Bank personal credit is affected by factors such as inadequate management and lagging risk information management system. Bank default risk analysis is needed to improve the ability of bank credit risk management. Therefore, a bank customer default risk analysis based on embedded microprocessor wireless communication is proposed. Firstly, it analyzes the risk assessment parameter evaluation system of personal credit, constructs the quantitative analysis model of personal credit risk, calculates the grade gradient value in the bank’s personal credit risk standard, carries out the mathematical modeling of bank customer default risk assessment, strengthens the implementation of “three checks,” tracks and manages the borrower, supervises the use of credit funds, improves the social credit investigation system, and on this basis, optimizes the mathematical model of bank customer default risk assessment. The experimental results show that this method can realize the bank’s quantitative evaluation and control of personal credit risk, improve the bank’s credit risk prevention and control ability, and provide a reliable basis for the bank’s credit risk evaluation operation and management.

1. Introduction

With the increasingly significant impact of Internet finance, the business model of traditional banking industry has been greatly challenged [1, 2]. Although banks still have great advantages in the financial market from the current situation, with the rapid development of Internet technology under the new technology and new platform, the traditional business of banks, not only large companies and enterprise customers, but also more individual customers, will be affected by Internet finance [3, 4]. In recent years, after several rounds of regulation and standardization in China, Internet finance has become more and more mature, and shows a trend from rapid growth to rational return. However, the pressure on banks has not been reduced, because Internet finance has had a great impact on the capital accumulation of banks and traditional financial industry, and more and more bank customers, especially individual customers, are further losing [5, 6].

In recent years, with the rapid development of the real estate industry and small- and medium-sized enterprises, China’s customer credit has developed rapidly, and there is a large gap in customer credit and financing. Especially for small- and medium-sized enterprises, it is necessary to apply for customer credit to banks to solve the problem of capital shortage and realize the original accumulation of financing and capital. China’s small- and medium-sized enterprises play an important role in China’s economic development and are of great significance in absorbing employment and creating social production value. However, for small- and medium-sized enterprises and entrepreneurs, the constraints of many factors lead to financing difficulties, capital
shortage, and adverse effects on the development of enterprises. The customer credit provided by banks facilitates customers and enterprises in need of financing [7, 8]. However, due to the high risk of customer credit and the influence of market risk, nonmarket risk, and other factors, banks lag behind in risk control and risk assessment of customer credit, resulting in a large number of bad and dead debts, especially the “subprime mortgage crisis” and Asian financial turmoil in recent years, and the subsequent turmoil of the global financial situation. It challenges the bank’s control and evaluation of customer credit. The accuracy of bank’s risk assessment of customer credit is an important index to evaluate the safe and healthy operation of banks.

It is of great significance to study the analysis of bank customer default risk. Relevant literature has been studied. Reference [9] proposed a research on bank customer credit risk rating system based on data mining and deeply analyzed the construction of the customer credit risk rating index system based on association rules. The construction of rating model is based on the BP neural network, and the construction of classification result refinement visualization module is based on a variety of data mining technologies. Reference [10] puts forward the analysis of bank default risk propagation in the supply chain. Before the study, there was a question about how the bank default risk affected the default probability of nonfinancial business? This problem is solved by paying attention to the direct impact of banks on corporate customers—which proves that banks lead to the increase of corporate default probability. By analyzing the direct and indirect impact of bank default risk on bank default risk in the UK, we can study this problem in the absence of micro-economic data linked to the supply chain. Although some progress has been made in the above research, the computational cost is large, the practicality is poor, and the dynamics of risk assessment is poor. The accuracy and precision of customer credit risk assessment are low. Therefore, a bank customer default risk analysis based on embedded microprocessor wireless communication is proposed. Embedded microprocessor wireless communication has the advantages of real-time online, billing by volume, fast login, high-speed transmission, and free switching. Therefore, it is widely used in the fields of data acquisition, wireless Internet access, environmental monitoring, industrial control, and finance. The performance is verified by experiments, which shows the superior performance of the research content in this article in realizing the analysis of bank customer default risk. It shows a good application value.

2. Bank Customer Default Risk Analysis

2.1. Risk Evaluation Parameter Evaluation System of Personal Credit. To promote and improve the credit process and management mechanism of credit, major banks have formulated the credit process of credit, simplified the credit steps, and strictly reviewed the credit data, so that borrowers can get the loan as quickly as possible. At the same time, it has also strengthened the follow-up investigation of loans and ensured the use of credit. Figure 1 shows the bank loan process.

According to the bank loan flowchart, this article constructs the quantitative analysis model of personal credit risk and puts forward a quantitative analysis model of bank customer default risk assessment. Firstly, the risk evaluation parameter evaluation system of personal credit is constructed, and then, the test evaluation function is constructed using the existing data to obtain the grade gradient value in the bank customer default risk standard [11]. The factors of bank risk factors are constructed through feedback error control, mainly including the influencing factors of unreasonable internal structure of the bank, personal credit, and internal defects of the borrower. According to the constraints of the external environment, the social science statistical software package SPSS11.0 is used for statistical analysis, and the hierarchical difference control function of the bank’s credit risk is obtained as follows:

$$
\min_{0 \leq a \leq c} \left( \sum_{i,j=1}^{l} K(x_i, x_j) + a \right) \leq \alpha
$$

where $K(x_i, x_j)$ is the action cell of the bank’s internal structure and $a$ is the Lagrange operator, which dynamically predicts the three types of elements of the bank’s personal credit risk control, and the sample set of prior data is as follows:

$$
S = \{(x_1, x_1), \ldots, (x_l, x_l)\}.
$$

According to the actual selection of ten important factors affecting credit risk, calculate the first-order partial derivative and mean square error of the sample data $W$, and the quantitative condition discriminant of each influencing factor of bank personal credit can be obtained as follows:

$$
G_i = \sum_j \alpha_i y_j K(x_i, x_j) + y_i b - 1.
$$

Carry out multilayer step-by-step dynamic prediction on the evaluation coefficient corresponding to the risk assessment model, ignore the role of other secondary factors in the ideal state, and obtain the risk discriminant of bank personal credit:

$$
G_i = \begin{cases} 
\geq 0, \alpha_i = 0 & S_R \\
0, 0 < \alpha_i < C & S_S \\
\leq 0, \alpha_i = C & S_E 
\end{cases}
$$

where $\sum_{i=1}^{l} \alpha_i = 0$. $S_R$, $S_S$, and $S_E$ represent three subsets of evaluation function $Y$, critical value $CY$, and grade gradient values $AAA +$, $AAA$, and $AA +$, respectively. Through the quantitative analysis of the borrower’s age and marital status, the constraint parameters of personal credit are as follows:

$S_R$—marital status score coefficient, risk prediction is carried out through adaptive scheduling to obtain the redundant set of subprime mortgage risk;

$S_E$—attribute subset of the proportion of installment payment in actual monthly income.
Through the above analysis, the bank personal credit evaluation system is constructed, and the most alternative data method is used to fit the state characteristics of the parameters. The fitting results are as follows:

\[
x(t) = (x_0(t), x_1(t), \ldots, x_{k−1}(t))^T.
\]  \hfill (5)

For \(x(t)\), with reference to the Beth model, the characteristic factor of credit and risk of the borrower of personal credit is \(c_1, c_2, \ldots, c_m\), and the weight function is \(U\), where \(\sum U = 1\), the sample set of normative analysis and empirical analysis of personal credit customers of the bank is obtained, and the risk evaluation parameter evaluation system structure model of personal credit is obtained, as shown in Figure 2.

As can be seen from Figure 2, in the risk assessment parameter evaluation system of bank personal credit, the person in charge occupies a dominant position, and the resources of personal credit information need to be integrated to obtain more comprehensive data information, such as financial information and capital deposits of customers, so that bank risk managers can connect multiple levels of information, timely early warning of customer risks, so as to improve the probability of early detection and identification of risks.

2.2. Design and Implementation of Quantitative Analysis Model of Personal Credit Risk. On the basis of the above constructed personal credit risk assessment parameter system of the bank, the quantitative analysis mathematical model is constructed by using the multilayer step-by-step dynamic assessment method to realize the mathematical fitting and quantitative analysis of risk assessment. On the basis of collecting and establishing the personal credit system of the whole society, the personal income, credit, crime, and other records of the borrower are analyzed, The dynamic weighting vector obtained is

\[
d_j = \sum_{i=0}^{k-1} (x_i(t) - \omega_{ij}(t))^2, \quad j = 0, 1, \ldots, N - 1,
\]  \hfill (6)

where \(\omega_j = (\omega_{0,j}, \omega_{1,j}, \ldots, \omega_{k−1,j})^T\) represents the weighting coefficient of personal credit rating. In the whole process of credit risk control, the regulation threshold of bank customer default risk with minimum correlation distance can be obtained [12, 13], where \(d_j = \min_{\omega \in \Omega_{j−1}} \{d_j\}\). According to the credit limit \(N_{j,0}\) and risk management level, the customer’s reputation is adaptively weighted to obtain \(N_{j,t}\), and the cooperative control of credit and risk is carried out in the geometric neighborhood \(NE_{j,t}(t)\). The multilayer step dynamic prediction value of the bank’s personal credit is as follows:

\[
\omega_{ij}(t + 1) = \omega_{ij}(t) + \alpha(t)(x_i(t) - \omega_{ij}(t)),
\]  \hfill (7)

where \(N_j \in E_{j,t}(t), 0 \leq i \leq k - 1\), and \(0 \leq \alpha(t) \leq 1\) are the training speed when there is no reputation imbalance and fraud. Based on the commitment mechanism, the risk characteristics of personal credit are obtained as a variable, and the samples continue to be input in the approximate hyperplane. If there is no negotiation between lender A and bank B, the grey prediction model GM (1,1) is used for spatial dimensionality reduction. Because the capital source of personal credit is greatly affected by market liquidity, it is necessary to decompose the covariance of the economic data of personal credit. At this time, the adaptive cycle method is adopted. When \(t = t + 1\), the cycle iteration is adopted, in which \(\alpha(t)\) decreases with the passage of time. The impact of banks on personal credit shows the following important characteristics. \(\alpha(t)\) and \(NE_{j,t}(t)\) take different forms, usually as follows:

\[
L_\xi = \begin{cases} 
A_1 |f(x) - y| - f^* \xi |f(x) - y| \geq \xi \\
0 |f(x) - y| < A_0
\end{cases}
\]  \hfill (8)
where $A_1$ is the largest neighborhood of the bank’s product structure, $A_0$ is the smallest neighborhood of the policy supervision prediction code $j^*$, $T_1$, and $T_2$ are the attenuation constants of personal credit risk assessment by means of financial asset securitization, and $A_2$ is the maximum learning degree of dispersed risk. Calculate the covariance matrix $C$ of the income data of the bank’s financing of personal credit as follows:

$$ C = \frac{1}{N} [X - \bar{X}] [X - \bar{X}]^T. $$

The SVM model is optimized. The sample fitting value of the bank's credit risk factors on the reputation of personal credit is as follows:

$$ X = [X_1, X_2, \ldots, X_m]. $$

The final sample fitting is obtained by bit difference between the coding sequence and the encryption sequence, and operates according to the bank payment key retransmission protocol, as shown in Figure 3.

Through the connected index function of the minimum connected set, the divided sets are effectively combined to realize the effective analysis of the overall continuity of the bank module. The result of set division reflects the consistency of data characteristics. In the set, the coding method of turbo coding can be used to encode the data to improve the coding efficiency. The codeword structure diagram of bank payment security key based on embedded microprocessor wireless communication is shown in Figure 4.

When the $X$ value is larger, it means that the fitting degree is more consistent. At this time, the control state characteristic equation of the bank’s credit risk factors on personal credit is expressed as

$$ (\lambda - S)U = 0. $$

Solve the eigenvalue $\lambda$ of the risk relationship model $S$ and the eigenvector $U$ corresponding to the predicted value $\lambda$ of the risk relationship. Through the above analysis, for $K$ input sample datasets input to support vector machine, the linear regression expression of personal credit risk estimation is

$$ f(x) = \omega^T (\phi)x + B, $$

where $\omega$ represents the risk relationship prediction and fitting value of personal credit in high-dimensional space, and $B$ represents the deviation vector of risk control. Through the above mathematical model construction, multilayer step-by-step dynamic prediction is adopted to realize the default risk assessment of bank customers, reduce credit risk through error feedback, and improve the risk prevention and control ability of banks for personal credit [14–16]. The mathematical model improvement design process of personal credit risk assessment is shown in Figure 5.

3. Mathematical Modeling of Bank Customer Default Risk Assessment

The basis of mathematical modeling of bank customer default risk assessment is that banking institutions master the lifeline of national funds and affect national economic development. Considering the difficulties in credit risk assessment and management of banking institutions, in the process of mathematical modeling and simulation analysis, they should assess the default risk of bank customers and strengthen the control of default risk of bank customers [17–19] and pay special attention to the following aspects.

3.1. Strengthen the Implementation of “Three Checks” in the Mathematical Modeling of Bank Customer Default Risk Assessment

In the middle of 90s, China’s major banking institutions began to implement the “three checks” system, namely, “preloan investigation, loan review, and loan checking.” Doing a good job of “three inspections” is the best means to avoid the default risk of bank customers. However, due to the imperfect bank management system, the investigation and handling departments of banks in China have not really played the management function of the “three inspections” system in the actual operation process. The vast majority of bank credit employees and employees of “three inspections” institutions [20] are in the process of credit business review. In order to cope with the performance appraisal, “three checks” are perfunctory and face engineering. In the final analysis, it is to maximize the economic benefits of bank operation and ignore the healthy, sustainable, and safe development of banks. In terms of
Figure 3: Bank payment key retransmission protocol flow.

Code word after CRC Coding:

Turbo coded codeword:

Retransmission V1: 1 1
Retransmission V2: 2 2
Retransmission V3: 3 3 3 3
Retransmission V4: 4 4 4 4

Combined codeword: 3 1 2 3 1 2 3 3 4 1 1 2 4 4 2 4

Figure 4: Codeword structure of bank payment security key based on embedded microprocessor wireless communication.

Figure 5: Mathematical model design process.
employee performance assessment and reward and punishment system and mechanism, it is also based on the economic benefits of the bank, which leads to the limitation and one sidedness of bank customer default risk assessment. In the process of evaluating and analyzing the default risk of bank customers, strengthen the implementation of "three inspections," reformulate the punishment mechanism, and strictly implement the new punishment mechanism, so as to not only take credit performance as the reward standard [21, 22]. In terms of short-term economic development, high-risk and high interest bank credit will indeed produce good profit space, but in the long run, the default risk of bank customers is increasing, which is not conducive to long-term stable development.

3.2. Strengthen the Tracking Management of Borrowers in the Mathematical Modeling of Bank Customer Default Risk Assessment. In the twenty-first century, the financial market fluctuates greatly, and there are a large number of unknown and uncertain factors. Affected by the external environment of the financial market, the credit repayment ability of credit borrowing enterprises and borrowers will also be greatly changed [23, 24]. Major domestic banking enterprises should build a credit risk assessment system and credit management system as soon as possible to avoid credit risks such as bad loans and nonperforming loans due to changes in external market conditions and imperfect internal management mechanism during the credit period. With its own credit management system, it continuously tracks, supervises and manages the borrower, and takes timely rescue measures for credit risk to reduce credit risk.

3.3. Strengthen the Supervision of the Use of Credit Funds in the Mathematical Modeling of Bank Customer Default Risk Assessment. During the mathematical modeling and simulation analysis of bank customer default risk assessment, increasing the tracking and supervision of the use of credit funds is conducive to reducing the bank customer default risk [25, 26]. The process of using bank credit funds by the borrower and the lender must be consistent with the contents agreed in the bank loan processing contract. The borrower cannot change the purpose of the loan on the way to avoid the loss of effective protection of the bank. After the completion of loan procedures, banks should strengthen the supervision of the capital flow of borrowers and lenders, and fully understand the purpose and flow of borrowers’ loans, so as to facilitate the bank’s credit risk assessment [27]. The bank can timely take remedial measures when the borrower violates the agreement, and require the borrower to increase loan mortgage and loan guarantee, so as to avoid economic losses caused by the bank, which is conducive to the risk assessment of bank customers’ default.

3.4. Improve the Social Credit Investigation System in the Mathematical Modeling of Bank Customer Default Risk Assessment. Social credit investigation system is a social management tool to evaluate credit and an evaluation and estimation activity to judge whether the borrower has the ability to fulfill the credit repayment responsibility. Improving the social credit investigation system is very conducive to the default risk assessment of bank customers [28, 29]. However, for a long time, the social credit investigation system has not been paid attention to, and banking institutions have not realized the value of the social credit investigation system, resulting in the government ignoring the investment in the construction of social credit investigation, and the development of social credit investigation has been seriously restricted. The low collection capacity of bank customer default risk assessment information [30] and asymmetric information have led to many cases of loan economic losses in Chinese banking institutions.

On the basis of adopting the mathematical modeling method of bank customer default risk assessment, the optimization design of bank operational risk control model is carried out, and a bank operational risk control method based on embedded microprocessor wireless communication is proposed to analyze the dispersion of bank operational risk with the scale effect of financial service channel, microfinance, and consumer finance [31, 32]. Using the methods of economic game theory and regression analysis, this paper evaluates the operational risk of banks with internal accounting control as the core, so as to effectively realize credit rating.

The global optimization of the bank’s operational risk characteristic sequence is carried out to obtain the global extreme value $G_{best}^d (t)$ and individual extreme value, and the deposit source of the bank is centrally managed [33]. The calculation formula of the financing proportion in the capital market of the bank’s operational risk assessment with internal accounting control as the core is as follows:

\[
\begin{align*}
V_{i}^d (t + 1) &= W \times V_{i}^d (t) + C_1 \times R_1 \times \left( P_{best}^d (t) - P_i^d (t) \right) + C_2 \times R_2 \times \left( C_{best}^d (t) - P_i^d (t) \right), \\
P_i^d (t + 1) &= P_i^d (t) + V_{i}^d (t + 1)
\end{align*}
\]

where $V_{i}^d (t)$, $V_{i}^d (t + 1)$, $P_i^d (t)$, and $P_i^d (t + 1)$ are the parameters of money supply, investment scale, and bank asset scale, respectively. Solve the optimal solution of the above equation, lock the growth rate of bank loans, and analyze the benefit gain output of bank operational risk under internal accounting control under loose credit policy [34, 35]. According to the heterogeneity of ownership structure, this article quantitatively evaluates the bank’s operational risk, forecasts the future fluctuation of monetary policy, and uses the quantitative quality analysis method of accounting.
information to predict the risk in the process of earnings manipulation.

Build the correlation analysis of bank operational risk and the optimal decision-making model of risk control from the perspective of accounting internal control, statistically analyze the bank operational risk data from the perspective of accounting internal control, and build the correlation relationship between variables. The oscillation fitting relationship model is as follows:

\[
\begin{align*}
    b_{20}(t; \lambda) &= \frac{1}{2}(1 - \lambda t)(1 - t)^3 \\
    b_{21}(t; \lambda) &= \frac{1}{2}[1 + (\lambda + 3)t - 3(\lambda + 1)t^2 + 4\lambda t^3 - 2\lambda t^4] \\
    b_{22}(t; \lambda) &= \frac{1}{2}(1 - \lambda + \lambda t)t^3
\end{align*}
\]  

(14)

Under the significance level test of 1%, the decision variables of bank operational risk control under internal accounting control are obtained:

1. The corresponding variables of asset size and loan growth rate are defined as \( Z_i \) (\( i = 1, 2, \ldots, 8 \)).
2. The sensitivity of bank operating performance is defined as \( W_k(i = 1, 2, \ldots, 6; k = 1, 2, \ldots, 6) \).
3. The relevance level of operating cash flow to financial distress is defined as \( X_{ij}(i = 1, 2, \ldots, 6; j = 1, 2, \ldots, 8) \).

The relationship model between accounting conservatism and manager overconfidence is used for comprehensive evaluation, the accounting conservatism of managers is investigated, the correlation analysis is carried out, the principal component characteristic quantity is constructed, and the subsamples obtained after grouping the business environment are used for regression analysis of bank operational risk under internal accounting control. The regression analysis model is as follows:

\[
Z_1 = B \sum_{w \in W} q^w - \sum_{a \in A} x_a \left[ t_a(x_a) + \beta v_a \right].
\]  

(15)

Through the above design, this article analyzes the bank operational risk prediction model under accounting internal control under loose credit policy, making the economic prediction model balanced and stable [36]. Considering the increment caused by the overconfidence of managers, the risk control of bank operational risk under internal accounting control is carried out, and the income characteristics under loose credit policy are as follows:

\[
S = \{(x_1, x_1), \ldots, (x_l, x_l)\}.
\]  

(16)

The regression analysis of the bank's operational risk is carried out by using the full sample and the subsample obtained after grouping according to the business environment. The objective function of the bank's conditional accounting conservatism control is

\[
G_t = \sum_j x_j y_j K(x_j, x_j) + y_j b - 1.
\]  

(17)

Taking the deviation measurement of earnings forecast as the constraint sample, combined with the quantitative statistical analysis method, this article analyzes the dispersion of bank operational risk with the scale effect of financial service channels, microfinance, and consumer finance, so as to improve the level of bank risk control.

4. Bank Customer Default Risk Assessment Based on Embedded Microprocessor Wireless Communication

4.1. Evaluation Method. To evaluate the default risk of bank customers, first determine the relevant index system parameters, then evaluate the quantitative variable value of the characteristic data of bank customers’ default risk in advance, input the adopted characteristic parameter value into the discriminant function formula, and finally, obtain the evaluation value of bank customers’ default risk. The specific formula of bank customer default risk assessment discriminant function is shown as follows:

\[
Q = \partial_1 X_1 + \partial_2 X_2 + \cdots + \partial_n X_n.
\]  

(18)

In the bank customer default risk assessment discriminant function, \( Q \) represents the final data of bank customer default risk assessment; \( X_n \) represents the quantitative variable value of the characteristic data for assessing the default risk of bank customers, that is, bank credit financial risk indicators and credit financial nonrisk indicators; and \( \partial_n \) represents the discriminant index of all quantitative variables in the credit risk characteristic data. Through the bank customer default risk evaluation and discrimination mode, the bank customer default risk is truthfully evaluated and judged according to the final calculated function value.

As the most traditional assessment management tool of risk assessment in China, discrimination has made great contributions to risk assessment and prevention in various economic fields in China. This article focuses on the regression mathematical modeling and simulation experiment to evaluate and analyze the default risk of bank customers. Regression mathematical modeling is the most popular risk assessment management tool in the current financial market. Compared with other models, the regression risk assessment management model has the advantages of simple use method, easy operation, less restrictions, low sample requirements, and more accurate final risk evaluation effect. The mathematical modeling function formula of regression bank customer default risk assessment is as follows:

\[
Z(X) = 1/(1 + e^{-X}).
\]  

(19)

In the regression mathematical modeling function formula of bank customer default risk assessment, when the obtained \( Z \) value is within the range of 0 and 1, the risk probability \( Z \geq 0.5 \) B indicates that the probability of bank customer default risk exceeds 50%, which can judge that the bank credit belongs to high-risk behavior.
4.2. Optimize the Mathematical Model of Bank Customer Default Risk Assessment. Firstly, the default risk assessment standards of different domestic bank customers are adopted to determine the value. Secondly, according to the non-financial information of domestic loan enterprises, carry out uncertain sampling and random inspection. Finally, import the above information data into the mathematical modeling to obtain the following formula form:

\[ a_1 = 34.21 - 3.32X_1 + 1.33X_2 + 3.22X_3 - 1.03X_4 \cdots + 2.35X_n \]  

(20)

Further calibrate the correctness of the risk probability obtained by the above model, you can import the enterprise real index parameters into the above formula to obtain the risk probability value \( a_1 \) and then import \( a_1 \) into formula (19) to obtain \( Z_1 \). The default risk limit of bank customers is 0.5. According to the above data, we can judge whether the enterprise loan risk belongs to high risk or safe credit behavior. Embedded microprocessor wireless communication has absolute advantages in data acquisition and data processing, which can effectively improve the accuracy and sensitivity of risk measurement of bank customer default risk assessment mathematical model, effectively proofread risk parameters, optimize risk rating model, and improve the ex ante risk identification and assessment ability of bank customer default risk assessment mathematical model, so as to play a basic regulatory function in credit utilization and risk mitigation, effectively promote the establishment of credit risk management mechanism, and optimize the mathematical model of bank customer default risk assessment.

5. Experimental Analysis

In order to test the performance of bank customer default risk based on embedded microprocessor wireless communication, experiments are carried out. The experiment is based on the MATLAB 2012b platform, and the hardware environment is configured as CPU: Intel (R) Core (TM) CPU t6600, 2.2 GHz. The software environment is configured as follows: the GPRS module communicates with the microprocessor through the serial port. The communication protocol between them is the at command set, most of which comply with the protocol. The microprocessor controls the GPRS module by executing the corresponding at command to complete the corresponding functions, such as TCP/IP data transmission, and call and short message functions. During the experiment, there are four types of factors for bank customer default risk variables. Among them, risk impact factor 1 is defined as the personal quality of the lender, risk factor 2 is defined as the bank’s internal management mechanism, risk factor 3 is defined as enterprise information, risk factor 4 is defined as the bank enterprise relationship, and risk factor 5 is defined as the financial policy environment. The types of banks are state-owned banks, joint-stock banks, and credit cooperatives. The bank is divided into provincial branches, municipal branches, sub-branches, and banking offices. According to the previous data analysis, the grade gradient value in the bank customer default risk standard is obtained, and the average value of the bank customer default risk impact factors is obtained, as shown in Table 1.

From the analysis in Table 1, it can be concluded that the types and grades of banks have great differences in the risk impact of personal credit. By adopting stop loss measures and credit tightening measures, risk control can be realized by optimizing the bank’s decision-making mechanism.

Personal credit involves multidimensional information of loan customers. Banks need to collect and sort out various information of customers and try to describe a complete customer portrait, so as to give some help to the study and judgment of customer risk. In this article, the embedded microprocessor wireless communication technology makes a cross-analysis on the social attribute and work attribute, and of loan customers. The label of social attribute is mainly for age, and the label of work attribute is mainly for income, in order to make a relatively perfect risk analysis of bank customer default.

According to the breach of contract in terms of social attributes, cross-analysis is carried out for customers of different ages. The results are shown in Table 2.

It can be seen from Table 2 that the number of people in breach of contract gradually decreases with the age entering the middle-aged and elderly, which is in line with the actual situation, because with the increase of age, people will be more stable, pay more attention to their credit, and will not easily breach the contract. According to the labels of work attributes, cross-analyze whether to default and income, and the results are shown in Figure 6.

As can be seen from Figure 6, the analysis of the label of work attribute dimension shows that with the increase of income level, the default rate gradually decreases, because with the continuous increase of income, the customer’s repayment ability also increases.

Check whether there are duplicate values in the data to confirm that each record is unique. Then, check the missing and abnormal values, and replace or delete the records with missing and abnormal values. After the data cleaning, the variables are analyzed. Due to the large number of dependent variables, the correlation between variables needs to be checked. When using the logistic regression model, if there is a problem of multicollinearity between independent variables, it will lead to the generation of singular matrix. Therefore, before building the model, the collinearity diagnosis of independent variables is carried out. Here, tolerance and variance expansion factor Vif are used for relevant judgment. Many empirical results show that when the tolerance is lower than the threshold value of 0.1 or the variance expansion factor Vif is greater than the threshold value of 10, there may be serious collinearity problems between explanatory variables. The results are shown in Table 3.

It can be seen from Table 3 that only the Vif of credit rating and annual loan interest rate is relatively high, and there may be collinearity. There is still a large gap between other variables, whether tolerance or variance expansion factor Vif, and the empirical threshold.
Table 1: Average value of bank customer default risk factors.

| Credit risk factor project | Personal quality | Internal management mechanism | Enterprise information | Bank enterprise relationship | Internal management |
|---------------------------|------------------|-------------------------------|------------------------|----------------------------|----------------------|
| Wholly state-owned bank   | 2.36             | 6.32                          | 6.22                   | 7.88                       | 3.14                 |
| Joint-stock bank          | 3.22             | 6.21                          | 6.32                   | 5.69                       | 4.22                 |
| Credit cooperative        | 3.01             | 6.00                          | 5.28                   | 4.69                       | 4.58                 |
| Provincial bank           | 3.58             | 2.08                          | 4.08                   | 3.33                       | 2.39                 |
| City branch               | 3.64             | 2.17                          | 4.12                   | 5.58                       | 2.69                 |
| Sub-branch                | 3.98             | 2.58                          | 5.45                   | 8.09                       | 2.98                 |

Table 2: Cross table of default age.

| Project               | Count | <30  | 31–40 | 41–20 | 50+  | Total |
|-----------------------|-------|------|-------|-------|------|-------|
| Default or not        |       |      |       |       |      |       |
| No                    |       |      |       |       |      |       |
| Proportion/%          |       |      |       |       |      |       |
| Count                 | 239   | 425  | 273   | 94    | 1031 |       |
| Proportion/%          | 23.2  | 41.2 | 26.5  | 9.1   | 100  |       |
| Yes                   |       |      |       |       |      |       |
| Proportion/%          |       |      |       |       |      |       |
| Count                 | 126   | 187  | 69    | 11    | 393  |       |
| Proportion/%          | 32.1  | 47.6 | 17.6  | 2.8   | 100  |       |
| Total                 | 365   | 612  | 342   | 105   | 1424 |       |
| Proportion/%          | 25.6  | 43.0 | 24.0  | 7.4   | 100  |       |

Figure 6: Customer default under different income conditions.

Table 3: Variable collinearity diagnosis.

| Model                                  | Tolerance | Collinearity statistics | VIF  |
|----------------------------------------|-----------|-------------------------|------|
| Loan purpose                           | 0.949     | 1.053                   |      |
| Loan amount                            | 0.568     | 1.761                   |      |
| Annual interest rate of loan           | 0.201     | 1.964                   |      |
| Credit rating                          | 0.109     | 9.198                   |      |
| Age                                    | 0.767     | 1.304                   |      |
| Education                              | 0.872     | 1.146                   |      |
| Marital status                         | 0.972     | 1.029                   |      |
| Income situation                       | 0.602     | 1.661                   |      |
| Is there any car production            | 0.691     | 1.446                   |      |
| Is there any real estate               | 0.601     | 1.663                   |      |
| Is there a car loan                    | 0.787     | 1.270                   |      |
| Is there a mortgage                    | 0.584     | 1.711                   |      |
| Company size                           | 0.409     | 2.447                   |      |
| Working hours                          | 0.846     | 1.182                   |      |
| Job title                              | 0.657     | 1.523                   |      |
| Company industry                       | 0.924     | 1.082                   |      |
| Work province                          | 0.980     | 1.020                   |      |
| Repayment term                         | 0.334     | 2.997                   |      |
6. Conclusion

The bank personal credit is affected by factors such as inadequate management and lagging risk information management system. It is necessary to build a quantitative analysis model for bank customer default risk assessment to improve the ability of bank customer default risk management. This article proposes a bank customer default risk analysis based on embedded microprocessor wireless communication. Firstly, the bank customer default risk parameter system is constructed, and then, the test and evaluation function is constructed with the existing data to obtain the grade gradient value in the bank customer default risk standard and realize the construction of the mathematical model. The embedded microprocessor wireless communication is used to realize the quantitative analysis and evaluation of credit risk. The research shows that this method can realize the bank’s quantitative evaluation and control of personal credit risk, and shows a good application value.

This article failed to study the deeper application of big data in the field of bank customer default risk. In the future, based on the crawling technology of big data, we can obtain the multidimensional information of bank customers, such as social network information and financial information, and integrate and analyze it with the existing information, so as to further improve the accuracy of bank customer default prediction, in order to reduce the credit default risk of bank customers and provide a reliable basis for the bank’s credit risk assessment.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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