Hindawi
Security and Communication Networks
Volume 2023, Article ID 9813962, 1 page
https://doi.org/10.1155/2023/9813962

Retraction

Retracted: Enterprise Financial Risk Prediction and Prevention Based on Big Data Analysis

Security and Communication Networks

Received 13 September 2023; Accepted 13 September 2023; Published 14 September 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] J. Cheng, "Enterprise Financial Risk Prediction and Prevention Based on Big Data Analysis," *Security and Communication Networks*, vol. 2022, Article ID 1442999, 12 pages, 2022.

Hindawi
Security and Communication Networks
Volume 2022, Article ID 1442999, 12 pages
https://doi.org/10.1155/2022/1442999

Research Article

Enterprise Financial Risk Prediction and Prevention Based on Big Data Analysis

Jinfeng Cheng

School of Finance and Accounting, Henan Industry and Trade Vocational College, Zhengzhou 451191, China

Correspondence should be addressed to Jinfeng Cheng; chengjinfeng@hngm.edu.cn

Received 10 June 2022; Revised 4 July 2022; Accepted 16 July 2022; Published 27 August 2022

Academic Editor: Jun Liu

With the rapid development of the times, the financial status of many enterprises has become the top priority, and the prediction and prevention of enterprise financial risks are more important. The financial risk prediction of enterprises under big data can better collect data and analyze it, which can help workers bring convenience. In order to make the public better understand the corporate financial risk forecasting, the research on the prediction and prevention of corporate financial risk based on big data analysis is as follows: (1) the broad and narrow senses of corporate finance readers gain a clearer understanding of the importance of corporate finance; (2) an introduction to the calculation algorithm of enterprise financial risk, which facilitates the staff to better calculate the financial risk of the enterprise and establish a financial risk model; (3) conduct an example investigation on a representative pharmaceutical company, analyze its various financial indicators, and compare with the indicators in the same industry to judge whether the financial data is normal; and (4) conduct comparative research on corporate finance under big data and find that big data can better prevent corporate financial risks. It is concluded that this risk prediction method is very effective. It shows that corporate financial risk is very important to social development, and based on big data, risks can be better predicted and prevented.

1. Introduction

Large datasets and big data analytics present significant challenges to the people. The data in the dataset comes from various fields, such as: social networks, science and technology, biomolecules, and many other aspects. A lot of information can be extracted from the data, and we process the data in innovative ways. This article describes an approach based on discrete signal processing (DSPG) data on graphs. The concepts and processing methods of DSPG are reviewed and compared with their counterparts in classical signal processing theory [1]. Virulence Factor Database (VFDB) is used to provide up-to-date knowledge about its development. For development purposes, we have recently improved two aspects of VFDB to make the dataset more complete and to improve data quality, promoting the availability of databases in the era of big data for bioinformatics mining of explosively growing bacterial VF data [2]. In many fields such as the Internet and e-commerce, the unanalyzed data is increasing rapidly, and parallel technology that can be processed should be invented. Relational data management technology has developed for 40 years and should develop its scalability. Relational technology does not handle data easily, and at the same time, there is no new force emerging and extending its application from web search to areas once occupied by relational database systems. Facing relational technology has many advantages [3]. Crowd sensing leverages the power of crowds to collect large volumes of characterization data through a large number of users of mobile and networked devices. This traditional method is quite challenging. Although several big data-based human behavior analysis methods have been proposed, the common characteristics have not been studied. This paper designs a community-centric approach for community activity prediction; specifically, we propose a method to extract community activity patterns by analyzing big data collected from the physical world and virtual social spaces [4]. With the continuous development, the data on the power user side increases exponentially, gradually forming the big data on the power user side. Traditional data analysis can no longer be satisfied, and a new data analysis model for analyzing and processing big data on the power user side is urgently needed. The sources of its data are analyzed, and various challenges faced by the data on the power user side are pointed out. Combined with cloud computing, the processing method and application of big data analysis on the power user side are given [5]. The term big data has received little attention in economics, although the availability of large datasets and the need for new methods is a new issue. Through interviews, this paper explores interdisciplinary perceptions of big data, the new types of data the researchers are using on economic issues, and the range of economists' responses to this opportunity [6]. The approach to handling huge datasets has shifted from a centralized architecture to a distributed architecture. Enterprises need to collect a large amount of data and cannot use centralized solutions to solve the problems. Not only it does not allow time, but also the efficiency is very low. With the help of distributed architecture, large organizations can better extract information and process the data [7]. Recent advances in high-throughput technologies have led to the emergence of systems biology as a holistic science that allows for more precise modeling of complex diseases. A lot of people have predicted the arrival of personalized medicine in the near future, however, we are moving from a two-tiered healthcare system to a two-tiered personalized medicine. Omics facilities are limited to affluent areas. Personalized medicine can widen the widening gap in healthcare systems between high- and low-income countries. This is reflected in the growing disconnect between our ability to create and analyze big data. Several bottlenecks are slowing the transition from traditional to personalized medicine: high-throughput, cost-effective data generation. Hybrid education and multidisciplinary team data storage and processing integrate and interpret personal and global economic data and correlations [8]. With the development of computer technology, there has also been a huge increase in the amount of data growth. Scientists are overwhelmed by the growing need for data processing in every field of science. How to make full use of these large-scale data to support decision-making has encountered great problems in various fields. Data mining is a technique that can discover new patterns from large datasets. Over the years, it has been studied in various application fields; so many data mining methods have been developed and applied in practice [9]. This examines how financial sector development policies can contribute to poverty reduction. This is especially done by supporting the growth of Small and Micro Enterprises (MSEs). Use case studies and empirical work on the changing role of MSEs in development and access to formal and informal financing for MSEs, including the role of microfinance [10]. The relationship between the capital needs of enterprises and economic efficiency and the adverse effects of credit barriers on industrial investment are discussed. Some of the insights gathered are then applied to financial intermediation and financial structuring. Trade credit is the subject of special scrutiny because it plays a key role in corporate financing in Kenya, as elsewhere. The causes of credit barriers are also examined in detail. Particular emphasis is placed on information and contract enforcement issues [11]. Entrepreneurship is elevated to an internationally disadvantaged labor market. The policy increasingly draws on the concept of social inclusion. In this article, we define a "corporate inclusion" policy as a right to recognize the opportunity to do a viable business and to support multiple disadvantaged groups in overcoming the powerful barriers facing businesses. We use a resource-based view of entrepreneurship to argue that viable business ownership depends on access to resources. We explore the relationship between access to a primary business resource—start-up capital—and intersecting social disadvantage. We report a complex pattern of financial exclusion [12]. Statistics, the areas under Routing of Service (ROC), are published in the diagnostic tests, where sensitivities and characterizations are relevant to the identified patients. Because estimation models can predict future risk or classify individuals into risk categories, in which case it is equally important to assess the validity of calibration tests, possibly the effect on statistics may be small. But the level of increased cardiovascular risk can increase from 8% to 24% over 10 years. Reference [13]. Better screening techniques for early detection of breast cancer are painless, which is why clinicians are committed to providing appropriate plans to protect the patients. These are especially important for family history of breast cancer. Moderate chemotherapy studies were performed on population data where cancer and steroid hormone studies were performed and on the risk assessment in women with a family history of cancer [14]. The guidelines recommend coronary heart disease risk (CHD) assessment for all adults to guide the severity of preventive treatment, although the Framingham Risk Score (FRS) is generally recommended for this purpose. However, it is recommended that additional tests, such as the Coronary Calcium Score (CACS), will improve risk assessment. Objective: To determine whether CACS and FRS assessments provide better prognostic information than either method in asymptomatic adults and whether this approach is associated with more precise prevention strategies in patients with risk factors for primary heart disease prevention [15].

2. Corporate Financial Capability

2.1. Generalized View of Corporate Financial Capability. According to the theory of enterprise competency, the financial capability of an enterprise is a subsystem composed of the corresponding part of the financial-related capability in the enterprise capability. If corporate finance can be viewed as a competency on the same level as other nonfinancial competencies (e.g., organizational competency, R&D competency, and strategic competency), then it includes any intrinsic financial competencies that contribute to these disclosed financial performance. This is a general view of a company's financial strength. Many researchers support a broad view of a firm's financial capability and examine what constitutes a firm's financial capability. Corporate financial capabilities mainly include corporate financial performance capabilities, financial work capabilities, and financial management capabilities. Among them, financial performance capability is the capability that clearly reflects the financial performance of an enterprise, such as profitability and solvency, and corporate finance and other financial business functions. Financial management capabilities, such as organizational coordination capabilities, such as financial capabilities, corporate financial capabilities include the company's financial operation capabilities, financial management capabilities, adaptability, and financial performance capabilities.

2.2. The Narrow View of Corporate Financial Capability. The narrow view of corporate financial capabilities holds that no matter how specific financial capabilities are subdivided, other financial capabilities will eventually manifest as explicit financial performance capabilities, mainly referring to the financial performance capabilities of enterprises. Regarding the composition of corporate financial performance capabilities, the current research mainly includes three classification methods: "three-point method", "four-point method", and "five-point method". The "rule of thirds" taxonomy generally divides a company's financial strength (performance) into profitability, solvency, and operating strength. The "quartile method" is a commonly used classification method. Generally speaking, the financial strength of an enterprise is divided into four categories: profitability, solvency, operating ability, and development ability (growth). It is a capability dimension that reflects the sustainable development of an enterprise and company. The conclusions of the "five points" classification are not uniform in related studies. The financial strength of a business can be divided into profitability, solvency, operating capacity, growth capacity, and creativity; some researchers believe that profitability, safety, productivity, growth, and activity reflect the ability to evaluate financially and business performance.

2.3. The Measurement of Corporate Financial Capability. With the development of related research, in addition to discussing theoretical issues such as the connotation, composition, and theoretical framework of corporate financial capabilities, the research on the measurement of corporate financial capabilities has also received more and more attention, especially with the emergence of relevant empirical research. Measuring a firm's financial capability directly affects the reliability of empirical research conclusions. To sum up, in the current research, there are two main methods to measure the financial strength of a company: the single indicator method and the comprehensive indicator system method.

2.3.1. Single Index Method. The single indicator method is a measurement method that directly uses a single financial indicator of the enterprise to measure the corresponding financial strength of the enterprise or selects several financial indicators without establishing an indicator system, and systematically distributes the composition of the company's financial status. It is relatively simple and convenient to measure the financial strength of enterprises with the single indicator method, but due to the complexity and comprehensiveness of the financial strength of enterprises, the comprehensiveness of this method is poor. According to the specific research objectives, when it is not necessary to comprehensively consider all the financial capabilities of the enterprise, but only the most important aspects, the single indicator method is used to measure the financial capabilities of the enterprise.

2.3.2. Comprehensive Index System Method. The comprehensive index system method is a general evaluation method. It selects several financial indicators and establishes an index system to measure the financial strength of enterprises through certain scientific methods. The comprehensive index system method uses a variety of financial indicators to combine the measurement of each component of the enterprise's financial status, which can comprehensively evaluate the actual status of the enterprise's financial status, and is widely used in the study of the enterprise's financial status.

3. Enterprise Financial Risk Prediction under Big Data

3.1. Calculation Framework for Corporate Financial Uncertainty. First, define $y_{jt}, Y_t\,(y_{Ir}, y_{2t}, L, y_{nt})$ as the set of economic variables that observe the financial uncertainty of the enterprise in period t, and define $U_{jt}^{y}(h)$ as the set of conditional fluctuations based on the sequence of economic variables in period t to predict the unpredictable part of the future $t+h$ period, namely,

$$U_{jt}^{y}(h) = \sqrt{E\left[y_{jt+h} - E\left(y_{jt+h} I_t\right)\right]^2}. \quad (1)$$

Among them, $j = 1, 2, L, N$; I_t represents the data information of the t period; $E(I_t)$ is the conditional period based on the data information of the t period seen. After calculating the uncertainty of a single variable, add up the uncertainty of the overall sequence at the same time point to obtain the financial uncertainty of the company at that time point, which can be expressed as follows:

$$U_t^{y}(h) = p\mathrm{lim}_{N_Y} a_{j=1}^{N_y} w_j U_{jt}^{y}(h). \quad (2)$$

Among them, w_j represents the weight of j economic variables in the economic series.

In order to obtain the overall financial uncertainty of the enterprise, it is important to measure $E(y_{jt+h} I_t)$ based on the data information of the t period. In order to obtain the predicted value, first consider a set of predictors based on the overall sample data. $\{X_{it}\}$ factor model is used to extract the common factors between variables, where a stationary data set $X_t = (X_t, X_{2t}, L, X_{nt})$ is defined, and it is assumed that X_t has a factor structure of the form as

$$X_{it} = U_i^{F} F_t e_{it}^{X}. \quad (3)$$

In the formula, F_T is the common factor of dimension r_F 1; U_i^F is the factor loading matrix of F, which is dimension r_F 1; e_{it}^X is the random error vector of F. In this factor structure, the random error vector can have limited cross-sectional correlation, and the number of factors must be significant and less than the number of variables.

Assuming that $y_{jt}Y_t(y_{1t}, y_{2t}, \ldots, y_{nt})$ is the target uncertainty sequence, the value of $t+h$ is estimated by the following model:

$$y_{jt+h} = f_j^y(L)y_{jt} + g_j^F(L)F_t + g_j^w(L)W_t + v_{jt+h}^y. \quad (4)$$

At the same time, because the factors have autoregressive characteristics of time-varying characteristics, the model can be expressed as an extended factor vector autoregressive model. Therefore, the prediction of the $t+h$ period based on the t period sequence can be obtained through this model, namely,

$$\begin{aligned} \begin{pmatrix} Z_t \\ Y_{jt} \end{pmatrix} &= \begin{pmatrix} \Phi^z & 0 \\ \wedge_j & \Phi_j^Y \end{pmatrix} \begin{pmatrix} Z_{t-1} \\ Y_{jt-1} \end{pmatrix} + \begin{pmatrix} v_t^Z \\ v_{jt}^Y \end{pmatrix}, \\ y_{jt} &= F_j^Y y_{jt-1} + v_{jt}^y, \end{aligned} \quad (5)$$

where U_j, U_j is the coefficient function of the lag term of y_{jt-1}, and the maximum eigenvalue of F_j^Y. If the maximum eigenvalue of F_j^Y is less than 1, the characteristic polynomial of the matrix can calculate all the eigenvalues of the matrix, and the largest one is the maximum eigenvalue of the matrix. We can calculate the characteristic root according to Equation (5), and this condition needs to be satisfied which is required to be less than 1, so the predicted expected value of the $t+h$ period is

$$E\left(y_{jt+h}\right) = \left(F_j^Y\right)^h y_{jt}. \quad (6)$$

At this point, the forecast error based on period t is

$$W_{jt}^y(h) = E_t\left[\left(y_{jt+h} - E_t y_{jt+h}\right)\left(y_{jt+h} - E_t y_{jt+h}\right)\right]. \quad (7)$$

The estimated error prediction value based on the matrix can be expressed as follows:

$$W_{jt}^y(h) = E_t\left[\left(y_{jt+h} - E_t y_{jt+h}\right)\left(y_{jt+h} - E y_{jt+h}\right)\right]. \quad (8)$$

Therefore, the uncertainty of a variable at time t can be expressed as follows:

$$U_{jt}^y(h) = \sqrt{1_j W_{jt}^y(h) 1_j}. \quad (9)$$

The overall corporate financial uncertainty can be obtained by weighting the univariate and expressed as follows:

$$U_t^y(h) = a_{j=1}^{N_y} w_j U_{jt}^y(h). \quad (10)$$

The weighting method can be based on principal component analysis to extract the weights of different economic variables, or it can be weighted by simple arithmetic average, so that the financial uncertainty of the enterprise can be obtained.

3.2. Establishment of Financial Risk Prediction Model. The quadratic exponential smoothing analysis method in the exponential smoothing model is very suitable for financial data with periodicity. The smoothing model also has certain shortcomings. We need to adjust the exponential smoothing. The second exponential smoothing method is a method of performing another exponential smoothing on an exponentially smoothed value. It cannot be predicted alone, and must be combined with an exponential smoothing method to establish a mathematical model for prediction, and then use the mathematical model to determine the predicted value. The two limiting factors of the primary moving average method only exist in the linear quadratic moving average method, the linear quadratic exponential, and the smoothing method can be calculated using only three data and one a value; Like to use linear quadratic exponential smoothing as a forecasting method. Coefficient: first, the rising and falling trends of the original data cause the forecast results to lag behind. The actual value; secondly, the most important factor for the success of exponential smoothing forecast is the smoothed value. The selection of traditional smoothing coefficients is based on empirical judgment. When choosing a smoothing value, the smoothing value should be determined when the error is minimal.

First, the smoothing coefficient is determined by the MAE method. Find the expected value with the smallest difference from the actual value, which is the smoothing coefficient, as shown in formula as follows:

$$MAE(\text{best\_}a) = \text{Min\_}MAE = \frac{1}{t}\sum_{i=1}^{t}\left|Y^i - y^i\right|. \quad (11)$$

In the above formula, $MAE(\text{best\_}a)$ represents the MAE value corresponding to the optimal smoothing value, and Min_MAE represents the minimum value of MAE.

The second step is to substitute the best_a value into the quadratic exponential smoothing model to calculate $S^{(1)}, S^{(2)}, Yi$, as shown in the following formula:

$$\begin{aligned} S_t^{(1)} &= (\text{best\_}a)y_t + [1 - (\text{best\_}a)]S_{t-1}^{(1)}, \\ S_t^{(2)} &= (\text{best\_}a)S_t^{(1)} + [1 - (\text{best\_}a)]S_{t-1}^{(2)}. \end{aligned} \quad (12)$$

From this, the primary and secondary smoothing values corresponding to the optimal smoothing coefficient a can be calculated. In the third step, substitute the values of $S_t^{(1)}$ and $S_t^{(2)}$ into the following formulas:

$$a_t = 2S_t^{(1)} - S_t^{(2)}, \quad (13)$$

$$b_t = \frac{a}{1-a}\left(S_t^{(1)} - S_t^{(2)}\right). \quad (14)$$

Finally, substitute a_t and b_t into the following formula:

$$Y_{t+T} = a_t + b_t \bullet T. \quad (15)$$

To sum up, the whole process of establishing the calculation model is as follows: the global configuration of the java deployment environment; the construction of the quadratic exponential smoothing method, and the establishment of the minimum error adjustment curve, including the data of 35 periods of financial indicators. Financial risk is one of the biggest risks it often faces in manufacturing and operating activities, and it has drawn the attention of business leaders. The company's operating ability, profitability, and solvency are the three most important elements in financial risk analysis. Among them, credit has the highest influence coefficient on financial risks. Credit status can also help enterprise managers to objectively analyze the current risk situation and effectively make business decisions. Financial risks based on solvency and entrepreneurs, owners, interests of creditors, and other parties. Therefore, when choosing research indicators, this paper divides the repayment ability into two levels: short-term and long-term.

3.2.1. Short-Term Level. The ability of inventory to repay current liabilities on time represents the level of repayment of a company's current liabilities and is considered very important by investors, creditors, and management. The data indicators to measure the short-term debt service level of a company are the current ratio and the quick ratio. The formulas for calculating the current ratio and quick ratio are as follows:

$$\text{current ratio} = \frac{\text{total current assets}}{\text{total current liabilities}} \times 100\%,$$
$$\text{quick ratio} = \frac{\text{total liquid assets}}{\text{total current liabilities}} \times 100\%. \tag{16}$$

Formula: quick ratio = (total current assets - inventory)/total current liabilities; conservative quick ratio = 0.8 (monetary funds + short-term investment + notes receivable + net accounts receivable)/current liabilities; standard set by the enterprise Value: 1; Significance: It is a better indicator of the company's ability to service short-term debt than the current ratio. Because current assets include inventories that are slow to realize and may have depreciated, current assets are deducted from inventories and then compared with current liabilities to measure the short-term solvency of the company. Analysis Tip : A quick ratio below 1 is generally considered to be low short-term solvency. An important factor that affects the credibility of the quick ratio is the liquidity of accounts receivable. The accounts receivable on the book may not be able to be realized, nor may they be very reliable.

3.2.2. Long-Term Level. A company's ability to repay its long-term debt on time is its long-term creditworthiness. An important indicator that can quantify a company's long-term debt repayment level is the asset-liability ratio, which refers to the ratio of a company's debt to its assets, as well as a company's debt ratio per dollar. The formula looks like this:

$$\text{assets and liabilities} = \frac{\text{total liability}}{\text{total assets}} \times 100\%. \tag{17}$$

The passivity of a company's assets is negatively related to its long-term solvency. In addition to the asset-liability ratio, a data indicator to quantify a company's long-term solvency is the equity ratio. The owner's share of the investment in the company's assets is called the equity ratio.

$$\text{Shareholders' equity ratio} = \frac{\text{shareholders' equity}}{\text{total assets}} \times 100\%. \tag{18}$$

4. Enterprise Financial Risk Prediction and Prevention

The financial status of an enterprise can present the financial risk situation of the enterprise. Therefore, it is necessary to analyze the financial status of the enterprise first to understand the current financial status, operating results, and cash flow of the enterprise, so as to pave the way for subsequent risk assessment. Take the financial situation of the company as an example to conduct surveys to better obtain data to study the business situation of enterprises and make risk predictions.

4.1. Balance Sheet Analysis. As can be seen from Table 1, the proportion of current assets of the company has increased year by year, from 41.07% in 2018 to 50.61% in 2020, and the proportion of non-current assets of the company has decreased year by year, from 58.93% in 2018 to 2020 of 49.39%. It can be seen that the asset structure of the company has undergone major changes in the past three years, from non-current assets accounting for more than 50% to current assets accounting for more than 50%, which shows that the elasticity of the company's assets has increased year by year.

The proportion of current assets in the industry has increased year by year, from 56.14% in 2018 to 57.62% in 2020. The proportion of non-current assets in this company has decreased year by year, from 43.86% in 2018 to 42.38 in 2020. It can be seen from Tables 1 and 2 that the proportion of current assets in the industry in the three years from 2018 to 2020 remained between 56% and 58%, which was higher than that of the surveyed companies. It can be seen that compared with the same industry, the elasticity of the company's assets is poor.

To sum up, compared with the same industry, the elasticity of the company's assets is poor, but there has been a trend of increasing year by year, and the company's asset structure is gradually developing towards the proportion of the industry's asset structure.

4.2. Analysis of Funding Sources. Because the total liabilities and owner's equity in Table 3 are increasing year by year, one of them indicates negative assets and the other indicates positive assets, so it is not easy to judge the overall operation of the enterprise. Generally, we analyze the proportion of both increases at the same time. In positive assets if the increase is more, the business condition of the company is good, otherwise it is not good. The positive assets of the pharmaceutical company in the particles in the article, that is, the owner's equity, have increased more, so the business situation of the company has improved in the past three years.

From Table 3, we can see that the proportion of current liabilities of the company has gradually decreased from

Table 1: Asset structure of an enterprise.

Project	2018	Constitute (%)	2019	Constitute (%)	2020	Constitute (%)
Current assets	73.5796.05	41.07	778677.15	42	1211128.91	50.61
Non-current assets	1055885.69	58.93	1075441.98	58	1182042.76	49.39
Total assets	1791681.74	100.00	1854119.13	100.00	2393171.67	100.00

Table 2: Average asset structure of the same industry.

Project	2018	Constitute (%)	2019	Constitute (%)	2020	Constitute (%)
Current assets	18478.9	56.14	19310.7	57.00	21673.5	57.62
Non-current assets	14434.2	43.86	14565.1	43.00	15938.7	42.38
Total assets	32913.1	100	33875.8	100	37612.2	100

Table 3: The source of funds of an enterprise.

Project	2018	Constitute (%)	2019	Constitute (%)	2020	Constitute (%)
Current liabilities	1070761.95	59.76	1008040.90	54.37	1175332.61	49.11
Non-current liabilities	169716.42	9.47	283672.84	15.30	512282.51	21.41
Total liabilities	1240478.37	69.24	1291713.74	69.67	1687615.12	70.52
Total owner's equity	551203.37	30.76	562405.39	30.33	705556.56	29.48
Total liabilities and owners' equity	1791681.74	100.00	1854119.13	100.00	2393171.67	100.00

59.76% in 2018 to 49.11% in 2020; the proportion of current liabilities has increased year by year, from 9.47% in 2018 to 21.41% in 2020%; the proportion of total liabilities has also increased year by year, from 69.24% in 2018 to 70.52% in 2020; the total proportion of owners' equity has decreased year by year, from 30.76% in 2018 to 29.48%. The total value of liabilities and owners' equity has increased year by year, from 17,916,817,400 yuan in 2018 to 23,931,716,700 yuan in 2020.

From Table 4, we can see the average assets and liabilities of the same industry. In 2018, the total liabilities averaged 137.447 million yuan, which increased year by year in the following two years. In 2020, the total liabilities reached 152.918 million yuan; in 2018, the total assets were 329.131 million yuan, which increased year by year in the following three years. By 2020, it will reach 376.122 million yuan; the asset-liability ratio has dropped from 41.76% in 2018 to 40.66% in 2020. Although liabilities are rising year by year, assets are also rising year by year and the ratio is faster than the total liabilities, so the asset-liability ratio will decrease year by year during 2018–2020.

From the comparison of Tables 3 and 4, it can be seen that the proportion of debt financing of the company is very high. From 2018 to 2020, the proportion of debt financing is between 69% and 71%, and it has maintained a growth trend in the past three years. However, in the past three years, the industry's asset-liability ratio has only remained between 40% and 42%, and it has maintained a downward trend in the past three years. This shows that in the same industry, the comprehensive strength of the company to repay debts is relatively poor, and the financial risk is relatively high. In addition, the proportion of current liabilities in the company's debt financing from 2018 to 2020 is much higher than that of the non-current liabilities, indicating that the company's short-term debt repayment pressure is very high.

Table 4: Assets and liabilities of the industry.

Project	2018	2019	2020
Total liabilities	13744.7	13970	15291.8
Total assets	32913.1	33875.8	37612.2
Assets and liabilities	41.76%	41.24%	40.66%

4.3. Identification of External Financial Risks. In corporate finance, there are not only internal corporate financial risks caused by insufficient capital flow, personnel changes, and changes in decision-making, but also external financial risks are huge hidden dangers, such as: policy change risks (because we are investigating the pharmaceutical industry as an example, here the pharmaceutical industry has also been taken as an example.) For example, with the reform and development of my country's pharmaceutical industry and the continuous introduction of industrial support policies, the prices of pharmaceutical products have continued to decline. At the same time, the implementation of policies such as drug registration, review, approval process optimization and consistency evaluation, and "4 + 7" volume procurement have changed the business model of pharmaceutical companies, making the pharmaceutical manufacturing industry face both opportunities and challenges and operating environmental risks. In recent years, the continuous improvement of environmental protection standards and increasingly strict drug quality supervision have made the original. The investment in materials, energy, labor costs, and environmental protection is constantly increasing. At the same time, raw materials, prices for labor, transportation, etc., are also rising. These factors have greatly increased the cost of enterprises and limited the growth of profits. In addition, the new crown pneumonia epidemic in 2020 has caused domestic production and business closures, most companies suffered heavy losses in the first quarter,

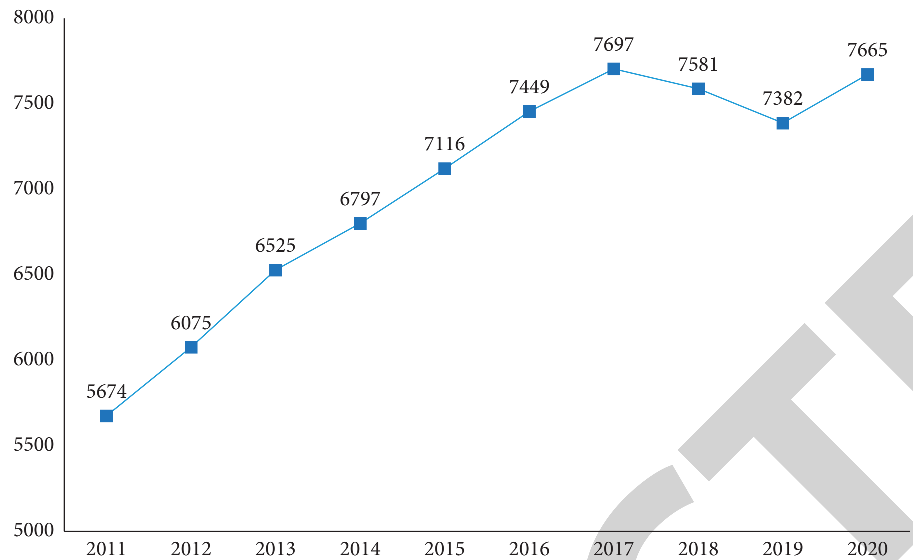

Figure 1: Number of companies in the pharmaceutical manufacturing industry from 2011 to 2020.

and some companies went bankrupt. In such a harsh external environment, companies and individuals are reducing purchases and consumption, the operating environment is very risky, and the fierce competition in the industry will also affect the external financial situation. We have investigated the industry competition of the pharmaceutical company as shown in Figure 1.

The data in Figure 1 shows the number of pharmaceutical manufacturing companies from 2011 to 2020. It can be seen that from 2011 to 2017, it increased steadily year by year, reached its peak in 2017, and then slightly decreased in 2018 and 2019, and then resumed in 2020. Back to the peak, from 2011 to 2017, with the development of the times, people paid more attention to health care, so the number of pharmaceutical companies continued to increase, and the competition became more and more fierce. In 2019, the pharmaceutical industry tends to be saturated and slightly down. In 2020, with the advent of the epidemic, the emphasis on medicine will be more extensive, so the number of pharmaceutical industry enterprises has reached a peak again.

As can be seen from Figure 1, the number of pharmaceutical manufacturing enterprises in the ten years from 2011 to 2020 showed an overall growth trend, from 5,674 enterprises in 2011 to 7,665 enterprises in 2020. In the past decade, new companies have continued to join to seize the market share. By 2020, more than 7,000 companies will compete together, resulting in increasingly fierce market competition in the pharmaceutical manufacturing industry.

4.4. Internal Financial Risk Identification

4.4.1. Analysis of Financing Methods. The main investment methods of enterprises in my country include bank loans, issuance of stocks, and issuance of bonds.

From Table 5, it can be seen that the company has a variety of financing methods. In 2016 and 2017, it mainly used borrowing, issuing bonds and other financing activities for financing. In 2018, it mainly used to absorb investment, borrowing, issuing bonds and other financing activities for financing. In 2019 and 2020 mainly through the absorption of investment, borrowing and other financing activities for financing. It is worth noting that from 2016 to 2020, the company raised funds by borrowing every year, and the amount of funds raised was huge. It can be seen that the internal financing structure in the financing method is unreasonable, and the annual increase in cash paid for debt repayment will continuously increase the financing cost, which will lead to the increase of financing risk.

4.4.2. Debt Maturity Structure Analysis. A company's debt maturity structure refers to the quantitative relationship between the company's long-term and short-term debts. An unreasonable debt maturity structure will increase the financing risk faced by the company. Due to the fast short-term debt maturity, if the short-term debt ratio is high and the maturity is concentrated, it will be difficult to repay the capital flow; due to the high interest rate of the long-term debt, if the long-term debt ratio is high and the maturity is concentrated, there will be high interest expenses, and it may face the risk of financial rupture.

From Table 6, it can be seen that from 2016 to 2020, the current liability ratio of the pharmaceutical company is very high, with a minimum value of 69.64%. It can be seen that the pharmaceutical company mainly uses short-term funds when using debt funds. Although this can reduce the cost of debt for enterprises, it requires high liquidity of assets. The liquidity of assets is generally reflected by the current ratio and the quick ratio. Generally, the current ratio is greater than or equal to 2, and the liquidity of the asset is higher when the quick ratio is greater than or equal to 1. However, from 2016 to 2020, the current ratio and quick ratio of the company did not meet the general standards. It can be seen that its asset liquidity is poor. Therefore, the short-term debt

Table 5: Changes in the company's financing (unit: ten thousand yuan).

Project	2016	2017	2018	2019	2020
Absorbed cash received from investments	0.00	0.00	10104.00	105800.00	136006.00
Get cash received from borrowing	447270.00	655287.00	724418.80	993979.68	1497125.84
Cash received from bond issuance	199800.00	199229.00	99700.00	0.00	0.00
Receive other cash related to fundraising activities	39200.00	56750.00	26768.12	138616.45	43832.43
Subtotal of cash inflows from financing activities	686270.00	911266.00	860990.92	1238396.14	1676964.27

Table 6: Debt maturity structure of the pharmaceutical company (unit: ten thousand yuan).

Project	2016	2017	2018	2019	2020
Current liabilities	910678.12	869517.50	1070761.95	1008040.89	1175332.61
Total liabilities	1118497.49	1187092.70	1240478.37	1291713.74	1687615.12
Current liability ratio	81.42%	73.25%	86.32%	78.04%	69.64%
Current ratio	0.74	0.78	0.69	0.77	1.03
Quick ratio	0.57	0.58	0.49	0.56	0.82

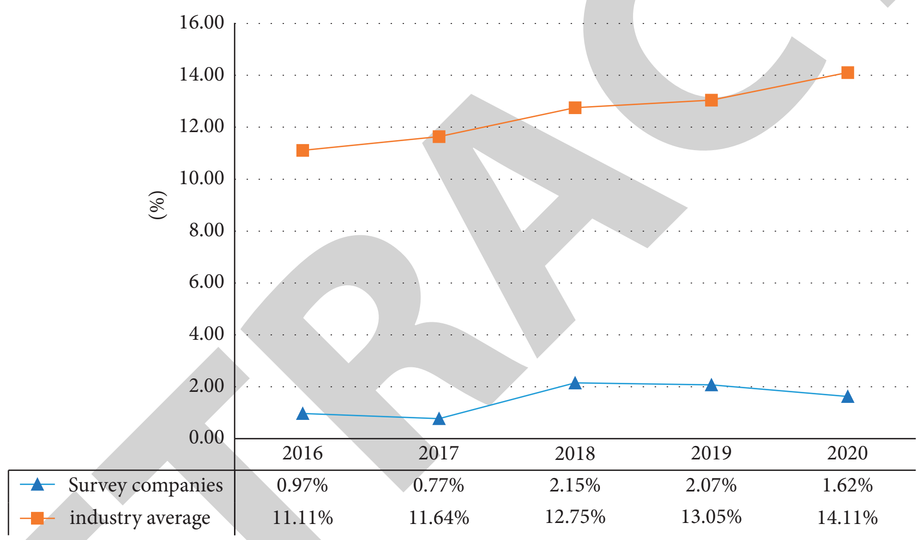

Figure 2: Investigate the sales profit margin of pharmaceutical companies and pharmaceutical manufacturing industries.

repayment pressure of the enterprise is relatively high, and the financial risk is relatively high.

4.4.3. Analysis of Sources of Debt Repayment. Profits from business activities are the main source of debt repayment.

As can be seen from Figure 2, the sales profit margin of the pharmaceutical company is significantly lower than that of the pharmaceutical manufacturing industry. From 2016 to 2020, the sales profit margin of H pharmaceutical companies has been lower than 3% and increased first and then decreased. In 2020, it dropped from the highest value of 2.15% to 1.62%. From 2016 to 2020, the sales profit margin of the pharmaceutical manufacturing industry was higher than 10% and showed an increasing trend, rising from 11.11% in 2016 to 14.11% in 2020. Therefore, under the influence of the new crown pneumonia epidemic at the same time, the sales profit margin of the surveyed pharmaceutical company is significantly lower than that of the pharmaceutical manufacturing industry, which shows that the pharmaceutical company's sales profitability is poor and there is a risk of debt repayment.

4.4.4. Inventory Risk Analysis. From Table 7, it can be seen that from 2016 to 2020, the pharmaceutical company's inventory showed an overall growth trend, from 1,502,323,200 yuan in 2016 to 2,452,923,400 yuan in 2020, indicating that the company's investment in inventory is increasing year by year. In addition, except for the inventory growth rate of -12.86% in 2016, the inventory growth rate of the surveyed pharmaceutical companies from 2017 to 2020 was all positive, indicating that the pharmaceutical company has a backlog of inventory. As can be seen from Figure 3, from 2016 to 2020, the proportion of the pharmaceutical company's inventory to current assets increased first and then decreased, from 22.44% in 2016 to 28.51% in 2019, and then to 20.25% in 2020. The mean changes tend to be roughly the same. Moreover, except for the proportion of the pharmaceutical company's inventory in current assets in 2020, which

Table 7: Inventory of the pharmaceutical company.

Project	2016	2017	2018	2019	2020
Stock	150232.32	173138.71	207367.61	221973.14	245292.34
Inventory growth rate	−12.86%	15.25%	19.77%	7.04%	10.51%
Inventory/current assets	22.44%	25.40%	28.18%	28.51%	20.25%

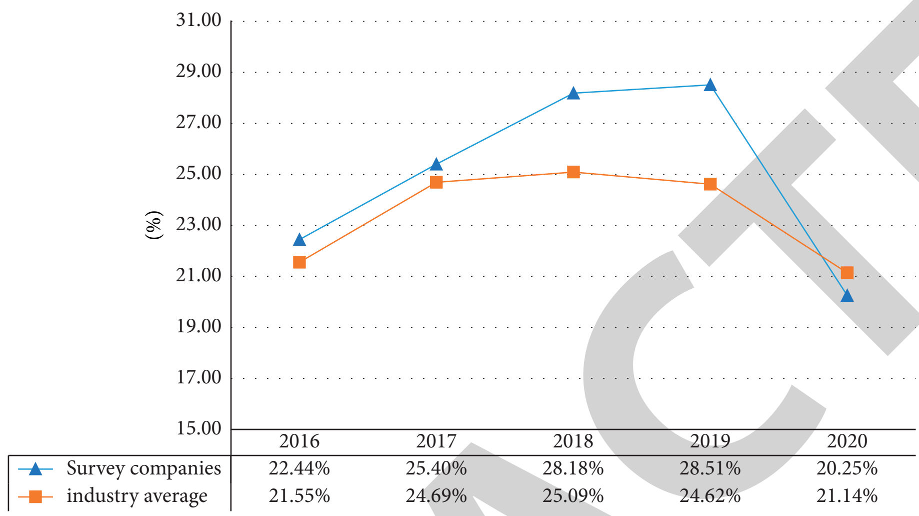

Figure 3: The ratio of inventories to current assets in the surveyed pharmaceutical companies and industries.

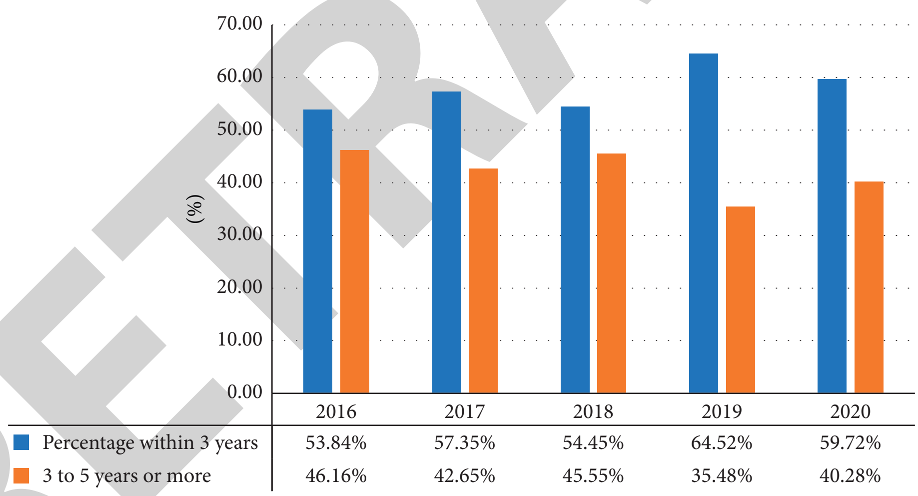

Figure 4: Investigate the aging of accounts receivable of pharmaceutical companies.

was slightly lower than the industry average, all other years were higher than the industry average, which shows that the proportion of the pharmaceutical company's inventory in current assets is high, and there is a backlog of inventory.

4.4.5. Accounts Receivable Analysis. As can be seen from Figure 4, from 2016 to 2020, the proportion of the pharmaceutical company's accounts receivable aged 3 to 5 years fluctuated, the lowest value was 35.48% in 2019, the highest value was 46.16% in 2016, and from 2019 to 2020, it showed an increasing trend, reaching 40.28%. Because the longer the account age, the less likely the receivables will be recovered. In addition, in the 5 years from 2016 to 2020, 4 of the accounts receivables aged 3 to 5 years accounted for more than 40%. It can be seen that there is a great risk in the collection of accounts receivable of the pharmaceutical company.

Accounts receivable turnover is the amount the business is owed, and it is an important factor in a business's financial health. The industry's highest accounts receivable in 2018 also indicates that the industry developed very well in 2018. In 2020, this data in the same industry is rising, while the surveyed companies are declining, which indicates that the surveyed companies have problems in their operations this year, the company's financial situation needs to be treated with caution.

From Figure 5, it can be seen that from 2016 to 2020, the accounts receivable turnover rate of H pharmaceutical companies generally increased first and then decreased,

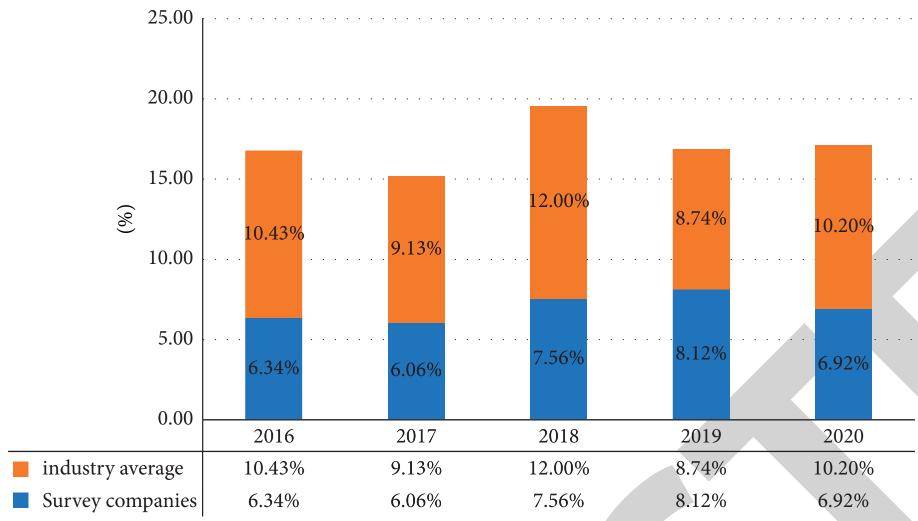

FIGURE 5: Analysis of accounts receivable turnover ratio of the pharmaceutical enterprise and pharmaceutical manufacturing industry.

especially in 2020, it dropped to 6.92%. It can be seen that in 2020, the collection of accounts receivable of the pharmaceutical company will deteriorate. From 2016 to 2020, the accounts receivable of the pharmaceutical manufacturing industry showed fluctuations, but in 2020, it rose to 10.2%. It can be seen that the recovery of accounts receivable in the pharmaceutical manufacturing industry will improve in 2020. In general, from 2016 to 2020, the accounts receivable turnover rate of the pharmaceutical company was significantly lower than that of the pharmaceutical manufacturing industry. It can be seen that compared with the industry, it is difficult to recover the accounts receivable of the pharmaceutical enterprises under investigation, and there is a greater risk.

After investigation and comparison with the same industry, we can predict the risks of the investigated pharmaceutical companies, and the companies have greater risks.

4.5. Enterprise Financial Risk Prevention. Enterprise financial risk prevention has many advantages, which is helpful for investors to invest; it helps management to strengthen internal control; it helps to improve the financial situation of enterprises. We also conducted a survey on the preventive measures of corporate financial risks. The survey results are as follows in Figure 6:

After our investigation of the four major corporate financial risk prevention methods currently used (1) to analyze the financial management environment, the audience of this method accounts for 20%. (2) Improving the scientific level of decision-making, this method accounts for 30% of the audience. (3) Risk transfer method: the audience of this method reaches 40% at most. (4) Diversified risk control method accounts for 10%. These methods can better help us prevent risks.

4.6. The Impact of Big Data on Corporate Finance. After the emergence of modern scientific and technological achievements such as the Internet of Things and cloud computing, a

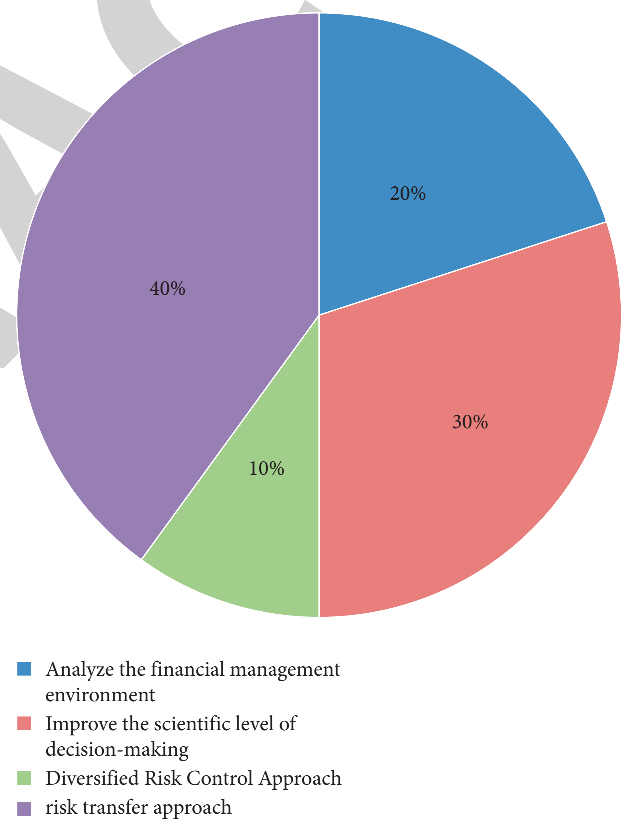

FIGURE 6: The proportion of the audience of risk prevention methods.

new technological change has emerged in today's world, that is, big data, which has had an extraordinary impact on various fields. The development direction of corporate financial management in the era of big data includes: cultivating the big data management awareness of corporate decision-makers, transforming corporate financial management functions, improving the level of financial management informatization construction, promoting the transformation of financial analysis from post-event

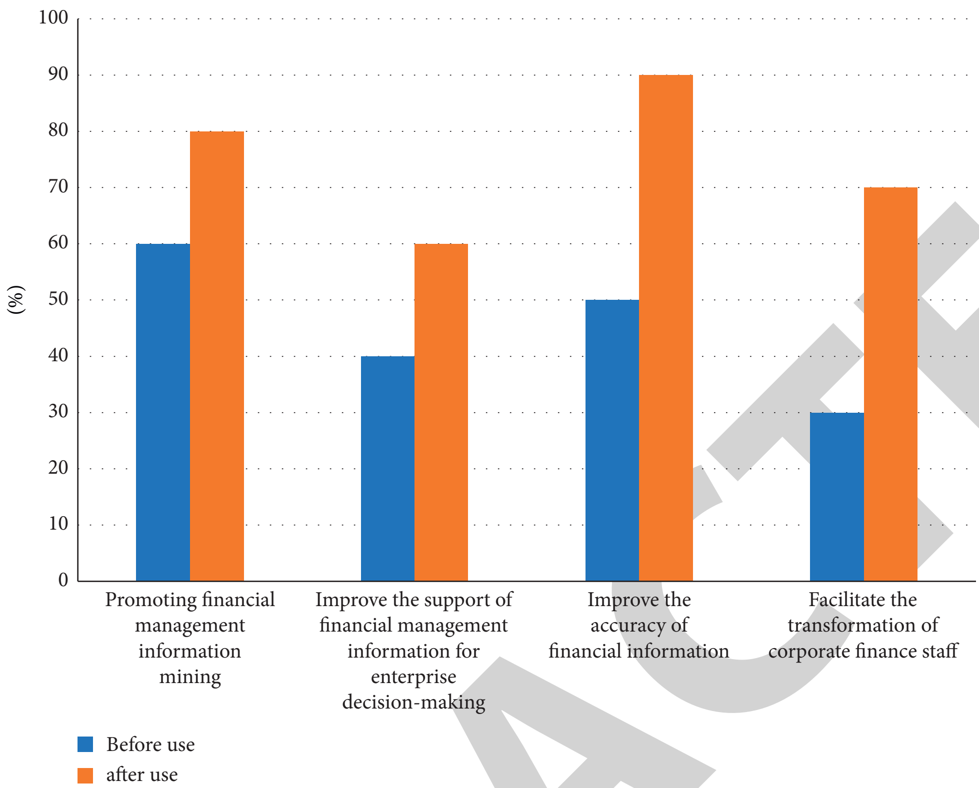

Figure 7: Comparison of progress in various aspects after using big data.

reflection to in-process control, and building large-scale financial management systems, and data finance talent team. In-depth analysis of the impact of big data on corporate finance will find that in the eyes of workers, the impact is roughly in the following aspects, as shown in Figure 7.

After the use of big data, many aspects of corporate finance have improved. After the survey, it was found that the improvement in the accuracy of financial information after application has increased to 90%, and the promotion of information mining has increased by 20%, increasing the influence of corporate finance on corporate decisions. A 20% increase and a 40% increase in the promotion of personnel transformation. Progress in all aspects can make the financial situation of the enterprise better, which is conducive to the reduction of risks. From this, it can be seen that the prediction and prevention of corporate financial risks under big data can improve efficiency and better prevent them.

5. Conclusion

This paper makes an in-depth study on the prediction of enterprise financial risk under big data. Corporate finance controls the lifeblood of corporate development and survival. We have analyzed the concept of corporate finance and better understand the definition of corporate finance. In the era of big data, we can better collect corporate financial data for risk assessment. The algorithm of financial risk assessment also better maintains the development of the enterprise and calculates the financial risk more quickly. The pharmaceutical enterprise in the example comprehensively demonstrates the enterprise risk assessment.

Data Availability

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

Conflicts of Interest

The author declares that there are no conflicts of interest regarding this work.

References

[1] A. Sandryhaila and J. Moura, "Big data analysis with signal processing on graphs: representation and processing of massive data sets with irregular structure," *IEEE Signal Processing Magazine*, vol. 31, no. 5, pp. 80–90, 2014.

[2] L. Chen, D. Zheng, and B. Liu, "Vfdb 2016: hierarchical and refined dataset for big data analysis—10 years on," *Nucleic Acids Research*, vol. 52, no. D1, pp. D694–D697, 2016.

[3] X. P. Qin, H. J. Wang, X. Y. Du, and S. Wang, "Big data analysis—competition and symbiosis of RDBMS and MapReduce," *Journal of Software*, vol. 23, no. 1, pp. 32–45, 2012.

[4] Y. Zhang, M. Chen, S. Mao, L. Hu, and V. Leung, "CAP: community activity prediction based on big data analysis," *IEEE Network*, vol. 28, no. 4, pp. 52–57, 2014.

[5] D. Wang and Z. Sun, "Big data analysis and parallel load forecasting of electric power user side," *Proceedings of the CSEE*, vol. 35, no. 3, pp. 101–112, 2015.

[6] L. Taylor, R. Schroeder, and E. Meyer, "Emerging practices and perspectives on Big Data analysis in economics: bigger and better or more of the same," *Big Data & Society*, vol. 1, no. 2, pp. 44–54, 2014.

[7] J. Nandimath, E. Banerjee, and A. Patil, "Big data analysis using Apache Hadoop," in *Proceedings of the IEEE International Conference on Information Reuse & Integration*, October, 2013.
[8] A. Akram, T. Michelle, and M. David, "From big data analysis to personalized medicine for all: challenges and opportunities," *BMC Medical Genomics*, vol. 60, no. 2, pp. 40–45, 2015.
[9] S. Maitrey and C. K. Jha, "MapReduce: simplified data analysis of big data," *Procedia Computer Science*, vol. 57, no. 3, pp. 563–571, 2015.
[10] C. J. Green, C. H. Kirkpatrick, and V. Murinde, "Finance for small enterprise growth and poverty reduction in developing countries," *Journal of International Development*, vol. 18, no. 7, pp. 1017–1030, 2006.
[11] T. Biggs, M. Fafchamps, and J. Conning, *Enterprise finance in Kenya*, vol. 40, no. 4, pp. 52–57, 1994.
[12] J. Rouse and D. Jayawarna, "Structures of exclusion from enterprise finance," *Environment and Planning C: Government and Policy*, vol. 29, no. 4, pp. 659–676, 2011.
[13] R. Nancy and Cook, "Use and misuse of the receiver operating characteristic curve in risk prediction," *Circulation*, vol. 56, no. 3, pp. 170–175, 2007.
[14] E. B. Claus, N. Risch, and W. D. Thompson, "Autosomal dominant inheritance of early-onset breast cancer. Implications for risk prediction," *Cancer*, vol. 73, no. 3, pp. 643–651, 1994.
[15] P. Greenland, L. LaBree, P. A. Stanley, and C. D. Robert, "Coronary artery Calcium Score combined with Framingham Score for risk prediction in asymptomatic individuals," *JAMA, the Journal of the American Medical Association*, vol. 89, no. 2, pp. 54–56, 2004.