameter in front, and the α parameter is the slope of the square field function. If the slope is large, it is easy to oscillate near the tip and fail to converge, resulting in failure to assemble. If the slope is too small, repeated iterations are required. Therefore, it is usually solved by using the method.

The difference between the Newton method and the gradient descent method is that a second derivative is added in the direction of descent, that is, the iterative process of the gradient descent method is

$$w = w - \alpha \frac{\partial J(w)}{\partial w}. \tag{15}$$

The iterative process of Newton's method is

$$w = w - H(w)^{-1} \frac{\partial J(w)}{\partial w}. \tag{16}$$

Among them, $H(w)$ is called the Hessian matrix. In fact, it is the second derivative of the field function with respect to the parameter w.

The influence of this second-order derivative on parameter update is first reflected in the change of parameter update direction, as shown in Figure 5.

The red line is the direction of Newton's parameter update. By using Newton's method to observe the second derivative, the best parameter update direction can be found. If the number of updates is the same each time, the number of updates can be saved by gradient descent.

(2) Principle of IV statistics

IV is derived from WOE, the full name of WOE is "Weight of Evidence," that is, the weight of evidence. WOE is an encoding form of the original independent variable. To encode a variable with WOE, the variable must first be discretized (i.e., grouped). After grouping, for the qth group, the calculation formula of WOE is

$$\text{WOE} = \ln\left(\frac{py_q}{pn_q}\right) = \ln\left(\frac{y_q/y_T}{n_q/n_T}\right). \tag{17}$$

Among them, py_q is the proportion of good data (that is, risk-free data) in this group to all good data in all samples, and pn_q is the proportion of bad data (that is, risk data) in this group to all bad data in the sample. y_q is the quantity of good data in this assemble, and n_q is the quantity of bad data in this assemble. y_T is the number of all good data in the sample, and n_T is the number of all bad data in the sample.

WOE actually represents the difference between the share of good data out of all good data in the current group and the share of bad data out of all bad data in the current group.

Formula (17) is simply transformed, and there is

$$\text{WOE} = \ln\left(\frac{py_q}{pn_q}\right) = \ln\left(\frac{y_q/y_T}{n_q/n_T}\right) = \ln\left(\frac{y_q/n_q}{y_T/n_T}\right). \tag{18}$$

The modified WOE can also represent the difference between the shares of good and bad data in the current group and the shares in all examples. The smaller the WOE, the smaller the variance and the less chance of good data in the group is. The higher the WOE, the greater the

Table 1: Experimental data sheet.

	Established	Type	Number of people
Platform 1	2012	Small and medium	50
Platform 2	2009	Small and medium	45
Platform 3	2010	Small and medium	50
Platform 4	2012	Small and medium	55
Platform 5	2014	Small and medium	50

variance and the greater the chance of good data in the group is.

IV (information value) can be used as both an information value and a reference value.

The value IV is a variable based on WOE. For aggregated variables, the WOE for the qth group is shown as

$$\begin{aligned} \mathrm{IV} &= \left(py_q - pn_q\right) * \mathrm{WOE} = \left(py_q - pn_q\right) * \ln\left(\frac{py_q}{pn_q}\right) \\ &= \left(\frac{y_q}{y_T} - \frac{n_q}{n_T}\right) * \ln\left(\frac{y_q/y_T}{n_q/n_T}\right). \end{aligned} \tag{19}$$

After calculating the IV value of each group of variables from formula (19), the sum of the IV values of each variable can be calculated by integrating the IV values of each group:

$$\mathrm{IV} = \sum_q^n \mathrm{IV}_q. \tag{20}$$

Among them, n is the number of variable groups.

It is not difficult to see that the WOE and IV of each group of variables are important for the prediction ability of the group for quality conversion, so why choose to calculate IV instead of WOE as the indicator display method? The main reason is that the IV value does not need to be a unified whole. The definition of the IV value represents the ratio of the number of people in the current group to the total number of people. These partial random groups can determine positive and negative samples. However, if the features are grouped unevenly, the WOE is very sensitive to the positive and negative samples of each group and negative numbers appear, which is inconvenient for large-scale feature processing. Therefore, this paper selects the IV value to screen the indicators.

3. Financial Risk Model Evaluation and Control Experiment Design

3.1. Experimental Process. In order to test how the Internet financial risk model based on big data should be compared with the traditional Internet financial model, this paper selects 5 Internet financial platforms for experimental testing. In order to avoid experimental errors, the scales of the 5 Internet financial platforms are not much different. Tests are carried out from four aspects: default rate, yield, risk control time, and model performance score. Five financial platforms are tested by using traditional financial models, and this test is the control group. Then, the five financial platforms are tested again by using the big data-based Internet financial risk model, and this test is the experimental group. Statistical of experimental results is analyzed.

3.2. Experimental Data. The specific data of the five Internet financial platforms selected in the experiment are shown in Table 1.

3.3. The Purpose of the Experiment. There are deficiencies in the existing Internet financial risk models. The big data technology is applied to the Internet financial risk model, and the Internet financial model is improved to make up for the shortcomings of the traditional Internet financial model.

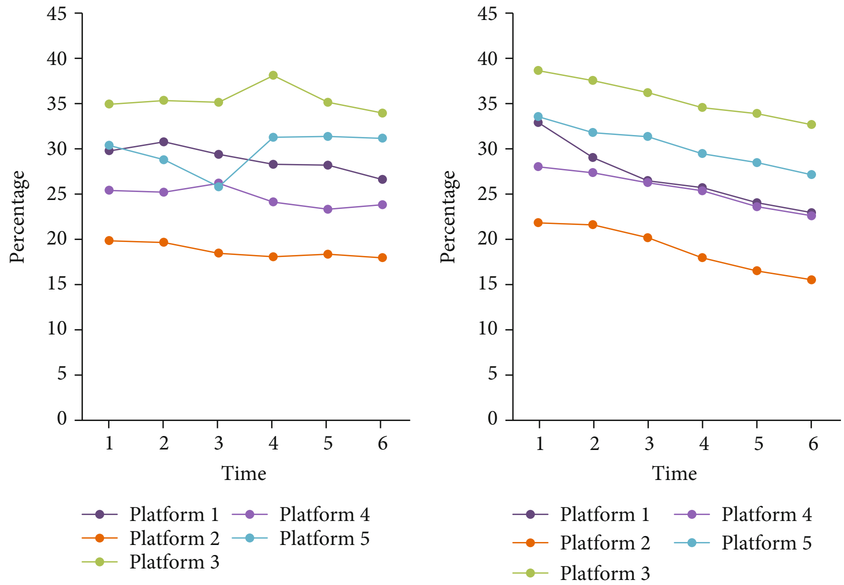
4. Results of Financial Risk Model Evaluation and Control Experiments

4.1. Default Rate. The customer default rate of 5 Internet financial platforms was tested for 6 months to observe the experimental results. The test results are shown in Figure 6.

The above figure shows that the platform default rate of the control group fluctuated up and down within 6 months of the test, which increased and decreased, but did not play a role in reducing the customer default rate. Compared with the control group, the default rate of the experimental group has a significant downward trend. The average default rate of the control group before the experiment is 28.26%, the average default rate after the experiment is 22.12%, and the default rate has dropped by 6.14%. The Internet financial risk model based on big data can reduce the customer default rate compared with the traditional Internet financial model, thereby reducing the occurrence of financial risks.

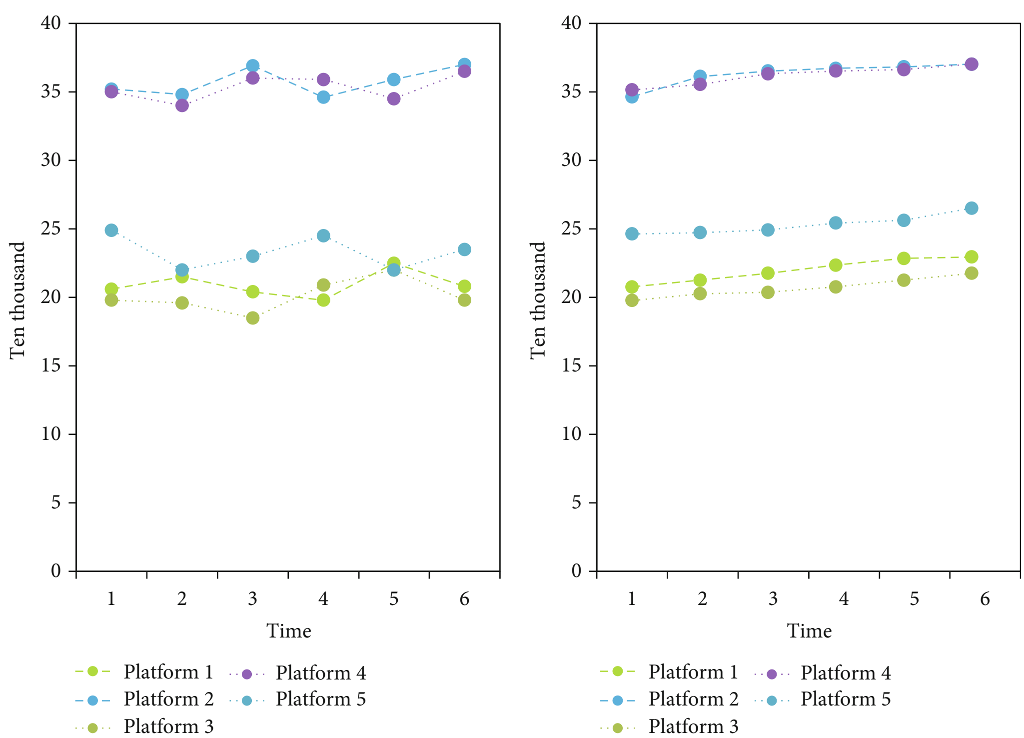
4.2. Yield. In order to test the changes in the rate of return of Internet financial platforms using big data technology, a 6-month follow-up survey was conducted on the rate of return of five Internet financial platforms. The traditional financial risk model and the big data-based financial risk model were used to conduct experiments, respectively. The test results are shown in Figure 7.

The above figure shows that the return rate of the control group using the traditional Internet financial risk model did not increase significantly, and the return rate was not stable and fluctuated during the testing process. Compared with the traditional financial risk model, the return rate of the



(a) Control group (b) Test group

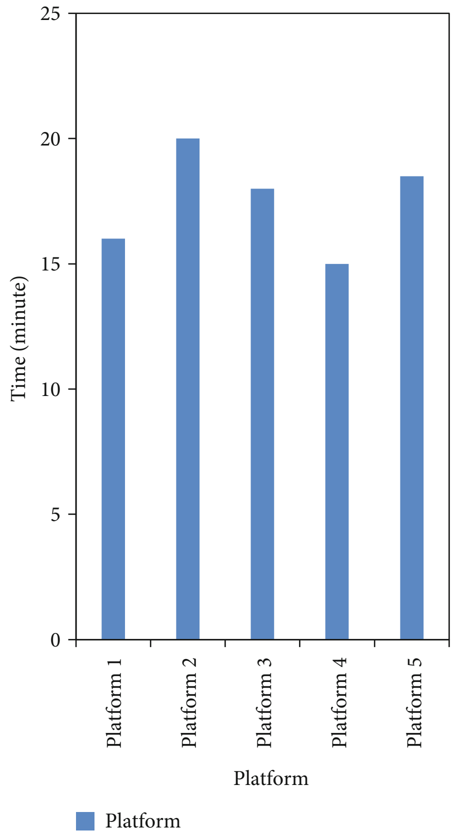
FIGURE 6: Default rate test results.



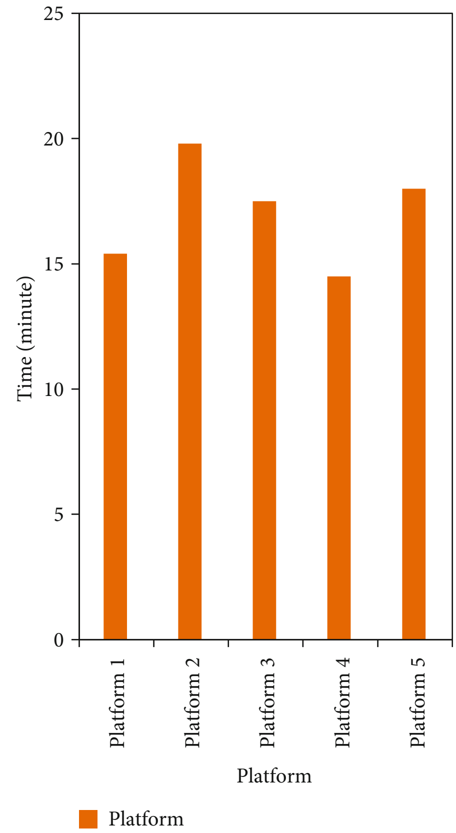
(a) Control group (b) Test group

FIGURE 7: Yield results graph.

Internet financial model based on big data was very stable, and it has grown steadily during the test period. The average income of the experimental group before the test is 272,800 yuan, the average income after the test is 293,600 yuan, an average increase of 20,800 yuan, and the rate of return increased by 7.6%. It can be seen that the application of big data to the financial risk model of the Internet can increase the income of the Internet financial platform, improve the platform's rate of return, and reduce the occurrence of financial risks.

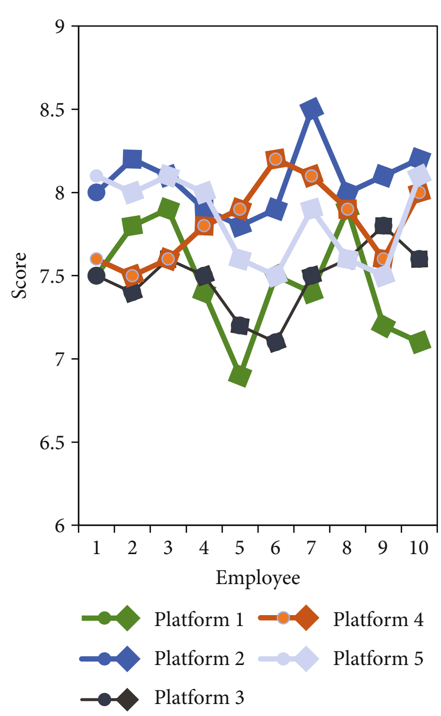


(a) Control group

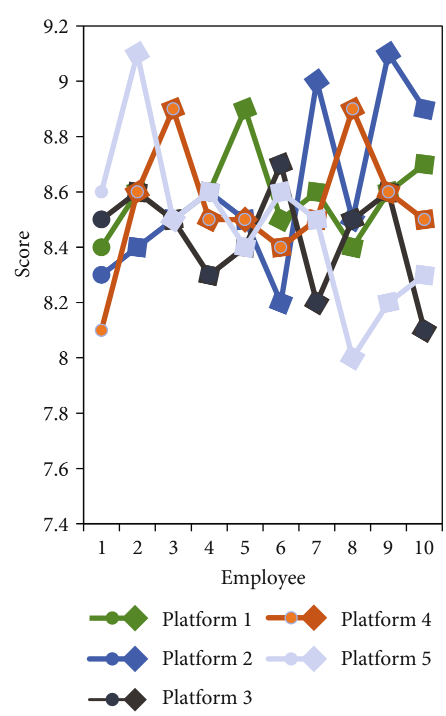


(b) Test group

Figure 8: Risk control time results.



(a) Control group



(b) Test group

Figure 9: Model performance score.

4.3. Risk Control Time. When there is a risk in the five Internet financial platforms, the traditional financial risk model and the Internet financial risk model based on big data are used to evaluate and control them. The control time of the two models is observed and compared, and the test results are shown in Figure 8.

The above figure shows that the risk processing time of the experimental group using the big data-based Internet financial risk model is shorter than that of the control group using the traditional Internet financial model. The average risk processing time of the traditional Internet financial model is 17.5 minutes, and the average risk processing time of the Internet financial risk model based on big data is 17.04 minutes, which reduces the risk processing time by 0.46 minutes. The use of the Internet financial risk model based on big data can better deal with financial risks, and the time to deal with financial risks is better.

4.4. Model Performance Score. 10 employees are randomly selected from each financial platform to score the performance of traditional Internet financial models and Internet financial models based on big data. The full score is 10 points. Which financial risk model is more favored by platform employees is observed, and the results are shown in Figure 9.

The above figure shows the average score of employees on the traditional Internet financial risk model is 7.734, and the average score on the Internet financial risk model based on big data is 8.53. The average score of the Internet financial risk model based on big data is 0.796 points higher than that of the traditional Internet financial risk model. The employees of the five financial platforms are more satisfied with the Internet financial risk model based on big data.

5. Discussion

In this paper, the big data technology is integrated into the financial risk model, the data existing in the financial platform is mined, the financial risk data is found and eliminated, and the security of the financial platform is ensured. Logistic regression algorithm and IV statistic principles are used to evaluate and control risk data, and firewalls are built to prevent risk data threats from a platform system. Experiments show that the Internet financial risk model based on big data can effectively evaluate and control financial risks. There may be some errors during the experiment, but it does not affect the final experimental results.

6. Conclusion

The intricate data on financial platforms leads to the occurrence of financial risks. The complexity of financial platform data leads to the occurrence of financial risks. This paper compares the Internet financial risk model based on big data with the traditional financial risk model and finds that big data technology can better capture risk data, reduce the probability of financial platform risks, and increase platform revenue. As a mainstream technology, big data technology can better analyze the modern financial system, control risk factors, and promote the continuous development of the financial industry.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

References

[1] X. Li, “Research on the influencing factors of internet financial risk and its prevention mechanism,” *Modern Economics & Management Forum*, vol. 3, no. 1, pp. 20–24, 2022.

[2] R. Wang, C. Yu, and J. Wang, “Construction of supply chain financial risk management mode based on internet of things,” *IEEE Access*, vol. 7, no. 99, pp. 110323–110332, 2019.

[3] C. Wu and Y. Chen, “An internet of things (IoT)-based risk monitoring system for managing cold supply chain risks,” *Industrial Management & Data Systems*, vol. 118, no. 7, pp. 1432–1462, 2018.

[4] C. Ullrich, “A risk-based approach towards infringement prevention on the internet: adopting the anti-money laundering framework to online platforms,” *International Journal of Law & Information Technology*, vol. 26, no. 3, pp. 226–251, 2018.

[5] Q. Yang, Y. Wang, and Y. Ren, “Research on financial risk management model of internet supply chain based on data science,” *Cognitive Systems Research*, vol. 56, no. 11, pp. 50–55, 2019.

[6] T. Zhao, “Models for evaluating the benefit risk and performance of internet financial product with triangular fuzzy information,” *Journal of Intelligent and Fuzzy Systems*, vol. 37, no. 2, pp. 1819–1826, 2019.

[7] Y. Yue, “Research on credit risk early warning based on RBF neural network—taking internet financial trading platform as an example,” *Modeling and Simulation*, vol. 10, no. 2, pp. 257–267, 2021.

[8] Y. Wang, L. A. Kung, and T. A. Byrd, “Big data analytics: understanding its capabilities and potential benefits for healthcare organizations,” *Technological Forecasting and Social Change*, vol. 126, no. 7, pp. 3–13, 2018.

[9] W. Xu, H. Zhou, N. Cheng et al., “Internet of vehicles in big data era,” *IEEE/CAA Journal of Automatica Sinica*, vol. 5, no. 1, pp. 19–35, 2018.

[10] X. Wang, Y. Zhang, V. Leung, N. Guizani, and T. Jiang, “D2D big data: content deliveries over wireless device-to-device sharing in large-scale mobile networks,” *IEEE Wireless Communications*, vol. 25, no. 1, pp. 32–38, 2018.

[11] Y. Chen and Y. Chi, “Harnessing structures in big data via guaranteed low-rank matrix estimation: recent theory and fast algorithms via convex and nonconvex optimization,” *IEEE Signal Processing Magazine*, vol. 35, no. 4, pp. 14–31, 2018.

[12] G. Ke, D. Tao, and J. F. Qiao, “Learning a no-reference quality assessment model of enhanced images with big data,” *IEEE Trans Neural Netw Learn Syst*, vol. 29, no. 4, pp. 1301–1313, 2018.

[13] I. Zualkernan and M. Rashid, “A smart home energy management system using IoT and big data analytics approach,” *IEEE*

Transactions on Consumer Electronics, vol. 63, no. 4, pp. 426–434, 2018.

[14] E. Zapevalova and Y. Chen, "Time optimization of multiple knowledge transfers in the big data environment," *Computers Materials & Continua*, vol. 54, no. 3, pp. 269–285, 2018.

[15] R. A. Ghaffar and S. Metawa, "A proposed framework for effective risk management in Egyptian sustainable development projects," *American Journal of Business and Operations Research*, no. 1, pp. 26–42, 2019.

[16] M. Abdel-Basset and M. Elhoseny, "Intelligent feature subset selection with machine learning based risk management for DAS prediction," *Journal of Cybersecurity and Information Management*, vol. 8, no. 1, pp. 8–16, 2021.

[17] F. A. Gobas, Y. S. Lee, J. C. Lo, T. F. Parkerton, and D. J. Letinski, "A toxicokinetic framework and analysis tool for interpreting organisation for economic co-operation and development guideline 305 dietary bioaccumulation tests," *Environmental Toxicology and Chemistry*, vol. 39, no. 1, pp. 171–188, 2020.

[18] Y. Chen, W. Zheng, W. Li, and Y. Huang, "Large group activity security risk assessment and risk early warning based on random forest algorithm," *Pattern Recognition Letters*, vol. 144, 2021.

[19] D. A. Marshall, "The role of internal audit in the risk management process: a developing economy perspective," *Journal of Corporate Accounting & Finance*, vol. 31, no. 4, pp. 154–165, 2020.

[20] B. Ziv and Y. Parmet, "Improving nonconformity responsibility decisions: a semi-automated model based on CRISP-DM," *International Journal of System Assurance Engineering and Management*, vol. 13, no. 2, pp. 657–667, 2021.

[21] W. Y. Ayele, "Adapting CRISP-DM for idea mining," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 6, pp. 20–32, 2020.

[22] L. Jia and L. Li, "Research on core strength training of aerobics based on artificial intelligence and sensor network," *EURASIP Journal on Wireless Communications and Networking*, vol. 2020, Article ID 164, 16 pages, 2020.

[23] L. Y. Sun, C. L. Miao, and L. Yang, "Ecological environmental early-warning model for strategic emerging industries in China based on logistic regression," *Ecological Indicators*, vol. 84, no. 7, pp. 748–752, 2018.