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Corporate Bankruptcy Prediction Model: A Systematic Literature Review

Fitriyah Insani

Ministry of Public Works and Housing, Indonesia
Corresponding author email: insanifitriyah@gmail.com

Grace T. Pontoh

Hasanuddin University, Makassar, Indonesia
Email: gracetpontoh@fe.unhas.ac.id

Darwis Said

Hasanuddin University, Makassar, Indonesia
Email: darwissaid@fe.unhas.ac.id

Abstract---*This study is a systematic literature review aimed at providing a comprehensive understanding of the use of various models such as Altman Z-Score, Springate, Zmijewski, Grover, Beneish, and Ohlson in the analysis of bankruptcy prediction for companies. The study details many research articles published in various academic journals and other reliable sources. Literature analysis involves identifying trends, common findings, as well as recent developments in the use of these models as bankruptcy prediction tools. This literature review indicates that despite significant advancements in the development of bankruptcy prediction models, challenges persist in applying these models universally across different contexts, particularly given contextual variations between industries and countries. The insights from this literature study are valuable for researchers, financial practitioners, and decision-makers in applying any models for bankruptcy prediction analysis. Furthermore, this literature review encourages further research in developing more sophisticated and timely bankruptcy prediction models.*

Keywords---*bankruptcy prediction, financial analysis, financial distress, systematic literature review.*

Introduction

Competition in the business world is getting harder every day, every company, both those that have gone public and those that are still private, are very likely to face financial problems or bankruptcy, every company should possess the capability to compete with other firms and be able to face all the risks that might occur. Generally, a company is not formed for a short time but rather aims to carry out its operations over a longer time or remain in operation. The primary goal of the company is to acquire optimal profits following the company's capabilities. To achieve this optimal profit, a good and appropriate step plan is needed.

In the era of globalization, companies will face various challenges and competition. Without having a backup plan in decision-making there is a concern that the company may lose the competition to other companies. Every company hopes to increase the amount of assets, profits, and sales to avoid loss, bankruptcy, or failure.

In the process of making financial decisions such as investing and providing capital, parties that borrow capital such as investors, banking institutions, and capital lending companies need to make careful selection of companies to maximize potential return profits. One critical aspect that must be considered is the potential bankruptcy of the company. Bankruptcy takes place when a company is incapable of fulfilling its debt obligations and petitions the court for debt restructuring or liquidation of its assets. Capital providers need to show accuracy in identifying companies that have the potential for bankruptcy in the future, this aims to avoid the risk of negative returns or even losing all capital due to company bankruptcy. Given the seriousness of the impact of this problem, bankruptcy

prediction models have become an interesting topic studied and developed by researchers, especially in the fields of accounting, finance, and computer science.

Bankruptcy is one of the most serious risks that potentially threaten the sustainability of a firm and holds considerable influence on stakeholders, including shareholders, creditors, and even the economy as a whole. Therefore, having an effective tool to anticipate the potential of bankruptcy in a firm is a must in financial risk management and timely decision-making.

Some of the most well-known and commonly used methods are financial failure forecast models such as Altman, Beneish, Ohlson, Springate, Grover, and Zmijewski. Each of these models was developed with a different statistical approach and often has specific advantages in identifying early signs of bankruptcy.

In recent decades, the Altman Model has become a well-known and frequently used bankruptcy prediction tool among financial professionals and researchers. This method, first developed in 1968 by Dr. Edward Altman, has undergone various modifications and adaptations to accommodate changes in the dynamic global business environment.

Altman is a classic model that uses some financial ratios and non-financial aspects to assess the financial health condition of a company. On the other hand, models such as Springate, Zmijewski, Grover, Beneish, and Ohlson provide an additional dimension to bankruptcy analysis by considering specific factors and unique characteristics of the company.

However, with the rapid growth of the literature, there is a need to systematically summarize the key findings of these studies. For this reason, The objective of this research is to present a comprehensive review of the existing literature on the use of multiple models in corporate bankruptcy prediction analysis.

Literature Review

Systematic literature check

The term Systematic Literature Check is used to refer to a specialized research and development methodology aimed at collecting and evaluating research related to a specific topic focus. The main objective of a Systematic Literature Check is to identify, review, evaluate and interpret all research relevant to a particular phenomenon, focusing on a specific research question. A Systematic Literature Check is essential in setting a research agenda, forms an integral part of a dissertation or thesis, and serves as a complementary element in research grant applications ([Triandini et al., 2019](#)).

Bankruptcy

Financial distress may be defined as the inability of a firm to carry out its operations to make a profit. As per [Adriansyah & Sherlita \(2022\)](#), Jauch and Glueck mentioned that there are elements factors leading to the financial downfall of a company:

- 1) General factors consist of social, technological, economic and governmental sectors.
- 2) External factors of a company consist of the supply sector, customers and competitors.
- 3) Factors from within the company involve the inability to repay consumers or clients in disbursing loans, resulting in eventual delinquencies.

Z-Score Altman

This model utilizes discriminant analysis to classify studies based on their characteristics. The Altman model uses five types of financial ratios. [Altman & Hotchkiss \(2010\)](#) compiled the model formula as follows:

$$Z\text{-score} = 1,2X_1 + 1,4X_2 + 3,3X_3 + 0,6X_4 + 1X_5$$

Description:

Z = Bankruptcy

X₁ = Working Capital to Total Assets

X₂ = Retained Earnings to Total Assets

X₃ = Earnings Before Interest and Taxes (EBIT) to Total

X4 = Market Value of Equity to Book Value of Total Liabilities

X5 = Sales to Total Assets

Cut-off point:

Consideration of the health or bankruptcy of the company relies on the Altman Z-Score value, with the following criteria:

- 1) If the value is less than 1,81, the company is considered to be in a state of bankruptcy.
- 2) If the value is $1,81 < Z < 2,99$, the company is in the grey category (it's uncertain whether the company is in good financial health or on the brink of bankruptcy).
- 3) If the value is $> 2,99$, the firm is considered not bankrupt.

Springate Model

Multidiscriminant analysis was used by Springate in 1978. This Springate model was developed with multidiscriminant analysis (MDA) by identifying financial ratios believed to impact an event, enabling the model to assist in concluding the occurrence (Sunaryo, 2015). The data process model used is as follows:

$$S = 1,03X1 + 3,07X2 + 0,66X3 + 0,4X4$$

Description:

S = Springate

X1 = WCTA

X2 = EBITTA

X3 = EBTCL

X4 = SATA

Cut off point which is an indicator that a company is said to be bankrupt or not is:

- 1) If the S value is less than 0.862 then there is a potential bankruptcy of the company
- 2) If the S value is more than 0.862 then there is no potential bankruptcy of the company

Zmijewski Model

The random sampling technique was used by Zmijewski (1984), in his research because he considered that this technique tended to show confusion in the results of previous studies. In the Zmijewski model, it is necessary to determine the proportion of the sample and population as early as possible. Zmijewski uses a statistical model in the form of logit regression with the model:

$$Z = - 4,803 - 3,599X1 + 5,406X2 + 1X3$$

Description:

Z = Zmijewski Model

X1 represents ROA (Net income to total assets)

X2 denotes Leverage (Total debt to total assets)

X3 corresponds to Liquidity (Current assets to current liabilities)

Zmijewski (1984), mentions that a business is deemed to be experiencing bankruptcy if the probability exceeds 0.5, which means that the Z value is equal to 0. Therefore, the applicable value threshold in this method is zero (0). This indicates that companies with a Z score greater than or equal to 0, or positive, are expected not to experience bankruptcy in the future. In contrast, companies with a Z score of less than 0 or becoming more negative are not expected to experience bankruptcy.

Grover Model

In 1968, Jeffrey S. Grover developed the Grover Model, a predictive model consisting of three financial ratio variables related to financial distress conditions, namely WCTA- Working Capital to Total Assets, EBITTA-Earning

Before Interest and Taxes to Total Assets, and NITA-Net Income to Total Assets. According to the explanation of Munawarah and colleagues (2019), this model is described as:

$$G = 1,650X1 + 3,404X2 - 0,0166X3 + 0,057$$

Description:

G-Score = Grover

X1 = represents Working Capital to Total Assets

X2 = corresponds to Earning Before Interest and Taxes to Total Assets, and

X3 = denotes Net Income to Total Assets

The boundary point of the Grover model is:

- 1) If a company's G-Score value exceeds 0.01, this indicates a prediction that the company is not facing financial difficulties.
- 2) If the value is less than -0.02, it is estimated that the company is experiencing financial difficulties.

Beneish Model

The Beneish M-score is a financial ratio first introduced by [Beneish \(1999\)](#). There are eight financial ratios proposed by Beneish, involving Receivable Gross Margin Index (GMI), Total Accrual to Total Assets (TATA), Days Sales Index (DSRI), Asset Quality Index (AQI), Depreciation Index (DEPI), Sales Growth Index (SGI), Leverage Index (LVGI), and Sales General and Administration Expenses Index (SGAI).

Mehta & Bhavani, as cited in Setyarini and Ginting (2019), explain that The Beneish M- Score is a mathematical model employed to identify potential fraudulent activities within financial data statements. This model is probabilistic, so it cannot with certainty predict the occurrence of financial statement fraud by 100%. [Beneish \(1999\)](#), as mentioned by Yanuari and Daniel (2018), states that companies involved in earnings manipulation on financial statements tend to show a notable rise in revenue and a significant decrease in expense accounts.

Ohlson Model

The logit analysis model is one type of multivariate analysis introduced by [Ohlson \(1980\)](#). From the results of his research Ohlson got nine indicators, namely:

- 1) SIZE = Natural logarithm (ln) of total assets to GNP implicit price deflator index.
- 2) TLTA = The ratio of total liabilities to total assets.
- 3) WCTA = The proportion of current assets minus current liabilities to total assets.
- 4) CLCA = The ratio of current liabilities to current assets.
- 5) NITA = The ratio of net income to total assets.
- 6) FUTL = The ratio of funds from operations to total liabilities.
- 7) INTWO = A binary variable, with a value of one if net income was negative for the last two years and zero otherwise.
- 8) OENEG = A binary variable, with a value of one if total liabilities exceed total assets and zero otherwise.
- 9) CHIN = The percentage change in net income from the current year to the previous year, divided by the sum of net income for both years. $(NIt - NIt-1) / (NIt + NIt-1)$

The following variables above are expressed in the equation:

$$Y = -1,32 - 0,407SIZE + 6,03TLTA - 1,43WCTA + 0,0757CLCA - 2,37NITA - 1,83FUTL + 0,285INTWO - 1,72OENEG - 0,521CHIN$$

The measure of bankruptcy according to the Ohlson model can be assessed by the formula:

$$p = \frac{1}{1 + e^{-y}}$$

Explanation:

p = probability of bankruptcy

e = natural logarithm value of e (about 2.718282)

y = multivariate function

Research Methods

The approach employed in this study is a Systematic Literature Review (SLR). This approach is done by recognizing, assessing, and explaining all existing research. Using this method, researchers systematically review and recognize journals, following predetermined steps at each stage (Triandini et al., 2019).

The research used official journals selected based on aspects: (1) analyzing bankruptcy predictions of a company or industry (2) analyzing bankruptcy predictions using several bankruptcy prediction models such as Beneish, Springate, Grover, Zmijewski, Ohlson, and Altman.

The journal literature search was conducted through Harzing's Publish or Perish by using google scholar, in addition, the search was also conducted on Scopus indexed international journals, WoS, and other related journals. Some of the keywords used in the journal literature search involved: Systematic Literature Review, Bankruptcy Prediction, Financial Analysis, Financial Distress (Corbet et al., 2019).

After completing the stage of searching for journals relevant to the topic, an evaluation of the results of the literature search was conducted. The literature found was then re-selected in order to meet a number of criteria that are considered the main standards in this study. These criteria involved: (1) the suitability of the literature to the predetermined topics and key aspects; (2) the literature is in the form of official journals published between 2013 and 2023; and (3) the literature is in the form of journals that can be accessed by the general public or are the result of proceedings.

Results and Discussion

There were 34 journals searched based on keywords from Google Scholar, Scopus, WoS, and other databases. The research is based on a literature review using variables from several bankruptcy prediction models. Research by Fitriani et al (2022), on the topic "Assessment of Bankruptcy Forecasting for Manufacturing Companies in the sector of consumer goods Industry during the COVID-19 pandemic utilizing the Altman Method" in 2022 resulted in 3 companies not affected by the pandemic, 4 companies affected by the pandemic, and 2 companies even experienced improvements during the pandemic.

Research by Agarwal & Patni (2019), on the topic "The Appropriateness of Altman Z- Score in Anticipating Bankruptcy for BSE Public Sector Undertakings (PSUs)" in 2019 with the conclusion that this research is a study that concentrates on the Indian business environment, particularly encompassing the SOE index on the Bombay Stock Exchange. This research investigates the suitability of Altman's Z-Score bankruptcy prediction model to test the financial health of companies operating in the industrial sector and the non-industrial sector. The study covered 53 firms spanning 6 years from 2013 to 2018. According to the research result, Altman's is a probability and not an exact forecasting. In terms of the company's finances, it might appear probable that financial failure is looming, but the management of the company might manage to turn things around. However, for investors who rationally, it is wise to be cautious about a financial stability of the company. The Altman model is not intended to predict when exactly a company will initiate the process of declaring legal insolvency. Instead, it serves as a tool for evaluation the extent to which a company is similar to other companies that have filed for bankruptcy.

Research by Utami & Kawulur (2020), on the topic "Assessment of Modified Altman Z-Score for Bankruptcy Prediction (A case study conducted at PT. BPR Primaesa Sejahtera in the city of Manado)" in 2020 resulted in an analysis of financial difficulties with the modified Altman method for the period 2015 to 2019 resulting in a Z-Score of 1.63, 1.45, -0.35, 0.30, and -0.47. This value implies that the company during the period 2015-2019 is sequentially in the gray area twice and bankrupt for 3 years.

Research by Sarumpaet (2021), on the topic "The Impact of Altman Z-Score Modified Approach on Stock Prices in Predicting Bankruptcy (A Study of privately-owned companies within the general banking sector Listed on the Stock Exchange of Indonesia from 2015 to 2018)" in 2021 resulted in a prediction analysis The state of financial well-being with Altman Modification has a beneficial impact on the stock value of private banks listed on the Indonesia Stock Exchange from 2015 to 2018.

Research by Akbar et al. (2020), on the topic "Predicting Bankruptcy through the Application of Altman Z-Score for PT Atlas Resources, Tbk from 2016 to 2018" in 2020 based on the negative scores obtained, the company was identified as experiencing bankruptcy during the three periods. The bankruptcy condition suggests that the company

is facing financial difficulties due to the accumulation of receivables, increased debt, and the existence of many subsidiaries that are not operating, which in turn can harm the company's financial performance. To overcome these financial challenges, companies can implement receivables control to accelerate cash flow and divest assets through sell off and spin off strategies to pay off debt and improve poor performance.

Research by [Susanto & Pramudena \(2022\)](#), resulted in: a) Liquidity positively and significantly influences the stock value of banking companies classified as LQ45. b) Return on Equity (ROE) negatively and significantly impact on the value of shares of banking companies included in LQ45. c) Return on Assets (ROA) positively and significantly influences the stock value of banking companies listed in LQ45.

Research by [Fitriani et al. \(2019\)](#), resulted in a poor level of financial condition in cement companies showing: a) The level of financial performance of PT Semen A is in a secure zone with a Z value greater than 3,5 to 8,8. b) The level of economic results of PT Semen B is in a safe area with Z between 7,2 to 14,3. c) PT Semen C also in secure zone with Z value between 10,9 to 15,9. In contrast to other cement enterprises, Indocement has the highest value indicates that this company outperforms others in terms of financial stability. d) PT Semen D. This shows that between 2014 and 2017, the financial performance was precarious, and in 2013, it was on the brink of bankruptcy. The Z value falls within the range of 0.818 to 2.792, considerably lower than its counterparts. It is imperative for this company to swiftly enhance its performance to avert bankruptcy.

Research by [Gopalakrishnan et al. \(2019\)](#), on the topic "Predicting Financial Difficulties in the Indian Steel Industry using Z-Score Model" in 2019 resulted in Among the companies in the industry, only 20% managed to achieve financial stability, and this occurred in the fiscal year 2017-2018. Interestingly, the two well-established large-scale companies are currently facing financial distress. However, there is a notable emergence of JSW Steel, indicating its potential to surpass the two major industry giants. Hisar and Metal industry SAL Steel are safe companies, though not operating on the scale of the others but still able to maintain liquidity and profitability thereby propelling the company towards growth.

Research by [Fitriani & Muniarty \(2020\)](#), on the topic "Examining Bankruptcy Forecasting at PT Aneka Tambang (Persero) Tbk to asses the financial status using Altman" in 2020 resulted in the performance of PT Aneka Tambang experiencing variations, where In 2012 and 2013, the company fell into the gray area, indicating financial difficulties. Losses continued to escalate from 2014 to 2017, placing the company in the bankruptcy category. By 2018, its performance remained in the gray area, signifying ongoing financial challenges. Aneka Tambang (Persero) Tbk was classified as having potential bankruptcy for four consecutive years. The Altman Z-Score discriminant analysis revealed a poor financial condition, with a negative value below the estimated 1.23 threshold, indicating a potential risk of bankruptcy.

Research by [Mokoginta & Wokas \(2022\)](#), with the topic " Forecasting corporate insolvency utilizing the Altman Z-Score Model: An Evaluation of Leasing Entities listed on the Stock Exchange of Indonesia from 2019 to 2021" in 2022 predictions using Altman Z-Score 2019-2021: a) 10 companies Clipan Finance Indonesia, BFI Finance Indonesia, Danasupra Erapasific, Pool Advista Finance, Mandala Multi Finance, Trust Finance Indonesia, KDB Tifa Finance, Adira Dinamika Multi Finance, Buana Finance, and Radana Bhaskara Finance are in good health. b) Verena Multi Finance is projected to face financial difficulties. Indomobil Multi Jasa and Intan Baru Prana are anticipated to experience bankruptcy. Wahana Ottomitra Multiartha is foreseen to be in a precarious financial situation in 2019, with an improvement to a healthy condition in 2020 until 2021.

Research by [Prasetyani & Sofyan \(2020\)](#), with the results of research on 6 companies evaluated using the Altman, there are 1 company predicted to go bankrupt, 3 gray areas, and 2 not potentially bankrupt. Meanwhile, Springate's predictions are that 3 companies have the potential to go bankrupt and 3 others do not have the potential for bankruptcy.

Research by [Sitorus \(2023\)](#), on the topic "Evaluation of Bankruptcy Prediction using Zmijewski, Springate, and Altman Z-Score Models in Companies within the Fisheries Sub-Sector from 2019 to 2021" in 2022 with the following results: a) Analysis using Altman Z-Score for the past 3 years, fisheries companies list for the 2019-2021 period which are expected to face bankruptcy are PT. Morenzo and PT Era Mandiri Cemerlang in the gray area sequentially for 2 years, namely 2019-2020, while in 2021 the financial status of the company is within the healthy category. Asia Sejahtera Mina in the last 3 years is also in good health. b) Derived from the examination of the Springate model for a three-year bankruptcy forecast, namely in 2019 to 2021, fishery companies list from 2019 to 2021, PT Era Mandiri Cemerlang is a company that has the potential for bankruptcy. PT. Asia Sejahtera Mina and PT. Morenzo Abadi Perkasa the financial state of the company is healthy. c) Derived from the information results of the 3-year Zmijewski bankruptcy prediction model analysis, namely in 2019 till 2021, fishery companies list in 2019 to 2021, no companies were found that had the potential to experience bankruptcy because the three companies were in good health.

Research by [Muzanni & Yuliana \(2021\)](#), on the topic "Comparative Assessment of Springate, Altman, and Zmijewski Models for Bankruptcy Prediction in Retail Companies in Indonesia and Singapore" in 2021 with the findings indicate notable distinctions among the Zmijewski, Altman, and Springate models when used in companies engaged in retail operations in Indonesia. The Zmijewski model is the most suitable model for predicting the bankruptcy of retail companies in Indonesia, whereas the Altman model is the most suitable for predicting the bankruptcy of retail companies in Singapore.

Research by [Winaya et al. \(2020\)](#), with the topic "Examination of Altman Z-Score and Zmijewski Bankruptcy Prediction in Telecommunication Sub Sectors Listed on the Indonesia Stock Exchange from 2016 to 2018" in 2020 with **Altman** estimates that in 2016 the number of telecommunication subsectors predicted to go bankrupt is 4 companies, in the telecommunication subsector which is predicted not to experience bankruptcy as many as 1 company. In 2017-2018 the number of telecommunication subsector companies predicted to go bankrupt was 3 companies, gray area conditions or gray conditions were 1 company, and telecommunication subsector companies were forecasted to face bankruptcy. not bankrupt in 1 company. The **Zmijewski model** estimates that in 2016-2018 the number of telecommunication subsector companies that are forecasted to go bankrupt is 1 company, and telecommunication subsector companies that are forecasted not to bankrupt are 4 companies. There are variances in the analysis results between the Altman Z-Score model and the Zmijewski model.

Research by [Loppies \(2023\)](#), et al with the topic "Analysis of Predicting Bankruptcy through Altman Z-Score, Grover Model, and Springate S-Score (An Investigation in Retail Companies Listed on the Indonesia Stock Exchange during the Period 2014-2018)" in 2020 with research results: **Altman Z Score** - PT Matahari Department Store Tbk from 2014 to 2018 is in the healthy category, PT Matahari Putra Prima Tbk has a Z value that tends to decrease since 2014 - 2017, PT Ramayana Lestari Sentosa Tbk has a Z value that tends to increase since 2007 - 2018 and is always in the healthy category. **Springate S Score** - PT Matahari Tbk is a company that experienced bankruptcy in 2017 and 2018, PT Matahari Dept. Store Tbk is constantly declining in financial condition even though it is still in the healthy category, PT Ramayana Lestari Sentosa Tbk has an S-Score that tends to increase even though it fluctuates. **Grover Model** - PT Ramayana Lestari Sentosa Tbk is classified as a healthy company with a score that tends to increase from 2014 to 2018, Matahari Department Store Tbk is also in the healthy category even though it has a score that tends to decrease, PT Matahari Putra Prima Tbk has a score that tends to decrease and finally crossed the threshold of the bankruptcy category in 2017.

Research by [Shafitranata & Arshed \(2020\)](#), on the topic "Comparative Analysis of Springate and Altman for Forecasting Bankruptcy in Islamic Banking in Indonesia" in 2020 a) by using Altman Z-Score to forecast bankruptcy in Islamic financial institutions From 2013 to 2019, certain companies were forecasted to be susceptible to bankruptcy, PT. Maybank Syariah in 2018 with Z value of 2.73 meaning that in the gray area. b) By utilizing the Springate model for predicting bankruptcy in Islamic Banking from 2013 to 2019, some companies consistently showed a forecast of bankruptcy, specifically PT. Bank BRI Syariah and PT. Bank Muamalat, with an SScore consistently below 0.862. There were also companies predicted to face bankruptcy, but their SScore fluctuated each year. These included PT Bank BNI Syariah, PT. Bank Mega Syariah Indonesia, PT. Panin Dubai Syariah Bank, PT Bank BJB Syariah, PT Victoria Syariah, PT Bukopin Syariah, PT Maybank, and PT Bank BTPN Syariah. This study can serve as a policy brief for Islamic banking in Indonesia, evaluating the financial performance of companies, considering the utilization of assets for profit generation, and assessing operational efficiency. Notably, PT Bank BCA Syariah and PT Bank Syariah Mandiri were identified as companies without the potential for bankruptcy. c) Considering the assessment of the Altman and Springate models and their correlation with the company's financial status from 2013 to 2019, the Modified Altman model exhibits a notably higher accuracy in predicting bankruptcy compared to Springate. The Altman Z-Score model incorporates three distinct classifications, namely bankruptcy, the gray zone, and non-bankruptcy. This classification serves as a valuable indicator, offering a cautionary signal for the company to enhance its overall performance.

Research by [Mulyadi \(2020\)](#), on the topic "Predictive Analysis of Business Bankruptcy using Altman Z-Score and Springate Methods (Case Study at PT Holcim Indonesia TBK)" in 2020 with the results of the study describes the results of the company's financial performance with ratio analysis from the period 2010 to 2014 illustrating that the company is in good condition because there are no adverse (negative) results even though each year it fluctuates. The results of bankruptcy analysis using the Altman Z-Score method in the time span from 2010 to 2013 are included in the criteria for not bankrupt and 2014 is included in the criteria for the gray area or doubtful. The results of the analysis of potential bankruptcy using the Springate method from the period 2010 to 2012, showed that the company was in the non- bankrupt category and from the period 2013 to 2014 the company was in the bankrupt category.

Research by [Hiong et al. \(2021\)](#), on the topic "Estimating and Forecasting Financial Difficulties: Non-Financial Companies in the Bursa Malaysia" in 2021 with results from Out of the 84 companies examined, 52 were identified

as having a high risk, while 32 were classified as low risk. The study utilized secondary data extracted from the financial statements of the selected companies for analysis. The results of this research affirm the applicability of the Altman model in predicting corporate financial distress. This dispels uncertainties regarding the model's validity and underscores its practical utility for forecasting the likelihood of bankruptcy in a company. These findings carry substantial implications for investors, creditors, and management. Portfolio managers can enhance decision-making by avoiding investments in companies that have demonstrated susceptibility to financial distress, particularly when they comprehend the contributing variables to such distress (Hotchkiss et al., 2008; Mselmi et al., 2017).

Akra & Chaya's (2020), with the outcomes from the Altman Model revealed that 22 out of the 30 selected companies were experiencing financial difficulties. This implies that Altman identified financial distress in 73% of the sample companies, indicating a significantly high rate. Both Beneish and Altman demonstrated substantial predictive power within the context of entities listed on the Kuwait Stock Exchange. However, Altman's effectiveness varied across different types of companies, with exceptions noted, particularly in real estate and manufacturing sectors. The diminished predictive power in these sectors was attributed to factors such as inventory cycles. Despite these limitations, Altman accurately highlighted issues like working capital shortages and other indicators of financial distress. It is acknowledged that the model may have lower predictive power for industrial and real estate firms in developing countries due to prolonged billing cycles and elevated inventory levels. To address these challenges, recalibrating intervals to accommodate industry-specific idiosyncrasies is recommended. Additionally, Beneish is recognized as an effective tool for financial analysts and external auditors in detecting early earnings manipulation, offering high predictive power through its retroactive calculations and year-to-year ratio analysis, distinguishing it from Altman's focus on a one-year ratio analysis. Consequently, the researcher advocates for an integrated approach, combining both models for enhanced accuracy in financial distress prediction.

Research by da Silva Mattos & Shasha (2024), with the topic Bankruptcy prediction in 2023 extends beyond previous research conducted on this matter, which predominantly relied on data from public or audited companies. However, such datasets differ significantly from the majority of global companies, which are private and lack the same level of oversight for their accounting reports. To address this disparity, this study utilizes a uniquely compiled and balanced dataset comprising Brazilian private companies that underwent reorganization, featuring varying degrees of accounting transparency. The findings diverge from expectations based on earlier studies in explaining default and bankruptcy, a discrepancy noted by other author. In the realm of low-quality financial information, it becomes evident that lenders prioritize variables less prone to manipulation, such as tangible assets held by distressed firms, over performance metrics dependent on unreliable accounting reports. Institutional factors, serving as proxies for financial statement quality, play a pivotal role in this context. Additionally, the study identifies the potentially problematic influence of special counsel in trial outcomes, suggesting a tendency to navigate the system in favor of distressed firms, irrespective of their underlying financial fundamentals. Furthermore, the research underscores the superiority of machine learning models over traditional statistical approaches, aligning with existing literature that emphasizes non-linear performance improvements in datasets characterized by inherent vulnerabilities and synergistic causality among their features (Winata & Budiasih, 2022).

Research by Gajdosikova & Gabrikova (2023), on the topic "Prediction of Corporate Bankruptcy: A Thorough Review of the Literature and Comprehensive Bibliometric Analysis" in 2023 with the results The capacity to generate and maintain an optimal balance of assets stands as a crucial aspect of a company's financial evaluation. Generally, financial stability is integral to the assessment of competitiveness and serves as a cornerstone for the financial and economic efficacy of the company. Predicting financial health is a fundamental component of a comprehensive company review, providing insights into the company's prospective financial stability. Various models, leveraging historical data, are employed to predict a company's likelihood of bankruptcy, offering a probability-based assessment of whether the company is susceptible to financial distress. The developed bibliometric map reveals that keywords such as bankruptcy prediction and classification, as well as bankruptcy prediction and financial ratios, exhibit the closest associations within the research landscape.

Research by Altman (2018), on the topic "Utilization of Distress Prediction Models: Insights Gained Over In 2018, an evaluation of '50 Years from the Z-Score Models' reflected on the extensive application and impact of the Z-score model over more than five decades since its inception for forecasting financial distress and corporate bankruptcy. During this period, numerous practitioners and several researchers have employed the Altman model, deeming it a dependable and readily replicable standard. Altman et al. (2017), is a notable reference highlighting its widespread adoption. The model's application can be categorized into two main forms: (1) External use by analysts outside the company, primarily for credit and investment purposes; (2) Internal use by managers and board members within struggling companies to assess strengths, weaknesses, and guide financial turnaround efforts. The external application of the Altman Z-score has become the standard in the banking industry and other lending institutions for

building internal models to estimate default probabilities and potential losses, aligning with capital allocation requirements under Basel II and III.

Research by [Balasubramanian et al. \(2019\)](#), with the title "Creating a model for predicting financial turmoil in corporate entities utilizing both financial and non-financial variables: A study of Indian companies listed on the stock market" in 2019. The results showed that models involving financial variables had a prediction accuracy rate of around 85.19 and 86.11 percent. Meanwhile, models that combine financial and non-financial variables show a relatively higher level of accuracy, which is around 89.81 and 91.67 percent. Factors such as longterm debt equity ratio, company age, net asset value, institutional ownership, ROI, retention ratio, and pledged promoter ownership proved to be important predictors in both financial and non-financial terms in anticipating financial distress.

Research by [Altman et al. \(2013\)](#), with the results upon examination, it becomes evident that Altman's Z-Score model can be utilized in the Italian manufacturing landscape, albeit with certain considerations. Application of the indicator to the sample in the European Union (EA) underscores a notable percentage of companies falling within the distress zone. The gray zone, or the ambiguous area, is relatively narrow compared to the Z-Score model, at least in terms of average classification. Notably, the study focuses on companies of a specific size, specifically those with a minimum of 200 employees and a complete balance sheet. The dimensions of the Italian manufacturing industry appear limited when considering the entire population of 174,010 companies, as the study employs a sample of 1,602 companies, representing less than 10% of the total. To make generalized hypotheses by applying the model on a larger scale, parameters adaptable to large, small, and medium-sized firms need to be defined. Despite some exceptions, large Italian manufacturing companies still share certain characteristics with their smaller counterparts. Qualitative and strategic aspects, such as financing and governance options, remain relatively unchanged. Therefore, while the application of Z-Scores in the Italian context provides valuable insights, it comes with inherent complexities. Nevertheless, such a model can offer substantial assistance to investors, regulators, and even policymakers.

Research by [Hosaka \(2019\)](#), on the topic "Predicting Bankruptcy with Convolutional Neural Networks and Financial Ratio Images" in 2018 with the results of researchers has Suggested an approach to implement Convolutional Neural Networks (CNN) in the context of bankruptcy prediction. In this methodology, a collection of financial ratios is translated into a grayscale image, where each financial ratio is mapped to a specific pixel position. Subsequently, the resulting image serves as the training data for the CNN using the GoogLeNet architecture. The numerical assessment demonstrates that assigning closely related financial ratios to adjacent pixel positions is more suitable for the research objective compared to random placement. The analysis also shows that the proposed approach surpasses commonly used conventional methods such as LDA, Altman, MLP, SVM, AdaBoost, CART, and MLP. In addition, the proposed approach of transforming financial ratios into image representations also proved to be more effective. The potential application of this approach extends beyond bankruptcy prediction to general numerical data in diverse contexts. However, distinguishing the relative impact of individual financial ratios on bankruptcy prediction is challenging compared to certain traditional methods.

Research by [Kim-Soon et al \(2013\)](#), on the topic "Examining Companies Facing Financial Challenges on the Malaysian Stock Exchange Using Financial Liquidity Ratios and Altman's Model" conducted in 2013 revealed that both liquidity ratios and Altman's model are effective tools for identifying financial difficulties in companies. Moreover, it was observed that not all companies listed under PN17 experienced financial failure. Conversely, the study identified instances of financial distress among non-PN17 listed companies.

Research by [Lord et al \(2020\)](#), on the topic "Forecasting Financial Challenges in Nursing Homes using Z-Score" in 2020 with the research results is this study is the pioneer in developing a financial distress prediction model specifically tailored for the nursing home industry, employing a modified Altman Z-score. The utilization and implementation of this model present an additional tool for policymakers and decision-makers to forecast financial difficulties in nursing homes. Similar to other organizations, nursing homes operate on the premise of a "going concern," assuming that the entity will continue its operations in the foreseeable future. Entities that deviate from being a "going concern" often exhibit deteriorating assets or operational challenges, impeding their ability to deliver services or products efficiently and effectively. Nursing homes that no longer qualify as a "going concern" face such challenges or that are experiencing financial difficulties are likely to lack the resources that are critical in providing good quality care.

Research by [Mo et al. \(2021\)](#), on the topic "Financial difficulties and commodity risk management: Empirical findings from Canadian oil companies" in 2021 with the results of previous research on the theoretical relationship between financial difficulties and commodity risk management decisions. This empirical investigation presents observations derived from the experiences of Canadian oil producers spanning from 2005 to 2015. The study reveals a positive correlation between the anticipated cost of financial distress, represented by the debt ratio and Altman Z

score, and the hedging activities of Canadian oil producers. The findings underscore the significance of concurrently modeling corporate hedging and debt ratios, considering the endogeneity of the latter.

Research by [Najib & Cahyaningdyah \(2020\)](#), on the topic "Examination of Corporate Bankruptcy Using Altman Model and Ohlson Model" in 2020 with The findings indicated that the Altman model achieved an accuracy of 58.3%, whereas the Ohlson model exhibited a higher accuracy of 79.2%. In summary, it can be inferred that, for predicting the health status of delisting companies on the Stock Exchange in Indonesia during the 2015- 2019 period, the Ohlson model outperforms the Altman model with an accuracy of 79.2%, while the Altman model showed an accuracy of 58.3%.

Research by [Srinivas \(2023\)](#), on the topic "Applying The study on the Altman Z- Score Model for Predicting Financial Distress in a Subset of NIFTY 50 Companies on the Indian Stock Market in 2023 yielded the following outcomes: a) The researcher determined that out of the 39 chosen companies from NIFTY 50, 15 were categorized as being in the "Too Healthy" Zone. These companies exhibit no signs of bankruptcy concerns, ensuring the safety of stakeholders' investments. b) Within the sample of 39 companies from NIFTY 50, 15 were classified in the "Healthy Zone." This suggests that these companies need enhancements in their financial health. With improved financial conditions, they are not likely to face failure. However, failure is a possibility within two years if their financial condition remains unimproved. c) Among the 39 selected companies from NIFTY 50, 9 are situated in the bankruptcy zone. The financial outlook for these companies is unfavorable, indicating a higher likelihood of bankruptcy.

Research by [Barboza et al. \(2017\)](#), with the title "The study conducted in 2017 on Machine learning models and bankruptcy prediction" revealed the following outcomes: Bankruptcy prediction, closely linked to credit risk, has gained prominence, particularly in light of the recent financial crisis. Mathematical learning models have demonstrated notable success in various financial applications, prompting numerous investigations into their effectiveness in predicting financial distress. Despite the prevalence of models such as Altman and Ohlson, renowned for their predictive prowess and straightforward, practical framework, few studies have surpassed their results in terms of forecasting accuracy or model simplicity. Concerning accuracy ratios, the study found that traditional models (MDA, LR, and ANN) exhibited lower predictive capacity (ranging from 52% to 77%) compared to machine learning models (ranging from 71% to 87%). This aligns with the findings of prior studies by [Breiman \(2001\)](#), [Kim & Upneja \(2014\)](#), [Chen \(2011\)](#).

Research by [Jabeur & Serret \(2023\)](#), on the topic "Predicting bankruptcy through the utilization of convolutional neural networks employing fuzzy logic in 2023 with the results Companies that are not under pressure possess a higher average yield on existing assets, suggesting that their leadership is adept at generating profits from current assets, with a consistently positive average profitability ratio each year of the research duration. This is not the case for failed companies, which show a decline in profitability ratios from day to day. In addition, failed companies have greater leverage when compared to healthy companies. Bankrupt firms are marked by adverse profit margins, unfavorable gross margins, and negative earnings before interest and tax. Moreover, prosperous companies exhibit a higher average return on total assets compared to their unsuccessful counterparts.

Research by [Cindik & Armutlulu \(2021\)](#), on the topic "A modification of the Altman Z-Score model and a comparative examination of predicting financial distress in Turkish companies" in 2021 with the following results: a) In the empirical results section, the accuracy of the original Altman Z score has been calculated and has a predictive power of 76.25% to classify companies in distressed and non-distressed conditions (likely to experience bankruptcy). b) The revised model is calculated and it is seen that the accuracy is higher than the original model. In particular, the prediction power of non-distressed companies is 92.5%; out of 40 non-distressed companies, only 3 are misclassified. c) Random Forest is evaluated and has an accuracy of 95% compared to other models.

Research by [Kitowski et al. \(2022\)](#), on the topic "A Case Study in Poland - Identifying Signs of risk of the bankruptcy Using Prediction Models" conducted in 2022 yielded the following outcomes: a) Confirmation of (H1): Despite the elapsed time, specific discriminative and logit models demonstrated bankruptcy prediction effectiveness comparable to the findings reported by their original developers in the training sample. b) Affirmation of (H2): The direct application of the Altman model (originally developed based on an American companies sample) for assessing the bankruptcy risk of Polish companies is methodologically incorrect and generally produces unreliable results.

Grouping based on journal search results

The results of the search process are taken from 34 journals that have been searched from various sources that have met the criteria, namely journals related to bankruptcy prediction and journals published in the 2013-2023 time span. The following can be seen the grouping of journals based on their sources:

Table 1
Journal sources used in the study

| No. | Journal Name | Total |
|-----|---|-----------|
| 1. | Accountability | 1 |
| 2. | American Journal of Humanities and Social Sciences Research (AJHSSR) | 1 |
| 3. | Dynasty International Journal of Digital Business Management (DIJDBM) | 1 |
| 4. | Economics & Law | 1 |
| 5. | Energy Economics | 1 |
| 6. | European Journal of Scientific Research | 1 |
| 7. | Expert Systems with Applications | 3 |
| 8. | ECONOMICS: Journal of Islamic Economics and Business | 1 |
| 9. | Ilomata International Journal of Management (IJM) | 1 |
| 10. | Ilomata International Journal of Tax & Accounting | 1 |
| 11. | International Journal of Applied Business and International Management (IJABIM) | 1 |
| 12. | International Journal of Business and Management | 1 |
| 13. | International Journal of Financial Studies | 1 |
| 14. | International Journal of Innovation, Creativity and Change | 1 |
| 15. | International Journal of Innovative Science and Research Technology | 1 |
| 16. | International Journal of Law and Management | 1 |
| 17. | International Journal of Production Technology and Management (IJPTM) | 1 |
| 18. | Journal of Applied Finance | 1 |
| 19. | Journal of Asian Finance, Economics and Business | 1 |
| 20. | Journal of Commerce & Accounting Research | 1 |
| 21. | Journal of Critical Reviews | 1 |
| 22. | TIEMB Journal | 1 |
| 23. | Kulliyah of Economics and Management Sciences IIUM | 1 |
| 24. | Management Analysis Journal | 1 |
| 25. | MDPI | 1 |
| 26. | National Accounting Review | 1 |
| 27. | Qeios | 1 |
| 28. | Research in International Business and Finance | 1 |
| 29. | Industry Spectrum | 1 |
| 30. | The International Journal of Applied Business (TIJAB) | 1 |
| 31. | The Journal of Health Care Organization, Provision, and Financing | 1 |
| 32. | Turkish Journal of Computer and Mathematics Education | 1 |
| | TOTAL | 34 |

Data source: processed by researchers, 2023

From the table above, it can be seen that the 34 articles used in the research come from a variety of different journals. Some are taken from national journals such as the TIEMB Journal from Politeknik Negeri Sriwijaya, but most are from reputable indexed international journals such as the Scopus and WoS indexes. This diversity of journals is expected to produce quality and representative research in research related to bankruptcy prediction in a company or industry.

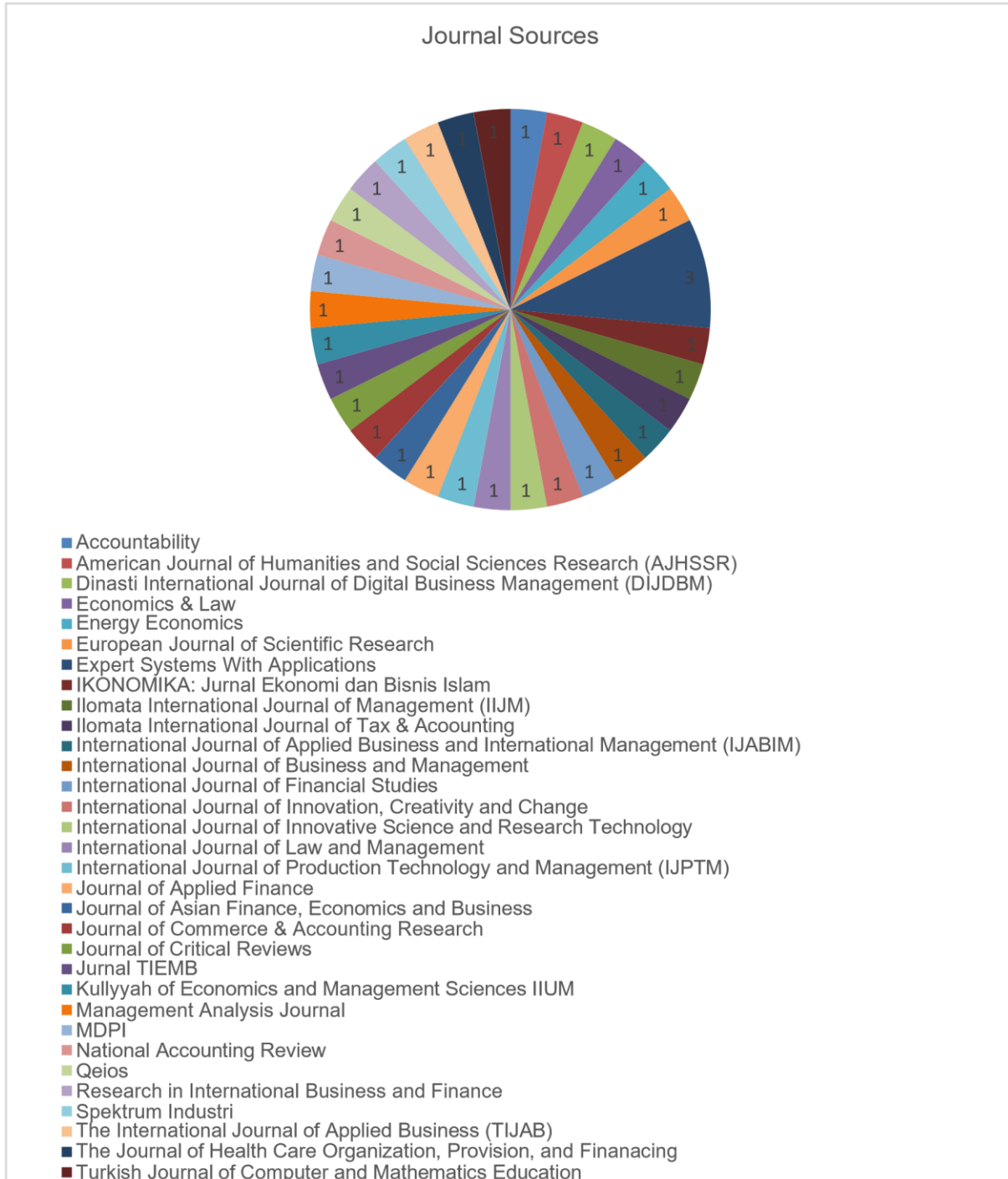


Figure 1. Journal Sources

Bankruptcy predictions in some countries

Bankruptcy prediction in some countries may involve the use of various bankruptcy prediction models developed to match the economic conditions, financial policies, and business practices typical of each country. It is important to note that bankruptcy prediction should be tailored to the local context and economic characteristics of each country.

Models that are successful in one country will need to be customized or combined with local elements to improve accuracy in other countries.

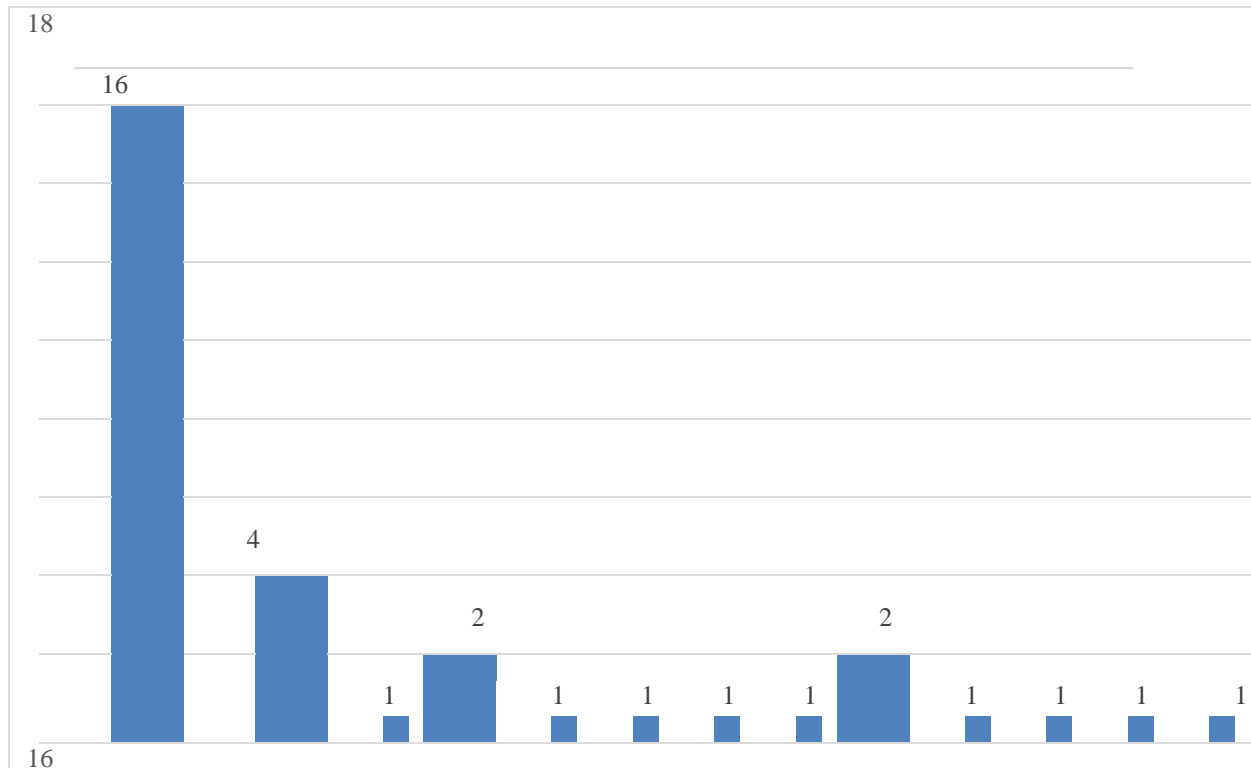
In addition, changing global economic conditions and changes in the business environment may affect the effectiveness of these models over time. Therefore, caution and constant updating of bankruptcy prediction models are key to ensuring their relevance in responding to evolving business dynamics. The following can be seen research in several countries related to bankruptcy prediction using different models.

Table 2
Countries by number of journals in the study

| No. | Country | Number of Journals |
|-----|-----------|--------------------|
| 1. | Indonesia | 16 Journals |
| 2. | India | 4 Journal |
| 3. | Singapore | 1 Journal |
| 4. | Malaysia | 2 Journals |
| 5. | Kuwait | 1 Journal |
| 6. | Brazil | 1 Journal |
| 7. | Italy | 1 Journal |
| 8. | Canada | 1 Journal |
| 9. | USA | 2 Journals |
| 10. | Poland | 1 Journal |
| 11. | Turkey | 1 Journal |
| 12. | France | 1 Journal |
| 13. | Japan | 1 Journal |

Data source: processed by researchers, 2023

From the table above, it can be seen that there are 13 countries that are the place of research on bankruptcy predictions, namely Indonesia, India, Singapore, Malaysia, Kuwait, Brazil, Italy, Canada, USA, Poland, Turkey, France and Japan. Of these 13 countries, Indonesia occupies the highest position with 16 journals followed by India with 4 journals.



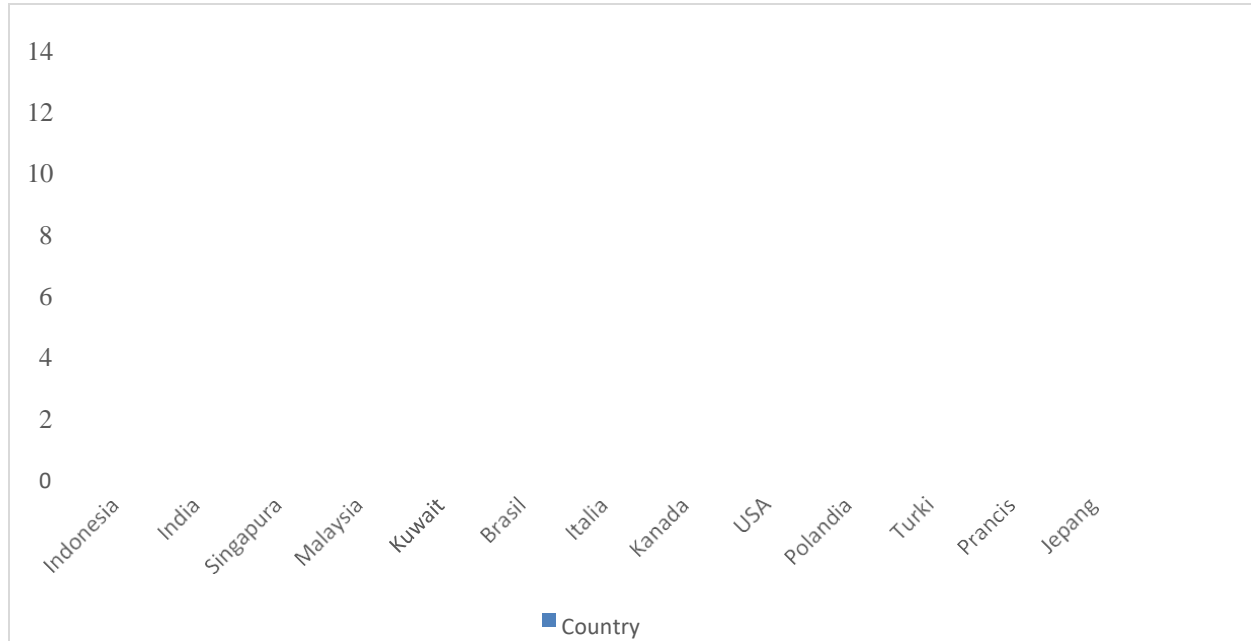


Figure 2. Country of the research

The model used to forecast bankruptcy

There are several methods that can be used to forecast the bankruptcy of a company or industry. These models can be used alone or collaborated to obtain more precise prediction results. This is because each model has its own advantages and disadvantages, here can be seen some models that are usually used in research:

Table 3
The model used to forecast bankruptcy

| No. | Bankruptcy Prediction Model | Total |
|-----|-----------------------------|-------|
| 1. | Altman Z-Score | 24 |
| 2. | Springate | 13 |
| 3. | Zmijewski | 7 |
| 4. | Grover | 3 |
| 5. | Beneish | 2 |
| 6. | Ohlson | 8 |

Data source: data processed by the author, 2023

Based on this table, there are 6 financial condition prediction models used in the research of 34 journals that are used as systematic literature reviews. Of the 6 models, the most widely used is the Altman model.

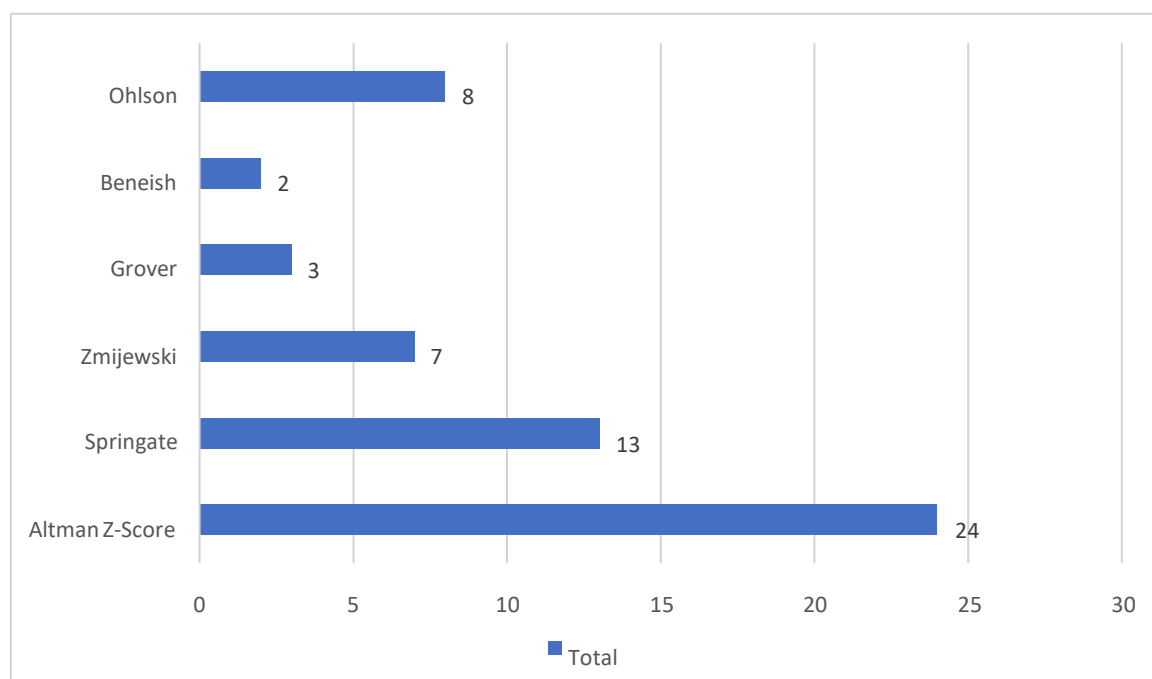


Figure 3. Bankruptcy Prediction Model

Conclusion

The conclusion that can be drawn from this literature review research on bankruptcy prediction with the Springate, Grover, Altman, Ohlson, Beneish, and Zmijewski models is that many studies have been conducted to evaluate and compare the effectiveness of each model in different contexts. The Altman model, with its Z score, proved to be a powerful tool in identifying potential bankruptcy risk based on financial ratio analysis. However, to further improve the accuracy of bankruptcy prediction, the Altman model can be collaborated with other models as well.

The Springate, Zmijewski, and Grover models also make significant contributions by focusing on critical factors in financial statements. On the other hand, the Beneish model stands out in detecting potential financial statement manipulation and fraud. Ohlson's model, which considers market value and company performance factors, also provides a holistic view of financial stability. Overall, the integration of these various models can improve the accuracy of bankruptcy predictions and provide more comprehensive insights to stakeholders. The importance of this holistic approach reflects the complexity and dynamics inherent in corporate financial analysis, which can provide significant benefits in managing financial risk and strategic decision-making.

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