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*Research Article*

# Financial Risk Control and Audit of Supply Chain under the Information Technology Environment

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With the continuous improvement of society's recognition of supply chain finance and the development of domestic enterprises, the scale of Chinese supply chain financial service market has become larger and larger, and the status of supply chain financial services has gradually become clear. This emerging financing method can solve the problem of financing difficulties for small- and medium-sized enterprises. Many commercial banks are involved, but there are also many risks. As a representative of industrial integration, how commercial banks manage risks and improve the financial service supply chain is the focus of the article's research. The article designs a set of risk management system based on machine learning and trains similar models to verify consumers by learning user behavior patterns. The system realizes the server-side authentication module and the intelligent terminal protection module and achieves the purpose of real-time protection of the intelligent terminal system. The system will adapt to mainstream Android and IOS on the market, including portable terminal devices and smart wearable devices. If it is found that the device has not been operated by the user, the user will be provided with corresponding feedback results, and a series of automatic protection operations such as device lock and system alarm will be provided. At the same time, we provide two modes of online detection and offline detection. The device only needs to have our cloud user model to authenticate users in an offline environment to ensure that systems in different environments can run. The article solves the imbalance between user data and negative samples and most unlabeled user data and designs a set of management learning methods to ensure user certainty. By cooperating with enterprises, we can learn and analyze this set of data in our system. The results show that the accuracy rates of effective operation and user static data are 93.77% and 95.57%, respectively.

## 1. Introduction

The era of rapid development of information technology has arrived. With the emergence and gradual development of the concept of big data, information is gradually replacing traditional content media, which is more suitable for many companies in the market, and its competitors are also growing. With the continuous and rapid development of the global financial integration trend in the financial market, higher requirements are put forward for the development and management of commercial banks. Banks' emphasis on the use of information technology is gradually shifting from traditional businesses to electronic and centralized data management and data management decision-making. The progress of e-banking gradually replaces traditional banking services, and it has become the main battlefield for competition among large commercial banks. The processing of a large number of customer information, accounts, and transactions generated by the commercial bank network will undoubtedly increase the amount of information, such as timely access to important information, and risk management plays an important role in the entire economy. If an accident occurs, risk management cannot solve it, and good risk management should be a theoretical step to avoid accidents in advance. With the advent of the era of big data, the ability of individuals to collect and use information is further improved, making accurate analysis and decision-making based on as much data as possible. In recent years,

commercial banks have attached great importance to bank risk management. Large commercial banks conduct big data mining on existing data to increase customer and bank revenue to analyze, monitor, and remind customers of abnormal credit behavior to reduce credit risk.

The problem of commercial bank information asymmetry has a significant impact on the development of the commercial bank's financial service supply chain, the most important of which is to increase the possibility of credit risk. However, in the process of granting loans to financing parties, banks will inevitably include customer group surveys. During this period, once information asymmetry occurs, the possibility of credit risk will increase significantly.

By integrating and adapting the data storage structure of commodity banks, establishing a risk management business data mart, analyzing historical business data, dividing the data mart into multiple business segments, and using data mining, commercial banks provide technically reliable data management and consider loan income. Risk monitoring and early warning can mine detailed customer account information, related party information, funds, and other information flows, calculate the potential risks of customer activities, and provide an auditable way to monitor the risk dynamics of lenders. It focuses on the information integration before, during, and after the bank's credit extension, analyzes the historical data of loan customers, effectively integrates the information shared by the bank before, and filters and analyzes the data, uses the method of technical communication to assess the credit risk of loan customers, and provides leading ideas for customers' loan issuance and approval of bank loans. Through data mining technology, the similarity of bad customers can be found, and the evaluation can evaluate loan customers more effectively, manage the overall risk of customers, and provide credit more effectively.

## 2. Related Work

In the field of risk control and auditing, domestic and foreign experts also have a lot of research. Tajani F's research aims to propose a decision support method for public and private entities involved in the enhancement of public property. In particular, with regard to the circumstances in which abandoned public properties can be sold, and the functional scope of the best use is determined, the developed model allows to evaluate the financial feasibility of these measures in the corresponding investment risk [1]. Hosack GR developed a practical method of a priori derivation to derive the parameters and model structure of the Bayesian generalized linear model. The predictive derivation of the subjective probability distribution is used to evaluate the effectiveness of risk control options (RCOs) in reducing the risk of collisions between Australian territorial waters and ships in the exclusive economic zone [2]. The coal mine occupational safety and health management and risk control technology and related software developed by Zhou LJ can standardize and effectively support coal mine occupational safety and health management and can also scientifically and effectively control accident risks. Its effective implementation can further improve the coal mine occupational safety and health management mechanism and further improve risk management methods [3]. PM ascini concluded that the governance of privatization risk control presents the formidable challenge of finding an appropriate balance between public goals and the involvement of private interests. By excluding or marginalizing the most vulnerable groups, privatization of risk control does not always achieve the equal opportunities pursued by social investment policies [4]. Zhao B assesses the critical link between safety and change over time. It further analyzes the changing trend of system risk under this joint effect and demonstrates how the function of the organization should be synchronized with different levels of automation transformation [5]. Du *J* proposes a multilevel threshold public goods game model and introduces an insurance compensation mechanism to discuss risk control and study the evolution of global cooperation. It is found that high risks and high thresholds are conducive to global cooperation [6]. Although these studies are relatively comprehensive, they are not in-depth enough, and the public acceptance rate is generally low.

## 3. Development of Risk Control System in Information Technology Environment

*3.1. Data Warehouse Technology.* Data warehouse is abbreviated as DW or DWH. A data warehouse is different from a database. This is mainly manifested in that it is a collection of data in a multi-distributed database. It deliberately introduces redundancy and adopts anti-paradigm design methods to make the data warehouse not a database product in the traditional sense, but a data collection platform. Its meaning is to organize and manage multiple data, additionally mine data resources, and use comprehensive analysis tools to provide a basis for management decision-making [7]. So far, there is no absolute definition of data warehouse, and the definition given in the expert book is generally accepted: the data warehouse is topic-focused, integrated, and nonvolatile, data collection reflects time variation, and it uses decision-making support. A data warehouse is a form of organization used to store and manage information and data. Its physical nature is still a computerized data storage system. However, since the purpose of use is different, it is necessary to compare the quantity and quality of the stored data. The data warehouse function is shown in Figure 1 [8].

*3.2. System Business Architecture Design.* According to the analysis of user needs, the system architecture generally consists of a support layer, a business layer, and a management layer: from the support layer, it includes a system management subsystem and an interface management subsystem. From the business level, it includes customer management subsystem and credit rating subsystem, credit management system, loan management subsystem, post-loan management subsystem, non-asset management subsystem execution, credit line management, and early warning subsystem throughout the entire process. From a

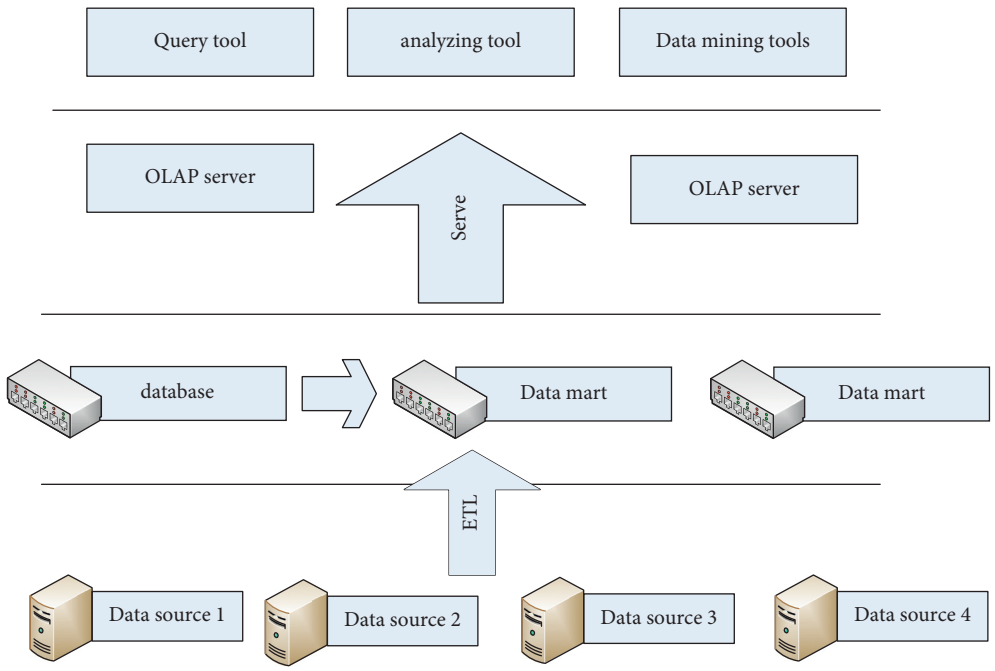


Figure 1: Schematic diagram of data warehouse functions.

management point of view, it includes a report query subsystem, a decision analysis subsystem, and a BCU supervision subsystem. The business architecture of the system is shown in Figure 2 [9].

The system architecture adopts the MVC design pattern, which separates the input, processing, and output of the system. Applications using MVC are divided into three core components: model (M), view (V), and controller (C). They each deal with their own tasks. The modules in the system are loosely coupled. The interaction between each module is realized through the interface access defined by each. One module is not allowed to directly access the database tables involved in another module. The figure is the interface that the user sees and interacts with. For previous Web applications, the viewer interface contains HTML elements. In today's Web applications, HTML still plays an important role, but some new technologies have emerged one after another, including Adobe, Flash, and some markup languages, as well as XHTML, XML/XSL, WML, and other Web services, and it is harder to deal with application interface issues. One of the greatest benefits of MVC is that it can handle many different views for the application. In fact, there is no real visual processing even if the data are stored online or the employee list, the view can only be used as a way to output the data and allow users to manipulate it [10].

*3.3. System Function Design.* Because the bank credit risk control system involves a wide range of external systems, with numerous input data, complex functions, and rigorous processes, it is unrealistic to describe all functions and processes one by one in a paper. The article uses credit rating as a typical function. Carrying on the key analysis, the design and realization of other functions can draw inferences from one another, and so on. Here, we take credit rating as an example to illustrate its functional design. After analyzing its main business process, the details of its business process can be further deepened, as shown in Figure 3 [11].

After an in-depth analysis of the business process of credit rating, the main functional module structure can be summarized, as shown in Figure 4.

*3.4. Construction of Indicator Data Mart.* Risk prediction must first determine the object of evaluation. Obtaining data through risk indicators is one of the important methods. A risk assessment model is a combination of risk indicators. A single risk indicator explains a single risk point. These indicators can be combined because of different risk assessment models to serve different management goals flexibly. Risk indicators are indicative descriptions of risk points in data mining. Risk indicators should be classified from different perspectives. Individual lenders are taken as an example to analyze the construction process of risk indicators [12].

The "5C″" evaluation standard is taken as an example to sample and extract data. From the "5C″" evaluation criteria, it can be seen that the following five aspects should be considered: financial strength, qualifications, operating conditions or business cycles, character and prestige, and analysis of the borrower's credit status. The sampled data should include the information of the five aspects. However, in actual operation, not all data items can be used as factors for analyzing the credit of the borrower. It must be combined with the expert evaluation method to determine the risk index system for the collected data.

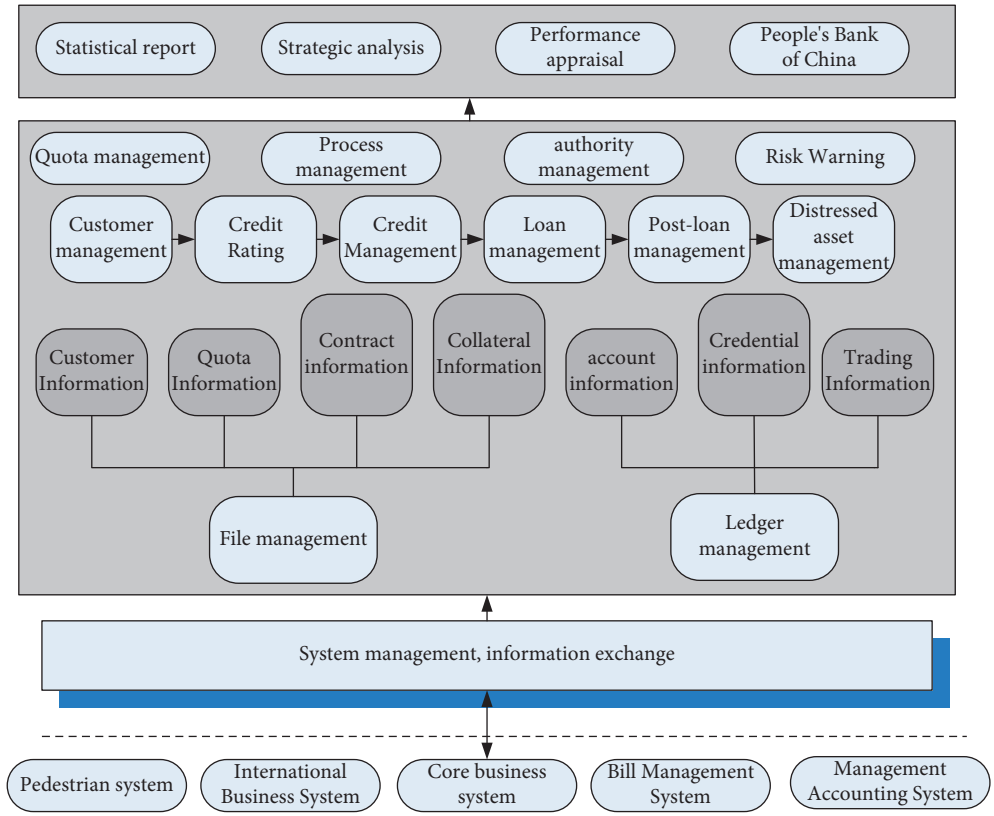


Figure 2: Layered diagram of system business architecture.

The "5C" method is used to analyze the credit status of the borrower from five aspects: character, capacity, capital cash, collateral, and condition.

Through comprehensive consideration to evaluate the credit of the lender, the following four factors should be considered: the professional situation of the borrower, the business dealings with the bank, the family situation, and the natural situation of the borrower [13]. Each factor can include the following factors.

Family situation: family monthly per capita income and debt-to-income ratio.

Occupation status: company nature, title, position, working years, and monthly income.

Business dealings with banks: accounts, business dealings, deposits, and loans.

Natural conditions: gender, education level, age, marriage, health status, and housing nature.

The external data of the risk control system come from the bank's data warehouse, which provides historical business data of the bank, most of which are standardized structure data, while the data of the risk control system come from the risk data mart. Personal credit information in the system mainly includes "personal basic information form" (name, ID number, gender, education background, residential address, marital status, occupation, position, job title, working years of the unit, industry, annual income, communication telephone, etc.) and "personal credit information form." The fields collected according to risk indicators are shown in Table 1 [14].

Among the 25 factors collected, some are not suitable as data for the general credit scoring model and should be adjusted again. For example, the main source of income, contact address, and contact phone number should be deleted.

The quality assurance of data cleaning includes the accuracy, consistency, completeness, completeness, and validity of the data. The data uploaded by the data market must ensure that the above functions are realized. Table 2 is an example of some types of data source errors. Data cleaning must first complete the completeness of the data, then perform a consistency check and accuracy check when the data are completed, and finally fill in the missing data, splicing the split wrong data, and so on. The data preprocessing process is shown in Figure 5 [15].

In the process of data preprocessing, the missing data required for the calculation of the risk control system will be supplemented by manual Excel upload. Manual data supplementary recording will be operated through a browser, and at the same time, functions such as setting up, uploading, verifying, reviewing, and downloading supplementary data will be realized.

Banks face a variety of risks all the time in their daily business activities, these risks are not isolated and unrelated, but mutual influence and interconnection. Therefore, commercial banks must conduct multidimensional management of the risks they face. Multidimensional risk management integrates the risks faced by banks from multiple angles and provides technical

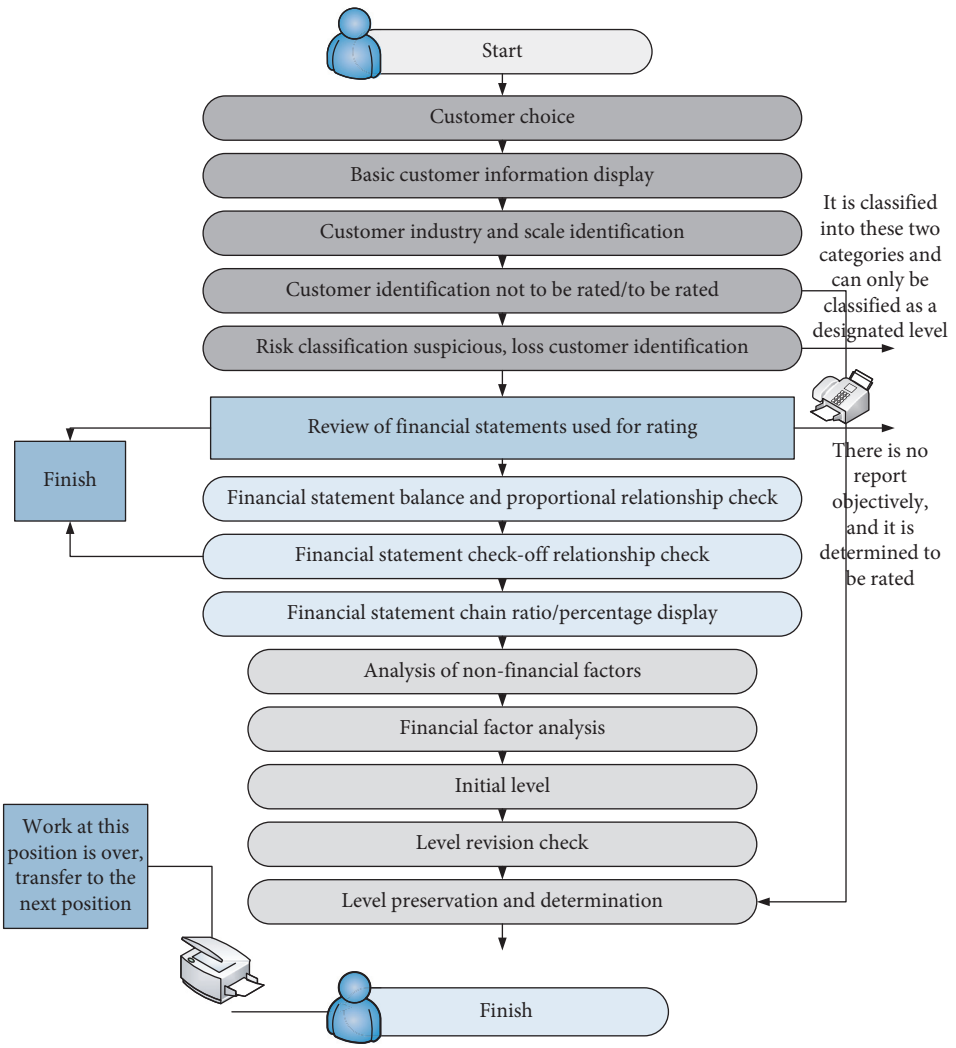


Figure 3: Flow chart of credit rating "preliminary evaluation."

support for bank risk prevention and control. Credit risk multidimensional analysis is to perform statistics, analysis, and mining on the intermediate table data that have been loaded in the indicator library to find out the potential risks in loan customers. The analysis theme will be determined first, and then, the model will be designed based on the analysis theme.

CreditRisk + Model

The model does not make assumptions about the causes of defects, but it is a random event by default, and people cannot predict the time and number of defects. If the default scale of each loan is small and the defaults of each loan are independent of each other, it can be verified that the number of default events in the portfolio follows a Poisson distribution, which is as follows:

$$\Pr(\text{nbreachesoccurred}) = \frac{e^{-L}L^{n}}{n!}. \tag{1}$$

$$G_j(z) = \sum_{n=0}^{m} P(\text{nbreachesoccurred})zm = \sum_{n=0}^{m} \frac{e^{-L}L^{n}}{n!} z^{m!} = e^{-L_j+L_j z^{l}}. \tag{2}$$

The probability generating function of the portfolio is as follows:

$$G(z) = \prod_{i=1}^{m} Gi(z) = e^{-\sum_{fm1}^{n} L_j}. \tag{3}$$

It can be deduced that the probability that the loss is nL is as follows:

$$p(nL) = \frac{d^{n}G(z)}{n!dz^{n}}\beta_{z=0}. \tag{4}$$

*3.5. Raw Data Processing.* We mainly use the data of the gravity sensor to process the raw data collected by the collection system. The main work is data calibration and movement status recognition. In daily life, the user may spend most of the time the mobile phone is not in use but is habitually thrown on the table. Therefore, this part of the data cannot be used as user behavioral habits for learning. The reason for this part of the data will be briefly described here: when the WeChat and other applications pushed

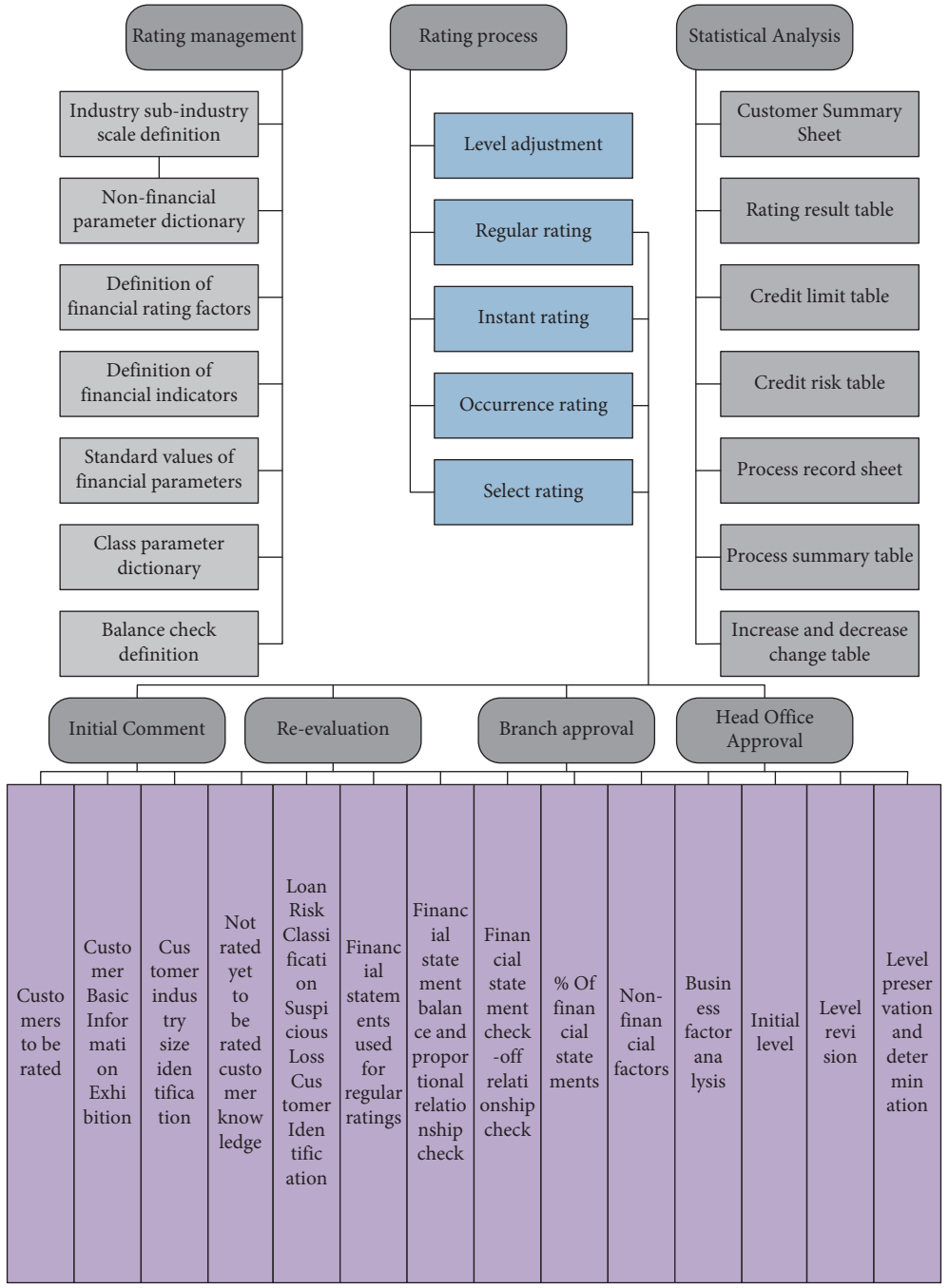


Figure 4: Credit rating function module structure.

information, the user did not pick up the phone, but the phone screen is automatically lit and the application is in the loading stage at this time, so the article work will collect sensor data within 3s. There can be a clear dividing line to define the characteristics of the gravity sensor data of this part of the smart terminal placed on the plane and the gravity sensor data used by a user in a normal state:

$$\left\{-1.5 < X_{gr}(k) < 1.5\right\} \cap \left\{-1.5 < Y_{gr}(k) < 1.5\right\}. \tag{5}$$

$$\left\{9 < \left|X_{gr}(k)\right| < 10\right\}. \tag{6}$$

We use the difference between the acceleration sensor and the gravity sensor to analyze the user's motion state. Since whether the user is in motion or not is directly related to the acceleration that the user is in, and the acceleration sensor value of the smart terminal is synthesized by the user's acceleration and gravitational acceleration, so the difference is the absolute acceleration of the user, (7) defines the absolute acceleration.

$$d(i) = \left(X_a(i)X_{gr}(i),\ Y_a(i) - Y_{gr}(i),\ Z_a(i) - Z_{gr}(i)\right). \tag{7}$$

$$\frac{\sum_{i=1}^{K} |\vec{d}(i)|}{K} \rangle |\vec{A}|. \tag{8}$$

Table 1: Collected data.

| Variable | Type | Width |
|---|---|---|
| Gender | String | 2 |
| Age | String | 4 |
| Marital-status | String | 4 |
| Education | String | 12 |
| Industry | String | 30 |
| Position | String | 40 |
| Title | String | 12 |
| Working_year | String | 12 |
| Hous_ state | String | 12 |
| Economic_sources | String | 20 |
| Address | String | 40 |
| Telephone | String | 16 |
| Health_ state | String | 4 |
| Credit_card | String | 2 |
| Health_card | String | 2 |
| Endowment_ card | String | 2 |
| Deposit | String | 2 |
| Income_ren_ months | Number | 10DEC:0 |
| Loan amount | Number | 10DEC:0 |
| House_income_y | Number | 10DEC:0 |
| Repayment-months | Number | 10DEC:0 |
| Income_months | Number | 10DEC:0 |
| Default _payments-m | Number | 10DEC:0 |
| Cumulative_default_m | Number | 10DEC:0 |
| Asset_liability | Number | 10DEC:0 |

Table 2: List of common partial errors.

| Error type | Error example | Revise | Error index |
|---|---|---|---|
| Data correctness | Customer liability amount -999999.999 | The debt amount cannot be negative, and it may be an error in the data report but cannot be determined, so to ensure accuracy, only this piece of customer data can be removed. | 0.02 |
| Consistency error | Contract ID: CD53321312032013 corresponds to two loan customers A and B | It may be that the customer name is duplicated, and the customer ID can be used to rematch | 1.21 |
| Split error | Registration area: the area name is split | Concatenate the split fields | 2.15 |
| Integrity error | The ID of a contract participant cannot be associated | Eliminate such invalid data | 1.56 |
| Missing data | Participating subject industry type is empty | Rematch according to the industry ID of the participant | 3.21 |

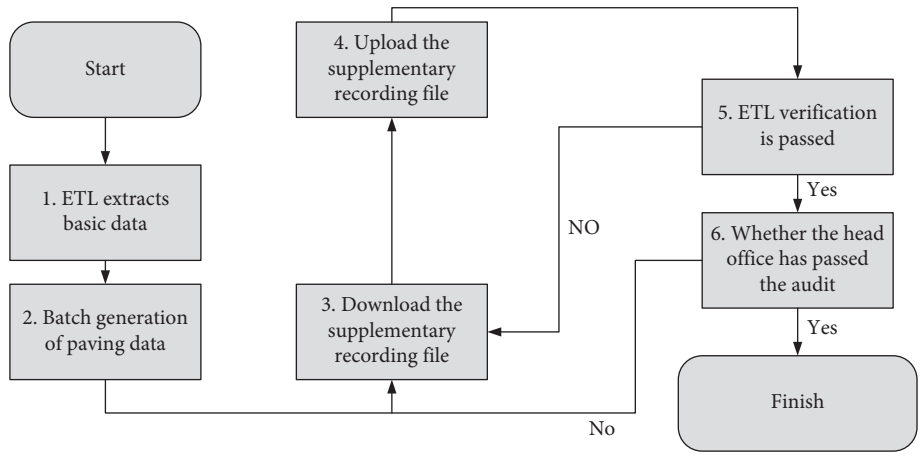


Figure 5: Data preprocessing process.

The model uses motion sensor data to distinguish user characteristics. However, this part of the data is a set of data arranged in time series, and traditional classification algorithms cannot be used directly to calculate on this set of data. Table 3 shows the data collected by our collection service within three seconds of users. This part of the data is discrete time-series data and does not reflect the user's operating habits during this time period. Therefore, the work in this study extracts a series of feature values from the original data to describe the user's exercise habits.

First, we segment the original data into 0.2s-segment segments, so that there are 10 sensor data in every 0.2s, and we extract the 0.2s behavioral features based on these 10 sensor data. In the following, the features of this set of data are described as a vector with $p$ feature values. Among them, the subscript $i$ represents the ith group of vectors:

Table 3: Data collection table.

| Sensor | $t = 0$s | $T = 0.02$s ~ $t = 2.98$s | $T = 3$s |
|---|---|---|---|
| Xa | 2.84935 | ..... | 2.989334 |
| Ya | 6.2918396 | ..... | 5.9676056 |
| Za | 4.96371 | ..... | 6.8680725 |
| Xgy | -0.008712769 | ..... | -0.0062561035 |
| Ygy | 0.02015686 | ..... | -0.06413269 |
| Zgy | 0.011703491 | ..... | -0.021270752 |
| Xgr | 2.9546714 | ..... | 2.9980776 |
| Ygr | 6.3256245 | ..... | 5.9881134 |
| Zgr | 6.8867106 | ..... | 7.1641064 |

$$Fi = \{F1_i, F2_i, \ldots Fp_i\}. \tag{9}$$

We adopted a 50% sliding window and chose a balanced scale between the amount of calculation and accuracy:

$$\left\{X_a(k), Y_a(k), Z_a(k), X_{gy}(k), Y_{gy}(k), Z_{gy}(k), X_{gr}(K), Y_{gr}(K), Z_{gr}(K)\right\}_{K=1}^{10} \Rightarrow F1. \tag{10}$$

$$\left\{X_a(k), Y_a(k), Z_a(k), X_{gy}(k), Y_{gy}(k), Z_{gy}(k), X_{gr}(K), Y_{gr}(K), Z_{gr}(K)\right\}_{K=5}^{15} \Rightarrow F2. \tag{11}$$

Table 4 describes the average AVG and standard deviation STD of these values. It can be seen that the average radius is much smaller than the average Euclidean distance between cluster centers. Therefore, we believe that the user's motion sensor data can be used as the user's electronic fingerprint for user identity authentication.

Our system uses these statistical features described in Table 4 and extracts 56 feature values through the above sliding window method:

Average value:

$$\frac{\sum_{K=1}^{K} x(K)}{K}. \tag{12}$$

Maximum value:

$$\max\{x(k) | k \in \{1, \ldots K\}\}. \tag{13}$$

Standard deviation:

$$\sqrt{\frac{\sum_{K=1}^{K} \{x(k) - \overline{x}\}^2}{K-1}}. \tag{14}$$

Minimum:

$$\min\{x(k) | k \in \{1, \ldots K\}\}. \tag{15}$$

Average difference:

$$\frac{\sum_{K=1}^{K} |x(k) - \overline{x}|}{K-1}. \tag{16}$$

Zero crossing rate:

$$\frac{\sum_{K=0}^{K-1} \| \operatorname{sgn}([x(k+1)]) - \operatorname{sgn}[x(k)] \|}{K}. \tag{17}$$

Root-mean-square value of skewness:

$$\frac{\sum_{K=1}^{K} [x(k) - \overline{x}]^3}{K\sigma^3}. \tag{18}$$

Kurtosis:

$$\frac{\sum_{K=1}^{K} [x(k) - \overline{x}]^4}{K\sigma^4} - 3. \tag{19}$$

Average Euclidean distance:

$$\frac{\sum_{K=1}^{K} \sqrt{x(k)^2 + y(k)^2 + z(k)^2}}{K}. \tag{20}$$

The model of sample storage in the cloud is shown in Figure 6. In the preprocessing operation, the data collected each time will be divided into a static state and a motion state. Then, this time the data will be stored in the corresponding location in the form of a single file and contain a triple tuple (timestamp, motion state, and file absolute path) to describe it.

## 4. Financial Risk Control and Audit

To facilitate the calculation results, the indicator scores are adjusted accordingly, and the total is taken. The weights are as follows: transaction asset evaluation (13%), core enterprise strength evaluation (25%), supply chain operation status (30%), and financing company evaluation (32%). In addition, supply chain finance emphasizes risk management in the transaction process, so it is the focus. When designing the form, first the strength of the core business is checked, its strength is understood, the operation of the supply chain is understood, and transaction attributes are checked. The second is the evaluation of small- and medium-sized enterprises. The four dimensions add up to 100 points, as shown in Table 5 [16].

Table 4: User data gap assessment table.

| | Still | Execute |
|---|---|---|
| AVG (ri) | 7.27 | 5.31 |
| STD (ri) | 7.24 | 1.93 |
| AVG (dcij) | 10.66 | 18.83 |
| STD (dcij) | 4.47 | 10.02 |

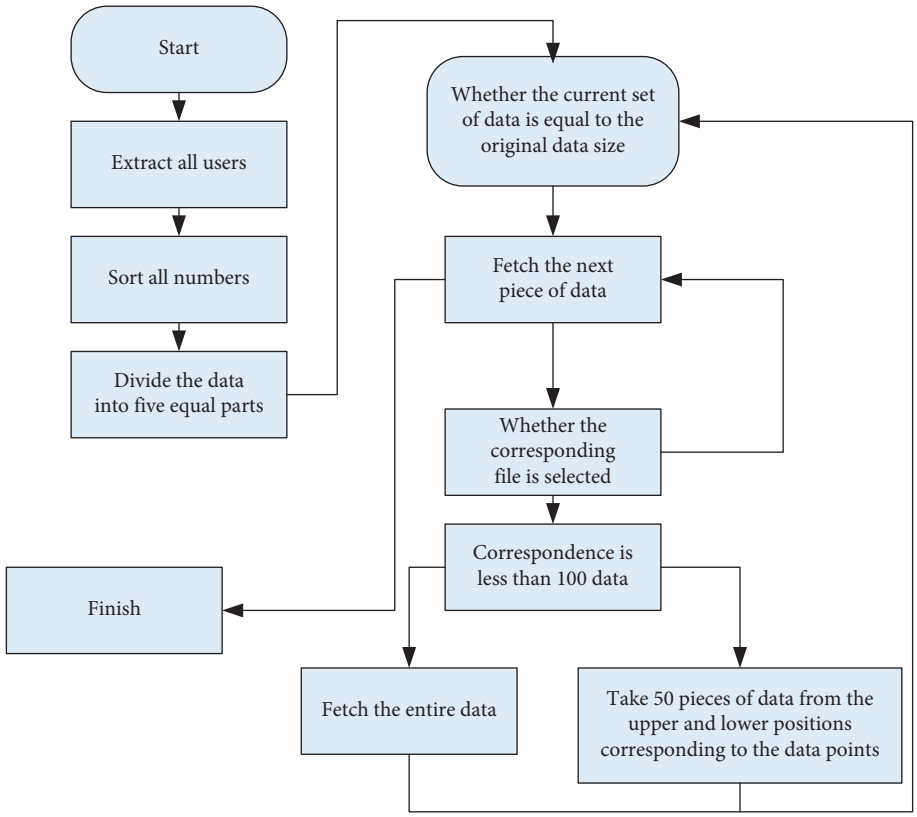


Figure 6: Flow chart of stratified sampling.

Table 5: Supply chain finance credit rating score.

| | Core enterprise strength evaluation | | | | | |
|---|---|---|---|---|---|---|
| First level indicator | Comprehensive strength (11 points) | | Industry evaluation (9 points) | | Contingent liabilities (5 points) | |
| Secondary indicators | Industry status (7 points) | Credit rating (4 points) | Industry development stage (4 points) | Industry environment (5 points) | External guarantee situation (3 points) | Potential legal dispute (2 points) |
| Index description | Comprehensive evaluation of the company's total assets, sales revenue, and industry rankings | The credit rating of the company in the rating agency or banking system | Emerging industries, growing industries, mature industries, declining industries | Comprehensive judgments of the industry's political environment, competition status, legal environment, etc. | Measured by the ratio of the guarantee balance to the company's net assets | Whether there is a large amount of contract disputes or legal proceedings affecting the reputation of the company |
| Score | High: 7 points<br>Middle: 4 points<br>Low: 2 points | AAA: 4 points, above AA: 3 points, above A: 1 point, below A: 0 points | Mature industry: 4 points<br>Growth industries: 3 points<br>Declining industries: 1 point, thriving industry: 1 point | Good: 5 points<br>Middle: 3 points<br>Bad: 1 point | | None: 2 points, yes: 0 points |
| | 1.536 | 5.5453 | 3.57857 | 7.13462 | 2.57 | 1.657 |

The credit rating is shown in Table 6.

Case analysis takes the upstream supplier S company as an example, and K bank and S company have regular business transactions, dealing with current loans, bank receipts, bills of exchange, securities, discounts, and other credit services and liquid loans. So far, the bank has accumulated more than 40 million yuan in collection fees, and it has a good historical credit. Figure 7 shows the company's main financial indicators from 2018 to 2019.

S Group is a state-authorized investment institution and state-owned enterprise. It is a comprehensive petroleum company that implements the integration of upstream, midstream, and downstream production and marketing, and cross-border and cross-industry operations. *Z* Petroleum Group has a strong momentum, strong comprehensive energy, high credibility, and a comprehensive energy rating of 11 points. Over the past five years, the overall domestic petroleum industry has been operating relatively robustly, with the output of most products increasing at a rate of 1° per year. Due to the slow growth of consumer demand, the growth rate of refined oil consumption was initially lower than expected. In 2015, the national crude oil processing volume was nearly 467.9 million tons, a year-on-year increase of 3.73%. In 2016, the domestic crude oil output was nearly 208.25 million tons, a year-on-year increase of 1.7%. The crude oil processing volume was nearly 44.398 billion tons, an increase of 6.9% over the previous period, and the industry appreciated. The level is 9 points. The external guarantee rate does not exceed 50%, there are no contract disputes and lawsuits that affect the company's reputation, and there are 3 points for contingent debts.

80% of S company's accounts receivable are well managed and the account period is short, and they can all be restored within one year. 1 point is calculated for the billing period and ageing. The company basically has no repurchase positions, the return record is given 2 points, the lender's accumulated debt ratio is less than 1% and is given 2 points, and the total transaction asset valuation is 10 points [17].

S company's products are widely used in the energy field. The energy industry is a state-supported industry with a relatively high growth rate. The company government supports the development of small and medium enterprises and implements priority policies such as tax relief and loan interest relief. *Z* Petroleum Group has cooperated with S company for many years [18]. The way of cooperation is to sign a cooperation agreement for the following year at the end of each year, which includes fees, packaging conditions, adoption procedures, settlement procedures and deadlines, liability for breach of contract, and dispute resolution procedures. *Z* Petroleum Group uses the ERP system to place orders with suppliers at the beginning of the month, providing information such as the number of products required per month and the delivery date. The company arranges related products according to the content of the order, puts the products and invoices to the place of delivery designated by the Petroleum Group, and prepares to receive the goods. The duration is 120 days. Therefore, in the evaluation of the supply chain index S by K Commercial Bank, the relationship length is 7 points, the relationship strength is 11 points, and the past performance is 3 points. The status of third-party logistics companies in the industry is not high, but the warehouse management is relatively standardized, and a relatively complete database gets 5 points. All projects are scored according to the position of the S company, with a total score of 86. It is an A-level company worthy of the credit and reputation of commercial banks. All participating companies depend on each other in the supply chain to provide funds for credit risk, and the credit supply chain plan must address all levels of credit risk, but in fact, each level can only raise this aspect of credit risk management to a standard level. Credit incidents of upstream and downstream companies may harm the interests of these companies [19].

The nonperforming loan ratio from 2014 to 2020 remained at a relatively low level, which was 0.03% in 2016. After 2016, the management continued to withstand capacity risks, and the management bank K was in a downward market, and the loan rate showed no upward trend. In 2017 alone, nonperforming loans reached 745 million yuan, and the nonperforming loan ratio was 1.8%. This is also the first time that K Commercial Bank has seen total nonperforming loans. At the end of 2013, the balance of nonperforming loans was 649 million yuan, and the nonperforming loan ratio was 1.03%. The nonperforming loan ratios in 2019 and 2020 are 0.88% and 1.15%, respectively [20]. Although both were lower than the city's commercial banks' nonperforming loan ratio of 1.37% that year, they were still at a relatively high level for newly built and rapidly developing commercial banks. It can be seen that in our city, since the establishment of K Commercial Bank, the nonperforming loan rate has increased, mainly due to problems in bank information management and credit risk disclosure. From Figure 8, we can see the supply chain trend of financial risks so far [21].

The financing company currently provides pre-loan evaluation materials for K Commercial Bank loans. Because interest rates are flat, loans are unfair to borrowers in different risk situations, and low-risk loans will not get higher returns. Once the bank lends, the lender may bring moral hazard to the bank, because the lender can provide the company with false business information to maintain a higher interest rate, and the commercial bank will not be able to obtain accurate business information, nor can it accurately assess business operations.

When developing financial supply chain business, the four parties need to work together [22]. The basic business development process is shown in Figure 9.

In summary, the company obtained additional credit funds from K Commercial Bank after using hedging. Taking into account the margin expenditure, the company's actual capital use is also greater than the traditional financing business. Finally, the effective introduction of hedging avoids market risks caused by commodity price fluctuations, guarantees the credit protection of K Commercial Bank, and realizes market risk management.

Table 6: Credit rating.

| Score | Credit rating | Credit status | Numerical value |
|---|---|---|---|
| 90 points (inclusive) or more | AAA | Credit excellence | 56 |
| 80 points (inclusive)-90 points | AA | Good credit | 26 |
| 70 points (inclusive)-80 points | A | Good credit | 34 |
| 60 points (inclusive)-70 points | BBB | Average credit | 254 |
| 50 points (inclusive)-60 points | BB | Poor credit | 2156 |
| 40 points (inclusive)-50 points | B | Poor credit | 26 |
| 30 points (inclusive)-40 points | CCC | Bad credit | 31 |
| 20 points (inclusive)-30 points | CC | Very bad credit | 155 |
| 10 points (inclusive)-20 points | C | No credit | 261 |
| 10 points or less | D | No credit | 12 |

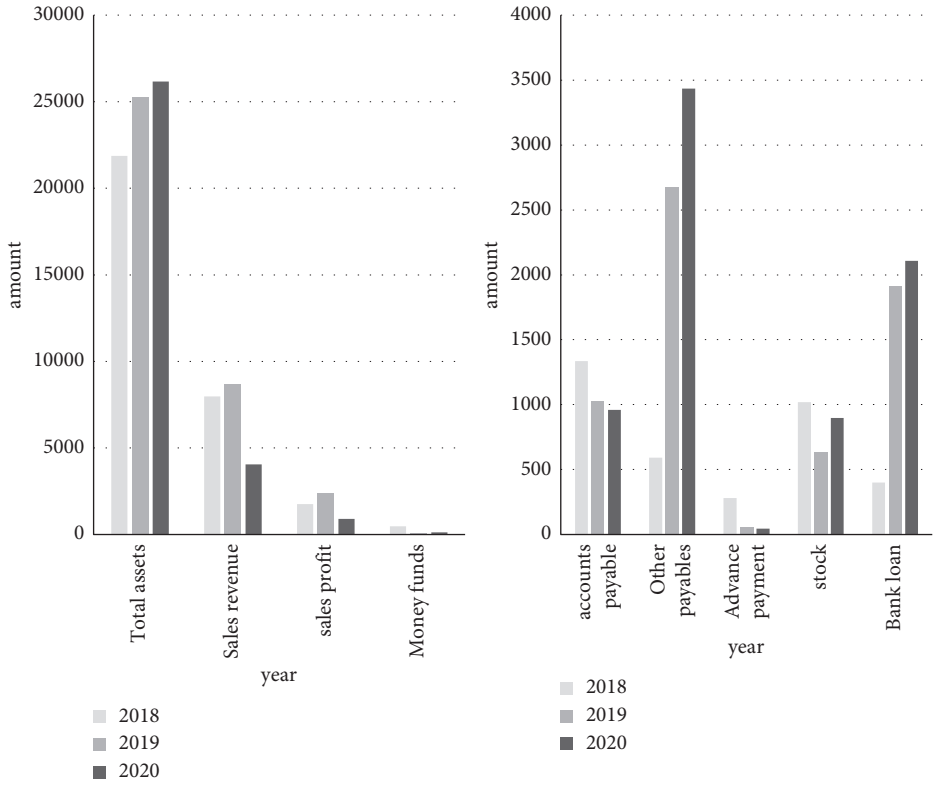


Figure 7: Company's main financial indicators from 2018 to 2020.

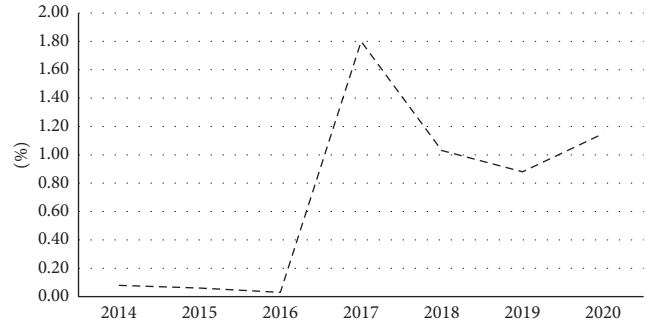


Figure 8: Trends in the NPL ratio of K Commercial Banks.

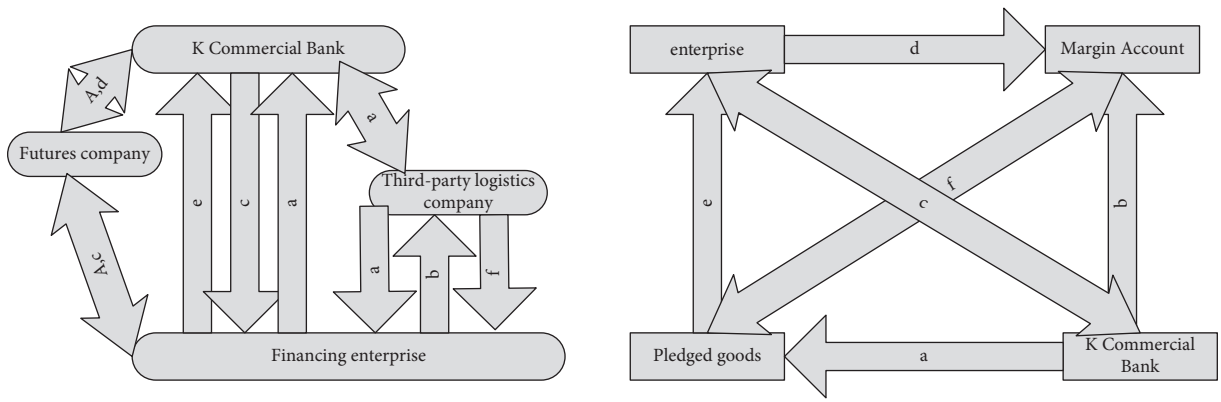


Figure 9: Risk control process in different situations. After using hedging, the business is compared, as shown in Figure 10.

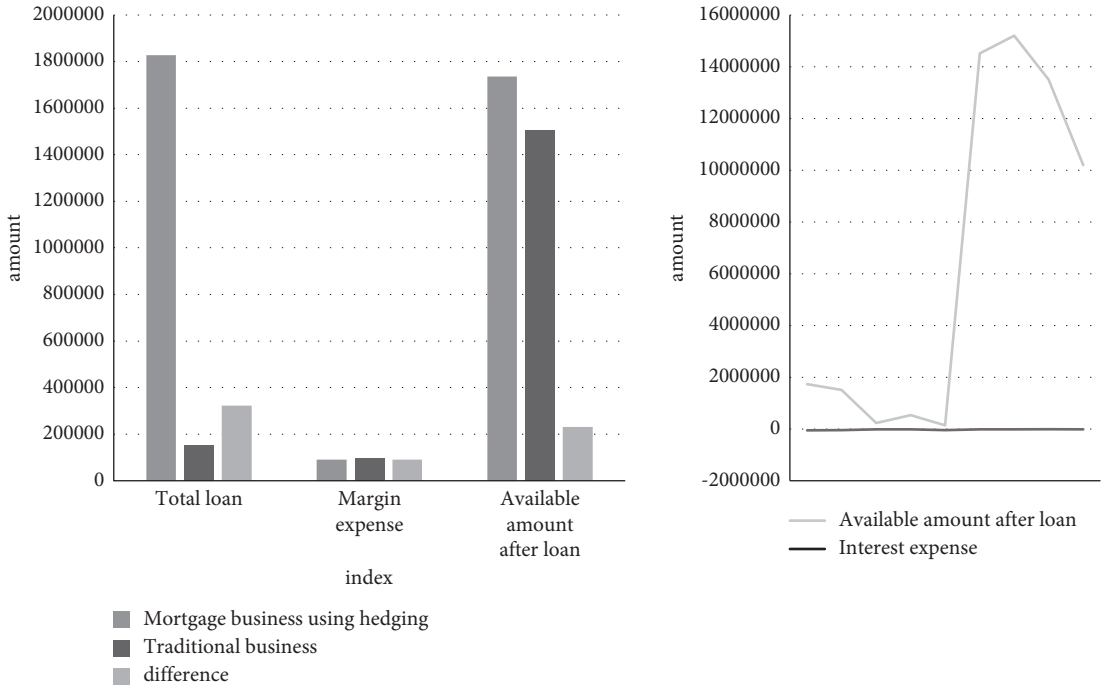


Figure 10: Comparison of the introduction of hedging business and traditional business.

## 5. Discussion

The article is based on the development of bank financial supply chain business, using literature research, comparative analysis, case analysis, qualitative and quantitative analysis, and other methods, including supply chain management theory and comprehensive risk management theory. Combining the development status of K Commercial Bank's financial supply chain business and three typical risk cases of K Commercial Bank, it examines the main theories of the agent, introduces the principle chain of financial supply risk analysis, quickly analyzes the basis for risk selection, and the supply chain financial credit rating. In the follow-up research, the supply chain financial risk management was investigated, and combined with the theoretical consequences of supply chain risk, it provided a method for improving the level of financial supply chain risk management, and the research results obtained are as follows [23].

K Commercial Bank launched an accounts receivable financing model for upstream financial supply chain companies. At present, the business background of risk management under this model is incomplete, and there are serious problems in dealing with the credit risk of key businesses, ineffective implementation of rules and regulations, and insufficient incentive and restraint mechanisms. Therefore, it is necessary to strengthen the audit of the validity of accounts receivable, prevent small and medium-sized enterprises from transferring accounts, do a good job in the payment management of CNPC's main business, and establish an account receivable financial management information ledger, and using scientific and technological means to strengthen the response and management of accounts receivable financing, establish an early warning

mechanism for customer financing risks, establish a special accounts receivable financial management department, cultivate professional talents, and effectively solve problems.

At this stage, K Commercial Bank created an integrated warehouse management financing model for financial companies under the supply chain. The risk management of this financing model is not commensurate with the bank's information technology and risk management system, and the professional quality of the practitioners needs to be improved. Progress measures include improving internal control, selecting third-party logistics with good credit ratings, setting a reasonable pledge rate, determining the source of funds, and using future resource hedging functions to correct market risks. For financial companies with upstream and downstream supply chain connections, K Commercial Bank has launched an inventory pledge investment model. The risk management of this financing model is that the involvement of third-party logistics companies increases financial risks and transfer risks. There are dual-negative effects between banks and enterprises. It can manage the risk management points of the financial operation of the entire supply chain and adopt the method of setting a reasonable rate of return and presenting financial resources to avoid market risks. At the same time, we must pay attention to the management of market risks and the management of future margin accounts. Finally, the purpose of avoiding risks and continuous improvement is achieved.

The risk management system mainly performs the following functions: 1. realizing risk prediction before borrowing, predicting the potential loan default risks of loan customers, and providing preliminary judgments for bank credit and credit approval personnel; 2. realizing post-loan risk monitoring and early warning, excavating loan customer account information, related party information, capital flow, and other information, dynamically monitoring loan customers, and providing services for banks to detect and avoid risks in a timely manner; 3. considering the aggregated information before, during, and after the bank's credit granting, integrating the previously divided information, and analyzing and predicting the credit risk of loan customers; and 4. enhancing the bank's credit management and risk control capabilities. Through data mining, the loan investigation cycle is reduced, the model is used to analyze the data, and the prospectiveness of bank risk monitoring is improved [24].

The system is currently operating stably. The report data obtained from the system display layer are consistent with the data pushed by the bank's front-end system. According to the banking business needs, new reports are continuously developed and regularly pushed to the report database to provide visual query and analysis functions for the service bank and regularly pushing the demand solidification report of each risk control project.

## 6. Conclusion

In the article, the risk control system is introduced. The method based on machine learning provides two modes of offline user authorization and authentication and online user authorization and authentication. Through the learning of the user sensor model, we have trained a model for the user to use the smart terminal, which is used to describe the specific way the user uses the device. Different from previous related research studies, we have no specific requirements on the user's exercise state and the placement of the equipment, and the user can train his own user model unconsciously. In addition, the ideal verification mode provided by the work in this article allows users to provide continuous authentication to users when the network is disconnected or the network environment is poor and to protect users' smart terminals anytime and anywhere. Through the data research of large-scale users, our system adopts the method of stratified sampling and semi-supervised learning to solve the problems that arise in the actual application environment such as unbalanced data sets and unlabeled data. This set of learning mechanisms enables the work of this study to perform user identification and authentication through data collected from enterprise suppliers. Due to the limited time and ability, this article has many shortcomings, which require continuous research and analysis. The research of the article is mainly based on K Commercial Bank, starting from the supply chain finance business model, and mainly considers the problem of commercial bank K supply chain financial risk management, so that in the next step, we can continue to study how to use bank financing to improve company performance from the perspective of K Commercial Bank to accelerate the company's capital operation, so that the company can get more benefits. It can also start to study the problem of gradual mergers from the capital level. The content of capital finance and logistics can be further discussed. As the core enterprises of the supply chain, K Commercial Bank and *Z* Petroleum Group have natural business advantages that other commercial banks in the town cannot match. Using CNPC's big data platform and industry financial information to further expand the supply chain, commercial finance is the key aspect that needs to be considered in the next step of how commercial bank K's supply chain finance manages risks. What we are taking is a new microloan technology innovation road of data plus the Internet. Regardless of whether it is the Internet or data, all that can be grasped is information, not assets; that is, Ali's approach to risk control is to have accurate judgments and correct decisions on risks and to control losses within an acceptable proportion. It is not the compensation that can be obtained after a certain business decision fails. This method of evaluating credit based on the Internet and past transaction data of enterprises may be the future direction of development, as well as the direction of future improvement and perfection of our system.

## 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.

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