Research Article

A Big Data Technique for Internet Financial Risk Control

Hengxin Xie¹ and Yufeng Shi ¹, ²

¹School of Statistics, Shandong University of Finance and Economics, Jinan 250014, China
²Institute for Financial Studies, Shandong University, Jinan 250100, China

Correspondence should be addressed to Yufeng Shi; xhx900705@mail.sdufe.edu.cn

Received 8 May 2022; Revised 9 June 2022; Accepted 17 June 2022; Published 15 July 2022

Academic Editor: Abid Yahya

Copyright © 2022 Hengxin Xie and Yufeng Shi. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The danger of losing funds on an investment or business enterprise is referred to as financial risk. Credit risk, liquidity risk, and operational risk are some of the most prevalent and different financial hazards. Financial risk control is an organizational activity that seeks to detect, monitor, and manage exposure to different risks associated with the usage of financial services. Conventional accounting risk control has relatively great timeliness and unpredictability; therefore, traditional accounting risk identification has numerous difficulties, such as high error rate, low precision, lengthy time, and risk. As a result, this research provides a unique financial risk control strategy in the Internet environment based on big data. First, the decision tree algorithm is used to classify the users who can face financial risks. Simultaneously, the user’s personal credit information is established and represented mathematically, and the 5C mathematical model is obtained. In this way, the user’s credit degree can be judged more accurately, and the user’s credit rating can be obtained, allowing quantitative analysis of users to be realized. Second, construct and weight the financial risk system index of the Internet in accordance with the existing financial system. Finally, the Internet financial risk control model based on big data is built, and the financial risk early warning threshold range is determined to achieve Internet financial risk control. The experimental findings reveal that the method’s risk identification error rate is minimal, accuracy is high, and control time is quick. It can match the actual risk level, which shows that the control effect of this method is good.

1. Introduction

The danger of incurring losses on an investment or business enterprise is referred to as financial risk. Credit risk, liquidity risk, and operational risk are some of the most prevalent and different financial concerns. Financial risk control is an administrative activity that seeks to detect, monitor, and minimize exposure to different risks associated with the usage of financial sector. All elements of human social evolution can now be conveyed digitally, due to the fast growth and popularization of information technology [1]. The whole world is accelerating the production having all types of data information at all times. Humanity has entered the “big data era,” and the big data has brought great impact to many industries. As the center of modern economy, the financial industry will inevitably integrate with big data [2]. Traditional financial data are mainly structured data, while the massive semi-structured and unstructured data of network finance are accelerating [3]. Obviously, the network financial risk has changed compared with the traditional risks in the past, especially the emerging network financial business represented by Internet finance. The Internet financial risk problem is very prominent; both the generated and nongenerated potential risks are more complex and changeable [4]. Once the risk becomes known, the impact will be felt throughout the Internet, and the damage will be serious. The final consequences are often difficult to estimate. As a result, to design, develop, and build an effective network financial risk control system and technique has become the study area [5].

The authors of [6] design a financial risk control model based on support vector machine (SVM). Using the risk status of six-carbon finance pilot markets as the study sample each month, this work develops a financial risk early warning model based on SVM to control financial risk. The results show that the SVM model built using the grid search
method and the radial basis kernel function can effectively
early warn financial risks, identify risk levels in different
regions after early warning the financial pilot market, and
finally make relevant recommendations based on the re-
search findings. The authors in [7] designed a risk control
model based on cluster analysis. First, use cluster analysis to
group financial indicators based on their association, and
then use the group bridge approach to identify relevant risk
indicators. Their results show that the model performs well
in identifying significant risk indicators and classification
prediction, and the advantages of the model become more
obvious with the enhancement of correlation for indicators.
It has an excellent classification impact and stability in the
empirical examination of listed businesses in the A-share
market. The authors in [8] proposed an early warning
method for extreme risks in the financial market under
unbalanced samples. Using the Shanghai and Shenzhen 300
indexes as research data, the Synthetic Minority Over-
sampling Technique (SMOTE) was used to solve the
problem of sample imbalance and the feature was extracted
using factor analysis. The prediction model “Synthetic Mi-
nority Oversampling Technique particle swarm optimiza-
tion least square support vector machine (SMOTE-PSO-
LSSVM)” is constructed through the least square support
vector machine (LSSVM) algorithm optimized by particle
swarm optimization (PSO). The SMOTE-PSO-LSSVM
model is used to predict the Shanghai and Shenzhen 300
index samples from 2007 to 2010. The data set comprises 193
extreme risk samples, of which the algorithm correctly
detected 154. The results show that the method has a strong
ability to identify financial risk data and samples accurately.
The study’s findings have implications for financial market
risk detection, market trend control, stock market trading
control, and investor decision-making.

The analysis shows that the above methods effectively
control the risks of the financial market to a certain extent
and improves the stability of financial market [9]. However,
with the growth of real-time financial data and changeable
characteristics of Internet data, these methods cannot ef-
effectively deal with the above problems. In controlling risk,
there is typically a high-risk identification error rate and low
accuracy, in order to solve these problems; this paper
proposes an Internet financial risk control method based on
big data algorithms.

The remainder of the paper composed of the following
sections: Section 2 is composed on the user risk behavior
measurement in the field of Internet finance, Section 3
contains Internet financial risk control methods based on big
data, Section 4 is the experimental verifications, and finally,
the paper conclusion is present in Section 5.

2. User Risk Behavior Measurement in the
Field of Internet Finance

As users are the primary group in the field of Internet risk
control, it is frequently important to determine whether a
user has risk behaviors such as basic preferences. Therefore,
before risk control, this paper first uses the decision tree
algorithm to analyze and identify users’ risk behavior [10].

The decision tree algorithm has fast classification speed,
suitable for binary classification problems, and has inter-
pretable characteristics, so it is widely used in the field of risk
control of Internet finance [11].

2.1. User Classification Based on Decision Tree Algorithm.
The fundamental for the development of a decision tree is
the growth of its nodes and how to set judgment criteria so
that classification decisions can be made quickly and ac-
curately [12]. The goal is that as each node of the decision
tree develops, part of the data set will be labeled with the
classified data, making the data set purer than before. In
general, the information gain is chosen as a function of
determining the purity of the information [13].

Before picking a certain user attribute as its classification
criterion, the information entropy of the data prior to
classification will be determined, which is the degree of
confusion and uncertainty in the data collection. Take a
sample data set A, assume that A contains 5 types of cus-
tomers, the proportion of the number of customers con-
tained in a certain category a to the total sample is
represented by $P_a$, and the information entropy formula
before node growth is

$$\vartheta (A) = \sum_{i=1}^{N} (a_i \times P_a) \log_2 (w_i). \quad (1)$$

Among them, $w_i$ represents statistical weight information.

For the sample data set A, when a certain user attribute $a_i$
selected as the node growth condition, the information
entropy of the data set after the attribute $a_i$ is classified as
$F_{a_i}(A)$. Assume that the attribute $a_i$ divides the data set into
$z$ parts and its calculation equation is

$$F_{a_i}(A) = \frac{\sqrt{A_z + K_z}}{\vartheta (A)}. \quad (2)$$

In equation (2), $A_z$ represents the user’s personal at-
tribution information and $K_z$ represents the user’s personal
preference information.

After the effect of attribute $a_i$, data set A becomes more
pure, the information entropy of A is reduced, and infor-
mation gain is a function that measures the difference in
information entropy of A, for which the calculation equation
is as follows:

$$\vartheta' (A) = F (A) - F_{a_i} (A). \quad (3)$$

The characteristic with the highest $\vartheta' (A)$ value on a node
serves as the best judgment condition during the decision
tree’s growing phase.

Figure 1 depicts a schematic representation of user
classification based on the design principles presented
previously.

2.2. Construction of User’s Personal Credit “5C” Model.
The behavior data generated by users on the Internet have
the characteristics of high complexity, large dimension, and
huge amount of data. Therefore, the rational utilization,
storage, and variable screening of data are the main problems in the current Internet financial control. In these circumstances, it is critical and urgent to predict the relationship between the entire data network, apply it to users’ credit rating as well as credit behavior prediction, anticipate whether it has the possibility of fraud based on its various attributes, and prevent this on time. Figure 2 shows a schematic diagram of user’s personal credit “5C” model.

The “5C” model assesses the credit quality of customers from five aspects: quality, capability, capital, guarantee, and conditions to determine the degree of risk. It is one of the common methods used by financial institutions to evaluate customer’s risks [14]. The definitions of these aspects are as follows:

1. **Quality**: It is a key indicator to evaluate the credit qualification of users, representing the customer willingness to repay and decide whether the accounts receivable may be repaid on time. Therefore, quality is believed as the most important factor in credit evaluation.

2. **Ability**: The ability represents the user’s repayment ability that is the quantity and quality of its current assets as well as the ratio of its current liabilities, usually based on the user’s existing credit repayment records and other information for judgment.

3. **Capital**: It represents the user’s financial status and strength and is used to describe the customer’s possible financial background when repaying the loan, such as the customer’s debit ratio, current ratio, net tangible assets, and other financial indicators.

4. **Mortgage**: It represents the fixed assets that can be used to repay the loan when the user is unable to make payment or refuses to pay. This is very important for users with low credit levels, poor qualifications, or no credit history.

5. **Conditions**: It represents the background and environment that can affect the user’s repayment; for example, when a client is experiencing financial difficulties or a financial crisis, the repayment record can be used to describe the user’s repayment possibility under unusual circumstances.

2.3. **Quantitative Analysis of User Risk Behavior**. The connection for identifying user risk behavior is responsible for discovering various potential risks. A risk record sheet is created when recognizable risks are discovered. If risk is in initial stage of risk control, then qualitative and quantitative analysis is required. Risk measurement is a quantitative analysis of risks, without providing system functions. In qualitative analysis, human analysis is carried out based on the description of risks [15]. In order to check the business content affected by risk, what steps must be taken and to what extent risk analysis and risk measurement must be carried out through risk rules, so as to judge whether early warning is needed. The processing flowchart of quantitative analysis for user risk behavior is shown in Figure 3.

It can be seen from Figure 3 that the quantitative analysis and processing process of user risk behavior mainly include the following functional contents. The first step is to get the risk measurement guidelines. Risk measuring rules fluctuate depending on the type of risk [16]. After obtaining the measurement criteria, the following step is to read the risks and then measure each risk individually. The measurement data are output after measurement to serve as a reference for further linkages.

3. **Internet Financial Risk Control Methods Based on Big Data**

Further study on Internet financial risk control concerns will be conducted based on the results of user risk behavior measurement. First, establish a risk evaluation system to obtain evaluation index weights based on calculations and then establish risk control models based on financial big data to acquire financial risk early warning threshold ranges as well as to control Internet financial risk.

3.1. **Internet Finance Risk Assessment**. The Internet finance risk assessment is divided into the following categories.

3.1.1. **Construction of Internet Financial Risk Assessment Index System**. According to financial risk realities, indicators are selected from aspects of Internet financial risks, financial market operation risks, real economy operation
risks, and local financial supervision. The operability, sensitivity, and dynamics of the indicator system are all taken into account while selecting indicators. In terms of Internet financial risk, this paper constructs Internet financial risk assessment indicators from the features of Internet financial payment method, information processing, and illegal fundraising, beginning with the characteristics of Internet finance. This article selects significant factors from four dimensions in terms of financial market operating risk: stock market value, real estate sales price index, bank loan, and real estate loan. This study offers financial risk assessment indicators for real economy operation risk based on three aspects: consumption growth rate, inflation rate, and growth rate of foreign capital. In terms of local financial supervision, it was discovered through an examination of the risk creation mechanism internal and external elements in the risk of local financial supervision cross-influence, which primarily comprise government revenue and spending as well as government debt. The financial risk early warning and monitoring index system are shown in Table 1.

### 3.1.2. Determine the Weight of Risk Assessment Indicators

Different weight values are applied to the risk assessment index based on the degree of effect it has on the financial sector, and eventually, the weight set of the evaluation risk index is obtained:

\[ x_i(k) = \left( x_{i1}, x_{i2}, \ldots, x_{in} \right) \]

In equation (4), \( n \) represents the number of evaluation indicators.

Collect the questionnaire and take the geometric average according to the results of the experts scoring; the technique for assigning the judgment matrix to the goal and criteria layers is shown in Table 2.

According to the judgment matrix, the Criteria Importance through Intercriteria Correlation (CRITIC) weighting method is used to determine the index weight. This technique is based on the strength of the contrast and conflict between the indications, while the findings are more objective and accurate. This approach is used in this article to estimate the weight of financial risk assessment indicators. The specific steps are as follows:

1. Calculate the variability between indicators: that is, normalize the original data and calculate the standard deviation of the indicator data.
2. Conflict between calculation indicators:
   \[ C_i = \sum_{j=1}^{N} \left( \frac{\left\| \bar{x}_j - x_m \right\|}{\sum_{j=1}^{N} \left\| \bar{x}_j - x_m \right\|} \right)^2. \]  \( (5) \)
3. In equation (5), \( \bar{x}_j \) represents the correlation coefficient between the evaluation index indicators and \( x_m \) represents the index importance scale.
4. Calculate the index weight:
   \[ W_i = \sum_{j \in M} y_j \times C_i. \]  \( (6) \)

In equation (6), \( M \) represents the index weight coefficient and \( y_j \) indicates the evaluation index’s effect on the index system.

According to the above steps, the weight values of the Internet financial risk assessment indicators are shown in Table 3.

### 3.1.3. Internet Finance Risk Evaluation

The purpose of Internet financial risk evaluation is to assess the probability of incoming risk occurrences in order to adopt preventative measures.
Table 3: Weights of Internet financial risk assessment indicators.

<table>
<thead>
<tr>
<th>First-level index</th>
<th>Secondary indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internet 0.35</td>
<td>Financial payment method 0.19</td>
</tr>
<tr>
<td></td>
<td>Information processing 0.24</td>
</tr>
<tr>
<td></td>
<td>Illegal fundraising 0.57</td>
</tr>
<tr>
<td>Financial market operation risk 0.21</td>
<td>Stock market capitalization 0.26</td>
</tr>
<tr>
<td></td>
<td>Real estate sales price index 0.15</td>
</tr>
<tr>
<td></td>
<td>Bank loan 0.33</td>
</tr>
<tr>
<td></td>
<td>Real estate loan 0.26</td>
</tr>
<tr>
<td>Real economy operation risk 0.19</td>
<td>Consumption growth rate 0.09</td>
</tr>
<tr>
<td></td>
<td>Inflation rate 0.52</td>
</tr>
<tr>
<td></td>
<td>Growth rate of foreign capital 0.39</td>
</tr>
<tr>
<td>Local financial supervision 0.25</td>
<td>Fiscal deficit 0.33</td>
</tr>
<tr>
<td></td>
<td>Financial expenditure 0.28</td>
</tr>
<tr>
<td></td>
<td>Government debt 0.39</td>
</tr>
</tbody>
</table>

and response actions. Internet financial risk evaluation encompasses both risk source and risk evaluation once the risk has occurred.

The risk source is evaluated using the probability assessment technique, and the probability expression of the prospective Internet financial risk is derived as

\[ G_i = \frac{\sum w_k v_i - v_{s_k}}{x_i} \]  

(7)

According to equation (7), \( G_i \) represents the probability of Internet financial risk incidents occurring and \( w_k \) represents the possibility of Internet financial risks occurring by the \( k \)-th risk source.

The number of occurrences of Internet financial risks is inferred from previous examples, and the predicted value of occurrence of Internet financial risks is derived. The expression is

\[ G_e = (A^T A)^{-1} \times A^T Z(k). \]  

(8)

In equation (8), \( A^T \) represents the number of occurrences of Internet financial risks in a certain period; \( Z(k) \) represents the number of operations for \( k \)-th risk source in a certain period.

According to equations (7) and (8), the probability of occurrence of Internet financial risks can be evaluated and the Internet financial risk event emergency warning can be realized according to the probability value of Internet financial risk event risk evaluation.

3.2. Internet Financial Risk Control Model Based on Big Data.

The Internet financial risk control model is composed on data collection module, database module, early warning module, business data, external sub-module interface interaction module, and a risk identification module. The data mining technology is used to establish a valuable database, and then, the early warning tracking is designed through machine learning algorithms. Module: the whole process is centered on big data. Figure 4 depicts the framework of the Internet financial risk control model based on big data.

3.2.1. Data Collection Module. Because the relevant index data of the financial risk control model contain unstructured data, it is difficult to collect, clean, and analyze it on the Internet and manual intervention is often required. Therefore, it is necessary to combine crawler technology and scanning monitoring technology. Comprehensive data collection and risk prediction are the basis of Internet financial risk control [17].

3.2.2. Database Module. The data obtained through the data collection module need further analysis, not just data mining technology assistance, but also big data analysis tools. The database module is the core of control model. The classification and summary of relevant indicators of control model are completed in the database module. The improvement of the database model directly affects the ability of Internet financial risk control [18].

3.2.3. Early Warning Module. Early warning reports are displayed in the form of indicator thresholds and warning intervals. After determining the risk analysis and predictive analysis, an early warning report is generated. Simultaneously, assess whether the early warning module meets actual needs, investigate the causes of forecast result deviations, improve related algorithms to improve the risk prediction function, close the gap between the two, as well as improve the accuracy and scientifically of the early warning module [19].

3.2.4. Business Data and External Sub-Module Interface Interaction Module. The data exchange sub-module exchanges a large amount of data with the external sub-module. The external sub-module mainly includes the quota management sub-module, the credit business management sub-module, the internal rating sub-module, and the financial management sub-module. The data of the external business module are the original data for financial risk control.

3.2.5. Risk Identification Module. This module includes risk reporting and risk early warning operations, and it follows up functional links for risk discovery and risk measurement. It is a back-end service function. By calling the risk algorithm, analysis is performed on the basis of the secondary results, the possible risks are analyzed, and the original data are converted into quantitative financial risk data [20].

The workflow of the Internet financial risk identification module is shown in Figure 5.

3.3. Realization of Internet Financial Risk Control. Multi-level fuzzy comprehensive evaluation method is used to comprehensively evaluate Internet financial risks, and different alarm thresholds can be set for different risk levels. The setting range of alarm threshold should be based on the development needs of financial enterprises and focus on reality. This article divides the Internet financial risk level
into five levels, namely, $R_1$, $R_2$, $R_3$, $R_4$, and $R_5$ that represent security, less risk, general risk, greater risk, and greater risk. The alarm threshold range and the corresponding risk level are shown in Table 4.

Table 4: Internet financial risk alarm threshold range.

<table>
<thead>
<tr>
<th>Risk level</th>
<th>Alarm threshold interval division</th>
<th>Degree of risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_1$</td>
<td>[0, 2]</td>
<td>Safety</td>
</tr>
<tr>
<td>$R_2$</td>
<td>[2, 4]</td>
<td>Less risky</td>
</tr>
<tr>
<td>$R_3$</td>
<td>[4, 6]</td>
<td>Fair risk</td>
</tr>
<tr>
<td>$R_4$</td>
<td>[6, 8]</td>
<td>Higher risk</td>
</tr>
<tr>
<td>$R_5$</td>
<td>[8, 10]</td>
<td>Very risky</td>
</tr>
</tbody>
</table>

In summary, Internet financial risk assessment yields the weight of numerous evaluation indicators as well as the influence of various risk indicators on financial risks. The Internet financial risk control model based on big data is then utilized to actualize financial risk detection and early warning, resulting in the construction of an Internet financial risk control technique.

4. Experimental Verification

In order to verify the effectiveness of the Internet financial risk control method based on big data designed, experiments are carried out in this section.

4.1. Sample and Data Description. This article will use listed companies as the study sample to increase the efficiency of data collecting. The sample period is 2015-2020, and the sample companies are those that were listed on the Shanghai and Shenzhen Stock Exchanges before the end of 2009. The samples are screened as follows: deleted organizations that have been suspended for more than six months, and second, removed information of companies that have incomplete data. A total of 798 sample companies were finally obtained. Part of the data in the 2015-2020 annual report of listed companies comes from cninfo.com.cn; part of the network data comes from the Internet and is compiled by the editor; other data come from the “China Stock Market & Accounting Research (CSMAR) China Listed Company Parameter configuration

Data acquisition module

Database module

Early warning module

Business data and external sub-module interface interaction module

Risk identification module

Internet financial risk control model

Figure 4: Framework of Internet financial risk control model.

Figure 5: Workflow of Internet financial risk identification module.
Financial Indicators Analysis Database” and “CSMAR China Listed Companies Financial Reporting Database.”

To validate the built model, use the MATLAB 7.1 application package. During model training, not only training data but also test data are necessary. As a result, the data must be separated into two groups, the first of which is the training sample while second group is test sample, and the specific distribution is shown in Table 5.

In this paper, the price inflation factor is excluded from each risk pressure index, in which the real interest rate—nominal interest rate—inflation rate, and the seasonal factors are adjusted to obtain the pressure index of financial system risk from 2015 to 2020, as shown in Figure 6.

Figure 6 shows that the risk pressure index of financial institutions exhibits a dynamic tendency of frequent swings around the 0 axis for the period 2015-2020, showing that changes in the financial risk pressure index are unstable. It is worth mentioning that the pressure index had a strong fall and surge between 2015 and 2018. The pressure index showed a dramatic decrease in 2015 and a high spike in 2018, indicating that the financial system was under significant stress throughout this time period. Analysis reveals that the source of this volatility is mostly attributable to the short-term impact of financial concerns.

Table 6 summarizes the main statistical characteristics of the financial risk pressure index, demonstrating that the time series distribution does not follow the normal distribution but has a spike form, the series correlation is not significant, and the level value is a stable time series.

4.2. Performance Measurement of Risk Control Methods. Performance metrics take the risk control error rate, accuracy, control time, and risk level as references to synthesize the performance of the risk control method.

(1) Error rate and accuracy are two commonly used performance metrics in control tasks. The calculation formula for error rate is

\[ E_r = \frac{e_i(t) - e(t)}{E_i}. \]  

In equation (9), \( e_i(t) \) represents normal samples, \( e(t) \) represents error samples, and \( E_i \) represents total samples.

The calculation formula of accuracy error rate is

\[ z_e(\kappa) = \sqrt{(x_i(a) - x_i(b))^2}. \]  

Among them, \( x_i(a) \) represents the true result; \( x_i(b) \) represents the control result.

(2) The control time is the time consumed in the financial risk control process; the risk level refers to whether the risk level under method control matches the real level.

The financial risk control model based on SVM and the risk control model based on cluster analysis are compared with the methods in this paper. The results are as follows.

4.3. Analysis of Experimental Results

4.3.1. Error Rate. For risk control, three approaches are applied, and the error rate comparison result is presented in Figure 7.

Figure 7 shows that there is a significant difference in the error rates of the three techniques for financial risk control. The error rate of the approach in this study for financial risk control is just 5%, whereas the error rate of the other two methods is the greatest. The figures are around 10.5 percent and 10%, respectively. The error rate of the technique in this study, on the other hand, is lower, indicating that the method has superior financial risk control accuracy.

4.3.2. Accuracy. Figure 8 depicts the accuracy comparison findings of three risk control methods.

The maximum risk control accuracy of the financial risk control model based on SVM is 87 percent, the maximum risk control accuracy of the risk control model based on cluster analysis is 77 percent, and the maximum risk control accuracy of the method in this paper is 95 percent, as shown in Figure 8. When compared to older approaches, this method’s risk control accuracy is greater, resulting in a superior Internet financial risk control effect.

4.3.3. Control Time. Three methods are used for risk control, and the control time comparison results are shown in Table 7.

According to the results in Table 7, using the approach in this article, the financial risk control model based on SVM
and the risk control model based on cluster analysis, there is a considerable disparity in the control time of financial risk under the same simulation scenario. This method’s control time is always kept below 3s, and the smallest duration is just 1.37s. The other two approaches’ control times are always longer than this method’s. This is because this technique uses the decision tree algorithm to assess the risk behavior of financial users prior to risk control. This approach has the benefit of a quick running speed, which boosts its control efficiency.

4.3.4. Whether the Risk Level Is Consistent with the Actual Level. Analyze if the risk level achieved throughout the control procedure is consistent with the real level to further validate the usefulness of the technique in this article.

5. Conclusion

Financial risk refers to the risk of losing money on an investment or business venture. Credit risk, liquidity risk, and operational risk are three of the most common and diverse financial risks. Financial risk management is an organizational activity aimed at detecting, monitoring, and managing exposure to various hazards linked with the use of financial services. Because traditional accounting risk control has a relatively high timeliness and unpredictability, it has various issues, such as a high error rate, low accuracy, lengthy duration, and risk. In order to solve the problems of high error rate of risk identification, low accuracy, long time, and un-corresponding risk levels in traditional methods, a big data-based Internet financial risk control method is proposed. The experimental results show that the highest value of error rate of financial risk control in this paper is only 5%, the highest value of risk control accuracy is 95%, the control
time is always kept below 3s, and the risk level is relatively similar and consistent with the actual level. The coefficient is close to 1, indicating that the control effect of this method is better.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by the National Key R&D Program of China (Grant no. 2018YFA0703900) and the National Natural Science Foundation of China (Grant no. 11871309).

References


