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UNRAVELLING CORPORATE FINANCIAL DISTRESS PREDICTIONS: A CONCEPTUAL OVERVIEW AND CONTENT ANALYSIS

Soumya Ranjan Sethi*, Dushyant Ashok Mahadik**

Abstract *The period preceding bankruptcy is known as financial distress. The final phase of a company's downfall, known as financial distress, occurs when there is a shortage of liquid cash. Predicting financial hardship has been a field of study by numerous scholars. Different financial hardship prediction models exist that have been investigated thus far. Consequently, the goal of this study is to examine the literature on financial distress forecasts for corporations, the financial distress impacting causes, and financial management guidelines for preventing situations of financial trouble. In addition to answering the question of how market sentiment and investor behaviour influence financial distress. According to the results of the literature review included in this work, the Altman Z-score model has been extensively employed to forecast financial difficulties in corporations. In addition, a content analysis was carried out to determine the critical themes for future research. The results additionally indicate that some of the fundamental ideas to remember in order to prevent financial hardship include the ideal amount of debt in a company's financial structure, ongoing observation of some necessary financial measures, such as total debt to total assets, net income to total debt, and cash flow to total debt assets.*

Keywords: *Financial Distress, Financial Management, Cash Flow, Financial Distress Prediction, Content Analysis*

JEL Classification: *G01, G33, G17*

INTRODUCTION

Predicting financial distress plays a vital role in detecting companies that may face financial collapse, enabling stakeholders to take preventive action to mitigate potential losses. This process utilises financial ratios, economic indicators, and sophisticated statistical and machine-learning techniques to estimate the probability of a company encountering financial difficulties (Sethi et al., 2024; Sethi & Mahadik, 2025A; Sethi & Mahadik, 2025B). Precise forecasting models are critical for investors, lenders, and executives to make well-informed decisions regarding investments, credit assessments, and long-term planning. As global markets become increasingly unpredictable and interconnected, the need for reliable financial distress prediction intensifies, bolstering the durability and longevity of businesses and enhancing overall economic resilience.

Businesses are essential to the nation's ability to generate cash and meet its economic needs. However, following the pandemic, the majority of businesses worldwide have been experiencing severe financial distress (Dash et al., 2023). The financial crisis of the last decade demonstrated the increasing complexity and unpredictability of modern markets, which has led to an uptick in interest in research into Financial Distress Prediction (FDP) (Sethi et al., 2024; Hendieh, 2023). Financial distress is inferred to be the state in which a business is unable to satisfy its financial obligations. Filing for bankruptcy occurs when a business or individual cannot repay their creditors the money they have loaned them (Siddhpuria, 2023). When a company is in financial crisis, it is in a late stage of decline and is experiencing liquidity issues. A monetary crisis in a company, it usually shows when it cannot pay back its debt. That situation is expected in the event of excessive leverage, poor profit margin per unit, and extended gestation time or revenue is influenced by the state of the economy. The impact of leverage on a company's return on investment depends on its business conditions and environment. Increased leverage can lead to a higher return on investment in a favourable business environment could negatively impact return on investment in the event of adverse business circumstances (Simiyu, Ngumi, Ngugi & Sporta, 2017). Estimating a financial crisis

* Research Scholar, Finance Area, School of Management (SOM), National Institute of Technology, Rourkela, Odisha, India. Email: grsoumya1697@gmail.com

** Assistant Professor, School of Management (SOM), National Institute of Technology, Rourkela, Odisha, India. Email: mahadikd@nitrkl.ac.in

is crucial to safeguarding the interests of the parties involved, including lenders, investors, and employees in general. The financial distress prediction model can assist the corporate sector by offering an early warning management should start corrective action far in advance to prevent financial hardship circumstance. Early detection and prompt corrective action are essential for enterprises and regulators to effectively address financial distress (Dash et al., 2023). Financial conditions and managers' incentives have typically been the causes of fluctuations in risk management. Mahadik and Mohanty (2024) examined the variations from a behavioural perspective using prospect theory, which posits that a "reference point" influences risk tolerance beyond the conventional risk-return relationship. Theories from the perspective of behavioural finance can help elucidate the underlying causes of financial difficulties. Research can investigate the impact of cognitive and heuristic biases on decision-making, which can result in financial hardship Sethi and Mahadik (2024). This research aims to review the literature based on the above topics. Predicting financial crisis, encompassing global financial hardship forecasting models and financial management guidelines to prevent difficult financial circumstances. The following research questions are addressed in this review paper.

RQ1: Evolution of financial distress prediction literature.

RQ2: An overview of the ways in which financial management principles might be used as a shield against financial hardship.

RQ3: How market sentiment and investor behaviour influence financial distress and help to close the gap between traditional financial metrics and market dynamics?

RQ4: To determine the future research direction of this study.

In answering these four essential research issues, our work contributes to the existing body of knowledge. First, it gives a thorough history of financial crisis prediction approaches, including everything from traditional statistical models to modern machine learning techniques while tracing their growth. Secondly, it delves into how financial management concepts may shield companies from financial troubles, providing helpful information for businesses to strengthen their resilience through financial planning. Third, the research fills a gap in the literature by investigating how investor mood and market dynamics impact financial distress; this improves the predictive potential of distress models by combining conventional financial measurements with market dynamics. Finally, the paper suggests areas for future research, highlighting the need to include behavioural finance, macroeconomic issues, and sustainability concerns in models that anticipate financial hardship. This would lead to a more comprehensive and future-oriented approach in the field. If academics, practitioners, and policymakers want to improve financial stability and organisational sustainability, this study is a great place to start.

There are eight sections in this study. The first section defines the introduction. The second section explains the methodology, and the third consists of a literature review. The fourth, fifth, and sixth sections address the research questions based on this study. The seventh section is for content analysis, and the final section summarises the study along with policy implications.

LITERATURE REVIEW

The hypothesis used a cash flow paradigm to explain financial distress. This approach is predicated on the idea that the main criterion for characterising a company's financial distress situation should be net cash flows relative to current liabilities. Businesses with positive cash flows are able to raise capital and obtain loans from the capital market; on the other hand, businesses with negative or insufficient cash flows can not do so. They run the risk of defaulting as a result. This hypothesis states that a company is likely to file for bankruptcy if its net cash flow or profit for the current year is negative or less than its debt load. We refer to this state as technical insolvency. When a company lacks liquidity and is unable to satisfy its ongoing financial obligations, it is considered technically insolvent (Altman & Hotchkiss, 2006). Liquidity and profitability fluctuations may serve as early warning signs of financial instability, according to theory. The reason for this is that a decrease in liquidity or profitability could lead to financial difficulty for the company (Altman, 1968). According to Hasi (1997), a company is seen as healthy when its indicators of liquidity and profitability are strong; when these indicators are weak, the company is seen as sick and vulnerable to bankruptcy. A statistical model called the Altman Z-score is used to forecast the likelihood that a business will declare bankruptcy during the next two years. Since its creation by Edward Altman in 1968, it has been extensively used by practitioners and scholars alike.

$$Z = .012X1 + .014X2 + .033X3 + .006X4 + .999X5$$

where X2 = Retained Earnings/ Total Assets and X1 = Working capital/ Total assets X3 Total assets / Earnings before interest and taxes X4 = Market Value Equity / Total Debt Book Value X5 = Total Assets/Sales. Z is the total index (formula given by Altman, 1968). According to research by Frank and Goyal (2009), businesses that depend significantly on outside funding are more likely to face financial difficulties. When a company's internal funding sources are insufficient to meet its financial demands, it must choose between external funding sources. According to the theory, businesses will prefer low-risk debt from outside financing sources over the issue of shares during this second stage (Yıldırım & Çelik, 2021) and the quantile regression method was employed to determine the relative importance of internal and external funding sources in the financing of firm investments. The empirical findings of the present study reveal that the pecking order theory is valid for the choice behaviour of firms listed on the Borsa Istanbul and that the sensitivity to internal funds and debts increases as investment levels increase. In addition, it is found that small firms act in accordance with the pecking order. The empirical findings show that the pecking order theory is not valid for high- and low-leverage firms; high-leverage firms prefer equity financing at high investment levels when internal funds are insufficient to finance investment expenditures, and low-leverage firms prefer to borrow as their first choice. Moreover, it is found that the firms acted in accordance with the financial hierarchy in the period before the global crisis (2000–2009. Similarly, a study on the comparison of Grover, Zmijewski, Altman, and Springate Models for Financial Distress Predictions by (Muzanni & Yuliana, 2021). The paper presents evidence regarding the relative importance of various accrual components, as provided by Dechow and Dichev (2002). It has been demonstrated that working capital accruals are more important than long-term operational accruals in minimising timing and corresponding issues in cash flows. Serret and Ben Jabeur's (2023) investigation indicated that the liquidity and profitability of insolvent and sound companies varied significantly. Additionally, a persistent decline in the business's operations and an increase in the required working capital volume are associated with decreased performance, which may ultimately lead to bankruptcy. In addition, Sehgal et al. (2021), with the help of five financial ratios (return on capital employed, cash flows to total liability, asset turnover ratio, fixed assets to total assets, debt to equity ratio, and a measure of firm size (log total assets)) appear to be highly significant in distress prediction, as indicated by the empirical findings of the study. On the other hand, Farshadfar and Monem (2013) found that the combination of accrual components and operational cash flow components is more beneficial for predicting future cash flows than earnings, operating cash flows, and total accruals, as well as the combination of operating cash flows and accrual components. These results are robust in the presence of various contextual variables, including the duration of the working currency cycle, industry membership, company size, profitability, and industry membership. On the other hand, Agrawal and Chatterjee (2015) and Parida and Mahadik (2023) observed that firms experiencing severe financial distress, as assessed by the Altman Z-score and distance to default, exhibit a reduced level of earnings management, and vice versa, when examining firms to which Indian rating agencies have assigned a "D" rating. Using the Altman, Grover, Springate and Zmijewski models, Patel et al. (2021) assessed the financial distress of the Indian automobile industry. In the same line, Chakraborty (2023) employed the modified Altman Z-score to ascertain and analyse the likelihood of GIC (General Insurance) Re's bankruptcy.

The research conducted by Barth et al. (2001) examined the potential of accruals to predict future financial flows. The model demonstrates how each accrual component reflects various information regarding future cash flows; however, this knowledge is obscured by aggregate earnings. As anticipated, the predictive ability is significantly enhanced by the deconstruction of accruals into their primary components: changes in inventory, accounts payable, accounts receivable, depreciation, amortisation, and other accruals.

From the above literature study, we found that limited studies related to our research were outdated and not systematically described, so in this regard, a proper review with a conceptual overview was addressed and added to the existing body of literature to answer the research questions. Also, we added content analysis and reviewed questions like RQ3, which will differentiate this study from other research.

METHODOLOGY

This literature study includes a number of publications on corporate financial hardship prognosis, elements that contribute to financial distress, and guiding principles for effective financial management in order to prevent situations of financial difficulty, which were sorted and examined. The literatures were divided into two main categories. Specifically "Risk of Financial Distress" and "Basis of For the research, "Financial Management to Avoid Financial hardship Situation." We used the Scopus data base for this study. The selection of Scopus was based on two factors: the content in Scopus and Web of Science (WoS) extensively overlaps, and Scopus has broader overall coverage than Web of Science (WoS) (Pranckutė, 2021). Similarly, Meho and Yang (2006); Sethi and Mahadik (2024); Acharya and Mahadik (in press) assert that Scopus is thought to be more precise, faster, and useful than Google Scholar. For this study, the keywords "Financial Distress Prediction" OR "Financial Default" AND "Prediction" OR "Forecasting" were chosen. The period of the search was from 1985 to 2023. During that period, the data from the selected papers was collected as accordance with our research question by reading the topic-related full papers. Finally, the review covered a total of thirty-nine articles on financial distress prediction. Additionally, a content analysis was done to determine the future research direction by adding a conceptual overview. The preferred reporting items for systematic reviews and meta-analysis (PRISMA) framework is depicted in Fig. 1.

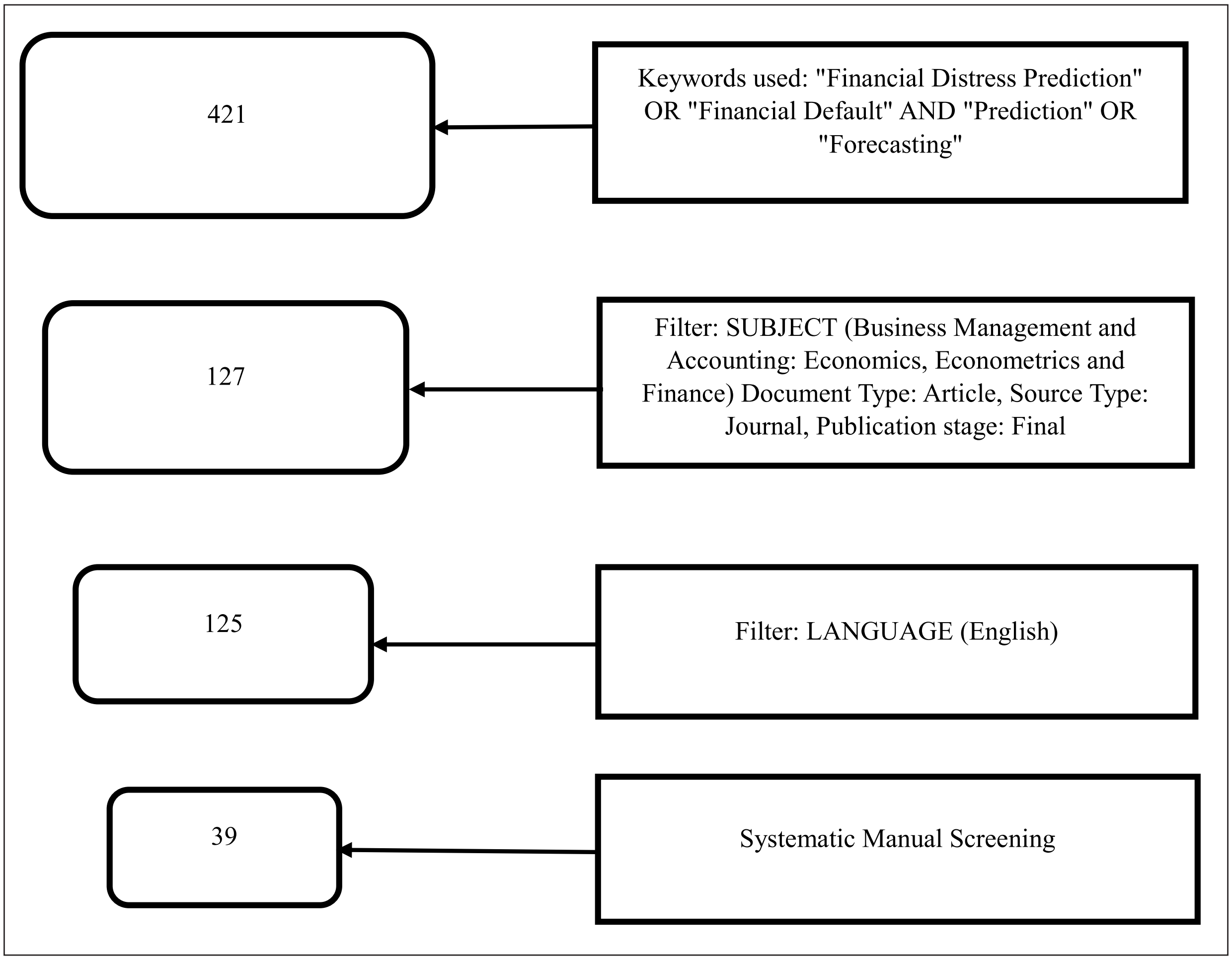


Fig. 1: PRISMA Model

EVALUATION OF FINANCIAL DISTRESS PREDICTION LITERATURE

Many researchers have been interested in FDP for a long time. In his research, Beaver (1966) examined financial ratios as indicators of failure and how well financial ratios could forecast financial trouble through an examination using a collection of thirty financial ratios. He examined a sample of 79 companies and used the financial information from the year 1954 to 1964 for analysis. The investigation discovered that not all ratios have the equivalent capacity to foresee a financial crisis. The ratios of finances that have proven to be more adept at anticipating financial difficulty include specifically, the relationship between total debt, net income, and total assets. Nevertheless, Altman (1968) expanded on Beaver's research and created the Altman Z-score, the first model for predicting financial distress using multiple discriminant analysis (MDA). Alterman developed the Z-score by combining five financial ratios. In addition to the proper weighting known as the co-efficient. The five monetary Working capital to total capital are among the ratios used to estimate the Altman Z-score include market value of assets, retained earnings to total assets, EBIT to total assets, and sales to total assets and equity to book value of total debt. In 1983, Altman looked at the Z-score once more and, in 2000, created two models: Model B: Z-score for businesses engaged in manufacturing, and Model A: Z-score for non-production businesses. Aziz and Dar (2006), however, compared three statistical models with other types of financial distress prediction models theoretical and artificially intelligent expert system models. The research revealed that models of artificially intelligent expert systems showed superior performance compared to the other two model types. Conversely, though in their research, Agarwal and Taffler (2008) contrasted the forecasting capacity of Hillegeist's market-based FDP models and the Altman Z-score model used by Bharath and Shumway, which is an accounting based forecasting model. The analysis sample comprised every UK non-financial industry company registered on the London Stock Exchange (LSE) between 1985 and 2001. According to the study, predicted the market- and accounting-based models' accuracy is marginally distinct from one another. However, the accounting-based approach was discovered to generate a sizable financial advantage over the market-based arrive. In a similar vein, Ciorogariu and Goumas (2011) contrasted the predicted power of two quantitative econometric techniques, specifically logistic regression and linear discriminant analysis (Altman Z-score).

According to the study, the Altman Z-score for linear discriminant analysis was 92.7% forecast accuracy, making it the most reliable model. However, Arasu et al. (2013), in their research, carried out an empirical evaluation of the Fulmer and Springate models' applicability for forecasting financial firms' solvency. The scientists deduced that Fulmer scores and scores from the Springate model can be helpful if recent financial data are put to use. In contrast, Gunathilaka (2014) examined the capacity of the Springate model as a solvency test to anticipate financial hardship & Altman's Z-score model in relation to Sri Lankan enterprises' insolvency. A sample of 82 companies that were listed on Colombo Stock made up the sample. Interchange between several industries. The financial information of these businesses during a five-year span, from 2008 to 2012, were gathered for the evaluation. According to the study, Altman's Z-model displayed a greater level of ability to forecast financial difficulties at least a year before the onset of distress. Accordingly, Geng, Bose and Xi Chen (2014) investigated the function the ability to forecast financial crisis using financial data. Thirty-one financial metrics were employed in the examination. The goal of the analysis was to comprehend the effectiveness of financial data pertaining to a longer period vis-à-vis the data pertaining to a shorter period. The study examined a sample of 107 Chinese companies that were designated as receiving "special treatment" by the Shenzhen and Shanghai stock exchanges between 2001 and 2008. The use of financial data related to a 5-year time span showed reasonable predictive performance over eight years, the researchers discovered.

On the other hand, Shaukat and Affandi (2015) evaluated the effect of financial distress on financial performance using the Altman Z-score. The study employed financial information from fifteen gasoline and energy firms that were listed on the Karachi Stock Exchange between 2007 and 2012. The study discovered a positive correlation between financial performance and financial distress (Z-score). Altman's Z'-score (1993), Alberici's Z-score (1975), and Bottani, Cipriani and Serao's discriminant function (2004) were compared in terms of of predictive accuracy by Madonna and Cestari (2015). In Italy, the sample comprised 100 healthy enterprises as of 2014 and 100 insolvent firms that collapsed between 2012 and 2014. The researchers concluded that Altman's Z-score approach is more appropriate for large-scale studies and more accurate in identifying the warning indicators of financial trouble. Nonetheless, Parvin, Nitu and Rehman (2016) used Altman's Z-score model to forecast the financial health of Bangladesh's banking sector. Over a five-year period (2010–2014), the researchers used the financial data of all six state-owned banks and six randomly selected private commercial banks, including local, international, and Islamic commercial banks in Bangladesh. The examination conducted by the researchers revealed that state-owned banks had superior financial health in comparison to their private sector counterparts. Over the years, the private banks' trajectory remained constant without improvement. Private banks ought to prioritise asset liability management more. Similarly, Bansal and Singhu (2017) used Altman's Z-score model to analyse the financial distress status of Indian automakers. The researchers divided the automakers into four groups: manufacturers of passenger cars, commercial vehicles, motorcycles, mopeds, scooters, and three-wheelers. Over a ten-year period (2007 to 2017), enterprises' annual accounts under each category provided the information needed to estimate the Altman Z-score. The Z-score model, according to the researchers, can anticipate financial crisis situations early on, which will be useful in preventing bankruptcy. The researchers came to the conclusion that the auto industry had been showing signs of financial crisis since 2007–2008 based on the estimated Z-score. Darmawan and Supriyanto (2018), on the other hand, used the Altman Z-score to examine how financial ratios affect financial distress. The sample comprised 119 mining businesses listed on the Indonesian Stock Exchange (BEI). The analysis covered the period from 2011 to 2014. According to the report, the ratios, specifically net working capital to total assets, retained earnings to total assets, book value of equity to total liabilities and EBIT to total assets had a positive effect on financial distress. AI-Manaseer (2018) investigated the Altman Z-Score model's predictive power for financial distress. From 2011 to 2016, he selected a sample of 21 insurance businesses that were listed on the Amman Stock Exchange. The study's findings led the researcher to the conclusion that the Altman Z-score model is helpful for both sustaining and tracking a company's financial success in addition to anticipating insolvency. The study suggested evaluating the companies' financial distress state using the Altman Z-score methodology. Similarly, Fredrick and Osazemen (2018) used Panel Corrected Standard Error (PCSE) approaches to examine the impact of capital structure on corporate financial distress of manufacturing enterprises in Nigeria. The annual data for 58 manufacturing companies listed on the Nigerian stock exchange from 2010 to 2016 comprised the sample taken into consideration for the analysis. The capital structure has a detrimental impact on business financial difficulty, the researchers discovered. However, Agarwal and Patni (2019) assessed the importance of five bankruptcies prediction models i.e., Sprate, Ohlson, Zmijewski, Grover, and Altman in their empirical research. Over the course of the last ten years, starting from the year that a company filed for bankruptcy, the researchers examined data from the financial statements of five companies that have declared bankruptcy or were about to file. The analysis was carried out in India. The researchers concluded that there are variations in the accuracy of the five bankruptcy prediction models when it comes to forecasting enterprise performance. The Springate and Zmijewski models have been shown to be early predictor of bankruptcy, so investors ought to pay them greater attention. Investors and policymakers should not merely depend on one bankruptcy model to forecast a firm's performance when making predictions about its future. On the other hand, Ashraf (2019) examined the predictive performance of conventional distress prediction models for Pakistani enterprises that were in both advanced and early state of distress between 2001 and 2015. For the analysis, the researcher took into account a sample of 422 businesses. According to the study, the Probit and Altman Z-score models can be used to forecast the financial difficulties of emerging markets. Octaviani and Umdiana (2024) investigated the effects of WCTA, RETA, EBITTA, MVEBVL, and STA on stock price as well as the impact of financial distress utilising the Altman Z-Score generating variables. The analysis's findings led to the conclusion that while the variables WCTA and MVEBVL influenced stock price, the variables RETA, EBITTA, and STA had no impact. The stock price was impacted by all of the Altman Z-Score variables combined.

A REVIEW OF THE LITERATURE ON FINANCIAL MANAGEMENT PRINCIPLES AS A PREVENTATIVE TOOL AGAINST FINANCIAL DISTRESS

Corporate financial distress is mostly caused by two factors: inadequate governance and mismanagement. Thus, avoiding situations of financial trouble requires a strong understanding of financial management principles. In 1994, Opler and Titman conducted an analysis of the financial distress risk associated with highly leveraged enterprises compared to less leveraged firms during an industry downturn. When evaluating the company's performance in relation to the industry average, they took into account three factors: operational income trends, returns on equity, and sales growth. According to the study, there are three reasons for a financial slowdown during an industry downturn: manager-driven loss, competitor-driven loss, and customer-driven loss. Firms with higher levels of leverage are more vulnerable to an industry downturn than those with lower levels of debt. In a similar vein, Platt and Platt (2006) examined the variables that contribute to financial trouble and bankruptcy in the future. Across 14 manufacturing industries, the researchers examined 276 financially troubled enterprises and 1,127 financially stable companies in the sample for study. The study found that the firm's activities, which led to its failure to pay off its debts, had an impact on financial distress. Merika, Syriopoulos and Ntzannatou (2007) examined the connection between leverage and a firm's financial performance. The investigation was conducted on a sample of 103 listed companies from Athens Stock Exchange. Growth in sales, profitability, and stock returns were the dependent variables that were utilised to evaluate the performance of the firms. According to the study, highly leveraged companies managed to sustain their financial performance in times of industry hardship because of effective management techniques. Conversely, Bonfim (2008) carried out an empirical investigation into the reasons behind corporate debt repayment defaults, taking into account both firm-specific and macroeconomic statistics. Data from over 30,000 firms were used in the analysis. The study discovered that both firm-specific and macroeconomic factors had an impact on the likelihood of defaulting on debt repayment. In contrast, Satish (2011), in his work "Turnaround Strategy Using Altman Model as a Tool in Karnataka's Solar Water Heater Industry," examined the creditworthiness of fifty clients of M/s Nuetech's clients over a three-year period using the Altman Z-score model. According to the study, the percentage of consumers who were bankrupt went from 20% to 24%, while the percentage of customers in good financial standing increased from 58% to 60%. The report also recommended that before granting credit for a sale, the creditworthiness of consumers should be verified.

Similarly, Lindner and Jung (2014) examined the effects of shifts in the non-financial corporate sector's financial vulnerabilities on the lending performance of Indian banks during the past 25 years. The researchers discovered that actions to address bank asset quality deterioration through strengthening the institutional and legal insolvency framework, structural reforms, improvements in the business climate, and decreased uncertainty would all be beneficial for increasing the economy's overall financial health. In their study "Predicting Corporate Turnaround of Listed Companies in South Africa," Chin and West (2016) examined data from 2007 to 2014 for companies listed on the Alternative Exchange (AltX) and JSE Securities Exchange (JSE). The researchers concluded that achieving "efficiency" during downsizing is a crucial tactic for a successful turnaround. Despite this, Ansari, Khandelwal and Prabhala (2016) examined the financial stress experienced by Indian corporations following the 2008 global crisis in their work "Financial Stress in Indian Corporates." According to the study, company risk grew as a result of unbalanced financing practices that continued to rely on debt rather than external equity. On the other hand, Drs. Sporta, Simiyu and Ngumi (2017) used financial data from a sample of 38 Kenyan commercial banks between 2005 and 2015 to analyse the impact of financial leverage on financial performance. According to the report, leverage affects Kenyan commercial banks' financial performance and is a factor in financial hardship. Company management should ensure that their financial decisions align with the goals of maximising shareholder wealth. To maintain proper asset use and lessen the impact of financial distress on financial performance, the firm's capital structure should include an optimal amount of debt financing. However, Bawa, Goyal, Mitra and Basu (2018) used a comprehensive framework of 31 financial parameters to analyse Non-Performing Assets (NPAs) of Indian banks. Over an eight-year period (2007–2014), they examined the financial information for 46 scheduled commercial banks in India. The researchers came to the conclusion that non-performing assets are crucial indicators of a bank's efficiency and profitability. In order to determine NPAs, operational capacity and intermediation costs are crucial variables that need to be closely monitored.

HOW MARKET SENTIMENT AND INVESTOR BEHAVIOUR INFLUENCE FINANCIAL DISTRESS HELPS TO CLOSE THE GAP BETWEEN TRADITIONAL FINANCIAL METRICS AND MARKET DYNAMICS?

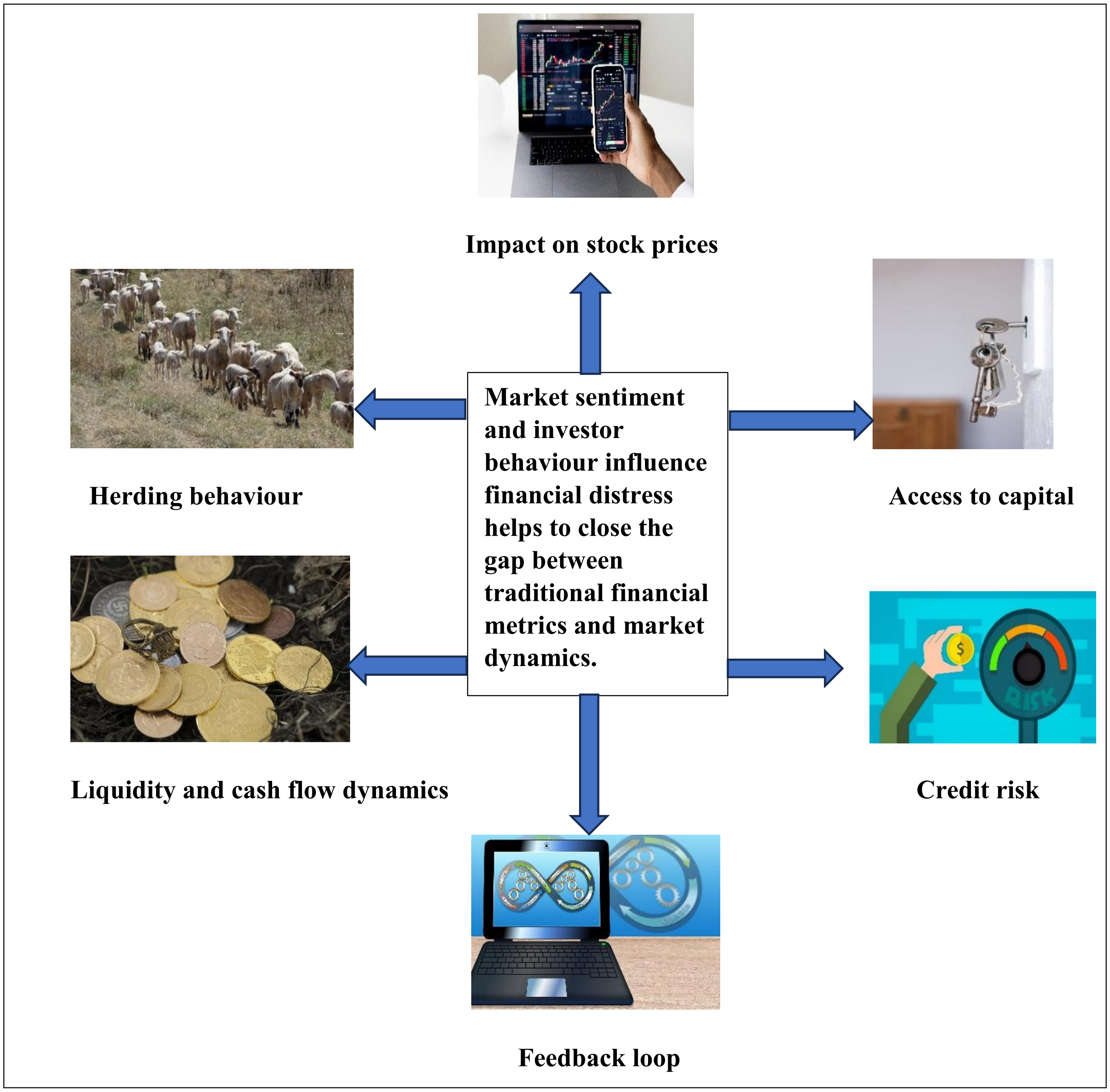
Understanding how market sentiment and investor behaviour influence financial distress helps close the gap between traditional financial metrics and market dynamics. Indeed, market sentiment and investor behaviour significantly impact the functioning of financial markets, as well as the occurrence and extent of financial distress. The following points explain how their effect serves as a bridge between traditional financial metrics to market dynamics and depicted in Fig. 2:

- *The Impact on Stock Prices:* Market sentiment usually leads to stock price variations and has since an effect on the way the market sees a company's financial health. Since market values can increase or decrease due to sentiment, companies may experience increasing distress despite strong financial fundamentals.
- *The Access to Capital:* Market sentiment is translated through investor behaviour into the company's ability to attract new capital or new debt in the form of debt or equity. When investors are unwilling to invest in firms perceived as overly risky, such companies may have difficult time obtaining the necessary financing to support their operations.
- *Liquidity and Cash Flow Dynamics:* Since market sentiment can create a downward spiral, companies may find themselves without the necessary liquidity in the event. Due to a bank run scenario or an increase in the interest rate, a firm may not be able to cope with the current asset obligations.
- *Credit Risk:* Negative market sentiment transmitted into investor behaviour means that several firms may have their credit ratings downgraded, and a fully leveraged company may default due to an increase in borrowing costs.
- *Herding Behaviour:* Sentiment tends to make people act in one way rather than evaluate a situation more comprehensive. In the end, sentiment leads to bubbles and busts, where firms do not know how to manage distress.
- *Feedback Loop:* Sentiment is usually the cause of market instability, and instability on one side is linked to the inability of firms to cope with unforeseen event.

CONTENT ANALYSIS

WordStat was used to perform a qualitative content analysis in addition to this review. The six most common subjects, including the most frequently used tools for financial difficulty, were determined by this analysis. These are some common topics, including cash flow, financial distress, SVM ensemble, deep learning, logistic regression, liquidity, and profitability. The majority of the research is focused on financial distress, which represents 100%. Its main focus is on financial distress and its prediction (Gordon, 1971; Lau, 1987; Oz & Yelkenci, 2017). It is depicted in Fig. 7, which indicates that financial distress is the most common topic and possesses the largest percentage.

Liquidity and profitability represented 70.19% of all topics. Studies have examined the role of liquidity and profitability



Source: Authors compilation.

Fig. 2

to measure financial distress and know the health of firms (Lilis Saputri & Asrori, 2019; Christopoulos et al., 2019; Dwiantari & Artini, 2021; Amoa-Gyarteng, 2021; Dirman, 2020). Fig. 5 depicts the importance of profitability and liquidity to measure financial distress, which ranks second after the topic of financial distress.

Deep learning accounted for 62.50% of the total topics. It includes studies that examine deep learning, a machine learning method that helps predict financial distress (Elhoseny et al., 2022; Li et al., 2021; Halim et al., 2021; Lanbouri & Achchab, 2015). Developing accurate and efficient FDP models through the use of two representative deep learning algorithms is highly significant (Jan, 2021). It means this is an important concept in financial distress prediction, as depicted in Fig. 4.

A total of 46.15 percent of the subjects were related to the SVM ensemble. Financial distress prediction by SVM ensembles, i.e., support vector machines, is more important than SVM classifiers (Sun & Li, 2012; Sun et al., 2017). According to experimental findings, when the number of base classifiers in an SVM ensemble is appropriately configured, the ensemble performs much better than a single

SVM classifier (Sun & Li, 2012). Fig. 3 depicts that SVM ensembles provide the most frequent topic as compared to others, like classifiers in the concerned field.

Logistic regression represented 23.08% of all topics. It's a traditional prediction model used to predict financial distress (Hassan et al., 2017; Hu & Ansell, 2005; Mahariyani et al., 2020). It acts as an early warning system (Filippopoulou et al., 2020; Wang et al., 2014; Zhou et al., 2022). Fig. 6 depicts that, as a traditional method, logistic regression is still important in the concerned field.

Cash flow accounted for 9.62% of the total topics. Studies have examined the impact of cashflow on financial distress prediction (Sayari & Mugan, 2013; Karas & Reznakova, 2020; Kordestani et al., 2011; Kamaluddin et al., 2019; Aziz & Lawson, 1989). Fig. 8 demonstrates that cash flow also gives important insights in the field of financial distress prediction (Table 1).

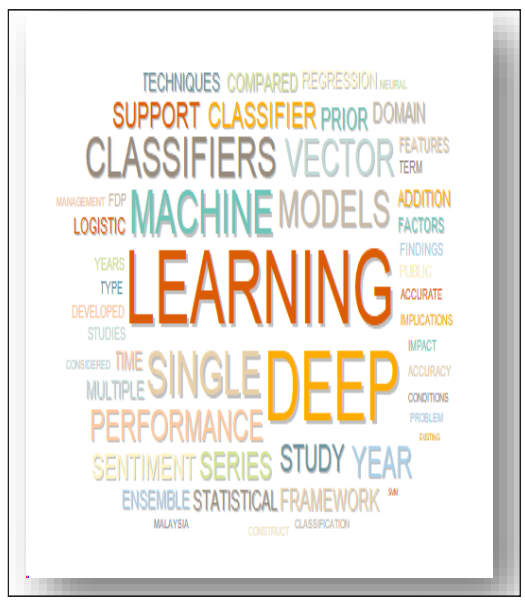
Table 1: Content Analysis of Papers on Financial Distress Prediction

Sr. No.	Topic	Keywords	Coherence (NPMI)	Eigenvalue	Freq	Cases	% Cases
4	SVM Ensemble	Ensemble; SVM; Classifier; Feature Selection; Modelling; Industry; Hybrid; Vector Machine; SVM Ensemble	0.504	2.46	173	48	46.15%
3	Deep Learning	Deep Learning; Machine; Classifiers; Models; Vector; Performance; Sentiment; Support; Classifier; Prior; Deep Learning Models; Deep Learning	0.499	2.81	173	65	62.50%
2	Liquidity Profitability	Liquidity; Profitability; Distressed; Debt; Business; Failure	0.477	2.60	144	73	70.19%
5	Logistic Regression	Logistic; Regression; Selection; Feature; Bankruptcy	0.463	2.15	36	24	23.08%
6	Cash Flow	Cash; Flow; Ratios; Liquidity; Profitability; Malaysia Cash Flow Ratios; Cash Flow	0.460	2.32	35	10	9.62%
1	Financial Distress	Financial; Distress; Corporate; Governance; Risk Management; Financial Sustainability; Corporate Financial Distress; Prediction Model; Financial Distress Prediction Model; Financial Statements; Financial and Non-Financial; Corporate Failure Prediction	0.422	2.97	887	104	100.00%

Source: Compiled by author from wordstat.

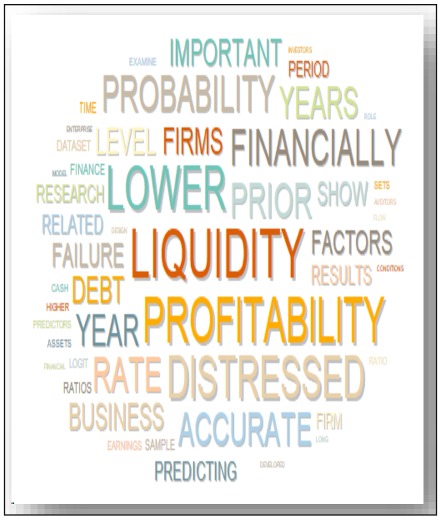
Source: WordStat.

Fig. 3



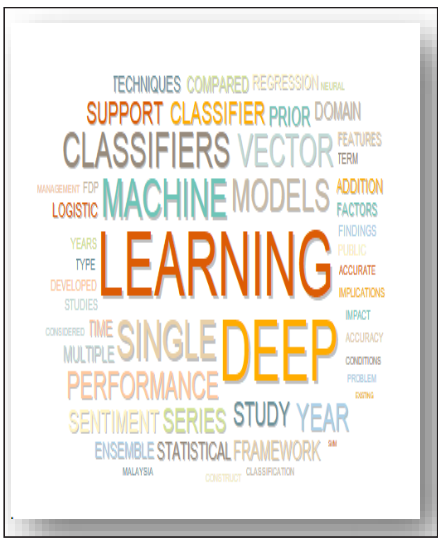
Source: WordStat.

Fig. 4



Source: WordStat.

Fig. 5

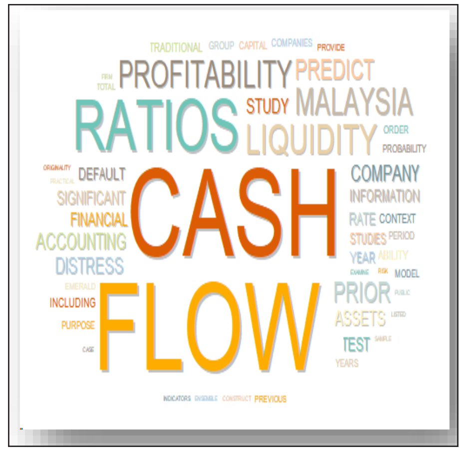


Source: WordStat.

Fig: 6

Source: WordStat.

Fig. 7



Source: WordStat.

Fig. 8

CONCLUSION, LIMITATIONS AND IMPLICATIONS

This paper's literature review reveals that the Altman Z-score model is a popular tool for predicting a company's financial problems. Financial hardship is positively impacted by the following financial ratios: net working capital to total assets, retained earnings to total assets, book value of equity to total liabilities, and EBIT to total assets. The forecast should be supported by an examination of financial data covering a more extended time frame at least five years. A company should keep a careful eye on the financial ratios, which include cash flow to total debt, net income to total assets, and total debt to total assets. Additionally, the company should keep its debt at the lowest possible level to guarantee proper asset use and lower the likelihood of financial difficulty. A larger risk of financial trouble arises for highly leveraged enterprises during industry downturns. However, by using sound management techniques, these businesses can continue to operate profitably even during a downturn in the industry. Reducing costs while increasing efficiency is one of the main tactics for getting out of a financial crisis. NPAs, or non-performing assets, are a crucial measure of a banks and non-banking financing company's profitability and efficiency and should be closely watched. Furthermore, five important research areas pertaining to financial distress, liquidity and profitability, deep learning, SVM ensemble, and logistic regression were identified by this study.

The general state of the economy is a significant factor in the financial difficulties of businesses. It has been discovered that actions to address the decline in bank asset quality through strengthening the institutional and legal insolvency framework, structural changes, improvements to the business climate, and less uncertainty all contribute to improving the overall financial health of the economy.

We acknowledge the ongoing limitations in our research. Our sole database of choice was Scopus. A limitation of the research is that various databases can produce entirely different results. So future researchers can use different others database like Google Scholar, Dimension etc. We advise future researchers to use bibliometric analysis, scientometric analysis, meta-analysis, and topographic perspective to provide a thorough overview of the financial distress literature, even though our study was based on a brief review of research questions. Subsequently, researchers are free to analyse using various keywords. Later, researchers may produce more creative studies to contribute to the corpus of knowledge.

Overall, the policy implications of examining corporate financial distress projections highlight the need for risk mitigation frameworks and effective regulatory scrutiny. By providing investors, creditors, and employees with improved visibility and early warning signals, the proposed approach allows the parties to design strategies to minimise their losses during distress periods. In addition, variations of such predictive algorithms may be used to update financial regulation practices, making them more responsive to signs of creeping depression. By considering these points, the readers can gain insights into how they can influence systematic risks and adapt their strategies to benefit from the changing market conditions while protecting their investments and the associated purchasing power.

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Data Availability

The sources of the data have been mentioned appropriately in this paper.

Compliance with Ethical Standards

Declaration of Competing Interest

No competing interests exist.

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