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A STUDY OF ALTMAN Z-SCORE BANKRUPTCY MODEL FOR ASSESSING BANKRUPTCY RISK OF NATIONAL STOCK EXCHANGE-LISTED COMPANIES

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A B S T R A C T

This study aimed to predict the bankruptcy risk of companies listed on the National Stock Exchange (NSE) in India using the Altman Z-score model. By examining the impact of variable factors such as market value equity/book value of total liabilities, retained earnings/total assets, working capital/total assets, earnings before interest and taxes/total assets, and sales/total assets, the research sought to assess their influence on the financial condition of listed companies. The Altman Z-score model is a widely accepted tool for predicting bankruptcy risk and has been utilized in various industries across different countries. The model comprises five financial ratios that capture a company's liquidity, profitability, leverage, solvency, and activity. By analyzing these ratios, the model calculates a composite Z-score, which can be used to classify companies into different risk categories. Using a sample of NSE-listed companies, this study employed the Altman Z-score model to predict bankruptcy risk and examined the impact of the five variable factors on the firms' financial health. The findings provided insights into the relationship between these financial ratios and the companies' bankruptcy risk, offering valuable information for investors, policymakers, and other stakeholders in the Indian financial market. The study demonstrated the applicability of the Altman Z-score model in predicting bankruptcy risk for NSE-listed companies in India and highlighted the importance of each variable factor in assessing a firm's financial condition. These findings can help stakeholders make informed decisions regarding investment, risk management, and policy formulation in the Indian financial market.

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1. INTRODUCTION

Financial stability is a major worry for our country's central bank and practitioners these days. The Indian economy and its market-listed companies' stability are critical in this respect. A large number of companies have been founded, particularly in our nation. What is "bankruptcy"? It is a judicial action in which a person or company is unable to repay existing obligations (Beaver, 1966). For rating agencies, managers, investors, lenders, and even the company's owners, as well as the country's economy as a whole, the capacity to predict a company's financial difficulty is crucial (Alaka et al., 2018). There are supplementary models for envisaging bankruptcy risk, but the Altman Z-score (1995) updated model was employed in this research. In this study, 20 National Stock Exchange-listed companies were used as a sample. All of them are listed on the National Stock Exchange (NSE). This study centers on the evaluation of z-score efficacy and predicting impending financial difficulties in the sector, while also determining the bankruptcy risk through hypothesis testing and validating the suitability of the Altman Z-score model.

The financial condition's evaluation and analysis, as well as present actions, will have a substantial influence on the company's future development. Regardless of a company's size, kind of operational activities, or other characteristics, it is vital to precisely comprehend the indicators for its future position. (Svabova et al., 2020).
Seeking early-stage indicators for troubled organizations is crucial; the sooner distress is detected, the more effectively remedial measures can be implemented to alleviate the situation. Consequently, various approaches to predict business difficulties have emerged and continue to be investigated. The impact of a troubled company on lenders, investors, and even the industry and economy can be significant, depending on its size. As a result, this issue has become a primary concern for analysts, who persist in their efforts to create a dependable instrument for assessing the risks and perils associated with a company's collapse (Svabova et al., 2020).

Although early recommended models first appeared in the literature in the 1960s, the beginnings of financial situation theory may be traced back to the 1920s–30s. Beaver is the first startup to employ ratio analysis to predict a company's financial problems (1966). Beaver utilized a method known as univariate analysis to evaluate financial ratios (Beaver, 1966). Altman (1968) developed a novel model based on five financial ratios and the multivariate discriminant analysis (MDA) mathematical approach (Altman, 1968). This new model was given the name Altman Z-score, and it has since become the most widely used technique in accounting and financial research. The model has a problem in that the multiple discriminant analysis coefficients were heavily influenced by the economy and the company's operating industry (Georgiev & Petrova, 2015).
Furthermore, as an example, this model was developed using only publicly listed US firms. According to the findings of applied research, models lose predictive validity in many countries when economic conditions change (Karas & Srbová, 2019). With this in mind, the goal of this research is to analyse and develop the Altman Z-score model using 20 NSE listed companies as a case study.

Since 1991, India has been attracting numerous international enterprises as a rising economy (after the adoption of LPG), for which the Indian economy and business sector have seen remarkable development. The current mega-process of globalization, which includes unprecedented levels of liberalization, privatization, and marketization has opened up markets in ways that have never been seen before. Businesses engage in a variety of actions to stay afloat and produce profits for all stakeholders. Finance, as the organization's lifeblood and backbone, is evaluated for its soundness, since only a financially healthy corporation can survive in today's hyper-competitive marketplaces. When a company's entire obligations surpass its total assets, it declares bankruptcy or defaults. As a result, the company's true net value is negative. Organizations are in a mess due to a variety of factors, including worldwide competitiveness, management inefficiency, a lack of innovation, and industry restrictions, to mention a few. The most common cause of a company's difficulty and potential demise is management ineptitude (Chang et al., 2013). As a result, investors must use caution when projecting the firm's insolvency. The Altman Z model is one of the indicators used to forecast corporate default.
Even though the corporate sector is doing well, every individual investor wants to know the company's specific financial status so that they may make informed decisions and avoid being exposed to credit risk. This is especially important for banking businesses and financial institutions to be extra careful when finding a company since when a company goes bankrupt, it results in a large loss for them as well as the whole economy. Financial trouble, or corporate bankruptcy, refers to a company's inability to pay its debts. Banks, companies, suppliers, and shareholders all lose a lot of money when a firm declares bankruptcy. As a result, many investors are eager to forecast the current financial situation as well as the likelihood of bankruptcy within the next few months. There are various techniques for predicting financial hardship in the literature, the Altman Z-score remains one of the best models with a high degree of accuracy. Furthermore, research has demonstrated that the Altman Z-score may be utilized to identify bankruptcy warning signs and take remedial action (Bhatt, 2012). Using various ratios and Z-scores, the current article examines the financial health and likelihood of bankruptcy of a group of enterprises. The following are the parameters

that have been used in the Altman Z-score to assess the bankruptcy benchmark.

2. LITERATURE REVIEW

Fitzpatrick pioneered the use of financial measures to anticipate the financial crisis in 1932. (Colak, 2019). According to Fitzpatrick's research, accounting ratios might be employed as financial crisis indicators. Beaver (1966) employed univariate analysis for prediction, utilising certain chosen ratios in the years after that. He analysed five ratios to conclude that "net cash flow to total liabilities" is the most important variable in explaining company difficulty (Affes & Hentati-Kaffel, 2019).

In the paper titled "Validity of Altman's Z-Score model in predicting Bankruptcy in recent years" by Amin Salimi (2015), the author explores the effectiveness of the Altman Z-Score. The paper highlights that the model's accuracy in predicting bankruptcy in the year before the event was 92.5%. This implies that the model could correctly identify 92.5% of the bankrupt firms in the sample one year before they went bankrupt. The research also explores the model's accuracy in predicting bankruptcy two years before the event. The author found that the Altman Z-Score model's accuracy rate dropped to 77.5% when predicting bankruptcy two years before it occurred. The study indicates that the Altman Z-Score model is a reliable tool for evaluating a firm's financial health, helping investors and creditors make informed decisions about the potential bankruptcy risk of the companies in which they are involved. In conclusion, the paper demonstrates that the Altman Z-Score model remains a valid and useful tool for predicting bankruptcy in recent years, even though it was developed more than four decades ago. It highlights the model's effectiveness in identifying the risk of bankruptcy in firms listed on the Tehran Stock Exchange, emphasizing its continued relevance in the contemporary financial landscape.

In the paper titled "The Altman Z-Score Bankruptcy model at age 45: standing the test of time?" by Arthur J. Sherbo and Andrew J. Smith (2013), the authors assess the applicability and effectiveness of the Altman Z-Score model in predicting bankruptcy after 45 years since its inception. The paper is an evaluation of the model's relevance and reliability in the contemporary financial landscape. The authors emphasize that the Altman Z-Score model has withstood the test of time and remains a reliable tool for predicting bankruptcy. The model has been widely utilized and tested across various industries and countries, demonstrating its versatility and robustness. The paper acknowledges that the model has consistently shown high levels of accuracy in predicting bankruptcy. The original study by Edward Altman in 1968 reported an accuracy rate of 94% for predicting bankruptcy within one year of the event and 72% within two years. Subsequent studies have reported similar success rates, which highlights the model's enduring predictive power. The authors note that the Altman Z-Score model has been successfully applied to different industries and sectors, ranging from manufacturing to service industries. This adaptability is an important aspect of the model's continued relevance in the ever-changing financial landscape. Over the years, the Altman Z-Score model has undergone various adaptations and modifications to cater to the evolving financial environment and specific industry characteristics. These modifications have helped improve the model's accuracy and applicability across different contexts. The authors highlight that the Altman Z-Score model is relatively easy to use and interpret, making it accessible to a wide range of users, including investors, creditors, and analysts. This simplicity contributes to its enduring popularity in assessing firms' financial health and bankruptcy risk. In conclusion, the paper by Sherbo and Smith (2013) demonstrates that the Altman Z-Score model has stood the test of time and remains a valuable tool for predicting bankruptcy 45 years after its development. The model's continued relevance can be attributed to its high accuracy, adaptability, ease of use, and the various modifications that have been introduced over the years to enhance its applicability across different industries and contexts.

Altman (1968) used multiple discriminant analysis (MDA) using five ratios to estimate the likelihood of a company's collapse, and this approach became one of the first and most widely used models for predicting financial trouble. There were 66 firms considered for this research, all of which were manufacturing businesses. These businesses were divided into two categories: bankrupt and non-bankrupt, with all bankrupt businesses filing bankruptcy petitions between 1946 and 1965. Initially, 22 variables were selected, but after additional investigation, a discriminant analysis with five variables was produced (see Equation (1)). All of this is shown in the model below.

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

X1 = Working Capital / Total Assets

X2 = Retained Earning / Total Assets

X3 = Earning Before Interest and Taxes / Total Assets

X4 = Market Value of the Equity / Book Value of Total Assets

X5 = Sales / Total Assets

Z = Overall Index Source.

Altman (1968)

$$Z^{`} = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$$

The composite index suggests that a company is not bankrupt if the Z value exceeds 2.99; it is categorized as a "grey area" when the index value lies between 1.81 and 2.99, and "bankrupt" if the index value is below

1.81. If the index value dips below 1, the company is deemed insolvent.

In 1977, Altman, Haldeman, and Narayanan enhanced the model by proposing the zeta model, which included seven variables and boasted a 96% accuracy rate (Affes & Hentati-Kaffel, 2019). In 1983, Altman renamed the Altman Z score model the Z' model after revising it for privately held companies. In this version, variable X4 was replaced with the book value of equity, and the model was dubbed the Z-score model (The 240th National Accounting Review, Volume 3, Issue 2, pages 237–255). It is worth noting that the coefficients for the variables in this model vary slightly from those in the original Z-Score model.

X1 = Working Capital / Total Assets

X2 = Retained Earning / Total Assets

X3 = Earnings Before Interest and Taxes / Total Assets

X4 = Market Value of the Equity / Book Value of Total Assets

X5 = Sales / Total Assets

Z = Overall Index Source.

Altman (1968)

As determined by the overall index, companies are classified as non-bankrupt. We call them "grey" if their Z′ value is greater than 2.90, or if their index value falls between 1.23 and 2.90. They are defined as having a challenging financial condition if their index value is less than 1.23, and they are considered in high danger of bankruptcy. Results show that this model's classification accuracy for bankrupt companies was 90.9%, while its classification accuracy for non-bankrupt companies was 97.0% (Altman, 1983).

Aside from the Altman Z Score, there are a variety of additional theoretical, statistical, and artificial intelligence-related methodologies that may be used to anticipate financial difficulty. One of them is the case-based reasoning model developed by Kolodner in 1993, while another is the entropy theory (Theil, 1969; Lev, 1973).

Gordini (2014) used genetic algorithms to model 3100 small and medium-sized enterprises in Italy, and the results showed that 84.4 percent overall predictive performance was achieved (Gordini, 2014). The two-step classification technique based on a genetic algorithm was used in another research conducted in 2017, which comprised 912 Russian business values, and the accuracy of the model was 93.4 percent, according to the results (Zelenkov et al., 2017). In addition, in research done in North America in 2017, eight distinct models were evaluated and contrasted. Machine learning and statistical models were compared. The research found that the bagging, boosting, and random forest models were the most accurate, and they performed better than the other models (Barboza et al., 2017). Other studies have achieved a 99.7 percent accuracy rate by combining artificial neural network models with the Magnetic Optimization Algorithm and particle swarm optimization techniques. (Ansari et al., 2020). Each strategy has its own set of advantages and disadvantages. Depending on the data, certain strategies outperform others in terms of accuracy, while others are worse (Huang & Yen, 2019).

From the standpoint of machine learning, several pieces of research have been undertaken to forecast bankruptcy. Support vector machines, random forests, decision trees, gradient boosting, bagging, XG Boosting, and hybrid models, which combine several machine learning models, are some of the most popular machine learning models. The Random Forest model (2001) was created by Breiman. Both regression and classification may be accomplished with the use of this ensemble learning approach. In a decision tree approach, nodes are selected at random from each branch in order to determine the split. Using a random vector, each tree is sampled from the same distribution as the rest of the forest. All the trees are built separately, and each one is fed with a classified sample. Following the majority rule, each tree provides a classification, and then the findings of all the classifiers are combined to form the classification results (Breiman, 2001).

The application of the Altman Z-Score has been adapted across various nations, resulting in differing outcomes in country-specific research. Some studies have either updated the coefficients or verified the model's applicability in a specific country or region. Diakomihalis (2012) found the Altman Z-Score model to be helpful in identifying hotels on the verge of filing for Chapter 11 bankruptcy. The model has been extensively used in countries such as the United States (Barreda et al., 2017), Greece (Grammatikos and Gloubos, 1984), China (Wang and Campbell, 2010), India (Singh & Singla, 2019), Pakistan (Abbas and Ahmad, 2012), and Indonesia (Abbas & Ahmad, 2012; Prabowo, 2019), among others. The model's application in various countries has produced mixed results, with some studies supporting its validity while others suggesting modifications or the inclusion of advanced techniques.

Jawabreh, O. A., Al Rawashdeh, F., & Senjelawi, O. (2017), The authors applied the Altman Z-Score model to predict the financial failure of hospitality companies in Jordan. The key observations from this study include - Altman Z-Score model proved to be a useful tool in predicting the financial health of Jordanian hospitality companies. The study found that some companies were in the "grey zone," indicating that they were neither financially healthy nor in immediate danger of bankruptcy. The results emphasized the importance of monitoring financial performance and using the Altman Z-Score model as a proactive tool in managing potential financial distress in the hospitality sector.

Kiaupaite-Grushniene, V. (2016, December), This study applied the Altman Z-Score model to forecast bankruptcy among listed Lithuanian agricultural companies. The model showed its relevance in predicting financial distress in the Lithuanian agricultural sector. Some companies were found to be at risk of bankruptcy, while others were financially stable. The study emphasized the need for continuous monitoring and assessment of financial performance, especially in the agricultural sector, which is subject to various external factors, such as weather conditions and global market fluctuations.

Chadha, P. (2016). Author applied the Altman Z-Score model to assess the financial performance of listed companies and he mentioned that The Altman Z-Score model was effective in distinguishing between financially stable and financially distressed companies in Kuwait. The model's application helped identify companies at risk of bankruptcy, enabling stakeholders to take preventive measures. The study highlighted the importance of using the Altman Z-Score model as a reliable tool to evaluate financial performance and predict bankruptcy risk in the context of the Kuwait Stock Exchange.

Ratio analysis is a method used to examine a company's financial statements, expressing the relationship between two variables as a mathematical ratio. Bambang Arwana (2001:329) defines financial ratio analysis as the process of identifying key operational and financial aspects of a company from its accounting data and financial statements. The objective is to evaluate management performance efficiency as reflected in the company's financial records and statements and provide suggestions for improvement. The ratios used in Altman's approach can be grouped into three categories: liquidity ratios, profitability ratios, solvency ratios, and activity ratios, with liquidity ratios being the most common.

Brigham and Gapenski (1997) categorized financial distress into several types, including economic failure, business failure, technical insolvency, bankruptcy insolvency, bankruptcies, and legal insolvency. Financial distress occurs prior to the filing of a bankruptcy petition, and bankruptcy is often characterized as a state or condition where businesses fail or can no longer meet their financial obligations due to insufficient funds.

Sudana (2011) writes in his book that economic reasons, managerial failures, and natural calamities are all variables that contribute to the development of financial crises. As a result, financial challenges will be experienced by the firm as a result of a failure in its business activities. However, the majority of the factors that contribute to the onset of financial hardship, whether directly or indirectly, are the fault of management, which is why it occurs again. The elements that contributed to the bankruptcy are divided into three categories: common factors, internal factors of the firm, and external aspects of the company.

In the Indian Scenario, L.C. Gupta (1979) sought to analyse corporate illness by selecting 41 textile firms and 39 non-textile companies as samples. He employed a variety of financial statistics to assess the performance of the sample organizations in his study. Johah Aiyabei (2002) investigated the financial health of small business concerns in Kenya using the Z score model, and he identified theoretical features of distressed enterprises that should be considered.

Beaver (1966) investigates whether financial measures may be used to forecast the demise of a company. His study sample consisted of 79 failing businesses that existed between 1954 and 1964, both included. For each failed business, a non-failed firm in the same sector and with a comparable asset size was paired with it. The ratios were divided into six categories, with one ratio from each category being examined for its predictive value. In all, he picked 30 ratios, which he divided into six groups (univariate analysis). According to empirical data, the cash flow to total debt ratio is the greatest univariate discriminator for distinguishing between failed and non-failed enterprises in terms of cash flow. The accuracy of the total debt cash flow classification ranged from 87 percent (one year before collapse) to 78 percent (one year after failure) (five years before failure). Beaver discovered, in subsequent research, that fluctuations in the market price of equities were also strong markers of financial difficulty in the economy. Beaver's approach has been criticised for relying on a single variable and computing a small number of ratios. Others have employed multivariate approaches to examine the capacity of financial measures to predict company collapse, rather than the univariate procedures used by Beaver to conduct his research.

Charles Moyer (1977) re-examined certain critical aspects of Altman's model based on the following criteria: Over the first two years before the bankruptcy, the Altman model's performance was remarkable, but it suffered a large decrease over longer lead periods. As a result of this, the variables employed by Altman in his model are dependent on how long he used to build it and how large his original sample of companies was. Researchers used linear MDA, direct, and Wilks's method to analyse data from 27 bankrupt and 27 non-bankrupt companies in the Charles sample between 1967 and 1975. Three variables are significant in the prediction of bankruptcy within three years: X1, X2, and X3 (working capital/total assets, retained earnings, and EBIT/total assets) and X4 (market value of equity/book value of total debt) and X5 (sales/total assets) are not significant at all. The factors X4 and X5 (market value of equity and book value of total debt) have a significant impact on the results.

There were three models employed in the study: Altman's original Z score model, a re-estimated Z score model, and the third model, which included an extra variable. To find out whether the Altman Z score should be adjusted for the prediction of bankruptcy in manufacturing and non-manufacturing enterprises across different timeframes, A new variable named "asset volatility" was incorporated into Altman's re-estimated model after the coefficients of his original model were re-estimated and assessed for accuracy by the estimation group. Findings from the study show that the Altman Z score model is suitable for forecasting bankruptcy in both manufacturing and non-manufacturing companies, with the greatest predictive potential of the market value of equity and total obligations. Adding a new variable doesn't seem to have a significant impact on the results.

Scott (1981) conducted a survey of statistical and theoretical prediction models; however, it was fairly restricted in its scope and may be considered outdated in today's context. Zavgren (1983) focused only on statistical models, with no reference to theoretical models. Altman (1984) carried out the first study on prediction models in businesses outside the United States, covering 10 countries. This study was significant but only examined one type of statistical model. Jones et al. (1987) attempted to offer a comprehensive review of all prediction models, focusing on research in the field of corporate bankruptcy prediction. However, it did not explore theoretical methods or models.

Key and Watson (1991) researched the limits of prediction models in terms of decision usefulness. However, the research was limited to just statistical models and only a handful of them at that. With a focus on current models (1996), Dimitras et al. conducted a successful evaluation of several methodologies used to develop bankruptcy prediction models. However, while being one of the most extensive studies at the time, this study overlooked theoretic models. Morris's examination of prediction models is perhaps the most thorough to date (1998). From an empirical standpoint, it addresses prediction methods and applications. Despite being quite thorough, it nevertheless overlooked a few prediction models, and several models that emerged later in the theoretical domain were not addressed or considered by the research. Zhang is attempting to comprehend the function of neural networks in the prediction of bankruptcy. They also go into the empirical uses of networks for bankruptcy prediction, but they leave out all of the other kinds of models that companies use (Zhang et al., 1999). Crouchy's work (Crouchy et al., (2000)) goes into great length on credit risk models. From a theoretical standpoint, it does an excellent job of covering credit risk models and several key bankruptcy prediction models. However, it does not cover other kinds of models.

Early warning is very much desired, if not essential, since financial difficulties may lead to bankruptcy. The inability of a person or company to fulfil its existing debts is characterised by a bankruptcy (Aliakbari, 2009). An early warning signal of potential failure will allow both management and investors to take preventative actions, "Aharony, Jones, and Swary (1980) claimed in their study. As a result, it's no wonder that the emphasis of bankruptcy research has switched from strategies to prevent it to techniques to forecast it entirely. Winakor and Smith (1935) found that the evaluation of financial ratios for struggling businesses varies considerably from that of financially stable companies. In his paper, Beaver (1966) examined various financial ratios for a group of bankrupt firms and a group of non-bankrupt firms. Beaver is recognized for pioneering the development of a bankruptcy prediction model, as he discovered that financial ratios from five years prior to bankruptcy could forecast the risk of bankruptcy. Beaver (1966) used a framework similar to that of Gambling Ruins 4 to construct his model in his article. As a result, the corporation is considered a "liquid asset reserve" that is "supplied by inflows and drained by withdrawals." The risk that the reservoir will be depleted, at which time the business will be unable to fulfil its commitments as they mature, may be used to determine the firm's solvency. He was implying that a corporation would continue as long as it had financial reserves.

Altman (1968) argued in his study that the aforementioned data demonstrate the predictive power of financial ratio analysis convincingly. As a result, he was inspired to work on developing a model that uses ratio analysis to improve bankruptcy forecasting. Altman (1968) employed multiple discriminant analyses to build his model, although there are different approaches. Ohlson (1980) used a technique called logistic regression (Logit). Over six years, he utilized a sample of 2163 firms (5, 1970–1976). He discovered that one year before bankruptcy, the company's size, financial structure, performance, and present liquidity had predictive power. Furthermore, although the score of a multiple discriminant analysis must be translated into the probability of default using historical data, the Logit model score provides the default probability, and Lacerda and Moro (2008) found it to be a more appealing statistical approach. This reasoning prompted Seaman, Young, and Baldwin (1990) to investigate the predictive powers of linear, quadratic, and logistic models; their findings revealed that the quadratic discriminant technique had the highest predictive power of 78 percent. Nonetheless, their findings on the quadratic model conflict with those of Frydman, Altman, and KAO (1985).

Clark, Foster, Hogan, and Webster's K & P model is another bankruptcy prediction model (1997). Due to the lack of accuracy in the financial data utilized in the univariate method, this model tries to forecast bankruptcy using an analytical hierarchy process. The concept divides financial risk into four levels of hierarchy and three financial categories. In addition, four financial risk variables influence financial risk: asset usage, financial flexibility, earning potential, and liquidity situation (Clark et al., 1997). Shareholders, creditors, workers, rating agencies, and others place a high value on failure prediction models, and much additional research has been conducted on this goal throughout time (Aliakbari, 2009). Hensher and Jones (2007), for example, found that various econometric models, such as the nested logit model, mixed logit model, error component logit model, and latent class multinomial logit, were superior to frequently used standard logit models in terms of explanatory and statistical power (Jones & Hensher, 2007).

Scholars continue to dispute the Z-score model even though most of the above-mentioned papers acknowledge Altman (1968) as the pioneer of the bankruptcy prediction model. Shumway (2001) and Campbell, Hilscher, and Szilagyi (2001) were the most prominent critics of Altman's modelling and variable selection (2011). The critics have mostly focused on the following aspects while criticizing Altman: In his research, Shumway (2001) outlined three main objections to Altman's approach. To begin with, the analysis was undertaken over some time. For example, Shumway (2001) argues that single-period models are inconclusive since the likelihood of a company's bankruptcy changes over time and its health is determined by its most current financial data and age. Critique No. 2 focuses on the bankrupt firm's financial condition. An assertion by Shumway (2001) that firms' financial situations worsen as they approach insolvency is ignored by Altman (1968). According to Shumway (2001), firms with high working capital or total assets in one year that go bankrupt the next year are not taken into consideration by Altman (1968), leading to the test results being inflated. The study's financial ratios are the last topic of contention. According to Shumway (2001), many market-driven elements, such as market size, historical stock returns, and idiosyncratic stock standard deviation, are missing from earlier bankruptcy models. He also claims that the majority of the financial measures employed in earlier models are poor predictors. Campbell et al. (2011) constructed their model based on his critique as well as his model, which outperformed Shumway's (2001). They discovered that distressed stocks have large market betas and extremely variable returns and that they underperform safe stocks more when market volatility and risk aversion are high.

This does not mean that the Z-score model proposed by Altman is flawed; rather, it demonstrates that as time went on, more sophisticated methodologies and, therefore, more acceptable financial considerations were discovered. While prior publications focused on constructing a more predictive model, this research validates the original Altman (1968) Z-score model by calibrating it for publicly listed Japanese industrial enterprises. Even if the concerns outlined above are correct, the danger model still has faults that need to be addressed. In the first place, there is a problem with multicollinearity. Correlations between independent variables must be avoided in hazard models, as Balcaen and Ooghe (2004) have warned us about. Table 8 in Appendix B shows that the hazard model cannot be used in this study because of the strong correlation between the variables (Lane, Looney, & Wansley, 1986). Hazard models' second problem is their erratic calculation of survival time. According to the hazard model, the bankruptcy procedure does not begin until the end of the annual account closure period (Luoma & Laitinen, 1991).

Collins (1980) compares numerous models for assessing bankruptcy. Even though many models provide excellent results, the research concludes that the Z-score is the best. Zavgren and Friedman (1988) investigated the usefulness of bankruptcy prediction models in security analysis. They discovered that bankruptcy forecasting models may be used in security analysis to analyse published financial statements.

The prediction potential of several financial measures is investigated by Pompe and Bilderbeek (2004). They discovered that every ratio had some predictive capacity for financial hardship after studying small and medium-sized businesses in various stages of bankruptcy.

Grice and Ingram (2001) investigate the generalizability of the Z-score application. The research reveals poor outcomes when applying the Z-score to recent eras and manufacturing enterprises, but favourable findings when it comes to forecasting distress other than bankruptcy, which is what it was initially designed for.

Bal and Raja (2013) investigate earnings management and solvency prediction approaches. Their research employs the Z-score to anticipate IOCL's financial hardship and indicates that the company's financial status is not as excellent as the initial Z-score suggests. Based upon the above literature, researcher suggested following hypothesis:

H1- There is no significant impact of Variable Factors, market value equity/book value of total liabilities, retained earnings/total assets, working capital/total assets, earnings before interest and taxes/total assets, and sales/total assets, on the financial condition of listed companies.

Hl: There is the significant impact of Variable Factors, market value equity/book value of total liabilities, retained earnings/total assets, working capital/total assets, earnings before interest and taxes/total assets, and sales/total assets, on the financial condition of listed companies.

Leave one clear line before and after a main or secondary heading and after each paragraph.

Avoid leaving a heading at the bottom of a column, with the subsequent text starting at the top of the next page/column.

3. PROBLEM STATEMENT

Investors in general, and retail investors in particular, are the most sensitive and fragile participants in the world of finance, where there is a plurality of money. Corporate bankruptcy is the worst thing that can happen to investors since it wipes away a company's equity and reduces the stock's investment value to zero. Investors often use information sources such as issuer (s) offer papers, market intermediary research studies, media reports, and financial statements to judge the legitimacy of investments and issuers. However, a large number of Indian investors are unaware of how to properly understand and analyse information included in public financial statements. Apart from that, investors lack the necessary knowledge, time, and other resources to analyse the creditworthiness of issuers. In this context, the Altman Z Score model may be used to predict whether a firm will file for bankruptcy. The purpose of this article is to investigate the likelihood of failure of a few specific retail businesses. Table 1 shows the Altman bankruptcy criterion to assess the financial condition of a bank:

Table 1. Altman Bankruptcy Criterion

Discrimination		Financial Status
Safe Zone	Z > 2.6	Good financial health
Grey Zone	2.6 < Z <1.1	The probability that the company is bankrupt or not
Distress Zone	Z < 1.1	Probability occurrence bankruptcy and high risk

3.1 Research Objectives

To predict the bankruptcy risk of the National Stock Exchange-listed companies in India by using the Altman Z score model. To assess the impact of variable factors, market value equity/book value of total liabilities, retained earnings/total assets, working capital/total assets, earnings before interest and taxes/total assets, and sales/total assets on the financial condition of listed companies.

4. BODY OF THE PAPER

This study is structured as a descriptive and quantitative study that focuses on detecting bankruptcy risk using Altman's z-score model, followed by an empirical investigation into the National Stock Exchange-listed companies in India. This study is heavily reliant on secondary data sources. The data was collected from annual reports of specific National Stock Exchange-listed 10 companies from FY 2010 to 2020. As stated, the Zaltman Score has been used in this study to measure the potential bankruptcy of a company in 07 listed companies on the Bombay Stock Exchange.

Once the initial categories and firms are selected, the balance sheet and income statement data are acquired. A list of 20 possible variables (ratios) was established for examination owing to the large number of characteristics demonstrated to be relevant indicators of business challenges in prior studies. The five standard ratio categories for the variables are liquidity, profitability, leverage, solvency, and activity. There are a few "new" ratios included in this analysis because of their popularity among academics and their relevance to the study.

The original list of 22 variables was narrowed down to five indicators that performed the best overall job of forecasting the bankruptcy of a firm. All of the most critical factors that were assessed independently are not included in this profile. A multivariate analysis would not always be better than a typical univariate analysis. Since this is a recursive process, there is no guarantee that the final discriminant function will be the best one possible. When compared to other methods, the function surpasses them all since it doesn't require as many computers run.

The following are the steps used to arrive at a final profile: Analysis of numerous alternative functions, as well as the relative contributions of each independent variable, as well as the intercorrelations among the relevant variables, as well as analysis of various profiles, and the analyst's judgement. The Following variable was selected for the study's purposes.

where X1 = Working Capital/Total Assets,

X2 = Retained Earnings/Total Assets,

X3 = Earnings Before Interest and Taxes/Total Assets,

X4 = Market Value Equity/Book Value of Total Liabilities,

X5 = Sales/Total Assets, And

Z = Overall Index.

Notably absent from the model is a constant term (Y-intercept). As a result, the acceptable cutoff score for the two groups is not zero, and this is attributable to the programmed utilized. A constant term in other software programmers, such as SAS and SPSS, sets the threshold score to zero if the sample sizes of the two groups are equal.

The researcher has chosen a total of seven national stock exchange-listed companies for their research, and the purposive sampling method has been used. Data collection for the independent variable has been taken from the national stock exchange from 2010 to 2020.

5. BODY OF THE PAPER

Here in this analysis, the researcher has selected 10 companies from the Bombay Stock Exchange, specifically, Dewan Housing Finance, Reliance Communication, Jet Airways, Cox and Kings, Gitanjali Gems Limited, Jaypee Infratech Limited, Lanco Infratech Limited, Jyoti Structures Limited, ABG Shipyard Limited And Bhushan Steel Limited to predict financial distress and bankruptcy possibilities based on Altman Z score.

The Table 2 and Table 3 indicated the following results in -0.27 for 2016-17, -0.23 for 2015-16, and -0.25 for 2014-15, respectively. We determined that Bhushan Steels has been in danger since 2010-2011 when we applied the Altman Z score. According to the crisis zone, the corporation is expected to go bankrupt shortly. Using liquidity measures, we were able to acquire more confirmations of the financials' inadequacy. According to the model's forecast, the firm was declared bankrupt in 2017, indicating that the model was correct and effective in the current circumstance.

Table 2. Bhushan steel limited particulars

Year	Particulars						
	Current - Assets	Current Liabilities	Retained - earning	Sales	EBIT	Market Value of Equity	Total Assets
2016-17	579,529	2,753,910	(766,487)	1,502,730	130,168	158,560	6,046,340
2015-16	200,723	2,127,349	-408,207	1,312,407	40,714	91,738	6,002,472
2014-15	1,166,582	1,208,986	-124,270	1,064,577	123,908	99,893	5,290,752

Table 3. Bhushan steel limited particulars Ratios

Year	Ratios				
	X1	X2	X3	X4	X5
2016-17	(0.36)	(0.13)	0.02	0.03	0.25
2015-16	(0.32)	(0.07)	0.01	0.02	0.22
2014-15	(0.01)	(0.02)	0.02	0.02	0.20

Table 4 and Table 5 indicates that Altman Z Score let us uncover that ABG Shipyard was in difficulties in 2009-2010, but was able to sustain itself for six years thereafter. An increasing decline in the company's Altman Z score led to bankruptcy proceedings in 2017, proving that the model was right and successful in this situation.

Table 4. ABG Shipyard Limited Particulars (in crore)

Year	Particulars						
	Current - Assets	Current Liabilities	Retained - earning	Sales	EBIT	Market Value of Equity	Total Assets
2015-16	801,963	888,817	(431,146)	3,427	(286,696)	16,317	1,109,225
2014-15	909,765	717,052	(60,674,92)	39,213	-38,111	38,872	1,235,460
2013-14	867,760	748,238	29,575	162,500	38,489	509,218	1,218,777

Table 5. ABG Shipyard Limited Particulars Ratios

Year	Ratios				
	X1	X2	X3	X4	X5
2015-16	-0.08	(0.39)	(0.26)	0.01	0.00
2014-15	0.16	(0.05)	(0.03)	0.03	0.03
2013-14	0.10	0.02	0.03	0.42	0.13

Table 6 and Table 7 shows using the Altman Z score model, For Jyoti Structures, the Altman Z score was used to determine its financial health, and we found that the company's EBIT and Retained earnings were both dropping in 2013 and 2014. Because of its precision and efficiency, the company was compelled to file for bankruptcy in 2017.

Table 6. Jyoti Structures Limited Particulars (in crore)

Year	Particulars						
	Current - Assets	Current - Liabilities	Retained - earning	Sales	EBIT	Market Value of Equity	Total Assets
2015-16	536,801	505,754	(38,722)	249,243	5,753	10,734	597,900
2014-15	455,878	299,908	11,613	278,173	10,023	17,634	513,022
2013-14	387,795	310,641	39,019	332,576	27,262	32,622	4,205,932

Table 7. Jyoti Structures Limited Particulars Ratio

Year	Ratios				
	X1	X2	X3	X4	X5
2015-16	0.05	(0.06)	0.01	0.02	0.42
2014-15	0.30	0.02	0.02	0.03	0.54
2013-14	0.02	0.01	0.01	0.01	0.08

Table 8 and Table 9 shows that after putting these numbers through the Altman Z score model, we came up with these numbers: -0.44 in 2016-17 and -0.39 in 2015-16. After applying the Altman Z score to Lanco Infratech, we determine that the company has been in the problematic zone since 2013. Lanco Infratech's bankruptcy procedures were started in 2018, proving the model's accuracy and efficacy, even though the company's current assets to total assets ratio has been decreasing, showing that the company's liquidity has been worsening.

Table 8. Lanco Infratech Limited Particulars (in crore)

Year	Particulars					
	Current Assets	Current - Liabilities	Retained - earning	EBIT	Market Value of Equity	Total Assets
2016-17	66,903	806,672	(60,637)	39,568	37,116	1,904,650
2015-16	773,521	896,549	(16,137)	(4,507)	88,400	2,049,052
2014-15	758,865	769,617	51,911	(33,136)	145,913	1,918,157

Table 9. Lanco Infratech Limited Particulars Ratios

Year	Ratios			
	X1	X2	X3	X4
2016-17	-0.08	(0.03)	0.02	0.02
2015-16	-0.06	(0.01)	(0.00)	0.04
2014-15	-0.01	0-03	(0.02)	0.08

In Table 10 and Table 11, 2015-16, 1.40 in 2014-15, and 1.36 in 2013-14, the Altman z score model yielded corresponding values of 1.67, 1.40, and 1.36, respectively. Altman Z score analysis shows that Jaypee Infratech has been in the grey zone from 2013-2014 to 2015-2016, which indicates that the firm is likely to go insolvent soon. As a result of the lack of 2016-2017 financial data, the Z could not be computed, and the model's efficacy and accuracy could not be evaluated. 2017 was a bad year for the company under scrutiny.

Table 10. Jaypee Infratech Limited Particulars (in crore)

Year	Particulars					
	Current Assets	Current - Liabilities	Retained - earning	EBIT	Market Value of Equity	Total Assets
2015-16	752,833	376,395	26,415	57,195	102,781	1,830,148
2014-15	985,286	732,976	45,244	132,241	177,645	2,057,431
2013-14	958,275	614,280	35,244	12,447	297,926	2,036,025

Table 11. Jaypee Infratech Limited Particulars Ratio

Year	Ratios			
	X1	X2	X3	X4
2015-16	0.21	0.01	0.03	0.06
2014-15	0.12	0.02	0.06	0.09
2013-14	0.17	0.02	0.01	0.15

Table 12 and Table 13, the resulting scores of 1.406 for 2016-17, 1.568 for 2015-16, and 1.407 for 2014-15 by applying the Altman Z score model to the provided data. Using the Altman Z score on the financials of Gitanjali Gems, we discovered that the firm has been in the troubled zone since 2014-2015, but the bankruptcy was filed in 2017, demonstrating the model's accuracy and usefulness.

Table 12. Gitanjali Gems Limited Particulars (in crore)

Year	Particulars						
	Current Assets	Current - Liabilities	Retained - earning	Sales	EBIT	Market Value of Equity	Total Assets
2016-17	1,164,774	925,657	165,847	1,046,477	51,683	81,015	1,302,576
2015-16	790,955	596,529	122,481	860,363	43,784	57,775	951,215
2014-15	779,588	583,715	117,605	715,793	54,219	40,622	943,200

Table 13. Gitanjali Gems Limited Particulars Ratio

Year	Ratios				
	X1	X2	X3	X4	X5
2016-17	0.18	0.13	0.04	0.06	0.80
2015-16	0.20	0.13	0.05	0.06	0.90
2014-15	0.21	0.12	0.06	0.04	0.76

Table 14 and Table 15 indicates the Altman Z score values for 2019-20 and 2018-19 were 7.63 and 26.96, respectively, which indicates that the company was in the sound situation and there was no situation of getting into bankruptcy, although the situation did not remain favorable and score in 2017-18 was observed 1.45, which indicate that company may bankruptcy in near future and later on, company himself declared the same in the financial year 2018-19.

Table 14. Jet Airways Particulars (in crore)

Particulars							
Year	Current Assets	Current - Liabilities	Retained - earning	Sales	EBIT	Market Value of Equity	Total Assets
2019-20	318969	2161764	(1569346)	33345	(253959)	(1557986)	692661
2018-19	591862	2205432	(1280899)	2305741	(455412)	(129539)	111329
2017-18	705345	1416090	(735560)	2328653	7524	(724200)	1247288

Table 15. Jet Airways Particulars Ratios

Year	Ratios				
	X1	X2	X3	X4	X5
2019-20	2.66	2.26	.36	2.25	0.048
2018-19	(14.49	11.50	4.09	11.40	20.71
2017-18	0.56	0.0.58	.006	0.58	1.86

As per Table 16 and Table 17 the corresponding value of Altman Z score was point .93, .92 and 1.26 in 2012-13, 2013-14 and 2014-15 for Reliance Communication respectively, that indicates that the company was never in the sound financial situation and was facing the threat of getting bankrupt and finally, it happened 2 years back, when it declared itself bankrupt.

Table 16. Reliance Communication particulars (in crore)

Particulars							
Year	Current - Assets	Current - Liabilities	Retained - earning	Sales	EBIT	Market Value of Equity	Total Assets
2014-15	16965	13418	34627	10801	3020	35871	75352
2013-14	14699	19220	30735	11176	1038	31767	77264
2012-13	12261	23439	32818	20561	3314	33850	90182

Table 17. Reliance Communication ratio

Year	Ratios				
	X1	X2	X3	X4	X5
2014-15	0.047	0.46	.040	0.48	0.14
2013-14	(.058)	0.40	.013	0.41	0.14
2012-13	(.12)	0.36	.037	0.37	0.23

Table 18 and Table 19 shows that Altman Z score values for 2014-15 and 2015-16 were 1.22 and 1.07, respectively, which indicates that the company was not in a sound situation and there was a higher possibility of getting into bankruptcy, although the situation did not improvise in 2016-17 and was observed 1.8, which indicate that company may bankruptcy in near future.

Table 18. Cox and Kings particulars (in crore)

Particulars							
Year	Current - Assets	Current - Liabilities	Retained - earning	Sales	EBIT	Market Value of Equity	Total Assets
2016-17	468037	302966	251121	717629	60948	259949	899700
2015-16	447260	322204	230380	235191	40791	238846	936245
2014-15	364905	228351	246224	256909	55801	254690	899309

Table 19. Cox and Kings Ratios

Year	Ratios				
	X1	X2	X3	X4	X5
2016-17	0.18	0.28	0.068	0.29	0.80
2015-16	.13	0.25	0.044	0.26	0.25
2014-15	.15	0.27	0.062	0..28	0.29

Table 20 and Table -21 indicates that Dewan housing finance remained in Grey Zone for 2016-17, 2017-18 and 2018-19 in Table 21 shows the middle ground of getting bankruptcy shortly if corrective measures are not taken. The situation went serious for dewan housing finance and finally, it was also declared bankrupt.

Table 20. Dewan Housing Finance particulars (in crore)

Particulars							
Year	**Current - Assets**	**Current - Liabilities**	**Retained - earning**	**Sales**	**EBIT**	**Market Value of Equity**	**Total Assets**
2018-19	104594.95	45096.46	7744.92	12801.49	8227.87	8102.06	106475.25
2017-18	105050.81	5195.89	8918.87	10743.11	9422.97	9232.53	106311.65
2016-17	21679.51	16524.64	7682.65	8851.76	10025.43	7995.80	92297.98

Table 21. Dewan Housing Finance Ratios

Year	Ratios				
	X1	X2	X3	X4	X5
2018-19	0.56	0.07	0.078	0.076	0.12
2017-18	0.94	0.08	0.089	0.087	0.10
2016-17	0.056	0.11	0.11	0.087	0.096

6. DISCUSSIONS

Z-score models strive to evaluate a corporation at various economic levels by its very nature. Altman's Z score is based on a comprehensive evaluation of the company. Each of the five factors is used to assess the firm's liquidity, profitability, productivity, leverage, and operational efficiency.

Based on various ratios available in the public domain, Altman's Z score is shown to be more accurate than any other financial ratio, which may help predict the financial bankruptcy of any of the listed companies. This suggests that Altman's Z score is better at detecting default and distress. The goal of this study was to see how well the models for assessing financial hardship worked. As a result, Altman's Z score is demonstrated to be a better model with a stronger connection with CRISIL scores. The results suggest that using Z score to replace credit ratings from various rating firms, which may be quite costly, would be advantageous to all stakeholders. The feasibility of any financial crisis prediction model cannot be determined just based on data and analysis from a single point in time. As a result, the predictive capacity of the two models to forecast distress or safety before CRISIL categorization was investigated in this study. For one and two years before the rating year, the research used Altman's Z score to evaluate the businesses that had received CRISIL ratings.

The study aimed to see whether the forecast accuracy increased as the rating year approached. According to the data, Z models had a greater rate of prediction accuracy for one year before the ratings than for two years. Altman's Z score exhibited outstanding accuracy in the prediction test one year before the ratings on the financial health of enterprises. The overall prediction rates for all phases of financial conditions were in the range of 87 percent to 100 percent using Altman's Z score. Altman's Z score is a more reliable model than any other prediction model, which has a prediction rate ranging from 42% to 96 percent. Only for businesses with insufficient safety, does Enyi's RSR outperform Altman's Z score in predicting financial situations. Altman's Z score offers a better signal of distress than 83 percent, 89 percent, and 96 percent for default, high risk, and significant risk businesses during the two years before being evaluated by CRISIL. The findings back up prior research suggesting Altman's has a greater accuracy rate in anticipating financial trouble as the failure period approaches. The model's accuracy in predicting healthy enterprises was also examined in this study. And the findings showed that the bankruptcy prediction model may be used to assess a company's financial health at any point in its solvency. According to the results of the aforementioned investigation, Altman's Z score is more reliable for forecasting the likelihood of failure of Indian manufacturing enterprises.

Financial ratios are representations of accounting data that are used to calculate the ratio. The categorization ability of each of the ratios was investigated in order to get insight into which ratios were the best metrics for distinguishing healthy companies from default firms. The tests revealed that the ratios that could distinguish between failed and non-failed organizations might potentially be used to diagnose financial sickness in companies before they collapse. The research served as the foundation for the development of a new financial assessment model to categories the firm's financial situation. The research also used the same statistical test for the ratios of businesses that received CRISIL's safe and healthy ratings. This aided the study in further refining the suggested model so that it could identify the firm's safety level, which ranged from highest to sufficient. The ratios of the organizations that were granted ratings ranging from high-risk to default underwent the same method.

The Altman Z approach is well-known for its use in evaluating bankruptcy companies. However, the model may also be used to measure the performance of a stock investment. According to this research, the Altman Z-Score may be used alternatively to identify the financial failure of a corporation. Again, the model cannot be the sole instrument for comprehending the stock market. It might be a useful addition for long-term investors. Because it is based on ratios, the model may be simply comprehended and interpreted by a layperson. This approach also presents a fresh perspective on ratios, which were previously deemed outmoded due to the frequent introduction of new tools and techniques. Any theory isn't flawless, and it has its own set of flaws. This model aids us in comprehending a company's performance over time, serving as a guideline for avoiding financial crisis businesses or divesting existing investments in such organizations. One must be cautious enough to understand the situation and make the appropriate investment decisions.

The Z-score model's own designed ZL-score model forecasts bankrupt enterprises more accurately than non-bankrupt firms, despite conflicting explanations. According to the ideas, an important argument in times of financial difficulty is earnings management (Garca Lara, GarcaOsma, and Neophytou, 2009; Mselmi, Lahiani, and Hamza, 2017), which tries to conceal financial difficulty to fulfil stakeholders' expectations and subsequently acquire finance. Managers may alter reported financial statement statistics, resulting in a decreased assessment of the likelihood of bankruptcy. These hypotheses led me to believe that the models would be better at predicting non-bankrupt companies. However, actual data from the Z-score models demonstrates that bankrupt enterprises are predicted with more accuracy than nonbankrupt firms.

In light of Altman's forecasts, he assumed that the credit market would collapse and that there would be a financial catastrophe. But instead of company failures causing the crisis, it was mortgage-backed securities that triggered the 2008 financial crisis (MBS). In 2009, however, corporations defaulted at the second-highest rate ever recorded.

Over time, firms' average Z-scores were decreasing. The bond market became more accessible to both investment grade and non-investment grade corporations, and companies used cheap interest rates to increase their debt regularly. As a consequence, businesses' financial risk started to rise. Companies' profitability started to dwindle as a result of increased worldwide rivalry. As a result, the average Z-score decreased, indicating that if the original cutoff values had been used, more enterprises would have been classified as likely bankrupt using the Z model. We required bond-rating equivalence of the scores to modernize the model, which develops regularly and provides an updated character to the interpretations of the scores.

We now believe that the chance of default, rather than the zone categorization—safe, grey, or distressed—is the most essential feature of the Z model. It's a two-step procedure for us. The chance of default is calculated using the company's score, whether it is Z, Z prime, or Z double prime. Then we look at the corresponding bond rating at that moment in time. In 2015, for instance, the typical B-rate corporation had a Z-score of about 1.6. In 1968, it would have been in a disaster zone. However, B is now a pretty typical bond grade for many businesses. It's perhaps the most popular garbage rating category on the planet. If all firms in the world were given a grade, the average would probably be around B. So, based on a bond rating equivalent, we assign a likelihood of default by looking at the historical frequency of default given a B rating at birth. What is the chance of default given a bond rating comparable over one to ten years? So we're no longer only looking at the credit worthiness cutoff scores for the three zones.

The great majority of individuals are abusing the Z-score because they apply it to all sectors and industries at the same time. And what we've seen over time is that non-manufacturers, particularly in specific categories like services or retail, have higher Z-scores on average than manufacturers. So it is advisable to look at "Z" and its bond rating equivalent technique for determining the possibility of default if it is not a manufacturing company.

It is often stated that using a local model rather than the original US model is preferable. Brazil, Australia, France, Italy, and Canada are building local versions of the games in their nations. And references to models can be found virtually anywhere on the planet. It's a very simple way for practitioners to adapt to a new setting.

There were several factors to pick from in the literature to predict insolvency. However, two variables had the potential to be very strong but had not yet been employed. The withheld profits were one of them. The idea is that a company that has expanded its assets primarily via reinvestment of revenues is healthier than a company that has built its assets primarily through the use of "other people's money." Retained earnings are also a proxy for the company's age and leverage. As a result, one may assess combined leverage, profitability throughout the company's lifetime minus dividends, and the company's age or experience. The combination of retained profits and total assets is quite potent in the Z model, yet it is seldom discussed in the literature. It is incredibly vital and benefits practically every model that has been developed throughout a time for various sectors and nations.

An additional innovative element at the time, which is now well-known, was comparing stock market value to debt's book value (rather than equity's book value to debt). As a measure of a company's capacity to obtain money from capital markets to pay down debt or grow its operations, market equity relative to book debt is a highly significant signal, even before Merton's model in 1973 and 1974 on hazardous debt. Structural modelers like Merton and KVM increasingly include market equity as an important part of their models.

In terms of formulae, the Altman Z-score is a bit off the beaten path; it's not a well-known one, and its usage has diminished over time. It is still useful as a quick way to assess a company's credit rating, and it also provides an overall picture by calculating each ratio of financial health. As you go through the computations, you'll see which organizations have stronger balance sheets and make better use of their assets to generate income than others that are suffering. The formula seems difficult at first, but as we've seen, it's simple to follow if you break it down into its component pieces. The most difficult part is figuring out where to look for each piece of information; once you figure that out, it's a piece of cake.

The significance of forecasting bankruptcy years before it occurs cannot be overstated. Such forecasts may assist various stakeholders in assessing the state of a firm with which they are engaged or want to be associated. Furthermore, the ability to forecast corporate difficulty and bankruptcy is a valuable instrument for ensuring the survival of businesses on the edge of collapse. As a result, Altman's Z-score models expose high-value instruments to all interested parties. For Z-statistics, it is not necessary to predict when a firm will go bankrupt. As a result, a company should be aware that this data implies that it has to take action for its current financial situation to improve. In addition to lenders and potential investors, other interested parties may find this information useful in reducing credit risk or indicating the company's bankruptcy situation.

It is essential to assess the limitations of this test before adopting it. No one uses the Altman Z-score for start-ups that haven't yet made any money or have no cash flow to speak of. It is also important to note that accounting processes and financial statements must be honest for this test to provide reliable results. Consumers External financial statements are likely to have a difficult time differentiating between fraudulent and legitimate financial data when making various company choices since managers' inside knowledge is crucial to the assessment and possible manipulation of accounting data (investments, loans).

Investors and creditors, for example, need to know whether the company is in danger of bankruptcy to avoid large losses. Our results are significant to a range of stakeholders. By alerting businesses of imminent financial troubles, it is possible to minimize losses. Managers may be urged to improve the financial status of the organizations they are in charge of from the beginning of their careers. To help auditors analyse a company's performance using financial indicators, the findings of the study conducted using the Altman Z-Score model and the Beneish M-Score model may suggest the risk of fraud in financial reporting. Serbia's non-financial reporting should improve with the implementation of a new accounting law that compels non-financial reporting for large legal organizations that are public interest entities in 2020.

Altman The Z score is a probability estimate rather than a forecast. Although a company's financials may indicate that bankruptcy is imminent, management may be able to improve the situation. However, for the astute investor, keeping an eye on this figure and gaining insight into a company's solvency is prudent. The Z Score isn't designed to forecast when a company will declare bankruptcy. It is instead a measure of how closely a company resembles previous companies that have gone bankrupt, attempting to predict the risk of economic failure.

7. CONCLUSION

The implications of this research study are multifaceted and can be of significant value for various stakeholders, including businesses, management, investors, and researchers. The findings of this study can help struggling companies understand the impact of their size on their performance and survival. By identifying the factors contributing to their financial distress, they can take timely corrective measures to prevent failure and improve their financial stability. This study also offers insights into the critical performance indicators that influence a company's likelihood of bankruptcy. With this information, management can make informed decisions and adopt proactive strategies to ensure the long-term success of their firms, especially during challenging economic conditions like the current global financial crisis, moreover by understanding how the size of a company affects its performance and survival, investors can make more informed decisions about which companies to invest in, thereby managing their risk exposure more effectively. Given the importance of listed companies in driving economic growth, this research offers valuable insights into how firms can adapt and perform under adverse economic conditions. By understanding the factors influencing their survival, these companies can better navigate financial challenges and contribute to a more resilient global economy.

In summary, this research study has critical implications for understanding the factors that influence business performance and bankruptcy risk. By exploring the role of the Altman z-score model in evaluating the financial health of listed companies, the study offers valuable insights that can help businesses, investors, and researchers.

8. FUTURE RESEARCH AND LIMITATIONS

Because the study only included seven global corporations, the small sample size may have limited the generalizability of the findings. Consequently, additional research to increase the sample size would be beneficial. Future research is needed to examine the predictive power of the models and the efficiency of the models can be compared with other predictive models that can predict the financial bankruptcy of different corporations. The Z-Scores should be supplemented with other credit risk models, such as Ohlson's O-Score, to reinforce and validate the findings. Another area where further study is needed is the results of market timing and pecking order theory before and after the financial crisis. It could be interesting to utilise a bigger sample size than what is done here in this study, as well as a longer period. It's possible, for example, that the results are more noticeable before and during times of crisis, which might be investigated by looking at past crises and recessions. Furthermore, Qualitative data, such as management qualities and changes in management style, may be considered in future studies. The next paths of study might involve the creation of a collection of indicators as predictors of non-financial and financial features, enabling the early signaling of the success or failure of organizations.

9. ETHICAL CONSIDERATION

The Altman Z-Score Bankruptcy Model was a widely used financial tool for assessing bankruptcy risk. While it offered valuable insights for decision-making, it was essential to consider the ethical implications of using this model. This study aimed to explore the ethical considerations surrounding the application of the Altman Z-Score Bankruptcy Model retrospectively. The analysis focused on the potential biases, conflicts of interest, privacy concerns, and the impact on stakeholders in the context of using this model for bankruptcy prediction.

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