A Research Review of Financial Distress Prediction

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Abstract: This study claims that two key points must be addressed in order to increase the success rate and robustness of financial distress prediction: firstly, a simplified financial prediction indicator system must be established based on a correct understanding and clearly distinguish about the concept of financial distress. Secondly, we establish a reasonable and plausible financial distress prediction model. It has been established that machine learning models can enhance financial distress prediction models' predictive power to some degree, bu the outcomes of these models vary. This is mostly due to a lack of knowledge about financial distress and a poor choice of indicators for predicting financial distress. This paper makes the case that there are three distinct, dynamic phases of financial distress. The financial strain stage is the initial phase. The financial distress at this stage is reflected in the financial indicators, as there are now some challenges with loan repayment due to the slowdown in the main business's revenue growth rate, the slowdown in operating cash flow, and the drop in the current ratio. The second stage can be called the financial crisis stage. The enterprise's ability to generate income is still declining, along with the quality of revenue and turnover rate. It's worth noting that gearing ratio, which will be approaching 50% or above at this stage. The third stage of financial distress is distress situation. In this stage, the firm's balance sheet structure keeps getting worse, and the gearing ratio keeps rising at an unprecedented rate. In the meantime, with growing revenue-cost-expense ratios and negative profits, profitability is still declining. At this stage, at least two of the three cash flows from financing, investing, and operating operations were negative in terms of cash flow.

Keywords: Financial Distress; Indicator System; Prediction Model; Theoretical Discussion

1. Introduction

Beaver's research, which was the first to describe financial distress as bank overdrafts, bankruptcy, default on preferred stock dividends, and non-payment of bonds, is the source of academic research on the topic. Since then, scholarly research on financial distress prediction has progressed from traditional predictive modeling using univariate and multivariate discriminant analysis to machine learning modeling (Beaver, 1966).

Financial distress was first studied in part because banks needed to assess a company's creditworthiness. Univariate discriminant analysis, or the study of ratios, was a popular method for predicting financial distress. In 1968, Altman came up with the innovative Z-score model (Altman, 1968) to do just that. Since then, the standard method for predicting financial distress has been multiple discriminant analysis. the research on the prediction of financial distress entered a white-hot empirical research stage in the following years as machine algorithms like neural networks, support vector machines, decision trees, etc. started to be widely used due to advancements in computer arithmetic power. When the term 'financial distress' was searched on CNKI as of October 31, 2023, 5329 results came up, with 754 articles categorized under the headings 'empirical research, ' 'prediction model, ' and 'financial warning. '

Financial distress prediction models have been developed, but their accuracy has not been consistent. A significant contributing factor is

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the overemphasis placed by researchers on model selection at the expense of theoretical analysis, including the notion and origins of financial stress. This results in a significant variation in sample selection and data cleaning, even though a very excellent model was chosen. This directly lowers the predictive power of the model.

Therefore, by organizing and defining financial distress, identifying its sources, and developing theoretical justifications for it, this work seeks to offer some fresh insights for academics studying financial distress prediction.

2. The Concept of Financial Distress

The study of corporate financial risk, business failure, and bankruptcy served as the foundation for the field of financial distress analysis. Beaver (1966) did not define financial trouble specifically, but of the 79 sample companies he chose, 59 were bankrupt, 3 were unable to pay their debts at maturity, and 16 were required to pay dividends on preferred shares. (Wu Shinong & Lu Xianyi, 2001). It could be inferred that Beaver defines financial distress as arising from one or more of the following three scenarios: failure to pay dividends on preferred stock; tardy repayment or non-payment of principal and interest on bank debt or bonds; and bankruptcy. When a company cannot pay preferred stock dividends, it indicates serious financial distress because preferred stock payouts are paid out preferentially to common stock. Bonds are an indicator of a company's creditworthiness, and they are also thought to be a sign of trouble for a company when principal and interest payments are not made on time.

In 1968, Altman added the current ratio to his list of indicators of financial trouble because he thought it was a symptom of poor cash flow. Ohlson (1980) contended that the timing of bankruptcy had a significant impact on the prediction of financial distress and used 10-K financial statement data rather than Moody's Manual data. Zmijewski (1984) contended that ‘oversampling’ of financially distressed firms severely affects the accuracy of financial distress predictions. On the one hand, he concused that one way to assess financial distress was through bankruptcy. It's also important to remember that Ohlson raised the hypothetical question, ‘Why foresee bankruptcy? “Another way to perceive this issue is that it ‘should simply be viewed as a descriptive statistic. ’”‘For the most part, research claiming to address the issue of financial distress has actually studied samples of bankrupt companies, ’ asserted Harlan D. Platt* and Marjorie B. (2006).

Zhu Guanxiang (1989) was the first Chinese scholar to study financial distress. He believed that the following factors were indicative of financial distress: a lack of turnover foreign exchange, rising raw material prices, insufficient liquidity, a lack of settlement discipline, and difficulty updating reorganization tasks. Clearly, the financial distress he raised was more akin to operational difficulties.

Wu Shinong (2001) carried on Altman's argument that financial distress equates to a financial crisis. He saw bankruptcy as the worst kind of financial difficulty because it is essentially a breach of contract when an enterprise files for bankruptcy due to financial difficulties. As a result, the financial situation is also known as default risk.

The equalization of financial distress and bankruptcy, according to Zhang Jinchang and Wang Dawei (2020), strengthens the ‘legal significance’ of insolvency in financial difficulty but lessens its ‘economic significance. ’ They contended that businesses were in financial distress when they ran the risk of breaking the financial chain.

When predicting financial distress, the majority of researchers base sample selection in empirical analysis on insolvent enterprises and health companies (Mu-Yen Chen, 2011; Chih-Fong Tsai, 2014; Ahsan Habib, et al., 2018; Dai Lijun, 2022; Guan Lili, 2023).

Financial distress is defined as ‘unusual and special treatment’ (ST). However, bankruptcy is only one of eight factors that lead to the special treatment of the risk warnings under the Shanghai Stock Exchange Rules and the Shenzhen Stock Exchange Listing Rules. Therefore, it is unreasonable to equate ST with bankruptcy and bankruptcies with financial distress. Scholars have also attempted to extract information that predicts financial distress or insolvency from text analyses, such as electronic memoirs (Chuanyi Tang, 2016) and negative media reports (Sunjie, Li, and Zhao Mengru, 2023). Many other scholars hold the view that financial distress is a dynamic process that deteriorates a company's financial condition over time.

Chinese academics like Zhang Zhiwang (2008) classify companies in financial distress as having past-due short-term loans or big accounts payable that have been outstanding for longer than three years. Listed firms that have been delisted following three years of losses are considered to be in financial distress and to have a broken capital chain, according to Zhang Jinchang and Fan Ruizhen (2012).

'A feeling of extreme worry, sadness, or pain' is how the Cambridge Dictionary defines distress, with the term "extreme" indicating how unbearably severe the distress is.

In the book the *Crown of Coronation, Volume of the Scriptures, Sixteenth*, the divine doctor Bian Magpie once talked about his medical view of his three brothers. He said, "My eldest brother looked after the disease and eliminated the cause of the disease when he realized that it had not formed, so his reputation did not spread out of the house. My second oldest brother cured the disease and eliminated the cause of the disease as soon as it sprouted, so his reputation couldn't reach the streets. Doctors like me prick the blood with needles, give strong medicines to the sick, and apply ointments to the skin so that my fame spreads out and I am known among the lords. " Bian Magpie talked about medicine, but it worthwhile to learn from his dynamic perception of disease.

This paper makes the case that the study of financial distress should be grounded in the financial domain. It compares the process of an enterprise experiencing financial distress to that of a sick person; it starts with mild symptoms, progresses to a serious situation, and ultimately results in the enterprise's inability to recover from its financial difficulties.

3. The Prediction Indicators of Financial Distress

Research on prediction indicators of financial distress has gone from univariate to multivariate, extending from the early focus on financial indicators to multidimensional indicators such as market and macro.

Fitzpatrick (1932), as the world's first empirical study of how to predict corporate financial distress, devoted himself to finding out among the many financial indicators that could predict corporate bankruptcy, and ultimately, he found that net equity and equity ratios were the best predictors of corporate failure.

Beaver (1966) selected thirty financial indicators: eight that represented corporate profitability, four that represented long-term solvency, seven that represented short-term solvency, and eleven that represented operational capacity. To create a Z-score model. Altman (1968) used the following ratios: working capital to total assets; retained earnings to total assets; earnings before interest and taxes to total assets; market value equity to the book value of total debt; and sales to total assets to predict the financial failure.

Olson (1980) developed a financial distress prediction model using nine financial variables. Zmijewski, ME. (1984) employed ROA and liquidity financial indicators as financial distress prediction indicators, using 400 operating enterprises in good standing and 40 insolvent companies as research subjects. In 2017, Altman added OM (operation margin), GA (assets growth), GS (sales growth), GE (growth of workers), and CPB (change in price to book) to his original financial crisis prediction indicator system.

Businesses are becoming more sensitive and passive as a result of the external business environment; they are no longer just focused on their own success as globalization and marketization continue to grow. Therefore, an increasing number of academics are focusing on the unexpectedly affecting elements of financial indicators in order to predict the financial challenges of organizations.

In terms of the market, market information may make predictions about the future of the business, whereas accounting information simply reflects the financial standing of the company in the past. As a result, a lot of researchers have started looking into how well market data can forecast financial distress. Beaver (2005) contended that the probability of corporate bankruptcy increases with market volatility, while Campbell (2008) combined financial indicators and stock market data. Campbell (2008) uses a logic model to combine financial and stock market information indicators and confirms the usefulness of market data in forecasting business financial trouble. Christidis and Gregory (2010) conducted an additional study

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to examine the predictive capacity of three market forecasting indicators. Their findings indicate that the inclusion of macroeconomic variables enhances the predictive potential of market-based accounting models, both inside and outside of the sample. to accounting methods based on the market.

Scholars have recently turned their attention to other predictors of financial distress, such as corporate governance. In their study of bankrupt firms in Taiwan, Lee and Yeh (2004) found that family-owned firms were more likely to be in financial distress because of their governance structure. Khaw et al. (2016) contended that male executives would act more aggressively during the course of firm operations. conduct, in contrast to the more traditional female executives.

As the chief executive officers of corporate strategic decision-making, Shi Jing & Yang Li (2021) contended that CEOs have their own cognitive foundation, risk preferences, and other personal attributes that influence organizational decision-making and strategy layout, which in turn affect corporate behavior. Using study samples of Shanghai and Shenzhen A-share listed businesses from 2010 to 2018, they empirically investigate the link between CEO risk appetite, financial difficulty, and corporate violation tendency. the findings indicate that companies led by risk-averse CEOs are more likely to break the law and that the major effect is mitigated by business financial difficulty.

Table 1. Key Variables in Predicting Financial Distress

	Variables	Author	Time
	Net equity margin and equity ratio	Fitzpatrick	1932
Accounting information	cash-flow ratios, net-income ratios, debt to total-asset ratios, liquid-asset to total-asset ratios, liquid-asset to current debt ratios, turnover ratios	Beaver	1966
	working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value equity/book value of total debt, sales/total assets	Altman	1968
	TLTA = Total liabilities divided by total assets. WCTA Working capital divided by total assets. CLCA Current liabilities divided by current assets etc.	Olson	1980
	ROA(return on assets), Total debt to total assets (financial leverage), LIQ = current assets to current liabilities (liquidity)	Mark E. Zmijewski	1984
	OM(Operation margin), GA(Assets growth), GS(Sales growth), GE(Growth of employees), CPB(Change in price to book)	Altman	1997
Market Information	market fluctuation	Beaver	2005
	market-to-book ratios	JOHN Y. CAMPBELL	2008
	volatility	Christidis&Gregory	2010
Macroeconomics	monthly change in the Industrial Production Index (INDPROD),	Christidis &Gregory	2010
	National short-term treasury rates and retail price index indicators	Tinoco &Wilson	2013
	inflation	Mare	2015
Corporate governance and other information	Family-owned business governance structure	Lee&Yeh	2004
	Executive gender differences	Khaw et al.	2016
	Electronic Word of Mouth	Chuanyi Tang	2016
	Executive risk appetite	Shi Jing&Yang Li	2021
	Societal Burden	Ma Yannan	2021
	Overinvestment	Guan Lili	2023
	Negative media coverage	Sun Jie et al.	2023

According to Guan Lili (2023), corporate overinvestment plays a mediating role in the way that industrial policy amplifies corporate financial stress. Industrial policy is said to lessen or enhance corporate financial distress by raising corporate overinvestment in the later two periods while decreasing it in the former. the link between corporate financial distress and executive power checks and balances is significantly moderated by these mechanisms; the more executive power checks and balances, the greater the contribution of industrial policy to the suppression of financial stress. the early warning indicator system of business financial crises has been expanded by some researchers to incorporate electronic word-of-mouth (Chuanyi Tang, 2016), unfavorable media reports (Sun Jie, Li Nengfei, Zhao Mengru, 2023), and social costs (Ma Yannan, 2021).

In general, there are benefits and drawbacks to integrating data on corporate governance, financial indicators, the macroenvironment, and markets to create a forecasting system for financial distress indicators. the benefit is mostly found in the financial metrics that integrate internal and external elements. When considering statistical analysis, it is certain that the enhancement of indicators would enhance the capacity to forecast corporate financial difficulty to a certain degree. Nonetheless, researchers should take into account the issue of indicator covariance. Second, there is not enough theoretical foundation for the selection of several indicators. The majority of researchers currently concentrate on the indicator system's predictive accuracy; however, since different enterprises have different life cycles and are concerned about how the indicators are changing dynamically, applying the same indicators to all of them ignores enterprise heterogeneity, industry variability, even differences between countries, and the stage at which an enterprise is developing. Predictive indicator systems will proliferate, and research will go off course due to a lack of theoretical underpinning, as **Table 1**.

4. The financial distress prediction model

Financial distress prediction has been a topic of interest and research for several academics since the 1960s. Studies on the prediction of financial stress have mostly used two approaches: Traditional financial prediction model and machine learning algorithms models.

4.1 Traditional Financial Prediction Model Machine Learning Algorithms Models

4.1.1: Univariate Discriminant Analysis(UDA)

Fitzpatrick (1932) is credited as being the first researcher to examine the topic of company financial trouble prediction scientifically. In order to predict whether a company would file for bankruptcy—since computer technology was not yet widely used—he gathered a large amount of financial data and selected specific financial indicators. In the end, he discovered that the equity ratio and net equity margin had the highest prediction rates for corporate bankruptcy.

Fitzpatrick's theory of using a single financial indicator to predict corporate financial distress was also adopted by Beaver (1966). the author screened thirty financial indicators and discovered that several of them, including the cash flow to debt ratio, the net interest rate on total assets, and the gearing ratio, have a very good predictive ability for financial distress.

The following issues may arise with univariate discriminant analysis, despite its simplicity and ease of understanding: (1) it is challenging for a single financial variable to accurately reflect a company's overall situation; (2) conclusions drawn from the same type of financial indicator may be diametrically opposed; (3) once a predictive indicator is identified, management has the ability and motivation to embellish the indicator and invalidate the prediction.

4.1.2: Multiple Discriminant Analysis(MDA)

Seeing the inherent flaws in univariate discriminant analysis, Altman (1968) developed and refined the technique of using many indicators to jointly forecast bankruptcy. This Z-score model was revolutionary in its ability to forecast financial trouble. Out of the 22 indications, he chose 5 and calculated their coefficients to create the Z-score. the Z-score was then used to establish the interval in which the Z-score fell, indicating the risk of a firm's financial difficulty. Following that, Altman continued to study the Z-score model for financial distress prediction. In 1977, he and other researchers created the ZETA model, a 7-indicator prediction model with greater accuracy, which enhanced the model system for forecasting the financial distress of businesses using a variety of indicators. The ZETA model's accuracy is greater than the Zscore model's in the year before bankruptcy, but it is lower than the Zscore model's in the year prior to non-bankruptcy, according to their comparison of the two models.

Chinese research on the prediction of corporate distress began in the 1990s, when Zhou Shouhua (1996) proposed the F-score model based on the Z-score, combined with the practice of Chinese companies. Over the next few decades, numerous studies based on multivariate discriminant analysis appeared all over the world. Up until the turn of the century, corporate financial stress was the subject of increasing numbers of Chinese academics. Zhang Ling (2000) classified financially distressed enterprises and financially sound firms using a multivariate discriminant analysis model. the authors created a discriminant function by selecting four indicators from 15 financial measures that had the maximum explanatory power.

When Hongyan Cai and Liyan Han (2003)

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examined the predictive power of financial indicators in corporate financial crises, they discovered that multivariate discriminant analysis outperformed one-dimensional discriminant analysis.

the use of multivariate discriminant analysis increases the accuracy of predictive diagnosis; however, it is subject to stricter statistical requirements, which also deters researchers from employing this technique. Specifically, the use of multivariate discriminant analysis requires that the predictor variables of the sample as a whole obey the normal distribution and that the predictor variables of the paired samples have the same covariance matrix.

4.1.3: Logit Regression Model(LRM)

The occurrence of corporate financial distress was predicted using a logistic regression model by Meyer & Pifer (1970) and Martin (1977), who found that six indicators, including the net interest rate on total assets, could predict the event with a relatively high degree of accuracy. Ohlson (1980) also employed a logistic regression model to predict the event of corporate financial distress and discovered that corporate size, capital structure, corporate performance, and liquidity could predict the event with an accuracy of more than 95%. The academic community refers to the logistic regression model that Ohlson (1980) and his colleagues constructed later for most scholars to learn as the Oscore model. Ohlson (1980) found that enterprise size, capital structure, corporate performance, and liquidity affect financial distress prediction accuracy by more than 95%. This approach has been utilized to anticipate financial distress and extended investigations in the following typical international research: Jones & Hensher (2004); Zavgren (1983); Casey & Bartczak (1985); Johnsen & Melicher (1994); Laitinen et al. (2000); Wijst & Westgaard (2001); Laitinen et al. (2000).

Wu Shinong and Lu Xianyi (2001) used logistic regression, multiple linear regression, and linear decision analysis, respectively, to predict the financial distress of 70 financially distressed companies and financially healthy companies. They discovered that while all three methods are capable of predicting financial distress, logit regression is the most successful. Using a logit regression model, Sun Ying and Cui Jing (2017) performed a financial forecast research on zombie enterprises. After downscaling 14 financial variables using factor analysis, the four components with significant coefficients were included to the Logit model for zombie enterprise prediction. The logistic regression model has a broader range of applications because its dependent variable is typically dichotomous and its independent variables do not have to adhere to the statistical constraints of multivariate discriminant analysis. However, the model's computational process is more complex, there are more approximations that affect the process's accuracy, and there are some theoretical flaws in the way multiclassification diagnosis is handled.

4.1.4: Probit regression(PG)

Zmijewski (1984) used Probit regression to screen 75 variables and found that four indicators, such as the return on investment and the balance sheet ratio, were the most effective in predicting financial distress. the probabilistic unit regression model requires the dependent variable to follow a cumulative normal distribution, so its application is not as extensive as that of the logistic regression model (Liu, Yanwen, 2009; Qin, Zhimi & Guo Wen, 2012). Lennox (1999) examined the reasons for 949 listed firms insolvency in the UK between 1987 and 1994.

the primary factors that determine bankruptcy include industry, business size, cash flow, profitability, leverage, and economic cycles. Cash flow and leverage have strong nonlinear impacts, as demonstrated by heteroskedasticity tests, and accounting for these nonlinearities enhances the model's explanatory ability. the authors came to the conclusion that logit and probit models, as opposed to discriminant analysis, are more accurate in identifying failing enterprises than prior research. Few domestic researchers have used models of probit unit regression to diagnose business distress. Using the probit model, Ning, Qingqing, and Zu Ming (2013) and Jiang, Yaqi (2014) performed a prediction study of business financial distress.

4.2 Machine Learning Algorithms Models

Almost all academics are always attempting to develop and evaluate different machine learning models to increase the prediction rate of financial distress since machine learning models were first employed for financial distress prediction, almost as if they were discovering a guiding light. Currently, the three most popular methods are support vector machines, genetic algorithms, and artificial neural networks.

4.2.1:Artificial neural network(ANN)

Leshno & Spector (1996) argued that the predictive ability of neural networks can be optimized by constant tuning of their parameters and that the predictive ability of the preferred neural network model is more accurate than that of the classical discriminant analysis model. Tsai & Wu (2008) argued that artificial neural networks, as an important artificial intelligence and machine learning technique, can already be used to solve all kinds of financial decision-making problems.

Zhou Min and Wang Xinyu (2002) proposed a financial distress prediction model based on fuzzy preference and a neural network that can learn the data in an inferential knowledge-based manner. With the increase in sample information, the learning information can be updated regularly to realize the dynamic prediction of distress, and thus this method is more advantageous than the traditional prediction method with a single function.

After organizing the literature related to financial distress, Bao Xinzhong et al. (2016) found that neural networks have some difficulties in the practical application of a single enterprise due to the need for massive learning data support, but the research of several scholars shows that neural networks tend to have a higher accuracy rate compared to other multi-category judgment prediction research methods.

4.2.2:Genetic Alogrithm(GA)

Back et al. (1996) predicted and diagnosed the bankruptcy problem of 37 bankrupt and 37 non-bankrupt enterprises in Finland in 1986–1989 using multivariate discriminant analysis, a logit model, a neural network model, and a genetic algorithm. the neural network model based on a genetic algorithm, which may reach 97% for the year before bankruptcy, has the best prediction accuracy, according to the authors' findings.

According to Sun Jannan and Qi Li (2019), who approached computer science from the standpoint of data analysis, the genetic algorithm has a high degree of practicality and increases the effectiveness of using the original training data. 303 organizations were split into a training set and a test set by Mi Wandong (Mi Wandong, 2022). She then utilized the Logit Regression Model (LRM) to make strong predictions, with an overall percentage of 90.8 percent. Nevertheless, following genetic algorithm optimization, the prediction's accuracy increased to 94.5%, and its dependability increased.

4.2.3:Support Vector Machine(SVM)

Fan and Palaniswami (2000) proposed the use of support vector machines for the prediction of corporate bankruptcy. They also found that the results of using SVMs for bankruptcy prediction were superior to those of using traditional statistical models.

Yang, Navy, and Tailei (2009) conducted an empirical investigation on the prediction of financial distress of listed businesses using fuzzy support vector machines, which helped them avoid the danger of misclassification and overfitting concerns of classical support vector machines. the outcomes demonstrate that the fuzzy support vector machine may increase prediction accuracy while more effectively addressing the overfitting issue and misclassification risk.

Sun Jie et al. (2021) developed a method based on the KNN subordination fuzzy support vector machine for multi-categorization of financial data of listed businesses. They employed a genetic algorithm to effectively determine the parameters of the fuzzy support vector machine. the empirical findings demonstrate that the fuzzy support vector machine may increase classification accuracy and more effectively address the overfitting issue.

In conclusion, when choosing forecasting models, nonlinear models outperform linear ones, particularly machine learning algorithms. In general, artificial neural networks outperform traditional financial prediction models, while support vector machines (SVMs) outperform both. As a result, the support vector machine is used in this work to construct the financial distress prediction model, as **Table 2**.

Table 2. Financial Distress Prediction Model

Prediction model	Author	Time
Multiple Discriminant Analysis		
Z-score	Altman	1968
ZETA	Altman et al.	1977

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F-score	Zhou et al.	1996
Logit Regression Model	Meyer & Pifer	1970
	Martin	1977
	Ohlson	1980
Probit regression	Zmijewski	1984
	Lennox	1999
	Liu Yanwen	2009
	Qin Zhimin	2012
	Ning Qingqing & Zu Ming	2013
	Jiang Yaqi	2014
Artificial Neural Network	Leshno & Spector	1996
	Tsai & Wu	2008
	Zhou Min et. al	2002
	He Sijing	2016
Genetic Alogrithm	Back	1996
	Sun Hianan&Qi Li	2019
	Mi Wandong	2022
Support Vector Machine	Fan & Palaniswami	2000
	Yang Haijun&Tai Lei	2009

5. Theories of Financial Distress Prediction Studies

There are several theories among academics as to why businesses face financial challenges. Currently, scholars mostly think that company life cycle theory, principal-agent theory, capital structure theory, and macroeconomic theory may all be used to explain financial challenges. According to the capital structure theory, businesses continuously raise their debt leverage in order to accomplish balance sheet expansion and optimize shareholder interests. As a result, the firm would experience financial difficulties due to the increase in debt payment risk. However, businesses will need expert managers to enhance the corporate governance framework in order to prevent financial troubles. (Donker H., 2009). This leads to the development of principal-agent theory. In contrast to shareholders, professional managers will take more aggressive business actions throughout the real business process; in other words, the enterprise's business risk rises. Furthermore, the enterprise's real controllers are more inclined to engage in the practice of "hollowing out" the organization (Zheng Guojian et al., 2013). Accordingly, the establishment of an efficient system for balancing interests and lowering the agency cost of businesses has gained significant importance in recent years, as supported by the principal-agent theory. Therefore, Manzaneque M et al. (2016) think that further research should be done on the percentage of independent directors, the board of directors' functional design, and the board's size.

According to the life cycle theory of businesses, financial troubles are unavoidable for businesses. As per the business life cycle theory, an organization requires substantial cash flow and capital during its start-up phase. This is because the start-up has to allocate a substantial amount of funds toward research and development, marketing, and other related operations. However, the firm will have financial issues due to the strain of functioning during the start-up phase and securing capital in the early stages. (Helfat C. E. &Peteraf M. A., 2003). According to the life cycle theory of businesses, financial troubles are unavoidable for businesses. As per the business life cycle theory, an organization requires substantial cash flow and capital during its start-up phase. This is because the start-up has to allocate a substantial amount of funds toward research and development, marketing, and other related operations. However, the firm will have financial issues due to the strain of functioning during the start-up phase and securing capital in the early stages. (Hu, N., and Jin, Q. L., 2018)

Overall, academics' understanding of business financial challenges has advanced to a relatively ideal level. They have not only focused on the internal issues of businesses but have also taken into account the influence of external variables. However, we should remember that the macro-factors themselves will have an effect on the internal financial situation of the enterprise; that is, there is some sort of endogenous relationship between the financial factors and the external factors themselves. We tend to focus too much on the extent to which government subsidies and inflationary factors affect corporate financial distress. Thus, biased outcomes may be avoided by shifting attention back to the financial data itself and applying it to forecast financial stress.

6. Conclusions and Outlook

As mentioned in the second chapter of the allusion to the ancient Chinese Bian Magpie, the process of an enterprise falling into financial distress is like a person suffering from a disease, which develops from the initial mild symptoms into a serious situation, and finally the enterprise will be like a person who has been sick for a long time, falling into a financial predicament that cannot be cured by itself.

This research claims that the dynamic growth of financial distress may be understood as complete, with the firm's listing as the beginning point and the ST stage preceding the enterprise's delisting as the endpoint. This stage is broken down into three phases in this paper: the first, the financial strain stage, begins with the enterprise's listing and ends with the financial crisis stage. the following financial indications point to a financial stress stage: a slowdown in the growth rate of primary company income, a slowdown in operational cash flow, a fall in the current ratio, and some issues with loan repayment. See Fig. 1.

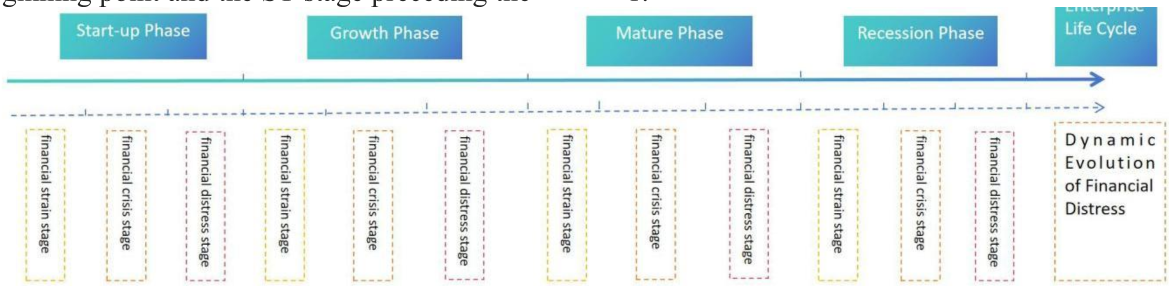

Fig. 1 Issues with Loan Repayment

The stage of financial crisis is the second. Four indications can be used to assess deterioration: 1. the company's ability to generate revenue is declining and is still getting worse. 2. the revenue's quality drops; at this stage, nearly all ST enterprises see a trend of revenue increase at the expense of net profit. 3. reduction in turnover; Liabilities rise when gearing surpasses fifty percent.

the stage of financial distress is the third. At this point, the company's balance sheet structure is still deteriorating, and the gearing ratio is still rising more quickly and severely. However, the revenue-cost-expense ratio is increasing, profitability is negative, and it is still declining. In terms of cash flow, at least two of the three cash flows from operating activities, financing activities, and investing activities are negative.

The enterprise life cycle theory serves as the foundation for the assessment of the dynamic evolution process of financial crises. Businesses that are able to achieve the A-share listing criteria are clearly not in the early stages of entrepreneurship, according to China's main board listing guidelines. Thus, only three stages—growth, maturity, and decline—fit the study of financial distress if we use Chinese listed businesses as a sample.

Growth-stage businesses prioritize earnings, expenses, and revenues. The expansion of funding channels following public listing reduces the likelihood of a financial crisis for the great majority of businesses at this point. Growing businesses will pay particular attention to changes in revenues and costs; during a period of healthy growth, operating income and net profit tend to increase steadily. At the same time, they must continue to increase their market share and enhance the quality of their products and services to ensure the enterprise's sustainable development. Additionally, businesses experiencing financial strain exhibit inconsistent increases in operating income and net profit. Three scenarios frequently occur: first, operational income is trending upward, but net profit is increasing more slowly. Second, while net profit is stable or even slightly down, operational income is increasing. the revenue curve and net profit curve in the first two examples above exhibit distinct and mutually independent tendencies. Third, there is a declining tendency in both sales and net income. the operational income curve and the net profit curve exhibit a nearly equal frequency of decreasing trends in this instance.

Mature businesses stabilize after going through the growth stage and have a sizable market share; thus, they must pay close attention to cash flow management to guarantee the smooth running of the business. Mature businesses also need to increase shareholder returns and optimize their capital structure. Financially speaking, strong businesses will continue to be able to generate more income

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throughout this time, and they will increase their profitability by lowering their gearing ratio. The most obvious indicator of the financial crisis stage is the continuous rise of the balance sheet ratio. Although in the process of operation, enterprises will adjust the balance sheet ratio by adjusting their business strategy, it can't be suppressed. the decline in operating income brought about by the financial crisis stage can't be solved from the root of the problem, which will ultimately lead to the rise of the balance sheet ratio of the enterprise.

When a company enters a recession, it pays more attention to cash flow, cost control, and expense reduction as its market share gradually shrinks and both operating income and net profit decline. Enterprises in recession also need to optimize their balance sheets and reduce debt stress. Enterprises that have gone through a financial crisis are already heavily indebted, and many have a T-1 balance sheet ratio of more than 100%, effectively reaching the point of insolvency, as **Table 3**.

Table 3. The Relationship Between Enterprise Life Cycles Theory and The Dynamic Evolution of Financial Distress

	The first stage	**The second stage**	**The third stage**
Enterprise life cycle theory	**Growth stage**	**Mature stage**	**Recession stage**
Business Performance	Revenues, expenses, and profitability are the main concerns of growth-stage businesses. They must raise the caliber of their goods and services and increase their market share. Growing businesses pay close attention to changes in expenses and revenues, which are best described as a convergence of gains in operational revenues and net profits, in order to ensure sustainable development.	To maintain stable operations, businesses at the maturity stage—which includes stabilization and a sizable market share—need to concentrate on cash flow management. Mature businesses also need to optimize their capital structure to increase shareholder returns.	Businesses in a recession must concentrate on cash flow management to reduce losses, as they are gradually losing market share and seeing a drop in sales and earnings. To lessen the burden of debt, businesses must also optimize their balance sheets.
Relationships between financial indicators of healthy enterprises	Converging Operating Income and Net Profit Growth	The company's revenue capacity will continue to increase gradually, and lowering the gearing ratio will increase profitability.	Businesses are steadily losing market share, seeing a decline in operating income and net profit, and focusing more on cash flow, cost management, and expense reduction.
Assumptions on the dynamic evolution of financial distress	**Financial strain**	**Financial crisis**	**Financial distress**
Business Performance	There are some challenges with debt repayment: the current ratio has decreased, the growth rate of income from core businesses has slowed, and cash flow from operations has also slowed.	It is unable to address the underlying cause of the diminishing operating revenue, which will ultimately cause corporate gearing to increase.	Companies' balance sheet structures are still collapsing, and gearing is still rising like a torrent. However, with a growing revenue-cost-expense ratio and negative profits, profitability kept declining. At least two of the three cash flows from financing,

			investing, and operating operations were negative in terms of cash flow.
Relationships between financial indicators of unhealthy enterprises	There are three possible outcomes when operating income and net income do not converge (the inflection point): first, operational income will increase, but net income will rise more slowly. Second, while net income is stable or even slightly down, operational income is increasing. the revenue curve and net profit curve in the first two examples above exhibit distinct and mutually independent tendencies. Third, there is a declining tendency in both sales and net income. the operational income curve and the net profit curve exhibit a nearly equal frequency of decreasing trends in this instance.	1. Corporate revenue capacity is declining and is still getting worse. 2. Revenue quality decreases; at this point, nearly all ST enterprises have seen a trend of revenue increase at the expense of net profit. 3. Reduced turnover occurs. 4. Liabilities rise, and the gearing ratio rises over 50%.	Companies are already highly leveraged, with many having T-1 gearing levels above 100%, which essentially puts them insolvent.

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