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RESEARCH ARTICLE

Comparative Analysis and Accuracy of Altman Z-Score, Springate, Zmijewski, and Grover Models in Predicting Financial Distress in Basic Industry and Chemical Sector Companies on the Indonesia Stock Exchange for the 2020-2025 Period

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ABSTRACT

This study aims to examine the comparative analysis and accuracy of the Altman Z-score, Springate, Zmijewski, and Grover models in predicting financial distress in basic and chemical industry sector companies on the Indonesia Stock Exchange for the period 2020-2025. This study uses a quantitative approach with a descriptive-comparative type. The study population is all companies listed on the IDX in the basic and chemical industry category according to JASICA sector code 3. The sample of this study is the basic and chemical industry sector companies listed on the IDX for the period 2020-2025 and meet all the established criteria. This study aims to answer three research questions; the conclusions of this study are described as follows. First, regarding the problem formulation regarding the results of financial distress prediction based on each model individually, the four models show different classification patterns according to the characteristics of their respective formulas. Second, regarding the formulation of the problem regarding whether there is a significant difference between the prediction results of the four models, the results of the non-parametric pairwise comparison test prove that there is a significant difference between the prediction results of the Altman Z''-Score, Springate, Zmijewski, and Grover models, both at the categorical classification level (Healthy/Distress) and at the underlying raw score level. Third, regarding the formulation of the problem regarding which model has the highest level of accuracy, the results of the accuracy test using a confusion matrix show that the Grover G-Score model has the highest level of overall accuracy compared to the other three models, so it is determined as the model with the highest level of accuracy in predicting financial distress in basic and chemical industry sector companies listed on the Indonesia Stock Exchange period 2020–2025.

Keywords: *Altman Z-Score, Springate, Zmijewski, and Grover, Financial Distress*

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1.0 INTRODUCTION

Industrial sector basics and chemistry is a strategic pillar industry manufacturing national which includes eight subsectors based on JASICA classification of the Indonesian Stock Exchange, namely cement (31), ceramics porcelain and glass (32), metals and the like (33), chemicals (34), plastics and packaging (35), feed livestock (36), wood and its processing (37), and pulp and paper (38). Products from this sector serve as fundamental inputs for almost all downstream manufacturing industries, thus affecting the stability of the national industrial value chain (Kristanti et al., 2024). The World Bank (2021) noted that COVID-19 caused the deepest global economic contraction since World War II, and the Central Statistics Agency (2021) noted that Indonesia's economic contraction of 2.07% in 2020 put pressure on the basic and chemical industries, thus requiring reliable early detection instruments to anticipate bankruptcy.

The eight subsectors exhibit diverse risk profiles: cement is procyclical to construction and infrastructure spending; ceramics, porcelain, and glass face pressure from gas energy costs and import competition; metals are exposed to global commodity price volatility; chemicals rely on imported petrochemical raw materials; plastics and packaging face increasingly stringent environmental regulations; animal feed is vulnerable to fluctuations in imported corn and soybean meal prices (Sumiati et al., 2025); and wood and its processing face limited roundwood raw materials and mandatory timber legality certification (SVLK) for export products (Khaliqi et al., 2025). The Ministry of Industry (2023) noted that although the sector grew in aggregate, some companies in the eight subsectors experienced contraction due to the uneven distribution of the impact of post-pandemic economic recovery. This emphasizes that aggregate industry performance does not always reflect the individual financial condition of each company, necessitating the need for accurate and contextual financial distress prediction instruments.

Financial distress in companies in this sector is observed in various forms, such as a sustained decline in operating profit, an increasing debt-to-equity ratio, and negative operating cash flow. Platt and Platt (2002) define financial distress as the stage of financial decline preceding bankruptcy, while Ross et al. (2019) define it as a company's inability to meet its financial obligations properly. If not detected early, this condition has the potential to harm investors, creditors, employees, and other stakeholders (Altman & Hotchkiss, 1993). To meet the need for accurate prediction instruments, financial academics have developed financial distress prediction models based on discriminant and regression analysis, including the Altman Z-Score (1968) based on multiple discriminant analysis with five financial ratios; Springate with a similar approach but different variable composition (Husein & Pambekti, 2014); Zmijewski (1984) based on probit analysis; and Grover as a revision of the Altman model with the addition of the return on assets variable (Prasetianingtias & Kusumowati, 2019). The differences in the construction of the four models have the potential to produce predictions that are not always consistent when applied to various sub-sector characteristics (Husein & Pambekti, 2014).

The urgency of this research can also be seen from the perspective of signaling theory: Spence (1973) stated that financial reports are a mechanism for conveying signals about a company's financial condition to external parties, and that deteriorating financial conditions, if detected early through appropriate prediction models, provide a significant negative signal to investors and creditors. Connelly et al. (2025) that signal quality depends on the instrument's ability to interpret information accurately, so selecting the most appropriate model for the basic and chemical industries is crucial considering the diversity of risk profiles between subsectors (Jensen & Meckling, 1976).

Previous research has shown inconsistent findings regarding the best prediction model: Christa and Mukti (2023) found a significant difference between Altman and Grover in the retail sector; Ramadhani et al. (2023) reported Zmijewski was most accurate in the transportation and logistics sector; while Prasetianingtias and Kusumowati (2019) found Grover to be most accurate in the agriculture sector. This cross-sectoral inconsistency indicates that the model's superiority is contextual (Sethi & Mahadik, 2024). Research that comprehensively compares the four models across the basic industry and chemical sectors is also very limited: Sari and Yunita (2019) only examined the metals and minerals subsector for the 2012–2016 period using three models without the Altman Z-Score, without including post-pandemic economic dynamics. There are four research gaps that justify this study: (1) there has not been a comprehensive study of all four models simultaneously across all sectors; (2) the 2020–2025 period, which represents the post-pandemic contraction-recovery-normalization cycle, has never been studied for this sector (World Bank, 2021); (3) the comparative testing methods of previous studies are generally descriptive without inferential statistical testing such as Cochran's Q or McNemar Test (Siegel & Castellan, 1988); and (4) the inconsistency of the best models across sectors emphasizes the need for separate empirical studies for the basic industry and chemical sectors (Sethi & Mahadik, 2024).

Based on the description, this study aims to comparatively analyze the ability and accuracy level of the four financial distress prediction models in basic and chemical industry sector companies listed on the Indonesia Stock Exchange for the period 2020–2025, considering that the effectiveness of prediction models varies greatly depending on industry characteristics, macroeconomic conditions, and observation periods (Sethi & Mahadik, 2024), so that it is expected to identify the most appropriate and accurate model that is useful for investors, creditors, management, and regulators in making decisions based on financial information (Platt & Platt, 2002).

2.0 LITERATURE REVIEW

2.1. Financial Distress

Financial distress has been a central concept in corporate finance literature since the 1960s. Wruck (1990) defines it as a situation where operating cash flow is insufficient to cover current liabilities, while Platt and Platt (2002) define it as a stage of financial decline that precedes formal bankruptcy. Ross et al. (2019) distinguish economic distress (where assets are lower than total liabilities) from pure financial distress (where assets are unable to meet short-term liabilities even though liabilities are greater than assets); Altman and Hotchkiss (1993) distinguish four tiered terms: failure, insolvency, default, and bankruptcy. Indicators of financial distress include sustained operating losses (Ross et al., 2019), a declining current ratio, an increasing debt-to-equity ratio, and sustained negative operating cash flow as the strongest indicator (Tran et al., 2023). Whitaker (1999) proposed four stages of bankruptcy: incubation, cash shortage, financial insolvency, and total insolvency; a good predictive model should detect distress signals as early as the incubation stage.

2.2 Bankruptcy Theory

Bankruptcy theory explains why and how firms become insolvent, through three main perspectives. First, Modigliani and Miller's (1963) bankruptcy cost theory argues that overleverage increases the risk of bankruptcy; Wruck (1990) shows that indirect bankruptcy costs, such as loss of customer confidence, often exceed direct costs. Second, Jensen and Meckling's (1976) agency theory explains that manager-shareholder-creditor conflicts of interest can increase the risk of distress, although Jensen (1988) asserts that the threat of bankruptcy also serves as a disciplinary mechanism. Third, an accounting-based predictive approach underpins the model in this study: Beaver (1966) first demonstrated that a single financial ratio can distinguish bankrupt firms, and Altman (1968) developed this approach through multiple discriminant analysis.

2.3 Signaling Theory

Signaling theory, introduced by Spence (1973), explains how parties with private information convey credible signals to parties without access to that information, with the principle that signals are only effective if the cost of sending them is negatively correlated with the quality of the signal. Connelly et al. (2025) argue that the core of this theory is communication under conditions of information asymmetry, which is inherent in a company's relationship with investors and creditors in the capital market. In the context of predicting financial distress, financial reports become the primary communication instrument: healthy companies are motivated to convey positive signals through good profitability, liquidity, and solvency ratios, while deteriorating conditions are negative signals that investors and creditors should be able to detect early (Bafera & Kleinert, 2023). The four prediction models are formal instruments that interpret financial signals: liquidity ratios convey short-term capability signals, profitability ratios relate to operational efficiency, leverage ratios convey solvency risk signals, and asset efficiency ratios convey productivity signals (Ross et al., 2019).

2.4 Financial Statement Analysis as a Prediction Tool

Financial statement analysis is an evaluation process to understand a company's financial condition, performance, and prospects, serving as a diagnostic tool that transforms raw data into meaningful information (Ross et al., 2019). The primary instrument is financial ratios, which Beaver (1966) first demonstrated to have significant predictive power up to five years before bankruptcy, paving the way for multivariate models such as Altman, Springate, Zmijewski, and Grover. The ratios used cover four dimensions: liquidity, profitability, leverage/solvency, and efficiency/activity (Altman, 1968; Zmijewski, 1984). Their advantage lies in objectivity, as they are derived from publicly available audited reports, and Habib et al. (2020) assert that financial ratios remain reliable predictors even in the era of machine learning, underpinning the choice of the four research models.

2.5 Financial Distress Prediction Model

2.5.1 Altman Model (Z-Score)

The Altman Z-Score model, the most widely studied financial distress prediction model in the international literature, was developed by Altman (1968) using multiple discriminant analysis with an initial accuracy of 95 percent. This model uses five variables: working capital to total assets, retained earnings to total assets, EBIT to total assets, market value of equity to book value of total debt, and sales to total assets. Threshold value the limit share three zones: $Z>2.99$ (safe zone), $1.81\leq Z\leq 2.99$ (gray zone), and $Z<1.81$ (distress zone) (Altman, 1968).

2.5.2 Springate Model (S-Score)

The Springate model was developed with adapt Altman's MDA methodology on Canadian samples, accuracy initial 92.5 percent from four ratio selected (Husein & Pambekti, 2014): working capital to total assets, EBIT to total assets, earnings before taxes to current liabilities (variable unique, measuring ability close obligation term short), and sales to total assets. The thresholds are dichotomous: $S\geq 0.862$ healthy, $S<0.862$ distressed. This model places greater weight on operational profitability, such as in basic and chemical industries (Habib et al., 2020).

2.5.3 Zmijewski Model (X-Score)

Zmijewski's (1984) model uses probit analysis, different from Altman and Springate's MDA, from a sample of 75 bankrupt and 73 healthy firms. This model use three Variables: return on assets (profitability), total debt to total assets (leverage), and current ratio (liquidity). Threshold The limits: $X>0$ has the potential for distress, $X<0$ is healthy. The advantages lies in its simplicity and probit approach that does not requires assumptions normality distribution as MDA, although coverage three its dimensions potential ignore signal from another dimension.

2.5.4 Grover Model (G-Score)

Grover's model revised Altman's model with a larger and more diverse sample, adding the return on assets variable as a major modification (Prasetianingtias & Kusumowati, 2019). This model uses three variables: working capital to total assets, EBIT to total assets (both the same as Altman's), and return on assets, plus a constant. The thresholds are: G≥0.01 healthy, G≤-0.02 distressed. With two profitability measures simultaneously, this model more comprehensively captures the profitability dimensions than Zmijewski; Prasetianingtias and Kusumowati (2019) reported an accuracy of 85.29 percent in the agricultural sector.

2.5.5 Comparison of Characteristics of the Four Models

In order to provide a systematic overview, Table 1 presents a comparison of the main characteristics of the four models:

Table 1. Comparison of Characteristics of the Four Models

Model	**Year**	**Statistical Methods**	**Variables Used**	**Amount Variables**	**Cut-Off Value**	**Initial Accuracy**
Altman Z-Score	1968	Multiple Discriminant Analysis	Working Capital/TA; Retained Earnings/TA; EBIT/FY; Market Value of Equity/Book Value of Debt; Sales/TA	5 variables	Z > 2.99 = Healthy 1.81 < Z < 2.99 = Gray Zone Z < 1.81 = Distress	95% (1 year before bankrupt)
Springate (S-Score)	1978	Multiple Discriminant Analysis	Working Capital/TA; EBIT/FY; EBT/Current Liabilities; Sales/TA	4 variables	S ≥ 0.862 = Healthy S < 0.862 = Distress	92.5%
Zmijewski (X-Score)	1984	Probit Analysis	Net Income/TA (ROA); Total Debt/TA; Current Assets/Current Liabilities	3 variables	X > 0 = Distress X < 0 = Healthy	~86%
Grover (G-Score)	2001	Altman Model + Regression	Working Capital/TA; EBIT/FY; Net Income/TA (ROA)	3 variables + constant	G ≥ 0.01 = Healthy G ≤ -0.02 = Distress	~90%

Sources: Altman (1968); Husein & Pambekti (2014); Zmijewski (1984); Prasetianingtias & Kusumowati (2019).

2.6 Basic Industry and Chemical Sector on the Indonesia Stock Exchange

The basic and chemical industry sector is a group of JASICA BEI issuers (sector code 3), a supplier of intermediate raw materials for almost all downstream manufacturing industries, covering eight subsectors: cement (31), porcelain and glass ceramics (32), metals and the like (33), chemicals (34), plastics and packaging (35), animal feed (36), wood and its processing (37), and pulp and paper (38) (Ministry of Industry, 2023), with shared characteristics of high capital intensity and sensitivity to macroeconomic cycles (Habib et al., 2020). The cement subsector (31) is procyclical to construction and infrastructure spending; ceramics-porcelain-glass (32) is sensitive to industrial gas prices and imports (Kristanti et al., 2024); metals (33) is exposed to global commodity volatility (Ministry of Industry, 2023); chemicals (34) relies on imported petrochemicals (Pindado et al., 2006); plastics and packaging (35), with the largest number of issuers, faces pressure from raw material prices and environmental regulations (Habib et al., 2020); and pulp and paper (38) adapts to the shift to paper-based packaging along with e-commerce.

The animal feed subsector (36) relies on corn and soybean meal imports, is vulnerable to fluctuations in global food prices and exchange rates, and is also at risk of animal disease outbreaks and regulations banning antibiotic growth promoters (Sumiati et al., 2025). The timber and processing subsector (37) faces limited roundwood supply due to logging restrictions and mandatory timber legality certification (SVLK) for export products, which increases competitiveness but increases compliance costs (Khaliqi et al., 2025). Despite their differences, the eight subsectors share common structural risks: capital-intensive with long-term debt dependence (Sari & Yunita, 2019), cash flow sensitivity to raw material prices, and dependence on external factors (Habib et al., 2020), which justifies the use of the same predictive model across the eight subsectors while also opening the question of which model is most responsive (Christa & Mukti, 2023), so the most accurate model needs to be confirmed empirically, not theoretically assumed (Sethi & Mahadik, 2024).

2.7 Conceptual Framework

The research flow consists of, presented in Figure 1.

INPUT DATA
Annual Financial Reports of Basic Industry and Chemical Companies Listed on the IDX for the 2020–2025 Period

↓

INDEPENDENT VARIABLE
Financial Distress Prediction Model
• Altman Z"-Score (MDA, 4 ratio)
• Springate / S-Score (MDA, 4 ratios)
• Zmijewski / X-Score (Probit, 3 ratios)
• Grover / G-Score (Altman revision, 3 ratios)

→ *compared with / tested for accuracy against*

DEPENDENT VARIABLE (Benchmark)
Actual Condition of Financial Distress
• Net loss for 2 consecutive years
• Negative operating cash flow
• Equity negative
(≥ 1 indicator fulfilled = Distress)

↓ ↓

TRACK 1 — COMPARATIVE ANALYSIS
(answer Formulation Problem 2)
Non- Parametric Difference Test:
Cochran's Q → Friedman Test → McNemar Test → Wilcoxon Signed-Rank (Bonferroni Correction)

TRACK 2 — ACCURACY ANALYSIS
(answering Problem Formulation 3)
Accuracy Test:
Confusion Matrix (Accuracy, Type I Error, Type II Error)
using the prediction scores of the four models (VI) compared to the actual conditions (VD)

↓ ↓

Results: significant differences in prediction results between models (answering RM2)	Results: the model with the highest accuracy was identified (answering RM3)

↓

RESEARCH OUTPUT
Identification of the most accurate financial distress prediction model for the basic and chemical industry sectors on the IDX, as well as practical recommendations for management, investors, and creditors

Figure 1. Conceptual Framework of the Research

There are two main analysis paths: the first path, comparative analysis, answers the second research question regarding whether there are significant differences between the prediction results of the four models; the second path, accuracy analysis, answers the third research question regarding the model with the highest level of accuracy. Both paths are sourced from the same data but use different statistical techniques, and their outputs are integrated to produce conclusions and recommendations for stakeholders. To ensure that each variable has a clear theoretical justification, Table 2 maps the relationship between the theoretical basis and the variables and the logic of their relationship (Sekaran & Bougie, 2016).

Table 2. Relationship between the Theoretical Basis and the Supported Variables and Logic

Theoretical basis	Supported Variables / Proxies	Logic of Relationship with Study
Bankruptcy Theory — Beaver (1966); Altman (1968); Zmijewski (1984)	All over ratio finances that form the formula for the four models: Working Capital/TA, Retained Earnings/TA, EBIT/TA, Book Value Equity/Total Debt, Sales/TA, ROA (Net Income/TA), Total Debt/TA, Current Ratio	Financial ratios from financial statements have been empirically proven to predict bankruptcy. The four models used are directly rooted in this premise: the predictive power of financial ratios as a basic instrument for early detection of financial distress (Beaver, 1966; Altman, 1968).
Signal Theory (Signaling Theory) — Spence (1973); Connelly et al. (2025)	All over ratio finance as a delivery medium signal ; Financial Distress (variable dependent) as an interpretation output signal aggregate condition financial company	Financial reports are a medium for conveying financial condition signals to external parties. Each financial ratio in the four models represents a different signal dimension: liquidity, profitability, leverage, and asset efficiency; these, in aggregate, produce a classification of financial distress (Spence, 1973; Connelly et al., 2025).

Source: Processed from various source (2025).

3.0 METHODOLOGY

3.1 Types and Approaches of Research

This study uses a quantitative approach with a descriptive-comparative approach. The quantitative approach was chosen because it relies on numerical data from financial reports, processed through a financial distress prediction model formula and analyzed using measurable and replicable statistical methods (Sekaran & Bougie, 2016; Creswell & Creswell, 2018). The descriptive approach describes the financial distress condition based on the scores of the four models individually, while the comparative approach compares the prediction results between models and tests their accuracy, answering all three problem formulations simultaneously (Sugiyono, 2019). The time dimension of this research is longitudinal (time-series), with data collected from annual financial reports for six consecutive years (2020–2025), providing a comprehensive picture of the dynamics of financial conditions throughout the contraction, recovery, and normalization phases post-COVID-19 pandemic (Central Bureau of Statistics, 2021).

3.2 Population and Sample

A population is a generalized area of objects/subjects with qualities determined by the researcher (Sugiyono, 2019). The selection of the basic and chemical industry sectors was based on relatively homogeneous structural characteristics across subsectors (Habib et al., 2020), as well as gaps in previous research that generally focused on only one subsector, such as Sari and Yunita (2019). The research population is all companies listed on the IDX in the basic and chemical industry category according to JASICA sector code 3: cement (31), porcelain and glass ceramics (32), metals and the like (33), chemicals (34), plastics and packaging (35), animal feed (36), wood and its processing (37), pulp and paper (38).

The sample of this research is the basic and chemical industry sector companies listed on the IDX for the 2020–2025 period and meet all the established criteria. The sampling technique used is purposive sampling, namely determining the sample with certain considerations or criteria set according to the research objectives (Sugiyono, 2019). The sampling criteria refer to the common purposive sampling practice in financial research based on financial statements of public companies in Indonesia (Sugiyono, 2019), namely: 1) The company publishes complete and continuous annual financial statements for the period 2020–2025, which have been audited to ensure data reliability ; 2) Financial statements are presented in Rupiah (IDR), to avoid distortions due to exchange rate fluctuations that can affect the validity of comparisons between companies; 3) All financial data required for calculating the variables of the four models are fully available and can be accessed through official data sources.

3.3 Types and Sources of Data

This study uses secondary data obtained through existing sources (Sekaran & Bougie, 2016), as financial information is publicly available through official audited reports. The data used are figures from the statement of financial position, comprehensive income, and cash flow, including total assets, current assets, current liabilities, net working capital, retained earnings, EBIT, EBT, net income, total debt, total equity, market value of equity, and net sales for 2020–2025. The data source comes from the official website of the Indonesia Stock Exchange (www.idx.co.id), which provides annual financial reports of all listed companies, as well as the official website of each sample company which contains a complete annual report along with audited financial reports.

3.4 Data Collection Techniques

The data collection technique used was documentation (Sugiyono, 2019): accessing the IDX website (www.idx.co.id) and the company's official website for audited annual financial reports for the 2020–2025 period; recording relevant financial items; cross-verifying between sources; and tabulating the data into a structured worksheet. All data were sourced from audited financial reports from public accounting firms recognized by the Financial Services Authority.

3.5 Data Analysis Techniques

The data analysis technique consists of three systematic stages (Sugiyono, 2019). Prior to statistical analysis, two preparatory procedures were performed: calculating the predicted score for each company per year using the formulas of the four models in parallel (Husein & Pambekti, 2014), and then calculating the financial condition based on the cut-off value in Table 3.

Table 3. Cut Off Condition Analysis Finance

Model	Healthy Category	Grey Zone Category	Distress Category
Altman Z-Score	Z" > 2.60	1.10 ≤ Z" ≤ 2.60	Z" < 1.10
Springate S-Score	S ≥ 0.862	—	S < 0.862
Zmijewski X-Score	X < 0	—	X > 0
Grover G-Score	G ≥ 0.01	-0.02 < G < 0.01	G ≤ -0.02

Sources: Altman (1968); Husein & Pambekti (2014); Zmijewski (1984); Prasetianingtias & Kusumowati (2019).

The results of the score calculations and classification form the basis for the following three stages of statistical analysis, using the assistance of Microsoft Excel and IBM SPSS Statistics (Salim & Ismudjoko, 2021).

3.5.1 Descriptive Analysis

Descriptive analysis describes the predicted results of each sample company per year based on the four models, answering the first problem formulation (Sugiyono, 2019), presented in a score and classification table (healthy, grey zone, distress) per firm-year, equipped with category proportions and descriptive statistics (minimum, maximum, average, standard deviation) (Sekaran & Bougie, 2016).

3.5.2 Comparison Test Between Models

The comparative test between models analyzes whether there are significant differences between the prediction results of the four models, considering that descriptive differences are not necessarily statistically significant (Sugiyono, 2019). Because the classification data is categorical without guarantee of normality, a non-parametric test (Siegel & Castellan, 1988) is used through four stages: Cochran's Q Test, comparing the proportions of three or more paired samples with dichotomous data; Friedman Test, tests the difference in raw score rankings of the four models directly; McNemar Test, if Cochran's Q Test is significant, a further test (post-hoc) is carried out; Wilcoxon Signed-Rank Test, if Friedman Test is significant, a further test is Wilcoxon Signed-Rank Test for ordinal/interval data on the same six pairs of model scores.

3.5.3 Model Accuracy Test

Model accuracy testing identifies the model with the highest accuracy, comparing the predicted results to actual conditions (Husein & Pambekti, 2014; Platt & Platt, 2002), using a confusion matrix (Fawcett, 2006).

Table 4. Confusion Matrix

	Prediction: Distress	Prediction: Non-Distress
Current: Distress	True Positive (TP)	False Negative (FN)
Actual: Non-Distress	False Positive (FP)	True Negative (TN)

Source: Fawcett (2006).

Five sizes calculated accuracy: Accuracy Overall = (TP+TN)/(TP+TN+FP+FN) × 100%; Sensitivity (Recall) = TP/(TP+FN) × 100%; Specificity = TN/(TN+FP) × 100%; Type I Error = FP/(FP+TN) × 100%; and Type II Error = FN/(FN+TP) × 100%.

Source: Fawcett (2006); Husein & Pambekti (2014).

Overall accuracy is the primary measure for ranking the four models (Husein & Pambekti, 2014; Salim & Ismudjoko, 2021). Type II Error receives special attention because misclassifying a distressed company as healthy is far more harmful than Type I Error for investors and creditors (Altman & Hotchkiss, 1993).

4.0 ANALYSIS AND FINDINGS

4.1 General Description of the Basic Industry and Chemical Sector on the Indonesia Stock Exchange

The basic industry and chemical sector is one of the largest manufacturing issuer groups on the Indonesia Stock Exchange, encompassing eight subsectors according to the Jakarta Stock Industrial Classification (JASICA), namely cement (code 31), porcelain and glass ceramics (32), metals and related products (33), chemicals (34), plastics and packaging (35), animal feed (36), wood and its processing (37), and pulp and paper (38). The Ministry of Industry of the Republic of Indonesia (2023) noted that these eight subsectors collectively serve as suppliers of intermediate goods for almost the entire national downstream manufacturing industry chain, from construction, automotive, packaging, processed food, to value-added wood products. This structural position makes the financial condition of issuers in this sector important to observe empirically, because financial pressure in one subsector has the potential to spread to various downstream industries according to its supply (Kristanti et al., 2024).

The latest data released by the Central Statistics Agency (2025) shows that the manufacturing sector grew 5.54 percent in the third quarter of 2025, with the performance of the basic metals industry and the chemical, pharmaceutical, and traditional medicine industry being the two main drivers of this achievement. This condition differs significantly from the starting point of the research observation period, when the Central Statistics Agency (2021) recorded a national economic contraction of 2.07 percent in 2020 due to the COVID-19 pandemic, which simultaneously depressed the performance of the cement, metal, and chemical subsectors. The 2020–2025 timeframe covered by this study therefore represents a relatively complete economic cycle, encompassing phases of contraction, gradual recovery, and post-pandemic expansion, thus providing sufficient variation in financial conditions to test the capabilities of the four financial distress prediction models (Habib et al., 2020).

4.1.1 Brief Profile of Sample Company

Table 5. Summary of Number of Samples per Subsector

JASICA Code	Subsector	Number of Companies	Percentage
33	Metals and the Like	10	19.6%
35	Plastic and Packaging	9	17.6%

32	Ceramics, Porcelain and Glass	7	13.7%
34	Chemistry	7	13.7%
31	Cement	6	11.8%
36	Animal feed	5	9.8%
38	Pulp and Paper	4	7.8%
37	Wood and Its Processing	3	5.9%
	Total	51	100.0%

Source: Processed data from Tabulation_IDK_FINAL_FIX_v3_TanpaSLJGlobal.xlsx, Sheet 1_Raw Data (2026).

Table 6 next serve profile complete 51 companies sample along with code issuers and JASICA subsectors respectively, from official data from the Indonesia Stock Exchange (2025) as has tabulated in study.

Table 6. Company Profile of Research Sample (51 Companies, 306 Firm-Year Observations)

No	Code	Company name	Subsector
1	INTP	Indocement Tunggal Prakarsa Tbk	Cement
2	SMBR	Semen Baturaja (Persero) Tbk	Cement
3	SMCB	Solusi Bangun Indonesia Tbk	Cement
4	SMGR	Semen Indonesia (Persero) Tbk	Cement
5	WSBP	Waskita Beton Precast Tbk	Cement
6	WTON	Wijaya Karya Beton Tbk	Cement
7	AMFG	Asahimas Flat Glass Tbk	Ceramics, Porcelain and Glass
8	ARNA	Arowana Citramulia Tbk	Ceramics, Porcelain and Glass
9	IKAI	Inti Keramik Alam Asri Industri Tbk	Ceramics, Porcelain and Glass
10	KIAS	Indonesian Ceramics Association Tbk	Ceramics, Porcelain and Glass
11	MARK	Mark Dynamics Indonesia Tbk	Ceramics, Porcelain and Glass
12	MLIA	Mulia Industrindo Tbk	Ceramics, Porcelain and Glass
13	TOTO	Surya Toto Indonesia Tbk	Ceramics, Porcelain and Glass
14	ALKA	Alaska Industrindo Tbk	Metals and the Like
15	STEEL	Saranacentral Bajatama Tbk	Metals and the Like
16	BTON	Betonjaya United Tbk	Metals and the Like
17	GDST	Gunawan Dianjaya Steel Tbk	Metals and the Like
18	HENNA	Indal Aluminum Industry Tbk	Metals and the Like
19	ISSP	Steel Pipe Industry of Indonesia Tbk	Metals and the Like
20	KRAS	Krakatau Steel (Persero) Tbk	Metals and the Like
21	LION	Lion Metal Works Tbk	Metals and the Like
22	LMSH	Lionmesh Prima Tbk	Metals and the Like
23	NIKL	Plating Timah Nusantara Tbk	Metals and the Like
24	AGII	Aneka Gas Industri Tbk	Chemistry
25	BUDI	Budi Starch & Sweetener Tbk	Chemistry
26	DPNS	Duta Pertiwi Nusantara Tbk	Chemistry
27	EKAD	Ekadharma International Tbk	Chemistry
28	INCH	Intan Wijaya International Tbk	Chemistry
29	MDKI	Emdeki Utama Tbk	Chemistry
30	SRSN	Indo Acidatama Tbk	Chemistry
31	AKPI	Argha Karya Prima Industry Tbk	Plastic and Packaging
32	APPLI	Asiaplast Industries Tbk	Plastic and Packaging
33	BRNA	Berlina Tbk	Plastic and Packaging
34	IGAR	Champion Pacific Indonesia Tbk	Plastic and Packaging
35	IMPC	Impack Pratama Industri Tbk	Plastic and Packaging

36	PBID	The Five Ideal Characters Tbk	Plastic and Packaging
37	TALF	Tunas Alfin Tbk	Plastic and Packaging
38	TRST	Trias Sentosa Tbk	Plastic and Packaging
39	YPAS	Yanaprima Hastapersada Tbk	Plastic and Packaging
40	ALDO	Alkindo Naratama Tbk	Pulp and Paper
41	FASW	Fajar Surya Wisesa Tbk	Pulp and Paper
42	KDSI	Kedawung Setia Industrial Tbk	Pulp and Paper
43	SPMA	Suparma Tbk	Pulp and Paper
44	CPIN	Charoen Pokphand Indonesia Tbk	Animal feed
45	CPRO	Central Proteina Prima Tbk	Animal feed
46	JPFA	Japfa Comfeed Indonesia Tbk	Animal feed
47	PLAY	Malindo Feedmill Tbk	Animal feed
48	SIPD	Sreeya Sewu Indonesia Tbk	Animal feed
49	IFII	Indonesia Fiberboard Industry Tbk	Wood and Its Processing
50	HERE	Singaraja Putra Tbk	Wood and Its Processing
51	TIRT	Tirta Mahakam Resources Tbk	Wood and Its Processing

Sourc: Indonesia Stock Exchange (2025); processed data from

Tabulation_IDK_FINAL_FIX_v3_TanpaSLJGlobal.xlsx, Sheet 1_RawData.

Existence three business entities state -owned in samples, namely Semen Baturaja (Persero) Tbk (SMBR), Semen Indonesia (Persero) Tbk (SMGR), and Krakatau Steel (Persero) Tbk (KRAS), also add dimensions interesting for study this, considering company plate red often face pressure financial resources No solely from market dynamics, but also from obligation assignment government (public service obligation) inherent in its operations (Ross et al., 2019). Thus, the overall sample profile of this study reflects the diversity of subsectors, business scales, and ownership structures sufficient to produce a picture of financial distress in the basic and chemical industries.

4.2 Data Description

4.2.1 Descriptive Statistics of the Scores of the Four Prediction Models

Descriptive analysis is used to provide a general overview of data distribution before further statistical testing is conducted, including the minimum, maximum, average, and standard deviation values of each variable studied (Sekaran & Bougie, 2016). A summary of the descriptive statistics for the four models is as follows:

Table 7. Descriptive Statistics of the Scores of the Four Financial Prediction Models Distress

Model	N	Minimum	Maximum	Average	Standard Deviation
Altman Z-Score	306	-18,062	62,428	4.64251	7,171680
Springate S-Score	306	-325,274	4,932	-0.33522	19.027240
Zmijewski X-Score	306	-6,072	23,163	-1.62005	3.088345
Grover G-Score	306	-4,357	2,145	0.52880	0.701462

Source: SPSS Descriptives Output (2026).

Table 7 shows that the four models have significantly different value ranges and levels of variability, as is common in financial distress prediction models constructed using different statistical methods and variable compositions (Habib et al., 2020). The Springate S-Score shows the widest distribution and highest standard deviation (19.03), far exceeding the other three models, indicating the presence of extreme values in the study sample. Conversely, the Grover G-Score shows the narrowest distribution (standard deviation 0.701), in line with the characteristics of this model, which uses only three ratio variables and a constant in its formula (Prasetianingtias & Kusumowati, 2019).

The negative mean Zmijewski X-Score (-1.62005) needs to be interpreted with caution, considering that the interpretation direction of this model is the opposite of the other three models: the more negative the X-Score value, the healthier the company's financial condition, while a positive value indicates an increasing probability of bankruptcy (Zmijewski, 1984). Thus, this negative mean X-Score illustrates the tendency of the majority of sample companies to be in a relatively healthy financial condition according to the Zmijewski model.

The extreme values in Table 7 provide an important initial insight, while also revealing the contribution of the wood and processing subsector, which was recently added to the research scope. The company with the lowest Springate score throughout this study (-325.274) as well as the lowest Altman score (-18.062) and the highest Zmijewski score (23.163, indicating the highest probability of distress) is Tirta Mahakam Resources Tbk (TIRT), an issuer in the wood and processing subsector, in 2024. The consistency of the direction of the findings across these three different methodological models strengthens the argument that the financial ratios underlying the financial distress prediction model do indeed reflect the company's fundamental condition relatively objectively, as emphasized by Beaver (1966) in his classic study on the predictive ability of single financial ratios, while the highest Altman score (62.428) and the lowest Zmijewski score (-6.072) were recorded by Duta Pertiwi Nusantara Tbk (DPNS) in 2025.

4.2.2 Data Description Based on Subsector

In order to obtain a more detailed picture of the variations in financial conditions between subsectors, Table 8 presents the average scores of the four models based on the eight JASICA subsectors covered by this study.

Table 8. Average Scores of the Four Models Based on Subsector

Subsector	N	Altman	Springate	Zmijewski	Grover
Cement	36	1,518	0.360	-1.121	0.136
Ceramics, Porcelain and Glass	42	5,177	1,189	-2,849	0.708
Metals and the Like	60	4,383	0.869	-1,379	0.577
Chemistry	42	11,144	1,351	-3,093	0.849
Plastic and Packaging	54	5,536	1,099	-2,277	0.676
Pulp and Paper	24	3,647	0.935	-1,889	0.497
Animal feed	30	2,824	1,236	-1,554	0.560
Wood and Its Processing	18	-2,981	-21,844	5.101	-0.462

Source: Processed data from SPSS Means output (2026).

Table 8. shows that subsector chemistry in a way consistent record an average score best in all three models that direction the interpretation unidirectional (Altman, Springate, and Grover, with mark increasingly tall increasingly healthy) and the most negative Zmijewski mean (-3.093, the healthiest in this model). In contrast, the timber and processing subsector, one of the two newly added subsectors to the study, consistently recorded the worst mean scores across all models, with a negative Altman mean (-2.981), a very negative Springate mean (-21.844), the highest positive Zmijewski mean (5.101, indicating a tendency for distress), and a negative Grover mean (-0.462). This pattern is in line with the structural characteristics of the timber subsector, namely limited supply of roundwood raw materials and the burden of timber

legality certification compliance, plus the extreme contribution of Tirta Mahakam Resources Tbk (TIRT) (Khaliqi et al., 2025).

Table 9. presents the percentage of companies categorized as distressed in each subsector according to the four models, in order to complement the picture of the average scores with a more concrete classification proportion.

Table 9. Percentage of Companies in the Distress Category Based on Subsector and Model

Subsector	Altman	Springate	Zmijewski	Grover
Cement	16.7%	88.9%	16.7%	16.7%
Ceramics, Porcelain and Glass	19.0%	45.2%	0.0%	16.7%
Metals and the Like	28.3%	56.7%	25.0%	15.0%
Chemistry	0.0%	26.2%	0.0%	0.0%
Plastic and Packaging	11.1%	53.7%	0.0%	7.4%
Pulp and Paper	16.7%	45.8%	4.2%	16.7%
Animal feed	36.7%	20.0%	6.7%	6.7%
Wood and Its Processing	55.6%	55.6%	55.6%	44.4%

Source: SPSS Crosstabs output (2026).

Table 9 shows that the level of consistency between models varies significantly by subsector. In the chemical subsector, all three models (Altman, Zmijewski, and Grover) agree on not finding a single firm in distress, but the Springate model identifies 26.2 percent of firms in the same subsector as distressed. A similar, more extreme pattern occurs in the cement subsector, where Springate classifies 88.9 percent of firms as distressed, far exceeding the 16.7 percent for the other three models. The wood and wood processing subsector appears to be the most consistently vulnerable subsector across all four models, with distress proportions ranging from 44.4 to 55.6 percent, while the animal feed subsector exhibits a more moderate pattern but still varies sharply across models (36.7 percent for Altman, only 6.7 percent for Zmijewski and Grover). This sharp difference is consistent with the findings of Sari and Yunita (2019) in the metal and mineral subsector, who also found that the proportion of distress classifications can differ significantly between models even when applied to identical research objects, and confirms the view of Sethi and Mahadik (2024) that the effectiveness of financial distress prediction models is highly dependent on the characteristics of the industry being studied.

4.2.3 Data Description Based on Observation Year (2020–2025)

Table 10 presents the development of the average scores of the four models from year to year to see whether the trend in the financial condition of the research sample is in line with the macroeconomic cycle.

Table 10. Average Scores of the Four Models Based on Observation Year

Year	N	Altman	Springate	Zmijewski	Grover
2020	51	3,881	0.806	-1,556	0.393
2021	51	4,188	1,051	-1,644	0.578
2022	51	4.113	1,051	-1,588	0.570
2023	51	4,696	-0.279	-1,571	0.532
2024	51	4,954	-5,466	-1,486	0.516
2025	51	6,023	0.826	-1,875	0.584

Source: Processed data from SPSS Means output (2026).

The Altman Z"-Score model shows a relatively consistent improvement trend throughout the observation period, increasing from 3.881 in 2020 to 6.023 in 2025. This trend is in line with the narrative of national economic recovery post-pandemic reported by the Central Statistics Agency (2025), where the manufacturing industry sector, including the basic metal and chemical industries, was recorded as the main supporter of growth in that period.

A very different pattern is shown by the Springate S-Score model, which plummeted sharply in 2023 (-0.279) and bottomed out in 2024 (-5.466) before returning to positive in 2025 (0.826). This 2024 anomaly is directly related to the extreme value of Tirta Mahakam Resources Tbk (TIRT) in the timber and processing subsector identified in subsection 4.2.1, given that the company's Springate score in 2024 (-325.274) was an outlier that pulled the year's average significantly downward. The Zmijewski and Grover models were relatively more stable, with the Zmijewski average ranging from -1.486 to -1.875 and the Grover average from 0.393 to 0.584 throughout the observation period. The difference in the sensitivity levels of the four models to extreme values of this kind indicates that the Springate model has a formula that is mathematically more sensitive to ratios with small denominators (Husein & Pambekti, 2014).

4.3 Data Analysis Results

4.3.1 Classification Results of the Four Financial Distress Prediction Models

The Altman Z"-Score is calculated using the formula Z"=6.56X1+3.26X2+6.72X3+1.05X4, with a threshold value of Z">2.60 categorized as Healthy, 1.10≤Z"≤2.60 categorized as Grey Zone, and Z"<1.10 categorized as Distress (Altman, 1968; Husein & Pambekti, 2014). Table 11 presents the distribution of the classification:

Table 11. Distribution of Altman Z''-Score Model Classification

Category	Frequency	Percentage
Healthy	186	60.8%
Grey Zone	58	19.0%
Distress	62	20.3%
Total	306	100.0%

Source: SPSS Frequencies Output (2026).

The majority of sample companies (60.8 percent) are in the Healthy category according to the Altman Z"-Score model, while 19.0 percent are in the Grey Zone and 20.3 percent are categorized as Distressed. The existence of a fairly large proportion of the Grey Zone is a distinctive characteristic of the Altman model that distinguishes it from Springate and Zmijewski, because this model accommodates the uncertainty zone between healthy and distressed conditions (Altman, 1968). In line with the findings in sub-chapter 4.2.1, the company with the lowest Altman score is Tirta Mahakam Resources Tbk (TIRT) in 2024 (Z"=-18.062), while the highest score is recorded by Duta Pertiwi Nusantara Tbk (DPNS) in 2025 (Z"=62.428). The Springate S-Score is calculated using the formula S=1.03A+3.07B+0.66C+0.4D with a dichotomous threshold value of S≥0.862 categorized as Healthy and S<0.862 categorized as Distress (Husein & Pambekti, 2014). Table 12 presents the results of the classification distribution.

Table 12. Distribution of Springate Model Classification S-Score

Category	Frequency	Percentage
Healthy	154	50.3%
Distress	152	49.7%

Total	306	100.0%

Source: SPSS Frequencies Output (2026).

The Springate model exhibits a stark contrast to the other three models, with nearly half of the sample (49.7 percent) categorized as Distressed. This proportion is significantly higher than the distress proportions generated by Altman (20.3 percent), Zmijewski, and Grover. The Springate model's tendency to produce a higher distress proportion was also found in Salim and Ismudjoko's (2021) study in the coal mining sector, which reported Springate's accuracy was the lowest among the four models compared. This indicates that Springate's threshold values tend to be more stringent (conservative) in classifying distress conditions than other models in capital-intensive industrial contexts such as the basic and chemical industries. The Zmijewski X-Score is calculated using the formula X=-4.3-4.5X1+5.7X2-0.004X3 with a dichotomous threshold value of X>0 categorized as Distress and X<0 categorized as Healthy (Zmijewski, 1984).

Table 13. Distribution of Zmijewski X-Score Model Classification

Category	Frequency	Percentage
Healthy	272	88.9%
Distress	34	11.1%
Total	306	100.0%

Source: SPSS Frequencies Output (2026).

In contrast to Springate, the Zmijewski model produced the smallest distress proportion among the four models, at only 11.1 percent of the total sample. The tendency of the Zmijewski model to produce a low distress proportion was also found in Ramadhani et al.'s (2023) study in the transportation and logistics sector, where this model was reported to have the highest level of accuracy compared to Altman and Grover. The probit analysis approach used by Zmijewski (1984), which differs methodologically from the multiple discriminant analysis in Altman and Springate, is suspected to be one of the factors explaining this model's tendency to produce a more conservative classification of distress status in the basic industry and chemical sectors.

The Grover G-Score is calculated using the formula G=1.65X1+3.404X3-0.016ROA+0.057 with a threshold value of G≥0.01 categorized as Healthy, G≤-0.02 categorized as Distress, and values between the two categorized as Grey Zone (Prasetianingtias & Kusumowati, 2019). Table 14 presents the results of the classification distribution:

Table 14. Distribution of Grover G-Score Model Classification

Category	Frequency	Percentage
Healthy	265	86.6%
Grey Zone	1	0.3%
Distress	40	13.1%
Total	306	100.0%

Source: SPSS Frequencies Output (2026).

Gray Zone category on Grover models only appear once during 306 firm-year observations, far more seldom compared to the Grey Zone in the Altman model which appeared in 58 observations (19.0 percent). This condition is consistent with the characteristics of Grover's Grey Zone range which is very narrow (-0.02 to 0.01) compared to Altman's Grey Zone range (1.10 to 2.60), so that practically the Grover model in this study can be treated almost completely dichotomous. The high proportion of Healthy (86.6 percent) in the Grover model is also in line with the findings of Prasetianingtias and Kusumowati (2019) who reported that the Grover model has a competitive accuracy level of 85.29 percent in the agricultural sector in Indonesia, indicating a general tendency for this model to produce a dominant Healthy classification in various sector contexts.

Table 15. Summary of Comparison of Classification Percentages of the Four Models

Model	Healthy	Grey Zone	Distress
Altman Z-Score	60.8%	19.0%	20.3%
Springate S-Score	50.3%	-	49.7%
Zmijewski X-Score	88.9%	-	11.1%
Grover G-Score	86.6%	0.3%	13.1%

Source: SPSS Frequencies Output (2026).

Table 15 shows a very wide range in distress proportions among the four models, ranging from 11.1 percent in the Zmijewski model to 49.7 percent in the Springate model, a more than fourfold difference even though all four models were applied to identical research objects and observation periods. This pattern of inconsistency is consistent with various previous studies comparing the four models in different sectors, such as Ulum et al. (2024) in the mining sector and Husein and Pambekti (2014) in companies listed on the Sharia securities list, which show that the superiority and sensitivity of each model are contextual (Sethi & Mahadik, 2024).

4.3.2 Results of Comparative Tests Between Models

Cochran's Q Test was used to analyze whether there were significant differences between the dichotomous classification results (Distress/Healthy) of the four financial distress prediction models (Siegel & Castellan, 1988). Considering that the Altman Z"-Score and Grover G-Score models have a Grey Zone category that Springate and Zmijewski do not have, the Grey Zone category in both models was first combined with the Non-Distress category.

Table 16. Frequency Distribution of the Dichotomous Classification of the Four Models

Model	Non-Distress	Distress
Altman Z-Score	244	62
Springate S-Score	154	152
Zmijewski X-Score	272	34
Grover G-Score	266	40

Source: SPSS NPar Tests output (2026).

Table 17. Results of Cochran's Q Test

Statistics	Mark
N	306
Cochran's Q	252,620
df	3
Asymp . Sig.	0,000

Source: SPSS NPar Tests output (2026).

The test results show a Cochran's Q value of 252.620 with a degree of freedom of 3 and a significance value of 0.000 ($p<0.05$). Thus, H0 is rejected, there is a significant difference in the proportion of dichotomous classification among the Altman Z"-Score, Springate, Zmijewski, and Grover models. In line with Husein and Pambekti (2014) who found significant differences between the four models in the list of sharia effects, as well as Ulum et al. (2024 similar patterns in the mining sector, so that differences in variable construction and statistical methods in each model result in different classification sensitivities even though they are applied to identical research objects.

As a complement to the Cochran's Q Test which tests differences at the categorical classification level, the Friedman Test was used to directly test the differences in the raw score ranks of the four models. The Friedman Test was chosen as a non-parametric equivalent for repeated measures paired sample designs, replacing the Kruskal-Wallis Test which is methodologically intended for independent sample designs and is less appropriate for application to data originating from identical observation objects in this study (Siegel & Castellan, 1988).

Table 18. Mean Rank Score of the Four Models (Friedman Test)

Model	Mean Rank
Altman Z-Score	3.56
Springate S-Score	2.97
Zmijewski X-Score	1.32
Grover G-Score	2.15

Source: SPSS NPar Tests Output (2026).

Table 19. Friedman Test Results

Statistics	Mark
N	306
Chi-Square	526,169
df	3
Asymp . Sig.	0,000

Source: SPSS NPar Tests Output (2026).

The results of the Friedman Test show Chi-Square value of 526.169 with degrees free 3 and significance of 0.000 ($p<0.05$), so H0 is rejected again rejected. Need to confirmed that the mean rank value is not can compared to in a way direct intermodal for conclude which model is the “tightest” or “loosest”, considering direction Zmijewski X-Score scale inverse with the other three models, namely increasing value negative precisely indicates conditions are getting worse healthy (Zmijewski, 1984). Zmijewski's lowest mean rank (1.32) is thus a mathematical consequence of the scale's direction, not an indication that this model is the most conservative. The significance value of the Friedman Test strengthens the results of the Cochran's Q Test, so that the existence of significant differences between the models is empirically supported by both categorical classification and raw scores.

Because Cochran's Q Test showed significant differences overall in the dichotomous classification data, a post-hoc test using McNemar's Test was conducted to identify which model pairs differed significantly, following the procedure used by Husein and Pambekti (2014) in a similar study. The test was conducted on six model pairs, and is presented in Table 20:

Table 20. McNemar Test Results for Six Model Pairs

Model Couple	N Discordant	Test Statistics	Sig.
Altman – Springate	108	Chi-Square=73.343	0,000
Altman – Zmijewski	32	Chi-Square=22.781	0,000
Altman – Grover	24	Exact Sig.	0,000
Springate – Zmijewski	124	Chi-Square=110.395	0,000

Springate – Grover	112	Chi-Square=110.009	0,000
Zmijewski – Grover	26	Chi-Square=0.962	0.327

Source: SPSS NPar Tests Output (2026).

Of the six pairs tested, five pairs showed significant differences ($p<0.05$): Altman-Springate, Altman-Zmijewski, Altman-Grover, Springate-Zmijewski, and Springate-Grover. In contrast, the Zmijewski-Grover pair did not show significant differences (Chi-Square=0.962; p=0.327). This finding indicates that although the four models differed in general, the Zmijewski and Grover models were particularly likely to produce final classification decisions (Healthy/Distress) in the basic industry and chemical sectors, a pattern not widely uncovered by previous studies such as Ramadhani et al. (2023) and Salim and Ismudjoko (2021) which compared the four models in aggregate without examining the similarities of specific model pairs.

As a complement to the McNemar Test applicable to dichotomous data, the Wilcoxon Signed-Rank Test was used as a follow-up to the Friedman Test to examine differences in raw score levels (ordinal/continuous) between six pairs of models. Given the six repeated pairwise tests on the same sample, a Bonferroni correction was applied with a significance threshold of 0.05 to 0.05/6=0.0083 to control for the cumulative increase in the risk of Type I error (Siegel & Castellan, 1988). Table 21 presents the test results:

Table 21. Wilcoxon Signed-Rank Test Results for Six Model Pairs (with Bonferroni Correction)

Model Couple	Z	Asymp . Sig.	Significant (α=0.0083)
Springate – Altman	-11,639	0,000	Yes
Zmijewski – Altman	-11,948	0,000	Yes
Grover – Altman	-11,703	0,000	Yes
Zmijewski – Springate	-12,470	0,000	Yes
Grover – Springate	-13,333	0,000	Yes
Grover – Zmijewski	-12,174	0,000	Yes

Corrected significance threshold (α) = 0.0083. Source: SPSS NPar Tests Output (2026).

The result is that sixth permanent model couple significant although has corrected with Bonferroni (all Sig. value = 0.000, far below corrected threshold 0.0083), including the Grover-Zmijewski couple who actually significant at the level score raw. This finding present nuances important to complement McNemar Test results: although the Zmijewski and Grover models tend to produce decision classification categorical similar endings (Healthy/Distress), mechanisms numerical and sensitivity score raw behind both models still different in a way significant.

4.3.3 Model Accuracy Test Results

To analyze the accuracy of the four models, a benchmark of the company's actual condition is required to compare the predicted results. As explained in Chapter III, actual financial distress is determined based on three objective indicators that can be verified directly from financial statements: net loss for two consecutive years, negative operating cash flow, and negative equity (Platt & Platt, 2002; Ramadhani et al., 2023). Companies that meet at least one of these three indicators are categorized as experiencing actual distress, while those that meet none are categorized as healthy.

Table 22. Distribution Condition Actual Financial Distress

Current Status	Frequency	Percentage
Healthy	231	75.5%
Distress	75	24.5%
Total	306	100.0%

Source: Processed data from Tabulation_IDK_FINAL_FIX_v3_WithoutSLJGlobal.xlsx, Sheet 3_VarDependen (2026).

The results of the actual condition determination indicate that 24.5 percent of the firm-year observations in this study actually experienced financial distress based on objective indicators of financial statements, while 75.5 percent were in a healthy condition. This proportion of actual distress of 24.5 percent serves as a relevant benchmark for assessing the tendency of each model to overestimate or underestimate the distress condition, in line with the approach used by Husein and Pambekti (2014) in determining the accuracy of the model based on comparison with actual empirical conditions. Confusion Matrix in table 23:

Table 23. Confusion Matrix of the Four Models (Predicted × Actual)

Model	TN	FP	FN	TP
Altman Z-Score	207	24	37	38
Springate S-Score	136	95	18	57
Zmijewski X-Score	221	10	51	24
Grover G-Score	220	11	46	29

Source: SPSS Crosstabs output (2026).

The four confusion matrices above show strikingly different patterns. The Springate model produced the highest number of True Positives (57) but also the highest number of False Positives (95), indicating that this model is aggressive in detecting distress but produces many false alarms. Conversely, the Zmijewski model produced the highest number of False Negatives (51), indicating that many companies are actually in distress but are missed by this model. This contrasting pattern forms the basis for calculating a more comprehensive accuracy measure in the next section, considering that the TP, TN, FP, and FN figures alone cannot describe the relative superiority of a model without being converted into comparable measures (Fawcett, 2006).

Table 24. Comparison of Accuracy Measures of the Four Models

Model	Accuracy	Sensitivity	Specificity	Type I Error	Type II Error
Altman Z-Score	80.07%	50.67%	89.61%	10.39%	49.33%
Springate S-Score	63.07%	76.00%	58.87%	41.13%	24.00%
Zmijewski X-Score	80.07%	32.00%	95.67%	4.33%	68.00%
Grover G-Score	81.37%	38.67%	95.24%	4.76%	61.33%

Source: Processed data from SPSS Crosstabs output (2026).

Table 24 shows that the Grover model recorded the highest overall accuracy (81.37%), followed by Altman and Zmijewski, which both recorded 80.07%, and Springate, which had the lowest accuracy (63.07%). However, the opposite pattern was found in the sensitivity and Type II Error measures: the Springate model recorded the highest sensitivity (76.00%) and the lowest Type II Error (24.00%), while the Zmijewski and Grover model, despite their superior overall accuracy, recorded very high Type II Errors (68.00% and 61.33%, respectively). This trade-off pattern is a common phenomenon in the evaluation of binary classification models, where models with high specificity (the ability to detect healthy companies) tend to sacrifice sensitivity (the ability to detect distressed companies), and vice versa (Fawcett, 2006).

The high Type II Error in the Zmijewski and Grover model has serious consequences, considering that Altman and Hotchkiss (1993) assert that misclassifying a company that is actually distressed as healthy is much more dangerous than Type I Error, because investors and creditors do not receive the early warning signals they should have received. Thus, although both models excel in overall accuracy measures, this superiority is largely contributed by their ability to recognize healthy companies (True Negative), not by the ability to detect distress early.

Referring to the criteria established in Chapter III, where overall accuracy is the primary measure for comparing and ranking the four models, the Grover G-Score model was determined to have the highest level of accuracy in predicting financial distress in basic and chemical industry companies listed on the Indonesia Stock Exchange for the 2020–2025 period, with an overall accuracy of 81.37 percent (Husein & Pambekti, 2014; Salim & Ismudjoko, 2021). This determination requires an important note considering the Grover model's relatively high Type II Error (61.33%). For stakeholders who prioritize minimizing general classification errors, the Grover model may be the right choice, but for stakeholders who prioritize sensitive early distress detection, the Springate model with the highest sensitivity (76.00%) and the lowest Type II Error (24.00%) has the potential to be a relevant additional consideration despite its lower overall accuracy (Platt & Platt, 2002).

4.4 Discussion of Research Results

4.4.1 Discussion of Differences in Prediction Results Between Models

The results of the Cochran's Q Test (Q=252.620; p=0.000) and the Friedman Test (Chi-Square=526.169; p=0.000) showed that there were significant differences in the prediction results of the Altman Z"-Score, Springate, Zmijewski, and Grover models in predicting financial distress in basic and chemical industry sector companies listed on the Indonesia Stock Exchange for the period 2020–2025, both from a categorical classification perspective and raw scores. This finding is consistent with the bankruptcy theory perspective: although all four models are rooted in the same belief that accounting information in financial statements reflects the financial health of the company (Beaver, 1966; Altman, 1968), differences in statistical methods of formation, ranging from multiple discriminant analysis in Altman and Springate to probit analysis in Zmijewski, produce different coefficient weights and sensitivities to the same financial ratio dimensions. This nuance suggests that conclusions about similarities or differences between models may depend on the level of measurement used, a methodological consideration rarely discussed explicitly in previous studies such as Christa and Mukti (2023) and Ramadhani et al. (2023) which generally only use one type of comparative test.

4.4.2 Discussion of Model Accuracy Level

The test results show a significant difference in accuracy between the four models, with the Grover G-Score model having the highest accuracy (81.37%). The finding that the Grover model is the most accurate in this study corroborates the findings of Prasetianingtias and Kusumowati (2019), who also reported that the Grover model has competitive accuracy (85.29 percent) in the agricultural sector in Indonesia. However, this finding differs from Ramadhani et al. (2023), who found the Zmijewski model to be most accurate in the transportation and logistics sector, and Ulum et al. (2024), who found the Altman model to be most accurate in the mining sector. This inconsistency in the best models across sectors further confirms the view of Sethi and Mahadik (2024) that the effectiveness of financial distress prediction models is highly contextual and dependent on industry characteristics. Therefore, generalizing the best model across sectors cannot be done without separate empirical testing in each specific industry context. From a signaling theory perspective, the high specificity but low sensitivity of the Grover and Zmijewski models can be interpreted as a tendency for both models to place greater weight on financial signals confirming soundness compared to signals indicating potential distress, in line with Connelly et al.'s (2025) argument regarding variations in the strength of signal interpretation across recipients. Conversely, the Springate model, which is more sensitive to distress signals, as reflected in its characteristic earnings before taxes to current liabilities variable, is more appropriately positioned as an early warning system, albeit with a higher false alarm rate, as also demonstrated by Husein and Pambekti (2014) in the context of companies listed on the Sharia-compliant securities list. These two models, with their contrasting characteristics, ultimately emphasize the importance of using more than one complementary prediction model, rather than relying on a single model, to obtain a more comprehensive picture of financial distress risk (Habib et al., 2020).

4.4.3 Interpretation of Findings from the Perspective of Bankruptcy Theory and Signaling Theory

The difference in accuracy levels between models, particularly the high Type II Error in the Zmijewski (68.00%) and Grover (61.33%) models, is in line with the perspective of bankruptcy cost theory developed from the capital structure theory of Modigliani and Miller (1963). Models that place a large weight on leverage ratios and aggregate profitability, such as Zmijewski and Grover, tend to be less sensitive to short-term financial pressures that are not yet visible in the overall capital structure, even though Wruck (1990) emphasized that indirect bankruptcy costs, such as loss of customer and supplier confidence, often appear long before such pressures are reflected in aggregate ratios. In contrast, the Springate model, which includes the variable earnings before taxes to current liabilities, proved more sensitive in capturing short-term liquidity pressures, resulting in the highest sensitivity (76.00%) among the four models. Connelly et al. (2025) assert that the strength of a signal depends heavily on how the receiver weights the information it receives, and the findings of this study provide clear empirical evidence of this: the four models, which are essentially formal instruments for receiving and interpreting financial signals, exhibit very different weighting patterns for identical signals, reflected in the highest proportion of distress classifications (49.7%) in the Springate model compared to the highest specificity (95.67%) in the Zmijewski model.

4.4.4 Comparison with Previous Research

In order to position the contribution of this research more clearly, Table 25 compares the main findings of this research with a number of previous studies related to the same financial distress prediction models in different sectors.

Table 25. Comparison Findings Study with Study Previously

Researcher (Year)	Sector	Best Model
Prasetianingtias & Kusumowati (2019)	Agriculture	Grover
Ramadhani et al. (2023)	Transportation & Logistics	Zmijewski
Ulum et al. (2024)	Mining	Altman
Salim & Ismudjoko (2021)	Coal Mining	Zmijewski
Study this (2026)	Basic and Chemical Industry	Grover

Source: Processed from various sources and results study this (2026).

Table 25 shows that the findings of this study, which conclude that there are significant differences between models with Grover as the most accurate model, are consistent with the general pattern of previous research where the four models consistently show significant differences from each other, although the most accurate model varies depending on the sector studied. This agreement with Prasetianingtias and Kusumowati (2019) who also found Grover as the best model in the agricultural sector indicates that this model may have a relative advantage in sectors with asset-intensive characteristics and rely on operational efficiency, a hypothesis that needs further confirmation through research in other sectors.

This study also directly addresses the research gaps identified in Chapter I, particularly the limitations of Sari and Yunita's (2019) study, which only covered the metals and minerals subsector with three prediction models without the Altman Z-Score, and the 2012–2016 study period, which did not include post-pandemic economic dynamics. By covering all eight JASICA subsectors, all four prediction models simultaneously, and the 2020–2025 period, which represents the cycle of economic contraction to recovery, this study provides a much more comprehensive picture of the behavior of the four models in the context of the basic and chemical industry sectors in Indonesia than previous available studies.

5.0 CONCLUSIONS

This research aims to answer three problem formulation; the conclusions of this research are described as follows.

a. First, regarding the problem formulation regarding the results of financial distress prediction based on each model individually, the four models show different classification patterns according to the characteristics of their respective formulas. The Altman Z"-Score model produces the majority of sample companies in the Healthy category, but also identifies a fairly large proportion of Grey Zone, reflecting the presence of a number of companies in the uncertainty zone between healthy and distress. The Springate S-Score model shows the most contrasting classification pattern among the four models, with a Distress proportion approaching half the sample, indicating that this model is the most stringent (conservative) in detecting financial distress. The Zmijewski X-Score model shows the opposite pattern, namely the smallest Distress proportion among the four models, indicating a tendency for this model to produce the loosest classification. The Grover G-Score model produces a dominant Healthy proportion with the Grey Zone category barely appearing, so that practically it can be treated as an almost completely dichotomous model. At the subsector level, the eight basic industry and chemical subsectors also showed sharp variations in predicted results, with the wood and processing subsector and the cement subsector generally showing higher vulnerability compared to the chemical subsector which consistently showed the healthiest financial condition.

b. Second, regarding the formulation of the problem regarding whether there are significant differences between the prediction results of the four models, the results of the non-parametric pairwise comparison test prove that there are significant differences between the prediction results of the Altman Z"-Score, Springate, Zmijewski, and Grover models, both at the categorical classification level (Healthy/Distress) and at the underlying raw score level. Further (post-hoc) testing of the six model pairs reveals that the differences are not uniform for each pair: the Zmijewski and Grover models tend to produce similar final classification decisions, although they are still proven to differ significantly at the raw score level. Thus, it can be concluded that the four financial distress prediction models as a whole cannot be used interchangeably in the context of the basic and chemical industry sectors, because each produces a statistically different assessment of financial condition.

c. Third, regarding the problem formulation regarding which model has the highest level of accuracy, the results of accuracy testing using a confusion matrix indicate that the Grover G-Score model has the highest overall accuracy level compared to the other three models, thus being determined as the model with the highest level of accuracy in predicting financial distress in basic and chemical industry sector companies listed on the Indonesia Stock Exchange for the 2020–2025 period. However, this determination needs to be accompanied by an important note that the Grover model shows a relatively high level of Type II Error, namely the tendency to pass companies that are actually distressed as healthy, while the Springate model is superior in minimizing Type II Error even though its overall accuracy level is lower than the Grover model. Thus, determining the "best" model is essentially relative to the criteria used, and model selection in practice needs to be adjusted to the priorities and risk tolerance of each user.

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