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*Retraction*

# Retracted: Evaluation of SMEs' Credit Decision Based on Support Vector Machine-Logistics Regression

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## References

[1] R. Xie, R. Liu, X. Liu, and J. Zhu, "Evaluation of SMEs' Credit Decision Based on Support Vector Machine-Logistics Regression," *Journal of Mathematics*, vol. 2021, Article ID 5541436, 10 pages, 2021.

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*Research Article*

# Evaluation of SMEs' Credit Decision Based on Support Vector Machine-Logistics Regression

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This article uses support vector machines, logistics regression, and other methods for the comprehensive evaluation of credit decision-making of small, medium, and microenterprises and comprehensively uses software programming such as MATLAB and SPSS Modeler to solve the problem. The results, such as credit risk evaluation index system, credit risk classification model, and credit decision-making comprehensive evaluation model, are obtained. Finally, this article starts from the credit decision of small, medium, and microenterprises and provides theoretical and practical suggestions for banks to control the risks of small, medium, and microenterprises and their own development.



## 1. Introduction

In the context of economic globalization, our country's economy is booming. Small- and medium-sized enterprises, known as the "new economic turning point," have sprung up. They have played a huge role in the country's industrial upgrading and economic construction and have gradually become the economic pillars of various regions. However, under negative conditions such as inadequate economic volume, loose economic system, and high financing costs, small, medium, and microenterprises are gradually in a disadvantaged position under the background of environmental competition and face the risk of being merged by companies in the same industry. They urgently need to "make blood" for enterprises through direct financing and indirect financing and solve the problem of financing difficulties, which is a stumbling block on the development of small, medium, and microenterprises.

The main reasons are the following two aspects: on the one hand, due to the pressure of the competitive environment in the same industry, small, medium, and microenterprises cannot provide the same accurate and reliable assessment information as mature enterprises, which causes commercial banks to face the challenge of credit risk management; on the one hand, due to a loose management system and insufficient managerial experience, legal loopholes and moral hazards appear, which affect the order of the credit market and disrupt the market balance. Nowadays, encouraging and protecting the active development of small- and medium-sized enterprises have become a new economic trend. Banks urgently need to solve the problems of whether to lend to enterprises and how much to allocate to enterprises.

The data in this article come from the 2020 China National College Students Mathematical Modeling Contest Question C: A bank's loan amount to companies determined to lend is 100,000 to 1 million yuan; the annual interest rate is 4% to 15%; the loan period is 1 year, which is known statistics on the relationship between 123 companies with credit records and 302 companies without credit records and the relationship between loan interest rates and customer churn rates in 2019. Through the establishment of a mathematical model, the bank's credit strategy for small, medium, and microenterprises is studied under certain conditions.

## 2. Literature Review

Regarding the evaluation of credit decision-making for small, medium, and microenterprises, Gen [1] took Shandong Province as an example to analyze the causes of credit rationing misbehavior and ways to correct them and provide a way to improve the efficiency of credit rationing and realize the Pareto improvement of credit resource allocation. Wang and Tang [2] compared the allocation of bank financing opportunities and the expected loans of enterprises and found that banks' credit decisions are based on rational risk control decisions, while the discrimination against SMEs in lending is due to the recognition of both banks and enterprises, caused by gaps in knowledge and lag in cognition. Wu [3] combined the actual characteristics of SMEs and used fuzzy analytic hierarchy process to determine the weight of SME credit risk evaluation indicators and constructed a scientific and reasonable credit risk evaluation indicator system for SMEs. Li [4] believes that our country's banking industry's credit decisions on SMEs have problems such as low quality of preloan review, long loan approval cycles, and difficulty in implementing postloan management. Commercial banks should control the production and financial status of SMEs. Reasonable evaluation of its guarantee capacity will improve the quality of credit support decision-making for SMEs.

The abovementioned documents all give relevant opinions on banks' credit for small- and medium-sized enterprises, but most of them are based on theoretical research in a specific situation and do not give a more universal model that includes dynamic factors. Aiming at the abovementioned shortcomings, this paper attempts to establish a relatively general credit model by establishing a related mathematical model.

## 3. Basic Assumptions

In order to facilitate the handling of the problem, the following assumptions are proposed: (i) assuming that when banks make loan decisions to SMEs, there is no corporate loan failure; (ii) assuming that there are no changes in macropolicy when banks make loan decisions to SMEs; (iii) assumptions: the average supply and demand of available companies can represent the stable value of supply and demand; (iv) assuming that the impact of unexpected factors on the enterprise is mainly the impact on the amount of sales invoices of the enterprise; (v) assuming that the reputation of small, medium, and microenterprises is only determined by the research variables in this article.

## 4. Based on Multiobjective Optimization, the Credit Risk and Strategy Research of SMEs when the Bank's Annual Total Credit Is Fixed

*4.1. Research Thought.* It is required to quantitatively analyze the credit risk of 123 companies in the data source when the loan period is one year and when the bank's annual total credit is fixed, and for companies that are determined to lend, the loan line of each company is 100,000 to 1 million yuan, and the annual interest rate is 4%–15%; give credit strategies to these companies. Based on the existing research literature, this article assumes that the credit strategy consists of four parts: whether to lend, loan amount, loan interest, and loan period. In principle, companies with a credit rating of $D$ will not lend. First, based on relevant data, calculate the relevant index values of the upstream and downstream corporate influence, strength, supply and demand relationship stability, and customer churn rate of each enterprise; then construct a bank profit maximization model based on nonlinear regression, a credit risk minimization model based on Logistics regression, and a comprehensive evaluation system based on principal component analysis. Finally the abovementioned three optimization models are transformed into a multiobjective optimization model to obtain the bank's credit strategy [5].

### 4.2. Analysis Procedure

#### 4.2.1. Bank Income Maximization Model Based on Nonlinear Regression

*(1) Research Steps.* First, process the corresponding original data in the data source. After referring to related books, this article believes that the formula for the upstream and downstream corporate influence of each company is as follows:

$$P_{i,j} = \frac{\left(\left|\alpha_0 S_{i,j}\right| - \left|\alpha_1 C_{i,j}\right|\right)}{\left(\left|S_{i,j}\right| - \left|C_{i,j}\right|\right)} \quad (i = 1, 2, \cdots, n;\ j = 1, 2, \cdots, 12), \tag{1}$$

where $P_{i,j}$ represents the upstream and downstream influence of the $i$-th company in the $j$-th month, $S_{i,j}$ represents the sum of the output bills of the $i$-th company in the $j$-th month, $C_{i,j}$ represents the sum of the input bills of the $i$-th company in the $j$-th month, and $\alpha_i\,(i = 1, 2)$ indicates that different companies place different emphases on output and input.

In order to comprehensively evaluate the comprehensive strength of each enterprise, this article considers the actual income, expenditure, tax amount, and monthly sales volume of the enterprise. On the basis of the existing literature research in the reference part, the average monthly tax payment of each company is obtained as an index to evaluate the comprehensive strength of the company, and the following formula is obtained:

$$\Delta T_{i,j} = Log\left(\frac{\left|TI_{i,j}/S_{i,j}\right| + \left|TO_{i,j}/C_{i,j}\right|}{N_{i,j}}\right) \tag{2}$$

$$(i = 1, 2, \cdots, n;\ j = 1, 2, \cdots, 12),$$

where $\Delta T_{i,j}$ represents the average tax payment of the $i$-th company in the $j$-th month, $TI_{i,j}$ represents the tax payment of the $i$-th company's output bill in the $j$-th month, $TO_{i,j}$

represents the tax payment of the $i$-th company's input bill in the $j$-th month, and $N_{i,j}$ represents the number of sales of the $i$-th company in the $j$-th month.

According to the checked literature and actual life experience, the stability of the supply-demand relationship of an enterprise will greatly affect the income of the enterprise, which will also affect the evaluation of the enterprise by the bank, so the supply stability value coefficient $G$ and the demand stability value are constructed. The coefficient $Q$ is used to quantify the degree of stability, and the specific formula is as follows [6–8]:

$$G_{i,j} = \beta_1 \log\left(\frac{\left|C_{i,j}\right|}{N_{i,j}^1}\right), \quad i = 1, 2, \cdots, n; j = 1, 2, \cdots, 12,$$

$$Q_{i,j} = \beta_2 \log\left(\frac{\left|S_{i,j}\right|}{N_{i,j}^2}\right), \quad i = 1, 2, \cdots, n; j = 1, 2, \cdots, 12, \tag{3}$$

where $G_{i,j}$ represents the supply stability of the $i$-th company in the $j$-th month, $N_{i,j}^1$ represents the demand of the $i$-th company in the $j$-th month, $Q_{i,j}$ represents the demand stability of the $i$-th company in the $j$-th month, $N_{i,j}^2$ represents the supply of the $i$-th company in the $j$-th month, and $\beta_1, \beta_2$ is a balance parameter.

The monthly comprehensive supply stability degree and demand stability degree of each company are as follows:

$$G_i = \frac{G_{i,j}}{\sum_{j=1}^{12} G_{i,j}},$$

$$Q_i = \frac{Q_{i,j}}{\sum_{j=1}^{12} Q_{i,j}}. \tag{4}$$

The formula for a company's customer churn rate is

$$M = \frac{R}{Z}. \tag{5}$$

Among them, $M$ represents the customer churn rate of the company, $R$ represents the number of voided output bills of the company, and $Z$ represents the total number of sales bills of the company.

*(2) Result Analysis*. First of all, from the meaning of the question, companies with a credit rating of $D$ do not grant loans in principle, so this type of corporate data is excluded when allocating the total amount of loans. Then, use the above formula to calculate the customer churn rate, upstream and downstream enterprise influence, strength, stability of supply and demand relationship, customer churn rate index value, and other data of each company with reputation ratings of A, B, and C. At this time, the desire to maximize the bank's profit is to ask the bank to deduct the amount of loan income from the profitable income from deposits in the same period. The expression for maximizing bank profit based on known conditions is as follows:

$$f(x) = \max \sum_{1}^{99} A_i (r_i - r_0)(1 - z_i),$$

$$\text{s.t.} \begin{cases} 10 \le A_i \le 100, \\ 4\% \le r_i \le 15\%, \\ \sum_{1}^{99} A_i \le a. \end{cases} \tag{6}$$

Among them, $A_i$ represents the loan amount to each company, $r_i$ represents the interest rate of the loan to each company, $r_0$ represents the bank deposit interest rate over the same period, $z_0$ means customer churn rate, and $a$ represents the annual bank credit value of a fixed total amount.

*4.2.2. Bank Credit Risk Quantification Model Based on Logistics Regression*

*(1) Research Steps*. According to Section 4.2.1, the company's reputation rating is divided into A–D, and when the risk is low, the reputation rating is A, and when the risk is high, the reputation rating is D. This article uses default as the dependent variable. Default is recorded as 1, and nondefault is recorded as 0. Therefore, a company with a reputation rating of A can be assigned a risk of 0.2, a company with a reputation of B can be assigned a risk of 0.4, a company with a reputation of C can be assigned a risk of 0.6, and a company with a reputation of $D$ can be assigned a risk of 0.8, with different quantifications credit risk of credit-rated companies [9].

At this point, the solving steps based on logistics regression are as follows:

Step1: Collect relevant data according to business goals;

Step2: Standardized data;

Step3: Analyze the data and preprocess the data;

Step4: Train the algorithm to find the best classification coefficient, ① Find the $h$ function (namely, hypothesis). ② Construct $J$ function (loss function). ③ Minimize the $J$ function and obtain the regression parameters ($\theta$);

Step5: Test algorithm and model evaluation;

Step6: Get new data and convert it into corresponding structured values. Based on the trained regression coefficients, you can perform simple regression calculations on these values to determine which category the new data belongs to.

*(2) Result Analysis*. Suppose the risk of bank loans is $R$, and the value is $0 < R < 1$. The closer the $R$ value is to 0, the lower the credit risk of the company and the better the credit rating of the company; the closer the $R$ value is to 1, the higher the financial risk of the company and the worse the credit rating of the company. The influencing factors are the influence of upstream and downstream enterprises' influence, strength,

stability of supply-demand relationship, customer churn rate index value, and other indicators. Banks should minimize the total risk of loans [10–12].

The quantified data and the original enterprise data were imported into SPSS, and the normality test and significance test passed. Then, proceed to principal component analysis, and the results are shown in Table 1.

According to the screening results of the above component score coefficient matrix, redefine the name of the principal component: $N_1$ is the amount of tax contribution, and $N_2$ is the relative fluctuation of sales.

At this time, two principal component factors $N_1$ and $N_2$ are used as research variables, and SPSS is used to do forward stepwise logistic regression on these two variables. The final model statistics are shown in Table 2.

The logistic reputation risk quantification model that can be established based on the above results is as follows:

$$R = \frac{l^{-1.274-0.107N_1-0.087N_2}}{1+l^{-1.274-0.107N_1-0.087N_2}}, \\ = \frac{1}{1+e^{1.274+0.107N_1+0.087N_2}}. \tag{7}$$

*4.2.3. Quantification Model of Corporate Reputation Risk Based on Analytic Hierarchy Process.*

(1) Principal component analysis method

Step 1: Standardize the original data and calculate the correlation matrix;
Step 2: Calculate the eigenvalues and eigenvectors of the correlation matrix;
Step 3: Take the first 2–3 principal components based on the cumulative contribution rate reaching 85%;
Step 4: Explain the principal components;
Step 5: Calculate the principal component score. That is, standardize each sample data and bring it into the principal component formula of the third step to calculate the first principal component score and the second principal component score;
Step 6: Regard the principal component score as a new dependent variable that can be linearly regressed.

(2) Establish an indicator system. This article summarizes the corporate reputation risk into three dimensions, namely, debt service capacity, credit guarantee situation, and macropolicy. Based on this, it is preliminarily subdivided into 10 specific corporate reputation risk indicator systems, as shown in Figure 1.

The quantified enterprise credit risk and original enterprise index data are imported into SPSS, and its normality test and significance test are passed. According to the screening results of the component score coefficient matrix, redefine the names of the first three principal components: $N_1$ is the debt service capacity, $N_2$ is the credit guarantee situation, and $N_3$ is the macropolicy.

(3) *Model Construction.* At this time, three principal component factors are used as research variables, and $O_i$ is used as the size of corporate reputation risk, and SPSS is used to perform forward stepwise logistic regression on these two variables. Based on the above results, a logistic corporate reputation risk prediction model can be established:

$$O_i = e^{\left[\left(1+\left(1/\ln N_1\right)\right)/\left(N_2+\left(e/\ln N_3\right)\right)\right]}. \tag{8}$$

*4.2.4. A Model for Maximizing Bank Revenue and Minimizing Credit Risk Based on Multiobjective Optimization.* According to the relationship between the interest rate and the customer churn rate in the data source, the relationship between the loan interest rate and the customer churn rate of three types of credit risk companies A, B, and C is constructed. The images are established in the order of A, B, and C companies from top to bottom, and the result is shown in Figure 2.

The specific equation results are as follows:

$$z_i = \begin{cases} 7.524r_A - 0.09793 \ldots\ldots (A), \\ 7.351r_B - 0.1178 \ldots\ldots (B), \\ 7.468\, r_C - 0.1379 \ldots\ldots (C). \end{cases} \tag{9}$$

Combining the two optimization models of bank profit maximization and enterprise credit risk minimization, the optimized objective function and its limiting conditions are as follows:

$$Y = \min \sum_1^{99} R_i + \sum_1^{99} A_i\left(r_i - r_0\right)\left(1 - z_i\right) + \sum_1^{99} O_i, \\ \text{s.t.} \begin{cases} O_i = e^{\left(1+\left(1/\ln N_1\right)/N_2+\left(N_3/\ln N_4\right)\right)}, \\ 10 \le A_i \le 100, \\ 4\% \le r_i \le 15\%, \\ \sum_1^{99} A_i \le a, \\ Z_0 = a^* p_a + b^* p_b + c^* p_c \left(a^*, b^*, c^* = \{0, 1\}\right), \\ \quad (i = 1, 2, \ldots, 99). \end{cases} \tag{10}$$

At this time, a*, b*, and c* represent the total amount of loans that can be allocated to companies A, B, and C, respectively. The value of the overall function should be as small as possible. Introducing the index value of each enterprise into the model, the loan interest rate and total loan amount of each enterprise are obtained.

Table 1: Component score coefficient matrix.

| Variable Zscore | Profit | Contribution tax | Relative sales fluctuation | Purchase fluctuation size | Customer churn rate |
|---|---|---|---|---|---|
| 1 | 0.871 | 0.876 | 0.198 | 0.426 | 0.525 |
| 2 | −0.107 | −0.018 | 0.849 | 0.406 | −0.441 |

Table 2: Variable coefficients in the equation.

| Variable name | B | S. E, | Wals | Df | Sig. | Exp (B) | 95% of EXP (B) C. I. | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | Lower limit | Upper limit |
| Z (size of contribution tax) | −0.107 | 0.223 | 0.23 | 1 | 0.631 | 0.898 | 0.58 | 1.392 |
| Z (relative sales fluctuation size) | −0.087 | 0.26 | 0.113 | 1 | 0.737 | 0.916 | 0.55 | 1.526 |
| Constant | −1.274 | 0.219 | 33.868 | 1 | 0 | 0.28 | — | — |

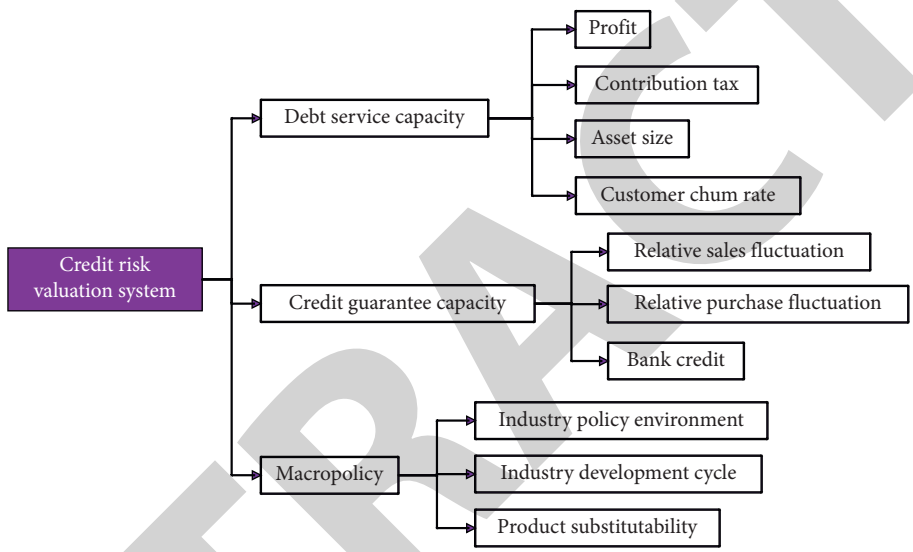


Figure 1: Corporate reputation risk evaluation index system.

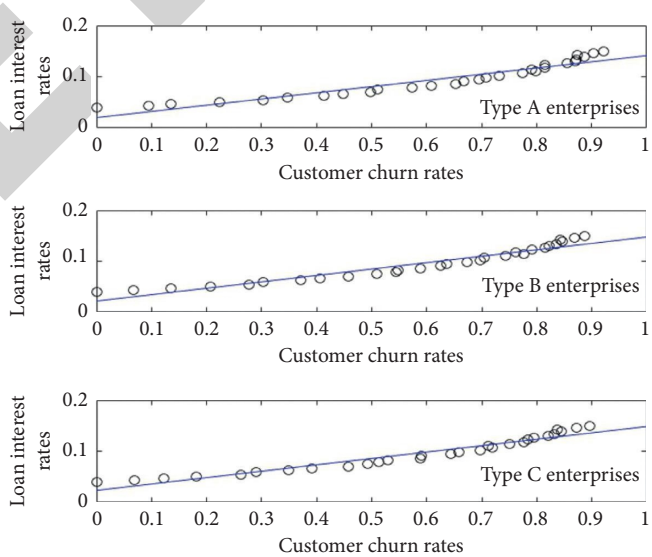


Figure 2: The relationship between loan interest rates and customer churn rates of three types of credit risk.

## 5. Research on the Classification of Credit Ratings of SMEs Based on Support Vector Machines and the Credit Risk and Strategy of Banks

*5.1. Research Thought.* It is required to quantify the credit risk of 302 companies in the data source and give the bank's credit strategy for these companies when the total annual credit is 100 million yuan. This paper first constructs a support vector machine training set to classify the reputation ratings of each company in the data source; then, according to the risk level of each company, after removing the company with a risk level of *D*, it is substituted into the model constructed in Section 4, and calculate the bank's credit strategy for 302 companies when the total annual credit is 100 million yuan.

### 5.2. Research Methods

*5.2.1. Research Steps.*

Step 1: Further process the relevant data according to the indicators in the previous section to obtain the corresponding indicator values;

Step 2: Perform normalization and cluster analysis on all data;

Step 3: Split the processed data into the training set and test set, and use support vector machine clustering analysis results to verify [13].

*5.2.2. Model Construction.* Perform cluster analysis on standardized data to obtain the proportions of all types of companies with loan records, as shown in Figure 3, and the proportion of all types of companies with no loan records, as shown in Figure 4.

Then, import the relevant data and classification results into MATLAB and perform support vector machine analysis on the accuracy of the classification results. The accuracy of the cluster analysis test set is close to 70%, and the classification results are acceptable. The classification and prediction results are shown in Figure 5 [14–16].

Based on the results of reputation risk classification, substituting into the multiobjective optimized bank revenue maximization and credit risk minimization models in the previous section [15], the partial results of the loans to enterprises and interest rates are shown in Table 3.

## 6. Credit Adjustment Strategy Model under the Influence of Emergencies Based on Analytic Hierarchy Process

*6.1. Research Thought.* This question requires comprehensive consideration of the credit risk of each enterprise in the previous section and the impact of possible emergent factors such as the new crown virus epidemic on each enterprise and gives the bank's credit adjustment strategy when the total annual credit is 100 million yuan. In response to this problem, this article treats emergencies as a single overall influencing factor, considering how it affects the first-level indicators

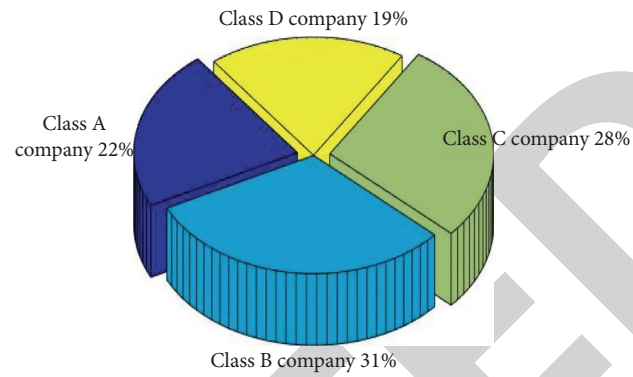


Figure 3: Visual pie chart of business classification with loan records.

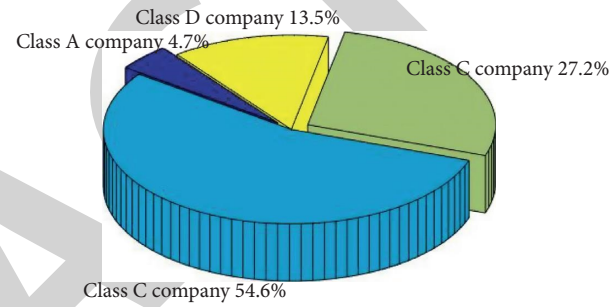


Figure 4: Visual pie chart of business classification with no loan records.

selected in Section 4 and then affects the second-level indicators. Therefore, the analytic hierarchy process is used to give different adjustment plans for different industries in emergencies. The processed values are respectively calculated on the relevant index values and brought into the existing model for calculation, and the bank's credit adjustment strategy when the total annual credit is 100 million yuan under the influence of unexpected factors can be obtained [17–20].

### 6.2. Research Methods

*6.2.1. Analytic Hierarchy Process.* Analytic hierarchy process is abbreviated as AHP, which refers to a decision-making method that decomposes elements that are always related to decision-making into goals, guidelines, and plans, and then conducts qualitative and quantitative analysis on this basis. The steps of the analytic hierarchy process are as follows:

Step 1: Establish a hierarchical structure model;

Step 2: Construct a pair of comparison matrix;

Step 3: Calculate the weight vector and do the consistency check;

Step 4: Calculate the combination weight vector and do the combination consistency test.

*6.2.2. Model Construction.* Based on the indicator system constructed in Section 5, and the impact of unexpected factors (such as the epidemic) on each company, according

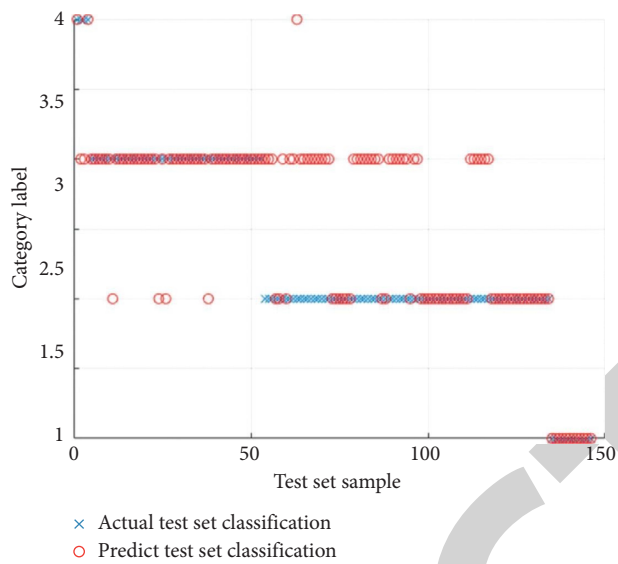


Figure 5: Results of corporate reputation risk classification.

Table 3: Screenshot of loan interest and loan limit of some of the 302 companies.

| Enterprise code | Reputation | Loan interest rate (%) | Loan limit (yuan) |
|---|---|---|---|
| E124 | A | 15.000 | 2896690.49 |
| E125 | A | 14.337 | 2910374.58 |
| E126 | A | 10.823 | 1753908.32 |
| E127 | A | 4.000 | 731860.94 |
| E128 | A | 15.000 | 861454.12 |
| E129 | A | 15.000 | 267664.16 |
| E130 | A | 12.481 | 352527.12 |
| E131 | A | 11.736 | 290436.29 |
| E132 | A | 8.650 | 525292.91 |
| E133 | A | 9.033 | 3486055.36 |
| E134 | A | 10.005 | 181575.50 |
| E135 | A | 9.502 | 1605406.61 |

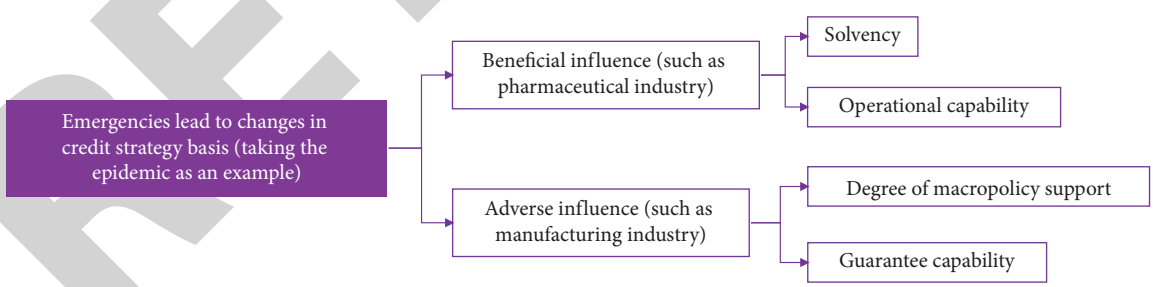


Figure 6: Credit adjustment strategy model under the influence of emergencies.

to the industry characteristics of each company, build a reputation risk evaluation system and bank loan strategy for companies in different industries. Taking the epidemic as an emergency factor as an example, for the pharmaceutical industry, the increase in the amount of its sales will increase its profits. At this time, it is more appropriate to use the company's debt servicing capacity as the main indicator to evaluate the loan strategy of the industry's enterprises; but for the manufacturing industry, due to the epidemic, it will not be possible to resume work and production. At this time, it is more appropriate to evaluate the company's guarantee capacity and the favorable situation of the macropolicy. The specific model is shown in Figure 6 [21–24].

Bring the processed index values into the final multi-objective optimization model in Section 4, and recalculate the results of the credit adjustment strategy of each enterprise when the total annual credit is 100 million yuan, as shown in Table 4.

Table 4: Loan lines and interest rates of adjusted enterprises.

| Enterprise code | E124 | E126 | E127 | E128 | E129 | E130 | E131 | E132 | E133 | E134 | E135 | E136 | E137 | E138 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Loan interest | 2.37% | 3.28% | 2.13% | 2.28% | 3.42% | 4.13% | 2.90% | 3.12% | 2.16% | 2.57% | 2.32% | 2.14% | 1.32% | 3.08% |
| Loan limit | 60836.357 | 371862.11 | 420713.59 | 399685.57 | 370961.49 | 366222.64 | 353626.29 | 375173.62 | 382690.82 | 397228.21 | 389641.77 | 352743.14 | 353712.4 | 389603.55 |

## 7. Conclusion

In Section 4, the analytic hierarchy process is used to quantify the corporate reputation risk. This method can be extended to the quantitative analysis of an unknown risk affected by multiple factors, such as the financial risk of the enterprise and the risk of stock trading; the method of using nonlinear regression to maximize bank returns can be extended to any conditional constraint solution. The method of using nonlinear regression to maximize bank revenue can be extended to any conditional constraint to solve the maximum value, such as finding the maximum value of production capacity under resource constraints. In Section 5, since the support vector machine is a small sample learning method, the category prediction of 302 companies without loan records has a natural advantage different from other machine learning algorithms. From the perspective of algorithm principles, the novel nonlinear mapping and optimal hyperplane ideas greatly simplify many traditional classification and regression problems. In addition, the method of using support vector machines to classify the credit risk of SMEs can be extended to classify any item according to specific attributes, such as classifying wine quality and classifying food quality [25–29].

However, it should be noted that in the data processing, this article uses the average value to represent the stable supply and marketing status of the enterprise. If the supply and marketing data of the company have a large extreme value, the average value will not represent the stable supply and marketing status. In addition, when calculating the customer churn rate in the analysis in Section 4, the absolute customer churn rate is used because the relative purchase amount of the churn customer is lacking in the data source. In view of these two shortcomings, when calculating the fluctuation value of supply and demand of small, medium, and microenterprises, the median can be used instead of the average to represent the stable supply and demand status, thereby reducing the influence of extreme values to assess the reputation risk of SMEs; at that time, the customer churn rate can be calculated using the relative customer churn rate, and the relative purchase volume of the relative customer churn is included in the calculation, so that the result is more objective and reliable.

## Data Availability

The data in this article come from Question C of the 2020 China National College Students Mathematical Contest in Modeling.

## Conflicts of Interest

Authors declare that they have no conflicts of interest.

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