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Research Article

Risk Assessment of Operator's Big Data Internet of Things Credit Financial Management Based on Machine Learning

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Credit risk evaluation innovation is of incredible importance to monetary establishments. AI innovation can fundamentally work on the precision and versatility of credit risk evaluation. This paper aims to study the risk assessment of operator big data Internet of Things credit financial management based on machine learning. It proposes machine learning-related algorithms, including the introduction of logistic model and decision tree model, as well as related concepts of credit financial management risk. This paper proposes that big data can be better used to reduce financial risk management problems and proposes specific actions based on the actual situation of the company. This paper selects company A for financial risk management evaluation through case analysis and compares it with three major e-commerce companies. The experimental results show that the earnings per share of company A is between −0.99 and 0. Company A is still in a state of loss in recent years, and there are certain debt risks, operational risks, and capital risks.

1. Introduction

Today's society is an information society. With the rapid development of science and technology, network applications are increasingly deepened. The global economy tends to develop in an integrated manner, and international exchanges are increasingly close. Network information has greatly changed the living environment of human beings. Great changes have taken place in social concepts, production methods, and social division of labor. People are in an era of unprecedented information explosion. It is undoubtedly of vital significance to carry out information extraction and knowledge mining in these massive pieces of information to obtain the required information. Web of Things endeavors with enormous information volumes are likewise confronted with a lot of data, for example, information stream, data stream, capital stream, and so on. Simultaneously, contest among administrators is turning out to be increasingly extreme [1, 2].

Monetary gambling the executives is the center of big business monetary administration. The degree of monetary gamble of an endeavor is a pointer to quantify the working state of a venture. Corporate financial risks often include management, creditors, and debtors. In the time of huge information, ventures should lay out center intensity and further develop monetary administration level to adapt to the vulnerability in the cutthroat climate. Through the analysis of the financial risk management mode and status quo of large-data Internet of Thing enterprises, this paper points out the risk management opportunities and challenges faced by enterprises in the era of big data. It uses a large amount of financial data to construct financial risk prevention measures for e-commerce enterprises to meet the needs of large-data enterprises in the e-commerce era and provide reference financial risk management for other enterprises.

The innovation of this paper lies in the application of machine learning to operators' big data Internet of Things credit financial management risk assessment, which is innovative and practical.

2. Related Work

With the approach of the period of large information, executives focus harder on their monetary gamble. Monetary gamble is especially vital to the endurance and improvement of an undertaking. Yang and Luo embraced a superior AdaBoost-SVM calculation to order the security and chance of shared loaning stages [3]. Lam and Siwingwa adopted an exploratory approach combining qualitative and quantitative. The aim is to identify the risk factors that lead to project cost overruns during the construction phase and to establish a reliable method for estimating unforeseen costs [4]. Nolde and Zhou reviewed the extreme value analysis method and its application in financial risk assessment [5]. Risk assessment in the Mukhlis and Damayanti study used the analytic hierarchy process to examine and reduce expert inconsistency [6]. The downside of these studies, however, is the inaccuracy of monitoring financial risk.

With the improvement of science and innovation, artificial intelligent innovation has entered into all parts of individuals' lives, and that is just the beginning and more researchers are concentrating on it. Buczak and Guven depicted an engaged writing survey of artificial intelligence (ML) and information mining (DM) techniques supporting organization examination for interruption discovery [7]. The purpose of Voyant et al. was to outline methods for predicting solar radiation using machine learning methods [8]. Zhou et al. presented the ML structure on large information to direct the conversation of its chances and difficulties. The system is ML-driven and follows the preprocessing, learning, and assessment stages [9]. The motivation behind Kavakiotis et al.'s study was to methodologically survey the utilization of AI, information mining strategies, and apparatuses in the field of diabetes research. Different AI calculations are utilized [10]. However, the shortcomings of these studies are that the model construction is not scientific and reasonable enough.

3. Machine Learning-Related Algorithms

3.1. Machine Learning and Credit Risk Assessment

3.1.1. Concepts Related to Machine Learning. The definition of machine learning has many forms, the more classic is "the behavior of computer to use experience to improve the performance of the system." Artificial intelligent calculations plan to find designs independently from a class of obscure information and afterward utilize this example to arrange the excess information or anticipate the following approaching information ahead of time [11, 12]. Accordingly, the reason for AI is to plan calculations that permit PCs to learn independently, subsequently understanding the utilization of man-made consciousness. The exploration of AI depends on the hypotheses of human learning system like physiology and mental science. It lays out a learning model or mental model by reenacting the human growing experience, concentrates on broad learning calculations and behaviors hypothetical investigation, and lays out task-situated learning models. Practice has proved that machine learning has played an important practical value in many application field, including data mining, speech recognition, image recognition, bioinformatics, and computational finance.

In recent years, artificial intelligence has become more and more popular. Many companies are more or less involved in artificial intelligence; otherwise, they will be regarded as not keeping up with the trend of the times. Furthermore, artificial intelligence in light of huge information has become exceptionally well known, on the grounds that it can understand the expectation of information and give assurance and premise to decision-production through the estimation of large information and the mining of stowed away information.

Machine learning can be viewed as a predictive technique. It learns rules from historical data and makes predictions on new data, and what it actually learns is a function. For the input to give the corresponding output, it can be divided into two applications: regression and classification, as shown in Figure 1 [13]. The learning process is essential to search for a function in the function space that can better fit the original data set and has a good generalization ability.

3.1.2. Machine Learning Algorithm Theory. A credit card scoring model is essentially a classification model within a machine learning algorithm. The following will bring the introduction of logistic regression, decision tree, and two model algorithms.

(1) Logistic Model. The calculated model is primarily used to look at the association between free factors and discrete ward factors [14, 15]. Subordinate variables are generally straight-out factors as "0-1.". In this investigation, the basic assessment content is private credit risk evaluation. The dependent variable B is a twofold element with values 0 and 1, independently. $B = 1$ addresses clients with default conduct, and $y = 0$ addresses clients without default records.

Suppose there are m-dimensional independent variables in the logistic model, denoted by $(A_1, A_2, A_3, \cdots, A_m)$. The dependent variable is whether the user has default behavior, which is represented by 0 and 1. After AI, the classifier of the strategic model will get the weight coefficient $(\alpha_1, \alpha_2, \cdots, \alpha_m)$ of a bunch of free factors, where x increments with the increment of M. The outcome is obtained by the direct weighting of the arrangement of loads and the example information:

$$\chi = \alpha_1 A_1 + \alpha_2 A_2 + \alpha_3 A_3 + \cdots + \alpha_m A_m. \quad (1)$$

Logistic is basically a discriminative model in light of contingent likelihood. Thus, the sigmoid capacity is presented here as the discriminant work [16]. The sigmoid capacity is

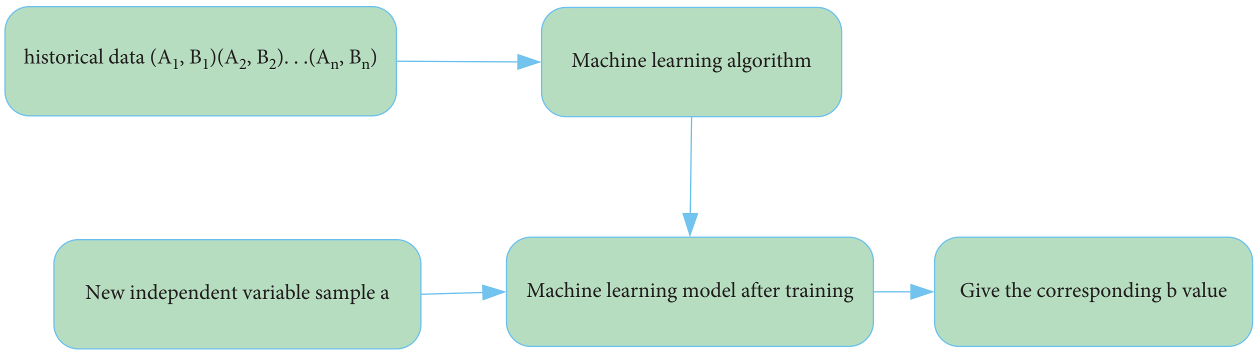

Figure 1: Schematic diagram of the machine learning process.

$$g(A) = \frac{1}{\left(1 + e^{-A}\right)}. \quad (2)$$

The larger the A, the larger the sigmoid; the smaller the A, the smaller the sigmoid. Figure 2 shows that the results are obtained by calculation, and 0.5 is used as a dividing point. If the result A >0.5, it belongs to the positive class with the class value of 1, and if A <0.5, it belongs to the negative class with the class value of 0. It puts the above fitting result as follows:

$$A = \alpha_1 A_1 + \alpha_2 A_2 + \alpha_3 A_3 + \cdots + \alpha_m A_m. \quad (3)$$

It is fed into the sigmoid function, which in turn gets a value from 0 to 1. In the actual credit approval classification, classification is performed by setting a threshold. Thus, the strategic relapse model can likewise be viewed as a likelihood assessment or, at least, the assessment of the default likelihood of the client [17].

(2) Decision Tree

(a) Decision tree-related concepts

Choice tree is a tree structure: a trait tree is built from the properties of each example in the preparation set. It is built start to finish. The leaf hubs of the tree are the classes utilized for characterization, the nonleaf hubs are feature ascribes, and the parts of the tree are choice circumstances. Decision tree is a graphical strategy, which is a somewhat instinctive characterization and relapse technique [18]. The classification decision tree model classifies the instances in a descriptive way, which is represented as a tree structure diagram. It can be seen from Figure 3 that what this decision tree does is to decide whether to meet the blind date. At each node, classification is done by a feature. Judging by age first, one category is less than or equal to 30, another category is greater than 30, and then the category less than or equal to 30 is classified according to the appearance. A complete decision tree is constructed until it is finally indivisible.

Determining branching criteria is undoubtedly the top priority in the decision tree grouping process. A complete decision tree model must determine the branching criteria. There are many types of branching criteria, and the information entropy gain

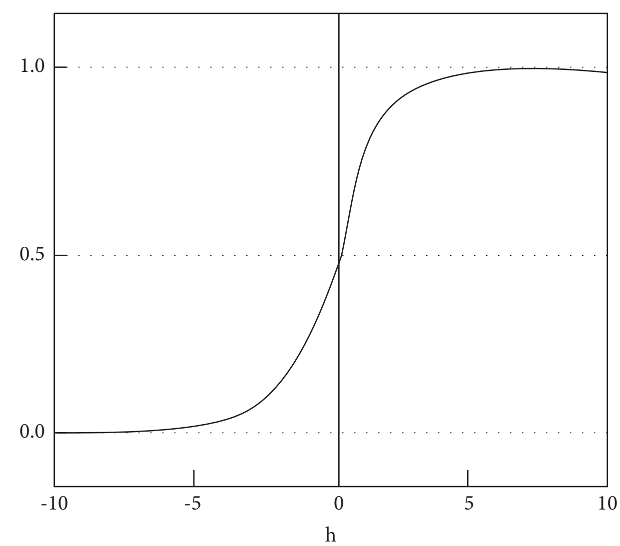

Figure 2: Sigmoid function.

method is a more commonly used one. According to the definition of physics [19], there are various energies in the surrounding space. And, entropy represents their distribution in space. The size of the entropy value is proportional to the uniformity of the energy distribution. A system reaches the highest entropy value when its energy system is uniformly distributed. Formula (4) is the calculation formula of entropy:

$$S(R_u) = -\log_2 q(R_u). \quad (4)$$

Information entropy can be understood as a mathematical expectation, which represents the mean value of the uncertain probability before the information is sent by the information source, which represents the expectation and is defined as a priori entropy:

$$Ent(R) = -\sum Q(R_u)\log_2 q(R_u). \quad (5)$$

If the probability distribution of the known signal R is Q(R) and the received signal, $J = j_v$, the probability distribution of the signal is $Q(R|j_v)$. From this,

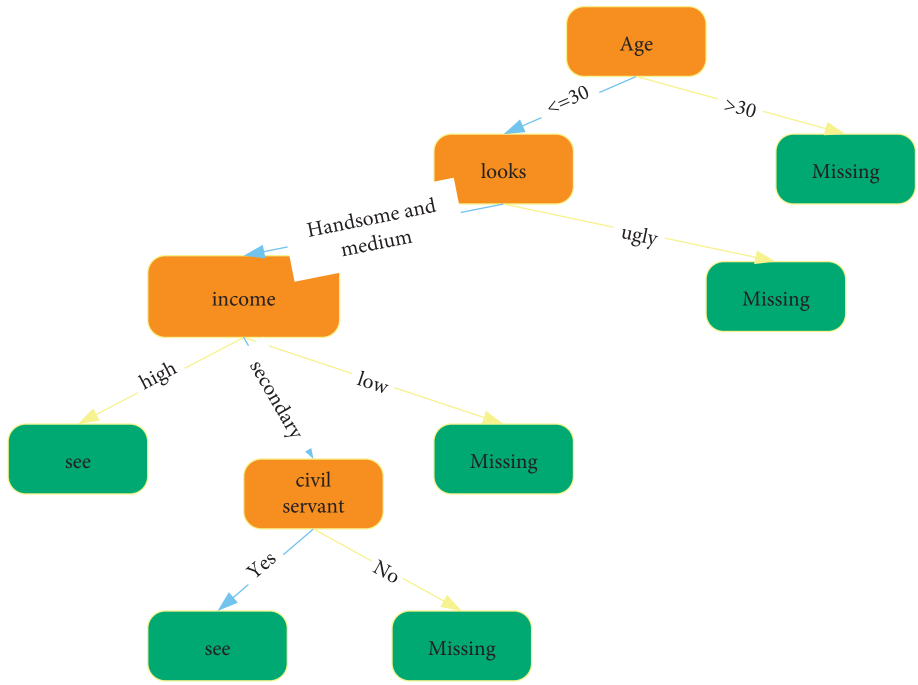

Figure 3: Decision tree model.

the mean value of the uncertainty probability of the signal source is obtained:

$$Ent\left(R \mid j_v\right)\log_2\frac{1}{q\left(r_u \mid j_v\right)} = \sum Q\left(r_u \mid j_v\right)\log_2 q\left(r_u \mid j_v\right). \tag{6}$$

This formula is called a posteriori entropy, and it expresses the mean value of the uncertainty probability of the signal U after the signal v has been received. Since the signal v is a random variable, the resulting expected posterior entropy is

$$\mathrm{Ent}\left(R \mid J\right) = \sum_v Q\left(j_v\right)\sum_v q\left(r_u \mid j_v\right)\log_2 q\left(r_u \mid j_v\right). \tag{7}$$

The size of the degree to which information eliminates random uncertainty is measured by the information gain:

$$\mathrm{Gains}\left(R, J\right) = \mathrm{Ent}\left(R\right) - \mathrm{Ent}\left(R \mid J\right). \tag{8}$$

In addition, common classification criteria are information gain:

$$\mathrm{Gains}\left(R, J\right) = \frac{\mathrm{Gains}\left(R, J\right)}{\mathrm{Ent}\left(J\right)}. \tag{9}$$

The Gini index is calculated as follows:

$$\mathrm{Gin}\left(P\right) = 1 - \sum_u^n q_u^2. \tag{10}$$

The upside of the choice tree calculation is that it can give clear choice rules and can be changed into a progression of if else rationale that is simple for people to comprehend. The drawback is that it can make decisions in view of the connection between a solitary trait and the forecast target. At the point when there are mind boggling connections between certain qualities, it is frequently challenging to precisely display the forecast target. Furthermore, it is not difficult to create overfitting, which is additionally a significant imperfection of this calculation.

(b) A typical decision tree algorithm—ID3 algorithm

The decision tree is derived from ID3 calculation, the optimal feature center is obtained through the calculation of information entropy, and then a differential decision tree is constructed [20].

ID3 calculation is the center calculation of choice tree. In the event that a likelihood circulation $(K_1, K_2, \cdots K_n)$ is given, how much data conveyed by that appropriation is known as the entropy of the likelihood dispersion. The complete entropy of the framework is

$$I\left(K_1, K_2, \cdots, K_n\right) = -\sum_{i=1}^n K_i \log_2 K_i. \tag{11}$$

Given a preparation set Q, the quantity of test focuses is indicated as $|Q|$. In the event that there are t various classes $B_i\ (i = 1, 2, \cdots, k)$, the example point in class B_i is $|Q_i|$. Utilizing $|Q_i|/Q$ to appraise the likelihood that any example has a place with B_i, then

$$I\left(\frac{|Q_1|}{Q}, \frac{|Q_2|}{Q}, \cdots, \frac{|Q_k|}{Q}\right) - \sum_{i=1}^k \frac{|Q_i|}{Q}\log_2\frac{|Q_i|}{Q}. \tag{12}$$

The entropy (anticipated data) of the subset separated by C is

$$E(C) = \sum_{i=1}^{k} \frac{\left|Q_{ij}\right| + \left|Q_{2j}\right| + \ldots + \left|Q_{kj}\right|}{|Q|} I\left(\left|Q_{1j}\right|, \left|Q_{2j}\right|, \ldots, \left|Q_{kj}\right|\right). \tag{13}$$

For a given subset D_j, the data entropy is

$$I\left(\left|Q_{1j}\right|, \left|Q_{2j}\right|, \ldots, \left|Q_{kj}\right|\right) = -\sum_{i=1}^{k} K_{ij} \log_2 K_{ij}. \tag{14}$$

Among them, $K_{ij} = |Q_{ij}|/Q$ is the likelihood that an example in Q_j has a place with A_i. The data gain of the entropy branch in property C is

$$\mathrm{IG}(C) = I\left(\frac{\left|Q_1\right|}{Q}, \frac{\left|Q_2\right|}{Q}, \ldots \frac{\left|Q_k\right|}{Q}\right) - E(C). \tag{15}$$

IG(C) is determined for each trait C while making a choice tree. The biggest is utilized as the test property of the preparation set Q. The fundamental issue of acquiring affiliation rules is the colossal measure of information to be investigated, so working on the proficiency of the algorithm is the most significant. If by some stroke of good luck one affiliation rule calculation is utilized and there are numerous information to be investigated, the execution season of the calculation will turn out to be extremely lengthy [21].

(c) Analysis of choice tree C4.5 calculation

The pruning strategy embraced by the C4.5 calculation in this assessment is skeptical stumble pruning. The C4.5 calculation apply to the following formula. A gauge of the misclassification rate is

$$G(t) = \frac{q(t)}{V(t)}. \tag{16}$$

The progression adjusted mistake rate is

$$G'(t) = \frac{q(t) + (1/2)}{V(t)}. \tag{17}$$

The misclassification rate of subtree T_t is

$$G(T_t) = \frac{\sum q(i)}{\sum V(i)}. \tag{18}$$

Among them, I takes each of the leaves of the subtree. The refreshed misclassification rate is then

$$G'(T_t) = \frac{\sum(q(i) + (1/2))}{\sum V(i)}. \tag{19}$$

Then,

$$G'(T_t) = \frac{\sum\left(q(i) + \left(V_{T_i}/2\right)\right)}{\sum V(i)}. \tag{20}$$

The standard deviation is determined as follows:

$$SE[u'(T_i)] = \sqrt{\frac{u'(T_t) * (V(t) - u'(T_i))}{V(t)}}. \tag{21}$$

Among them, for the node, there are

$$u'(t) = q(t) + \frac{1}{2}. \tag{22}$$

And, for subtrees, it has

$$u'(T_t) = \sum q(i) + \frac{V_{T_t}}{2}. \tag{23}$$

Consequently, in the event that the quantity of misclassifications in the wake of remedying levels is more noteworthy than the quantity of misclassifications subsequent to rectifying hubs, a strategy for it is proposed to prune levels. The benefit of this strategy is that a similar preparation set is utilized for tree development and pruning, and it is quick, requiring just a single output of every hub [22].

3.2. A Credit Risk Control Model Based on Operator Big Data

3.2.1. The Meaning of Credit Risk. Acknowledge risk, otherwise called default risk, alludes to the vulnerability of the wellbeing component of bank credit reserves. That is, the recipient cannot fulfill the commitment of reimbursing the head and premium, so the normal pay of the bank goes astray from the genuine pace of return. It is the principal kind of monetary gamble [23].

Credit risk arises for two reasons: macroeconomic activity and unique occasions that affect organizational activities. In this paper, it only analyzes the company's default risk through the company's financial statements and does not analyze the macro economy.

3.2.2. Characteristics of Credit Risk. The widespread existence of credit risk is an important factor in the current market economy. In this way, the purpose of assessing and monitoring credit risk is to grasp the quality of credit risk (Figure 4). The characteristics of credit risk are as follows: (1) asymmetry: the vacillation of market cost is fixated on its normal worth, for the most part focused on the two sides close to the mean worth. It tends to be approximated that the circulation of market risk pay is even, and essentially it very well may be utilized; (2) transitivity: credit risk is transitive, which leads to the accumulation of credit risk rather than zero-sum, and the credit risk of one party may spread to related parties, resulting in a total credit risk exponential

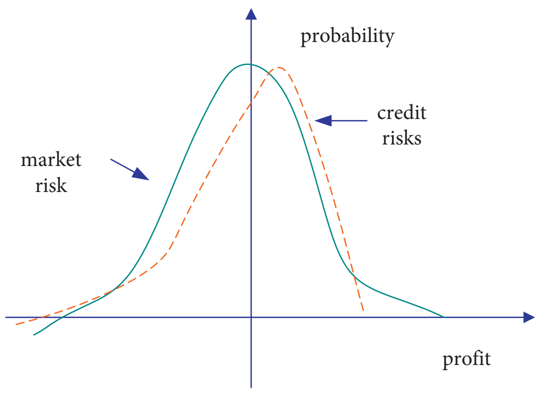

Figure 4: Credit risk distribution.

growth; (3) credit paradox phenomenon: in theory, when banks manage credit risk, they should use the idea of portfolio management to diversify and diversify investment, which is conducive to eliminating correlation and preventing credit risk concentration; (4) unsystematic: the risk management principle of diversifying and dispersing unsystematic risks is more suitable for credit risk management; (5) it is hard to gauge credit risk, and quantitative examination of credit risk is somewhat troublesome. The fundamental explanation is that perception data is scant and challenging to acquire.

It can be seen from Figure 4 that the distribution of credit risk is asymmetric, one end of the income distribution curve slopes to the lower left, and the probability density of extreme values in the loss area is larger than the corresponding normal distribution probability density curve, which is the so-called "thickness" "tail" problem. This characteristic is caused by the risk of loan default, that is, when the bank issues a loan, it is more likely to recover the loan and obtain the agreed income within the loan contract period, but once the loan violates the drug, the bank will have a relatively large risk, a loss of size (either the entire investment or most of it), which is much larger than the interest income. That is, the return on the loan is fixed and capped, and the bank cannot obtain the same proportion of the return from the business performance, that is, the expected return on the loan does not increase with the improvement of the business performance: on the contrary, the loss on the loan is variable and without a lower bound, expected losses on loans increase as business performance deteriorates.

3.2.3. Operator Credit Information System. A credit confirmation framework for administrators' extensive information includes an inspection subsystem, a rating subsystem, and a remote prepaid management subsystem. The validation subsystem recognizes client personalities and different authentication states and returns results in two configurations. The FICO assessment subsystem uses the wealth of the information provided by managers to plan a customer's credit scoring model. It also calculates the customer's credit score yield based on the model. The remote credit board subsystem processes the customer's early warning model and generates early warning data, as shown in Figure 5 [24].

A major information framework involves three issues: huge information storage, huge information censorship, and huge information management.

3.2.4. Credit Rating Model. The administrator's information mainly includes basic customer data, communication behavior, Internet behavior, customer assistance in appealing behavior, administrative use behavior, and different information, as shown in Figure 6.

Relational organizational information describes a customer's communication circle, texting friend network, and other relational connections. Conduct trademark information describes how customers communicate, the Internet, and behave differently. The credit risk evaluation issue is likewise a grouping issue. It is given a client record of loan repayment data set and expects to get familiar with an ideal capacity speculation. This capacity can fit the given preparation tests well and has the best speculation capacity. This issue is by and large the thing artificial intelligence is attempting to tackle. Artificial intelligent calculations have a decent capacity to manage nonlinear arrangement issues. The credit risk appraisal model in light of artificial intelligence can essentially work on the precision and versatility of credit risk evaluation. The data mining flow chart is shown in Figure 7.

4. Experiment of Enterprise Financial Risk Management System Based on Machine Learning Algorithm

With the advent of the era of big data, the aspects of identifying risks, managing risks, and evaluating risks in enterprise financial risk management need to keep pace with the time. Under the background, both the management and the executive layer need to strengthen risk awareness and use big data to improve the financial risk management capabilities of enterprises.

4.1. Debt Risk of Company A's Financial Risk Management. This paper selects company A for financial risk management assessment (data obtained from its financial statements). It compares the current ratio, quick ratio, and asset-liability ratio with the three major e-commerce companies (B, C, and D). Through the analysis of these 3 indicators, it aims to find out whether company A has certain solvency. Details are shown in Table 1.

In light of everything, the ongoing proportion (current assets/current liabilities) is 2 : 1, and the speedy proportion (fast assets/current liabilities) is 1 : 1. Expecting it falls underneath this worth, this demonstrates that the business needs liquidity of assets, lacks temporary solubility, and it is prone to bankruptcy, financial distress, and credit risk. From Tables 1 and 2, it can be seen that, during the period from 2013 to 2017, only the quick ratio in 2014 was above 1. The other 4-year quick ratios are all less than 1, and the current ratio is generally low. But for e-commerce companies, A's

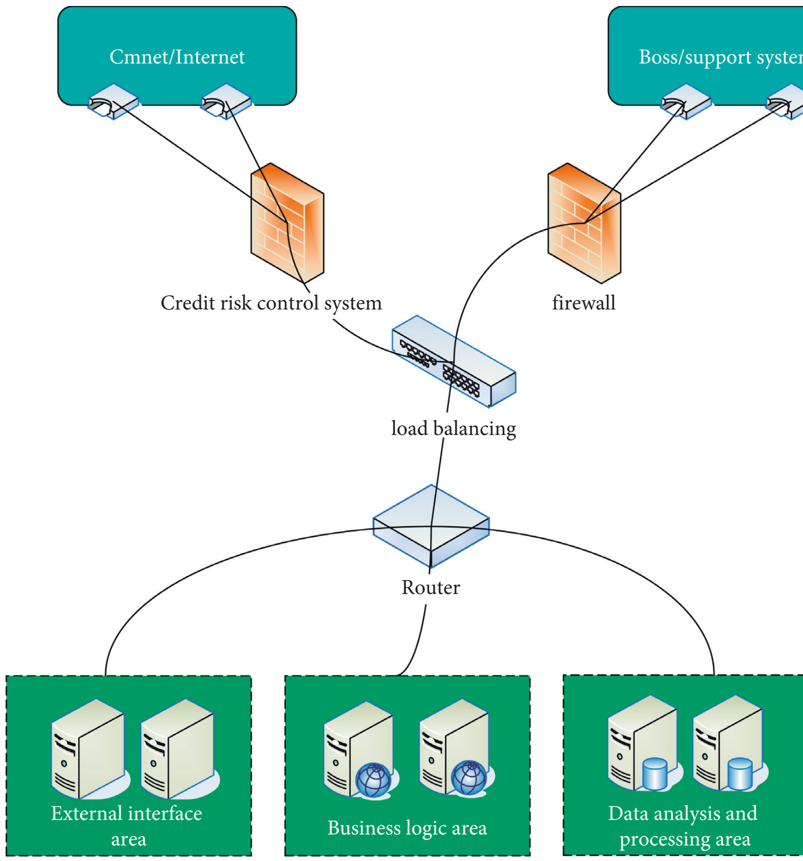

FIGURE 5: Deployment diagram of credit risk control system.

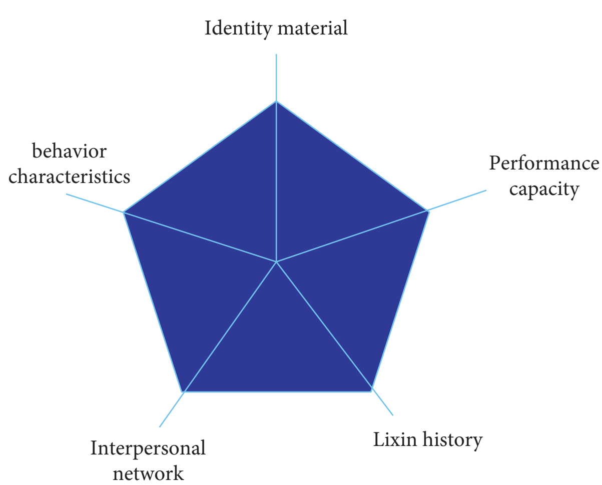

FIGURE 6: Dimensional classification of credit risk control models.

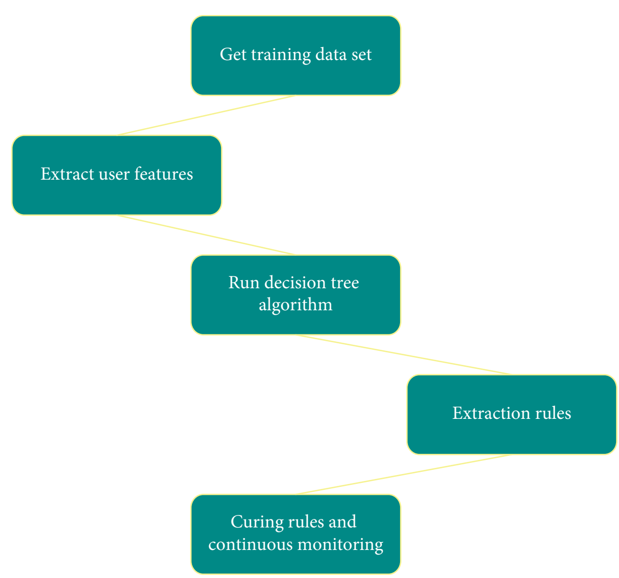

FIGURE 7: Data mining flowchart.

quick ratio and current ratio closely follow that of industry leader B, which is middle and upper in the industry. Because B is different from A in that it only provides a trading platform, so there is no need to worry about inventory issues. However, part of A's business is self-operated and requires a certain amount of warehousing and logistics costs.

It very well may be seen from Table 3 that the resource responsibility proportion is a critical marker to gauge the level of big business risk. In light of the resource risk proportion, the resource responsibility proportion of A is not hopeful in the business, and the value fluctuates between 40% and 75%. The asset-liability ratios of companies B, C, and D are far higher than those of A. It can be seen that the development trend of A's capital structure is not optimistic, with large fluctuations and certain debt risks.

Table 1: Current ratios of major e-commerce players.

Company	2013	2014	2015	2016	2017
A	1.33	1.70	1.22	1.01	0.98
B	1.81	3.60	2.56	1.94	1.94
C	1.06	2.10	1.25	0.88	1.05
D	1.24	1.31	1.02	1.06	1.37

Table 2: Quick ratios of major e-commerce players.

Company	2013	2014	2015	2016	2017
A	0.98	1.32	0.78	0.72	0.60
B	1.82	1.76	1.54	1.62	1.80
C	0.77	0.84	0.79	0.80	0.78
D	0.92	0.96	0.64	0.68	0.98

Table 3: Asset-liability ratios of major e-commerce companies.

Company	2013	2014	2015	2016	2017
A	0.66	0.43	0.65	0.77	0.75
B	0.85	0.64	0.80	0.88	0.69
C	0.77	0.82	0.82	0.79	0.81
D	0.79	0.86	0.79	0.79	0.64

4.2. Operational Risks of Company A's Financial Risk Management. By looking at the stock turnover proportions of the four significant Internet business organizations in Figure 8(a), it tends to be seen that the stock administration level of A in the beginning phase is top notch among online business organizations, far higher than that of web-based business organizations like B, C, and D. Be that as it may, A in the period of large information actually has some opportunity to get better in the computerized administration of stock. The return rate is a vital component influencing the resource of the executives of online business activities for Internet shopping. Since the return will unavoidably build the expense of the venture, these expenses include labor and material assets. Better yield rates additionally adversely affect the standing of the business and loss of clients, which thus adversely affects the presentation of business tasks.

From Figure 8(b), it can be seen that the overall trend of the accounts receivable turnover rate of e-commerce enterprises is decreasing year-by-year. A is in line with the industry trend, the realization of accounts receivable is slow, and the efficiency of operation management is not high. This reflects weakness in its core business. For e-commerce companies, working capital and inventory management capabilities are the focus of management. A has problems such as lax control over the management of funds, which indirectly indicates that it has certain operational risks.

From the perspective of earnings per share indicators, the earnings per share of A in the past five years have all been less than 0, which is the worst compared to the four selected e-commerce companies. According to the viewpoint of net resources per share, A's presentation is not hopeful. As should be visible from Figure 9, C's net resources per share are at a moderately significant level in the Internet business industry, a long way in front of different organizations. A's

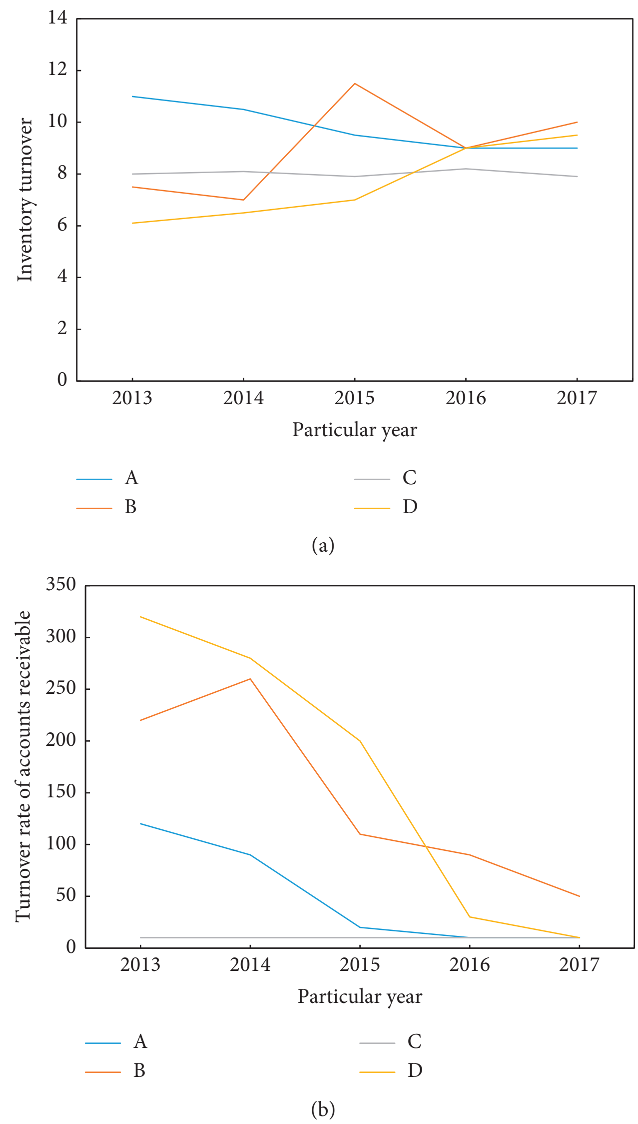

Figure 8: Comparison of inventory turnover ratio and accounts receivable turnover ratio with A in the same industry. (a) Comparison of inventory turnover ratio between A and the same industry. (b) Comparison of accounts receivable turnover ratio between A and the same industry.

net resources per share are in the center and lower spans of the business, it shows that its profit creation ability is not high, and its defense ability is poor when external factors affect the operation of the enterprise, and there are sure dangers.

Financial risk analysis summary, A is still in a state of loss in recent years. There are sure obligation gambles, functional dangers, and capital dangers. In the period of enormous information, the monetary gamble circumstance looked by A is not simply connected with A's own expense model, item structure, and monetary gamble the board framework, yet in addition to the effect of the outer climate. As of now, A has acquainted large information innovation with oversee corporate monetary dangers; however, the time is short and should be additionally moved along.

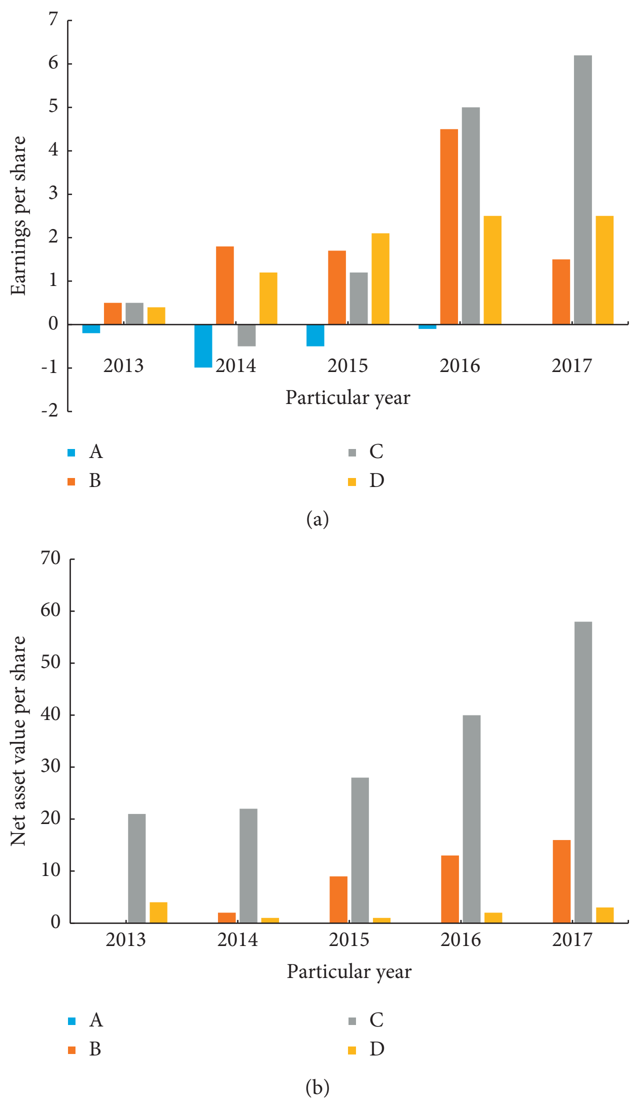

Figure 9: Comparison of industry earnings per share and net assets per share with A. (a) Comparison of earnings per share with peers. (b) Comparison of net assets per share with peers.

4.3. Financial Risk Early Warning Based on Big Data Platform. With the advent of the era of big data, the aspects of identifying risks, managing risks, and evaluating risks in enterprise financial risk management need to keep pace with the times. Under the background, both the management and the executive layer need to strengthen risk awareness and use big data to improve the financial risk management capabilities of enterprises.

On one hand, the big data platform can provide early warning of enterprise financial risks based on the financial early warning model, and on the other hand, it can also analyze some related risks.

For common financial risks of enterprises, the purpose of early warning can be achieved by establishing an early warning model as shown in Table 4 and using the data support provided by the big data platform.

The data support for early warning analysis of business risk indicators mainly includes market data, partner data, supplier data, and other external enterprise data and internal financial data, asset data, revenue data, transaction data, channel data, merchant data, and user data. The data support for the early warning analysis of capital risk indicators mainly includes the financial data, asset data, inventory turnover data, commodity data, and transaction data of the enterprise. The data support for the early warning analysis of debt risk indicators mainly includes data such as short-term loans (banks or individuals), bills payable, and special payables within the enterprise. The data support for the analysis of early warning indicators of fundraising investment projects mainly includes market data, partner data, investment project management data, and financial data.

5. Discussion

Financial risk analysis based on big data platform mainly includes the following aspects:

(1) Risk monitoring report/information disclosure

Risk monitoring report includes liquidity report, interest rate sensitivity report, and capital adequacy ratio report. Through the analysis of these reports, enterprises can better monitor the existence of risks and whether there are perfect measures to deal with the occurrence of risks. Big data can help enterprises in data acquisition and analysis and timely propose countermeasures through financial risk analysis.

(2) Market risk

The competition of e-commerce enterprises is very fierce, and there are a lot of market risks. Analysis of market risk based on big data technology can find out its market risk exposure value, liquidity management, and interest rate management. It enables enterprises to avoid some market risks in time and develop more healthily.

(3) Credit risk

Using big data technology can calculate the credit risk exposure value of enterprises, which cannot be done by traditional financial risk analysis. The calculation of this value can help enterprises to better control credit risks, including preloan control, inloan monitoring, and postloan analysis. It reduces the credit risk of the enterprise to a certain extent.

(4) Antifraud/antimoney laundering

Unlike traditional financial risk analysis, big data can unearth a large amount of financial data. This data can help companies define fraudulent transaction models and enable companies to establish early warnings of possible fraudulent transactions. In addition, the application of big data technology can also help companies analyze the distribution of fraudulent transactions, so that companies can improve their awareness of prevention in these areas and reduce their financial risks.

Table 4: Financial indicator requirements in the enterprise financial risk early warning model.

Classification	Alert category	Indicator name	Early warning area
Quantitative index	Operational risk early warning indicators	Profit margin of main business	Profit margin of main business income ≤5%
		Proportion of operating profit	Proportion of operating profit ≤50%
		Growth rate of main business income and	Main business income growth rate ≤30%
		Comparative analysis of growth rate of accounts receivable	Growth rate of main business income ≤0
		Turnover rate of accounts receivable	Growth rate of accounts receivable-growth rate of main business income ≥20%
		Return on net assets	Accounts receivable turnover rate ≤50% of the industry level
	Early warning index of capital risk	Analysis of cash flow structure	Return on net assets ≤0
		Asset liability ratio	Asset liability ratio ≥85%
		Current ratio	Current ratio ≤125%
		Quick ratio	Quick ratio ≤25%
		Inventory turnover	Inventory turnover times ≤50% of the industry level
		Profit cash ratio	Profit cash ratio ≤1
		Mandatory cash payment ratio	Mandatory cash payment ratio ≤1
	Debt risk early warning index	Current ratio	Current ratio ≤1.3
		Quick ratio	Quick ratio ≤L
		Asset liability ratio	Asset liability ratio ≥70%
		Interest earned multiple	Interest earned times $Q < 3.00$
	Early warning indicators of related party occupancy risk	Occupancy rate of asset related parties	Occupancy rate of related parties ≥5% (excluding current assets) Occupancy rate of asset related parties ≥40% (receivables are divisor)
		Income (cost) ratio of related businesses	Related business income (cost) Ratio ≥70%
	Early warning indicators of fundraising investment projects	Input output ratio	Input output ratio ≤ bank deposit interest rate level in the same period
		Completion rate of project investment schedule	Completion rate of project investment schedule ≤50%
	Early warning indicators of foreign investment risk	Long-term equity investment ratio	Long-term equity investment ratio ≥50%
		Return on investment	Return on investment ≤ return on net assets
Qualitative index		Major commitments	Failure to fulfill commitments
		Equity change	Changes in major shareholders and controlling shareholders
		Management changes	Suspected of corruption, fraud, smuggling, and other economic crimes; frequent changes
		Change of accounting firm	The reasons for the change are not disclosed in detail
		Mortgage guarantee matters	Guarantee for shareholders, no counterguarantee and other preventive measures
		Policy	Reform policies in finance and tax system

(5) Operational risk

Operational risk is the risk caused to the enterprise due to the operation error or intentional destruction of the financial staff of the enterprise. The use of big data technology can enhance the early warning mechanism of abnormal transactions, achieve post-supervision error inspection, strengthen the defense line of risk control, and ensure the normal operation of e-commerce enterprises.

6. Conclusions

It is common for companies to fall into financial distress due to poor financial risk management. Effectively managing and controlling financial risks can improve the efficiency of capital operations and the quality of management decisions. It is a powerful guarantee for the development of enterprises, especially in the face of the fierce competition of e-commerce enterprises. Through the analysis of the case of company A, it can be seen that the management of company A has a strong sense of risk. The annual report identified some potential risks, but detailed analysis also revealed flaws in financial risk management. Although company A has begun to use big data to manage and control financial risks, there is still discussion on how to use big data to improve the company's financial risk management.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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