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Analysis of Bankruptcy Prediction Accuracy Using the Altman Z-Score, Springate, Taffler, and Zmijewski Models in Property & Real Estate Companies Listed on the IDX (2020-2023)

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Abstract
Purpose – This research assesses bankruptcy predictions derived from various models to identify the most accurate approach, especially for real estate companies that are publicly traded and listed on the Jakarta Stock Exchange between 2020 and 2023. It also seeks to examine the bankruptcy tendencies of each chosen company, as indicated by the respective models.
Design/methodology/approach – Evaluating a company's financial stability necessitates a comprehensive analysis employing models such as the Altman, Springate, Taffler, and Zmijewski Z-score to forecast the potential hazards of future insolvency.
Originality – This research assesses the bankruptcy prognosis scores of real estate firms by comparing them to actual outcomes, as demonstrated by the net losses incurred between 2020 and 2023. To select the model exhibiting the highest accuracy and the lowest error rates, Type I and Type II error analyses are conducted.
Findings and Discussion – Taffler's model predicts real estate company bankruptcy best, followed by Altman Z-Score and Zmijewski, and Springate's least accurately. It recommends that enterprises continuously assess financial performance, refrain from incurring excessive debt, maintain adequate current assets to fulfill liabilities, and improve profit margins.
Conclusion – This study recommends that companies perform regular financial assessments, limit reliance on debt to finance assets, maintain sufficient current assets to cover liabilities, and work on improving profit margins.

Keywords - Accuracy Level, Altman Z-score, Springate, Taffler, Zmijewski

Introduction

The COVID-19 pandemic was an international crisis that profoundly affected the global economy. The economic crisis has had a direct effect on the performance and profitability of companies in Indonesia. The research by Hayaty and Rikumahu (2022) found that COVID-19 had a negative impact on stock price movements. This was reflected in the price movements of the Jakarta Composite Index (JCI).

Table 1. IHSG Movement Data for the 2020-2023 Period

No	Information	IHSG Price			
		2020	2021	2022	2023
1	Beginning of year	6.283,581	6.104,898	6.665,308	6.850,984
2	End of year	5.979,073	6.581,482	6.850,619	7.272,797
3	Lowest	3.937,632	5.760,584	6.568,173	6.565,728
4	Highest	6.325,406	6.723,386	7.318,016	7.303,888

Source: Processed data, 2025

Table 1 indicates that the Jakarta Composite Index (JCI) attained a historic low in 2020. As reported by metrotvnews.com (2025), property sector contributes significantly to the national economy, accounting for up to 16,5 percent of the Gross Domestic Product (GDP) each year. In addition, this industry is also one of the largest employers in Indonesia, providing jobs for 14 million people per year.

Figure 1. GDP Growth of Indonesia;s Property and Real Estate Sector for the Period of 2013-2023
Source: id.techinasia.com, 2025.

Based on figure 1, during the timeframe of 2013-2023, GDP growth of property and real estate sector declined by 78,13%. For the timeframe of 2020-2023, the GDP growth was declined by 38,36%. This decline in stock prices is believed to be due caused by shift in consumer priorities regarding property purchases. Consumers are more inclined to save money for emergencies or prioritize primary needs over asset additions.

This conditions is reinforced by various property and real estate firms that had share price reductions in 2020 include Pakuwon Jati (PWON), which decreased by 10.53%; Lippo Karawaci (LPKR), which declined by 11.5%; and Summarecon Agung (SMRA), which fell by 19.9%. Furthermore, several companies also demonstrated less than satisfactory financial performance, as evidenced by negative net income, such as Lippo Karawaci (LPKR) with -8.891 trillion rupiah, Lippo Cikarang (LPCK) with -3.654 trillion rupiah, Modernland Realty (MDLN) with -1.763 trillion rupiah, and Alam Sutera Realty (ASRI) with -1.027 trillion rupiah.

According to a Bank Indonesia survey in Q3 2021, residential property sales declined by 15.19% year-on-year, a sharper drop compared to the 10.01% contraction in the prior quarter (bi.go.id, 2021). This slowdown was driven by rising construction material costs, licensing and taxation challenges, and the down payment requirements for mortgages.

From 2020 to 2023, numerous property and real estate firms saw escalating debt levels, indicating a possible rise in financial risk. This risk is typically evaluated through the debt ratio, This indicates the ratio of a company's funding sourced from debt (Kasmir, 2018). An increased leverage ratio signifies a heightened dependence on debt and an augmented risk of insolvency. The leverage ratio is calculated by comparing total debt to the organization's equity. The table below presents diverse leverage ratios for companies in the property and real estate sector.

Table 2. Debt to Equity Ratio Calculation Data for Property & Real Estate Companies for the 2020-2023 Period

No	Companies	*DER (Debt to Equity Ratio)*			
		2020	**2021**	**2022**	**2023**
1	PT. Lippo Karawaci, Tbk	0,760	1,132	0,903	0,967
2	PT. Summarecon Agung, Tbk	0,753	1,297	1,278	1,252
3	PT. Pakuwon Jati, Tbk	0,224	3,361	3,301	3,702
4	PT. Duta Anggada Realty, Tbk	1,077	0,734	0,597	0,501
5	PT. Mega Manunggal Properti, Tbk	0,117	7,784	5,535	3,221
6	PT. Jaya Sukses Makmur Sentosa, Tbk	0,158	10,837	9,961	4,589
7	PT. Maha Properti Indonesia, Tbk	0,166	5,527	5,321	5,165

Source: Processed data, 2025

Considering the factors discussed, the property and real estate sector saw adverse conditions from 2020 to 2023. To improve this situation, management requires calculations to determine thestrategic policies needed for the company to survive and increase business growth. One step a company can take is to conduct a bankruptcy prediction analysis. Bankruptcy prediction analysis can help companies address the possibility of bankruptcy caused by financial problems (Effendi, 2018). Models for predicting bankruptcy include those developed by Altman (1968), Foster (1970), Springate (1978), Ohlson (1980), Taffler (1983), Zmijewski (1984), Fulmer (1984), and Grover (2001). Each prediction model utilizes several financial ratio calculations to create a comprehensive formula.

Altman's technique, established in 1968, is a bankruptcy prediction model utilizing multiple discriminant analysis (MDA). The Z-score is calculated using five fundamental financial ratios: working capital to total assets (X1), retained earnings to total assets (X2), earnings before interest and taxes to total assets (X3), market capitalization to book value of debt (X4), and revenue to total assets (X5). George Foster developed the Foster model in 1970–1971 to predict railroad company bankruptcies in the United States. He began with univariate models and later advanced to multivariate models, incorporating two key ratios: operating expenses to revenue and operating profit to interest payable. The Springate model, developed by Gordon L.V. Springate in 1978, seeks to predict bankruptcy. It use Step-Wise Multiple Discriminant Analysis (MDA) to identify four essential financial ratios from a total of 19 that effectively distinguish firms at risk of bankruptcy from those that are financially stable (Sari & Yunita, 2019). The ratios include working capital to total assets (X1), earnings before interest and tax to total assets (X3), earnings before tax to current liabilities (X6), and sales to total assets (X5). The Ohlson model, developed by James Ohlson in 1980, employs a conditional logit model for default prediction analysis. Ohlson employed logistic regression to address the limitations of multiple discriminant analysis, namely the weakness of certain statistical requirements.

The Taffler method, devised in 1993 for a manufacturing firm in London, predicts financial challenges through the examination of four financial ratios: profit before tax in relation to short-term debt, current assets vs total liabilities, current liabilities as a proportion of total liabilities, and net profit after tax (Ananta & Adiputra, 2024). Research by Prakoso et al. (2022) indicates that the Taffler method achieves high predictive accuracy, with a 96% success rate and only a 4% error rate. Conversely, Indrawan & Gusmarani (2023) report a much lower accuracy of 25%. These two examples demonstrate the persistence of inconsistencies in research on the Taffler method.

The Zmijewski model, conceived by Mark E. Zmijewski in 1984, is based on research conducted over a period of twenty years. The evaluation of a company's performance uses liquidity and debt indicators (Sari & Yunita, 2019), namely return on assets (X_7), the debt ratio (X_8) and the current ratio (X_9). In 1984, Fulmer introduced the Fulmer model, which employs a multi-step discriminant approach and incorporates ten financial ratios: retained earnings as a proportion of total assets (X2), revenues as a proportion of total assets, EBIT as a proportion of equity, operational cash flow as a proportion of total liabilities, total liabilities as a proportion of equity, current obligations as a proportion of total assets, working capital as a proportion of total liabilities, and the logarithms of fixed assets and EBIT to interest expense (Peter et al., 2021).

Previous studies indicate that no bankruptcy prediction model has demonstrated consistent accuracy. These mixed results prompted researchers to test similar models on different samples and datasets. The study is titled "Analysis of the Accuracy of Bankruptcy Predictions Using the Altman Z-Score, Springate, Taffler, and Zmijewski Models for IDX-Listed Real Estate Companies (2020-2023)". This research computed bankruptcy prediction ratings for property and real estate firms and analyzed them for accuracy to determine how well each model reflected their financial conditions. The company's reality is based on companies with negative net profit during the 2020-2023 period. Furthermore, further testing was conducted using error rate I and error rate II to determine the level of prediction error. This resulted in an accurate bankruptcy prediction model based on the highest accuracy and lowest error rate tests.

Literature Review

Bankruptcy

Bankruptcy, or financial difficulty, transpires when a company's liabilities surpass the fair value of its assets, rendering it incapable of fulfilling its financial obligations and sustaining operations, ultimately resulting in insolvency (Sitorus & Yulita, 2023). Before finally going bankrupt and becoming insolvent, a company will usually experience a decline in financial capacity, a phenomenon known as financial distress (Platt & Platt, 2002). In order for a company to have an accurate reflection of its financial distress, it needs to perform a financial ratio analysis. The purpose of financial statement analysis is to provide information related to performance, financial position, and changes in financial position that will be useful for users in making economic decisions (Irmawan & Irsan, 2023).

Framework

The following is a description of the framework of thought used in this research:

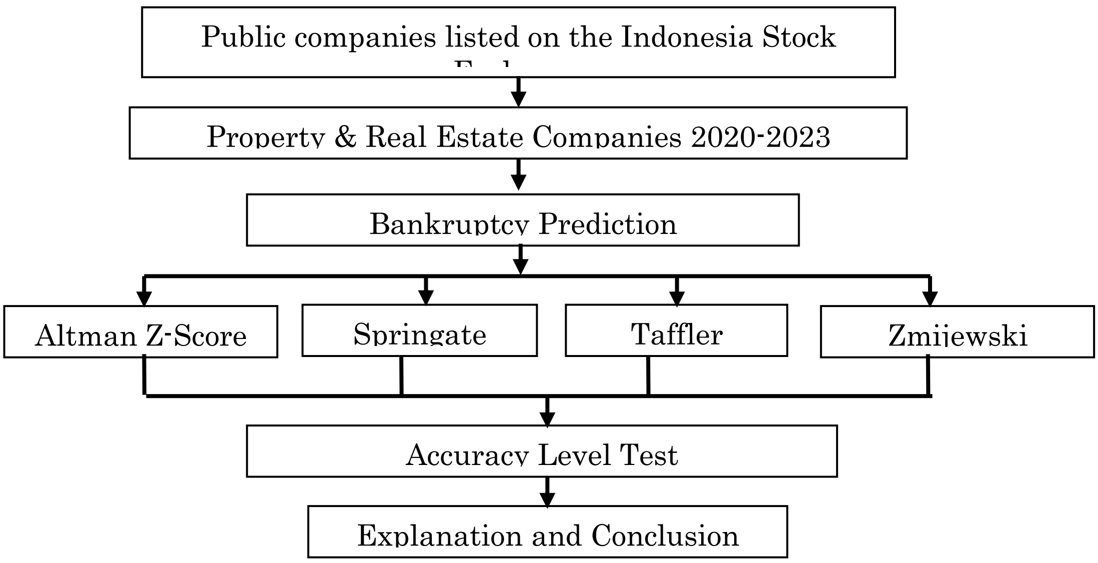

Figure 1. Framework

Methods, Data, and Analysis

This quantitative comparative analysis assesses the bankruptcy prediction efficacy of the Altman Z-Score, Springate, Taffler, and Zmijewski models for publicly traded real estate firms from 2020 to 2023.

Operationalization of Variables

This study evaluates the insolvency risk of real estate firms listed on the Jakarta Stock Exchange from 2020 to 2023 using bankruptcy prediction models, including the Altman, Springate, Taffler, and Zmijewski Z-scores. The following section delineates these models and scoring methodologies.

Table 3. Operationalization of Variables

No	Variable	Sub-Variable	Indicators	Scale
1	Altman Z-Score	Working capital to total assets (X_1)	$X_1 = \frac{Working\ capital}{Total\ assets}$	Ratio
		Retained earning to total assets (X_2)	$X_2 = \frac{Retained\ earning}{Total\ assets}$	
		Earning before interest and tax to total assets (X_3)	$X_3 = \frac{EBIT}{Total\ assets}$	
		Book value of equity to book value of debt (X_4)	$X_4 = \frac{Market\ Value\ Equity}{Book\ Value\ of\ Debt}$	
2	Springate	Working capital to total assets (X_1)	$X_1 = \frac{Working\ capital}{Total\ assets}$	Ratio
		Earning before interest and tax to total assets (X_3)	$X_3 = \frac{EBIT}{Total\ assets}$	
		Sales to total assets (X_5)	$X_5 = \frac{Sales}{Total\ assets}$	
		Earn before taxes to current liabilities (X_6)	$X_6 = \frac{EBT}{Current\ liabilities}$	
4	Taffler	Sales to total assets (X_5)	$X_5 = \frac{Sales}{Total\ assets}$	Ratio
		Earn before taxes to current liabilities (X_6)	$X_6 = \frac{EBT}{Current\ liabilities}$	
		Current assets to current liabilities (X_9)	$X_9 = \frac{Current\ assets}{Current\ liabilities}$	
		Current liabilities to total assets (X_{10})	$X_{10} = \frac{Current\ liabilities}{Total\ assets}$	
5	Zmijewski	Earning after tax to total assets (X_7)	$X_7 = \frac{Earning\ after\ tax}{Total\ assets}$	Ratio
		Total debt to total assets (X_8)	$X_8 = \frac{Total\ debt}{Total\ assets}$	
		Current assets to current liabilities (X_9)	$X_9 = \frac{Current\ assets}{Current\ liabilities}$	

Source : Processed Data, 2025

Population and Sample

This four-year study evaluates 92 Jakarta Stock Exchange-listed real estate businesses from 2020 to 2023, collecting 368 data points. Data was selected using purposeful sampling. Sample size is listed below.

Table 4. Number of Research Samples

No	Criteria	Total
1	Real estate companies listed on the Jakarta Stock Exchange for the period 2020-2023	92
2	Real estate companies that have not published consecutive financial reports on the Jakarta Stock Exchange for the period 2020-2023	(19)
Number of sample companies		73
Number of data samples (period 2020-2023)		292

Source: Processed data, 2025

Data Analysis Technique

Altman Z-Score Model

Z denotes the bankruptcy index, with X1 indicating Working Capital to Total Assets, X2 representing Retained Earnings to Total Assets, X3 signifying EBIT to Total Assets, and X4 reflecting the Market Value of Equity to the Book Value of Debt.

$$Z = 6{,}56\,X_1 + 3{,}26\,X_2 + 6{,}72\,X_3 + 1{,}05\,X_4$$

A corporation is deemed financially sound if $Z > 2.6$ (Safe Zone), may have financial challenges if $1.1 < Z < 2.6$ (Grey Zone), and is at significant risk of bankruptcy if $Z < 1.1$ (Distress Zone).

Springate Model

Working capital, profit before interest and taxes, income, and current liabilities are represented by X_1, X_3, X_5, and X_6.

$$S = 1{,}03\,X_1 + 3{,}07\,X_3 + 0{,}66\,X_6 + 0{,}4\,X_5$$

The obtained scores are then compared to a cut-off value of 0.862, where $S < 0.862$ indicates an unhealthy financial, while $S \geq 0.862$ indicates a financially healthy company.

Taffler Model

X5 denotes Sales to Total Assets, X6 signifies Earnings Before Taxes to Current Liabilities, X9 indicates Current Assets to Current Liabilities, and X10 represents Current Liabilities to Total Assets.

$$T = 0{,}53\,X_6 + 0{,}13\,X_9 + 0{,}18\,X_{10} + 0{,}16\,X_5$$

Taffler scores fall into three categories: $T > 0.3$ implies financial stability and little chance of bankruptcy; $0.2 \leq T \leq 0.3$ suggests ambiguity, with the corporation either solvent or in financial trouble; while $T < 0.2$ indicates financial distress and insolvency risk.

Zmijewski Model

X7 denotes Earnings After Tax relative to Total Assets, X8 signifies Total Debt in relation to Total Assets, and X9 indicates Current Assets compared to Current Liabilities.

$$X = -4{,}3 - 4{,}5\,X_7 + 5{,}7\,X_8 - 0{,}004\,X_9$$

The X-Score classification is bifurcated into two categories: $X \geq 0$ signifies that the company is forecasted to face bankruptcy, whilst $X < 0$ denotes that the company is anticipated to be free from bankruptcy danger.

Accuracy Level and Error Level Test

Accuracy testing is conducted by comparing each model's score calculation with the actual company conditions. This step is conducted to create the most accurate bankruptcy prediction model. Viciwati (2020) delineates the criteria for assessing accuracy as follows:

$$\text{Accuracy Level} = \frac{\text{Number of Correct Predictions}}{\text{Number of Samples}} \text{x}100\%$$

Alongside the accuracy level, the researcher also computed the error rate for each bankruptcy prediction model. The error rate refers to the discrepancy between projected outcomes and the actual state of the firm. Viciwati (2020) delineates the calculation of the error rate as follows:

a) Type Error The model forecasts a sample of non-bankrupt enterprises when they are. Type Error Formula for calculating I:

$$\text{Type Error I} = \frac{\text{Number of Type Error I}}{\text{Number of Sample}} \text{x}100\%$$

b) Type Error II occurs when a model predicts a sample of companies to be bankrupt when in fact they are not. Type Error II is calculated using the following formula:

$$\text{Type Error II} = \frac{\text{Number of Type Error II}}{\text{Number of Sample}} \text{x}100\%$$

The bankruptcy prediction model exhibiting the greatest accuracy and the minimal error rate will be deemed the most dependable model for anticipating bankruptcy.

Results and Discussions

In order to compare and produce accurate bankruptcy predictions, this study uses an approach based on negative net income throughout the 2020-2023 period based on each company's annual financial reports. The following is a list of property and real estate companies in the 2020-2023 period that recorded negative net income:

Table 5. List of Companies with Negative Net Income

2020		2021		2022		2023	
NO	COMPANY CODE	NO	COMPANY CODE	NO	COMPANY CODE	NO	COMPANY CODE
1	INPP	1	MPRO	1	MPRO	1	MPRO
2	RISE	2	INPP	2	LPKR	2	NIRO
3	LPKR	3	LPKR	3	BKSL	3	OMRE
4	BKSL	4	GMTD	4	GMTD	4	BBSS
5	ASRI	5	KIJA	5	KIJA	5	ELTY
6	GMTD	6	APLN	6	NIRO	6	MDLN
7	KIJA	7	NIRO	7	DILD	7	TRIN
8	MMLP	8	BEST	8	OMRE	8	DART

2020		2021		2022		2023	
NO	COMPANY CODE	NO	COMPANY CODE	NO	COMPANY CODE	NO	COMPANY CODE
9	APLN	9	OMRE	9	BBSS	9	RODA
10	SMDM	10	BBSS	10	CITY	10	EMDE
11	LPCK	11	ELTY	11	ELTY	11	BKDP
12	FMII	12	MDLN	12	DART	12	SATU
13	BEST	13	TRIN	13	RODA	13	ASPI
14	OMRE	14	DART	14	EMDE	14	NZIA
15	GWSA	15	BKDP	15	BKDP	15	BIPP
16	BBSS	16	SATU	16	SATU	16	TARA
17	ELTY	17	ASPI	17	ASPI	17	BAPI
18	MDLN	18	PAMG	18	NZIA	18	KOTA
19	DART	19	PUDP	19	PAMG	19	RBMS
20	RODA	20	BIPP	20	BIPP	20	MTSM
21	EMDE	21	BAPI	21	TARA	21	LAND
22	BKDP	22	KOTA	22	BAPI	22	BAPA
23	LPLI	23	BCIP	23	KOTA	23	BIKA
24	SATU	24	RBMS	24	RBMS	24	POSA
25	ASPI	25	MTSM	25	MTSM	25	PPRO
26	PAMG	26	BAPA	26	LAND	26	KBAG
27	PUDP	27	POLL	27	BAPA		
28	TARA	28	POSA	28	BIKA		
29	BAPI	29	ROCK	29	POSA		
30	KOTA						
31	RBMS						
32	MTSM						
33	LAND						
34	BIKA						
35	POSA						
36	PLIN						
37	ROCK						

Source: Processed data, 2025

Based on Table 5, it was found that in the 2020 period, there were 37 companies predicted to go bankrupt. In the 2021 and 2022 periods, there were 29 companies predicted to go bankrupt. Meanwhile, in the 2023 period, there were only 26 companies predicted to go bankrupt. The calculation then continued by calculating the Altman Z-Score, Springate, Taffler, and Zmijewski models in accordance with the variables of each model in measuring the health of companies in each period.

Altman Z-Score Model Calculation Results

Based on the Altman Z-Score model calculations for all sample companies from 2020-2023, the criteria for each company were as follows:

Table 6. Company Criteria Based on Altman Z-Score Model

NO	COMPANY CODE	ALTMAN Z-SCORE			
		2020	2021	2022	2023
1	BSDE	Safe Zone	Safe Zone	Safe Zone	Safe Zone
2	MKPI	Safe Zone	Safe Zone	Safe Zone	Safe Zone
3	CTRA	Safe Zone	Safe Zone	Safe Zone	Safe Zone
4	PWON	Safe Zone	Safe Zone	Safe Zone	Safe Zone
5	MPRO	Safe Zone	Grey Zone	Grey Zone	Grey Zone
6	INPP	Safe Zone	Safe Zone	Safe Zone	Safe Zone
7	SMRA	Grey Zone	Safe Zone	Safe Zone	Safe Zone
8	RISE	Safe Zone	Safe Zone	Safe Zone	Safe Zone
9	LPKR	Grey Zone	Safe Zone	Grey Zone	Safe Zone
10	JRPT	Safe Zone	Safe Zone	Safe Zone	Safe Zone
11	DUTI	Safe Zone	Safe Zone	Safe Zone	Safe Zone
12	DMAS	Safe Zone	Safe Zone	Safe Zone	Safe Zone
13	BKSL	Grey Zone	Safe Zone	Safe Zone	Safe Zone
14	ASRI	Grey Zone	Grey Zone	Safe Zone	Safe Zone
15	GMTD	Safe Zone	Safe Zone	Safe Zone	Safe Zone
16	RDTX	Safe Zone	Safe Zone	Safe Zone	Safe Zone
17	KIJA	Safe Zone	Safe Zone	Safe Zone	Safe Zone
18	MMLP	Safe Zone	Safe Zone	Safe Zone	Safe Zone
19	MTLA	Safe Zone	Safe Zone	Safe Zone	Safe Zone
20	APLN	Safe Zone	Grey Zone	Safe Zone	Safe Zone
21	NIRO	Safe Zone	Grey Zone	Grey Zone	Grey Zone

NO	COMPANY CODE	ALTMAN Z-SCORE			
		2020	2021	2022	2023
22	SMDM	Safe Zone	Safe Zone	Safe Zone	Safe Zone
23	LPCK	Safe Zone	Safe Zone	Safe Zone	Safe Zone
24	DILD	Grey Zone	Distress Zone	Grey Zone	Grey Zone
25	FMII	Safe Zone	Safe Zone	Safe Zone	Safe Zone
26	BEST	Safe Zone	Safe Zone	Safe Zone	Safe Zone
27	OMRE	Safe Zone	Safe Zone	Safe Zone	Safe Zone
28	ADCP	Grey Zone	Distress Zone	Distress Zone	Grey Zone
29	GWSA	Safe Zone	Safe Zone	Safe Zone	Safe Zone
30	BBSS	Safe Zone	Safe Zone	Safe Zone	Safe Zone
31	CITY	Safe Zone	Safe Zone	Safe Zone	Safe Zone
32	ELTY	Grey Zone	Grey Zone	Safe Zone	Grey Zone
33	MDLN	Distress Zone	Distress Zone	Distress Zone	Distress Zone
34	TRIN	Grey Zone	Distress Zone	Distress Zone	Distress Zone
35	DART	Distress Zone	Distress Zone	Distress Zone	Distress Zone
36	RODA	Safe Zone	Safe Zone	Safe Zone	Safe Zone
37	INDO	Safe Zone	Safe Zone	Safe Zone	Safe Zone
38	GPRA	Safe Zone	Safe Zone	Safe Zone	Safe Zone
39	URBN	Grey Zone	Grey Zone	Grey Zone	Grey Zone
40	AMAN	Safe Zone	Safe Zone	Safe Zone	Safe Zone
41	EMDE	Safe Zone	Safe Zone	Grey Zone	Grey Zone
42	SWID	Safe Zone	Safe Zone	Safe Zone	Safe Zone
43	BKDP	Distress	Distress	Distress	Distress

NO	COMPANY CODE	ALTMAN Z-SCORE			
		2020	2021	2022	2023
		Zone	Zone	Zone	Zone
44	LPLI	Distress Zone	Safe Zone	Safe Zone	Safe Zone
45	SATU	Safe Zone	Grey Zone	Grey Zone	Distress Zone
46	CBPE	Safe Zone	Safe Zone	Safe Zone	Safe Zone
47	ASPI	Safe Zone	Safe Zone	Safe Zone	Safe Zone
48	NZIA	Safe Zone	Safe Zone	Safe Zone	Safe Zone
49	PAMG	Safe Zone	Safe Zone	Safe Zone	Safe Zone
50	PUDP	Safe Zone	Safe Zone	Safe Zone	Safe Zone
51	BIPP	Safe Zone	Safe Zone	Grey Zone	Grey Zone
52	TARA	Safe Zone	Safe Zone	Safe Zone	Safe Zone
53	BAPI	Safe Zone	Safe Zone	Safe Zone	Safe Zone
54	KOTA	Safe Zone	Safe Zone	Safe Zone	Safe Zone
55	BCIP	Safe Zone	Safe Zone	Safe Zone	Safe Zone
56	RBMS	Safe Zone	Safe Zone	Grey Zone	Grey Zone
57	CSIS	Safe Zone	Safe Zone	Safe Zone	Safe Zone
58	REAL	Safe Zone	Safe Zone	Safe Zone	Safe Zone
59	DADA	Safe Zone	Safe Zone	Grey Zone	Distress Zone
60	MTSM	Distress Zone	Safe Zone	Grey Zone	Distress Zone
61	LAND	Grey Zone	Grey Zone	Grey Zone	Grey Zone
62	BAPA	Safe Zone	Safe Zone	Safe Zone	Safe Zone
63	BIKA	Distress Zone	Grey Zone	Distress Zone	Distress Zone
64	POLL	Distress Zone	Distress Zone	Distress Zone	Grey Zone

NO	COMPANY CODE	ALTMAN Z-SCORE			
		2020	2021	2022	2023
65	POSA	Distress Zone	Distress Zone	Distress Zone	Distress Zone
66	POLI	Safe Zone	Safe Zone	Safe Zone	Safe Zone
67	PPRO	Grey Zone	Grey Zone	Grey Zone	Distress Zone
68	PLIN	Safe Zone	Safe Zone	Safe Zone	Safe Zone
69	HOMI	Grey Zone	Grey Zone	Grey Zone	Safe Zone
70	KBAG	Safe Zone	Safe Zone	Safe Zone	Safe Zone
71	PURI	Safe Zone	Safe Zone	Safe Zone	Safe Zone
72	ATAP	Safe Zone	Safe Zone	Safe Zone	Safe Zone
73	ROCK	Safe Zone	Grey Zone	Safe Zone	Safe Zone

Source: Processed data, 2025

Table 6 illustrates the distribution of companies across financial health zones over four years. In 2020–2021, 53 companies were classified as safe, 12 as grey, and 8 as distressed. In 2022, the safe group slightly decreased to 51, the grey group rose to 14, while distressed companies remained at 8. By 2023, 52 companies were safe, 11 fell into the grey zone, and distressed companies increased to 10.

Springate Model Calculation Results

Based on the Springate model calculations for all sample companies from 2020 to 2023, the following criteria were obtained for each company:

Table 7. Company Criteria Based on Springate Model

NO	KODE PERUSAHAAN	SPRINGATE			
		2020	2021	2022	2023
1	BSDE	Unhealthy	Unhealthy	Unhealthy	Unhealthy
2	MKPI	Unhealthy	Unhealthy	Healthy	Healthy
3	CTRA	Unhealthy	Healthy	Unhealthy	Healthy
4	PWON	Unhealthy	Healthy	Healthy	Healthy
5	MPRO	Unhealthy	Unhealthy	Unhealthy	Unhealthy
6	INPP	Unhealthy	Unhealthy	Unhealthy	Unhealthy
7	SMRA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
8	RISE	Unhealthy	Unhealthy	Healthy	Unhealthy
9	LPKR	Unhealthy	Unhealthy	Unhealthy	Healthy
10	JRPT	Unhealthy	Unhealthy	Unhealthy	Unhealthy
11	DUTI	Unhealthy	Healthy	Unhealthy	Healthy

NO	KODE PERUSAHAAN	SPRINGATE			
		2020	2021	2022	2023
12	DMAS	Healthy	Healthy	Healthy	Healthy
13	BKSL	Unhealthy	Unhealthy	Unhealthy	Unhealthy
14	ASRI	Unhealthy	Unhealthy	Unhealthy	Unhealthy
15	GMTD	Unhealthy	Unhealthy	Unhealthy	Healthy
16	RDTX	Healthy	Healthy	Healthy	Healthy
17	KIJA	Healthy	Healthy	Healthy	Healthy
18	MMLP	Unhealthy	Healthy	Unhealthy	Unhealthy
19	MTLA	Unhealthy	Unhealthy	Unhealthy	Sehat
20	APLN	Unhealthy	Unhealthy	Healthy	Unhealthy
21	NIRO	Unhealthy	Unhealthy	Unhealthy	Unhealthy
22	SMDM	Unhealthy	Unhealthy	Healthy	Unhealthy
23	LPCK	Unhealthy	Unhealthy	Unhealthy	Unhealthy
24	DILD	Unhealthy	Unhealthy	Unhealthy	Unhealthy
25	FMII	Unhealthy	Unhealthy	Unhealthy	Unhealthy
26	BEST	Unhealthy	Unhealthy	Healthy	Healthy
27	OMRE	Unhealthy	Unhealthy	Unhealthy	Unhealthy
28	ADCP	Unhealthy	Unhealthy	Unhealthy	Unhealthy
29	GWSA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
30	BBSS	Unhealthy	Unhealthy	Unhealthy	Unhealthy
31	CITY	Healthy	Unhealthy	Unhealthy	Unhealthy
32	ELTY	Unhealthy	Unhealthy	Unhealthy	Unhealthy
33	MDLN	Unhealthy	Unhealthy	Unhealthy	Unhealthy
34	TRIN	Unhealthy	Unhealthy	Unhealthy	Unhealthy
35	DART	Unhealthy	Unhealthy	Unhealthy	Unhealthy
36	RODA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
37	INDO	Healthy	Healthy	Healthy	Healthy
38	GPRA	Healthy	Healthy	Healthy	Healthy
39	URBN	Unhealthy	Unhealthy	Unhealthy	Unhealthy
40	AMAN	Unhealthy	Unhealthy	Unhealthy	Unhealthy
41	EMDE	Unhealthy	Healthy	Unhealthy	Unhealthy
42	SWID	Healthy	Healthy	Healthy	Healthy
43	BKDP	Unhealthy	Unhealthy	Unhealthy	Unhealthy
44	LPLI	Unhealthy	Healthy	Healthy	Healthy
45	SATU	Unhealthy	Unhealthy	Unhealthy	Unhealthy
46	CBPE	Healthy	Healthy	Healthy	Healthy
47	ASPI	Unhealthy	Healthy	Unhealthy	Unhealthy
48	NZIA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
49	PAMG	Unhealthy	Unhealthy	Unhealthy	Unhealthy
50	PUDP	Unhealthy	Unhealthy	Healthy	Unhealthy
51	BIPP	Healthy	Unhealthy	Unhealthy	Unhealthy
52	TARA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
53	BAPI	Healthy	Healthy	Healthy	Healthy
54	KOTA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
55	BCIP	Unhealthy	Unhealthy	Unhealthy	Unhealthy
56	RBMS	Unhealthy	Unhealthy	Unhealthy	Unhealthy
57	CSIS	Unhealthy	Unhealthy	Unhealthy	Unhealthy
58	REAL	Healthy	Healthy	Healthy	Unhealthy
59	DADA	Unhealthy	Unhealthy	Unhealthy	Unhealthy

NO	KODE PERUSAHAAN	SPRINGATE			
		2020	2021	2022	2023
60	MTSM	Unhealthy	Unhealthy	Unhealthy	Unhealthy
61	LAND	Unhealthy	Unhealthy	Unhealthy	Unhealthy
62	BAPA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
63	BIKA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
64	POLL	Unhealthy	Unhealthy	Unhealthy	Unhealthy
65	POSA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
66	POLI	Unhealthy	Unhealthy	Unhealthy	Unhealthy
67	PPRO	Unhealthy	Unhealthy	Unhealthy	Unhealthy
68	PLIN	Unhealthy	Healthy	Healthy	Healthy
69	HOMI	Unhealthy	Unhealthy	Unhealthy	Unhealthy
70	KBAG	Unhealthy	Unhealthy	Healthy	Unhealthy
71	PURI	Unhealthy	Healthy	Unhealthy	Unhealthy
72	ATAP	Healthy	Healthy	Healthy	Healthy
73	ROCK	Unhealthy	Unhealthy	Unhealthy	Unhealthy

Source: Processed data, 2025

Table 7 shows that in 2020, 12 companies were classified as healthy, while 61 companies were classified as unhealthy. In 2021, 19 companies were classified as healthy, while 54 companies were classified as unhealthy. In 2022, 20 corporations were classified as healthy, while 53 enterprises were classified as unhealthy. In 2023, 19 companies were classified as healthy, while 54 companies were classified as unhealthy.

Taffler Model Calculation Results

Based on the Taffler model calculations for all sample companies from 2020 to 2023, the following criteria were obtained for each company:

Table 8. Company Criteria Based on the Taffler Model

NO	COMPANY CODE	TAFFLER			
		2020	2021	2022	2023
1	BSDE	Healthy	Healthy	Healthy	Healthy
2	MKPI	Healthy	Healthy	Healthy	Healthy
3	CTRA	Healthy	Healthy	Healthy	Healthy
4	PWON	Healthy	Healthy	Healthy	Healthy
5	MPRO	Unhealthy	Unhealthy	Unhealthy	Unhealthy
6	INPP	Unhealthy	Healthy	Healthy	Healthy
7	SMRA	Healthy	Healthy	Healthy	Healthy
8	RISE	Healthy	Healthy	Healthy	Healthy
9	LPKR	Unhealthy	Healthy	Healthy	Healthy
10	JRPT	Healthy	Healthy	Healthy	Healthy
11	DUTI	Healthy	Healthy	Healthy	Healthy
12	DMAS	Healthy	Healthy	Healthy	Healthy
13	BKSL	Unhealthy	Healthy	Healthy	Neutral
14	ASRI	Unhealthy	Healthy	Healthy	Healthy
15	GMTD	Unhealthy	Neutral	Healthy	Healthy
16	RDTX	Healthy	Healthy	Healthy	Healthy
17	KIJA	Healthy	Healthy	Healthy	Healthy
18	MMLP	Healthy	Healthy	Healthy	Healthy

NO	COMPANY CODE	TAFFLER			
		2020	2021	2022	2023
19	MTLA	Healthy	Healthy	Healthy	Healthy
20	APLN	Healthy	Healthy	Healthy	Healthy
21	NIRO	Healthy	Healthy	Neutral	Healthy
22	SMDM	Healthy	Healthy	Healthy	Healthy
23	LPCK	Unhealthy	Healthy	Healthy	Healthy
24	DILD	Neutral	Neutral	Neutral	Healthy
25	FMII	Healthy	Neutral	Healthy	Healthy
26	BEST	Healthy	Healthy	Healthy	Healthy
27	OMRE	Unhealthy	Unhealthy	Unhealthy	Unhealthy
28	ADCP	Healthy	Neutral	Neutral	Neutral
29	GWSA	Healthy	Healthy	Healthy	Healthy
30	BBSS	Healthy	Healthy	Healthy	Healthy
31	CITY	Healthy	Healthy	Healthy	Healthy
32	ELTY	Unhealthy	Unhealthy	Unhealthy	Unhealthy
33	MDLN	Unhealthy	Neutral	Neutral	Neutral
34	TRIN	Healthy	Neutral	Neutral	Neutral
35	DART	Unhealthy	Unhealthy	Unhealthy	Unhealthy
36	RODA	Neutral	Healthy	Healthy	Healthy
37	INDO	Healthy	Healthy	Healthy	Healthy
38	GPRA	Healthy	Healthy	Healthy	Healthy
39	URBN	Healthy	Neutral	Neutral	Neutral
40	AMAN	Healthy	Healthy	Healthy	Healthy
41	EMDE	Healthy	Healthy	Neutral	Unhealthy
42	SWID	Healthy	Healthy	Healthy	Healthy
43	BKDP	Unhealthy	Unhealthy	Unhealthy	Unhealthy
44	LPLI	Healthy	Healthy	Healthy	Healthy
45	SATU	Healthy	Neutral	Neutral	Neutral
46	CBPE	Healthy	Healthy	Healthy	Healthy
47	ASPI	Healthy	Healthy	Healthy	Healthy
48	NZIA	Healthy	Healthy	Healthy	Healthy
49	PAMG	Healthy	Neutral	Healthy	Healthy
50	PUDP	Healthy	Healthy	Healthy	Healthy
51	BIPP	Healthy	Healthy	Healthy	Healthy
52	TARA	Unhealthy	Healthy	Unhealthy	Unhealthy
53	BAPI	Healthy	Healthy	Healthy	Healthy
54	KOTA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
55	BCIP	Neutral	Healthy	Healthy	Sehat
56	RBMS	Unhealthy	Unhealthy	Unhealthy	Neutral
57	CSIS	Healthy	Healthy	Healthy	Healthy
58	REAL	Healthy	Healthy	Healthy	Healthy
59	DADA	Healthy	Healthy	Neutral	Unhealthy
60	MTSM	Unhealthy	Healthy	Neutral	Neutral
61	LAND	Neutral	Neutral	Unhealthy	Unhealthy
62	BAPA	Healthy	Healthy	Neutral	Neutral
63	BIKA	Neutral	Healthy	Healthy	Healthy
64	POLL	Neutral	Unhealthy	Healthy	Neutral
65	POSA	Unhealthy	Unhealthy	Unhealthy	Neutral
66	POLI	Neutral	Healthy	Healthy	Healthy

NO	COMPANY CODE	TAFFLER			
		2020	2021	2022	2023
67	PPRO	Neutral	Healthy	Neutral	Neutral
68	PLIN	Unhealthy	Healthy	Healthy	Healthy
69	HOMI	Neutral	Healthy	Healthy	Healthy
70	KBAG	Healthy	Healthy	Healthy	Healthy
71	PURI	Healthy	Healthy	Healthy	Healthy
72	ATAP	Healthy	Healthy	Healthy	Healthy
73	ROCK	Healthy	Healthy	Healthy	Healthy

Source: Processed data, 2025

Table 8 illustrates the distribution of companies across financial health zones over four years. In 2020, 46 companies were classified as safe, 9 as neutral, and 18 as distressed. In 2021, 54 companies were classified as safe, 10 as neutral and 9 as distressed. In 2022, the safe group slightly decreased to 51, the neutral group rose to 11, while distressed companies remained at 11. By 2023, 51 companies were safe, 12 fell into the neutral zone, and distressed companies increased to 10.

Zmijewski Model Calculation Results

Based on Zmijewski model calculations for all 2020-2023 sample companies, the criteria were as follows:

Tabel 9. Company Criteria Based on the Zmijewski Model

NO	COMPANY CODE	ZMIJEWSKI			
		2020	2021	2022	2023
1	BSDE	Healthy	Healthy	Healthy	Healthy
2	MKPI	Healthy	Healthy	Healthy	Healthy
3	CTRA	Healthy	Healthy	Healthy	Healthy
4	PWON	Healthy	Healthy	Healthy	Healthy
5	MPRO	Healthy	Healthy	Healthy	Healthy
6	INPP	Healthy	Healthy	Healthy	Healthy
7	SMRA	Healthy	Healthy	Healthy	Healthy
8	RISE	Healthy	Healthy	Healthy	Healthy
9	LPKR	Healthy	Healthy	Healthy	Healthy
10	JRPT	Healthy	Healthy	Healthy	Healthy
11	DUTI	Healthy	Healthy	Healthy	Healthy
12	DMAS	Healthy	Healthy	Healthy	Healthy
13	BKSL	Healthy	Healthy	Healthy	Healthy
14	ASRI	Healthy	Healthy	Healthy	Healthy
15	GMTD	Healthy	Healthy	Healthy	Healthy
16	RDTX	Healthy	Healthy	Healthy	Healthy
17	KIJA	Healthy	Healthy	Healthy	Healthy
18	MMLP	Healthy	Healthy	Healthy	Healthy
19	MTLA	Healthy	Healthy	Healthy	Healthy
20	APLN	Healthy	Healthy	Healthy	Healthy
21	NIRO	Healthy	Healthy	Healthy	Healthy
22	SMDM	Healthy	Healthy	Healthy	Healthy
23	LPCK	Healthy	Healthy	Healthy	Healthy
24	DILD	Healthy	Healthy	Healthy	Healthy
25	FMII	Healthy	Healthy	Healthy	Healthy

NO	COMPANY CODE	ZMIJEWSKI			
		2020	2021	2022	2023
26	BEST	Healthy	Healthy	Healthy	Healthy
27	OMRE	Healthy	Healthy	Healthy	Healthy
28	ADCP	Healthy	Healthy	Healthy	Healthy
29	GWSA	Healthy	Healthy	Healthy	Healthy
30	BBSS	Healthy	Healthy	Healthy	Healthy
31	CITY	Healthy	Healthy	Healthy	Healthy
32	ELTY	Healthy	Healthy	Healthy	Healthy
33	MDLN	Unhealthy	Healthy	Healthy	Healthy
34	TRIN	Healthy	Healthy	Healthy	Healthy
35	DART	Healthy	Healthy	Healthy	Unhealthy
36	RODA	Healthy	Healthy	Healthy	Healthy
37	INDO	Healthy	Healthy	Healthy	Healthy
38	GPRA	Healthy	Healthy	Healthy	Healthy
39	URBN	Healthy	Healthy	Healthy	Healthy
40	AMAN	Healthy	Healthy	Healthy	Healthy
41	EMDE	Unhealthy	Healthy	Healthy	Healthy
42	SWID	Healthy	Healthy	Healthy	Healthy
43	BKDP	Healthy	Healthy	Healthy	Healthy
44	LPLI	Healthy	Healthy	Healthy	Healthy
45	SATU	Healthy	Unhealthy	Unhealthy	Unhealthy
46	CBPE	Healthy	Healthy	Healthy	Healthy
47	ASPI	Healthy	Healthy	Healthy	Healthy
48	NZIA	Healthy	Healthy	Healthy	Healthy
49	PAMG	Healthy	Healthy	Healthy	Healthy
50	PUDP	Healthy	Healthy	Healthy	Healthy
51	BIPP	Healthy	Healthy	Healthy	Healthy
52	TARA	Healthy	Healthy	Healthy	Healthy
53	BAPI	Healthy	Healthy	Healthy	Healthy
54	KOTA	Healthy	Healthy	Healthy	Healthy
55	BCIP	Healthy	Healthy	Healthy	Healthy
56	RBMS	Healthy	Healthy	Healthy	Healthy
57	CSIS	Healthy	Healthy	Healthy	Healthy
58	REAL	Healthy	Healthy	Healthy	Healthy
59	DADA	Healthy	Healthy	Healthy	Healthy
60	MTSM	Healthy	Healthy	Healthy	Healthy
61	LAND	Healthy	Healthy	Healthy	Healthy
62	BAPA	Healthy	Healthy	Healthy	Healthy
63	BIKA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
64	POLL	Unhealthy	Unhealthy	Healthy	Healthy
65	POSA	Unhealthy	Unhealthy	Unhealthy	Unhealthy
66	POLI	Healthy	Healthy	Healthy	Healthy
67	PPRO	Healthy	Unhealthy	Unhealthy	Unhealthy
68	PLIN	Healthy	Healthy	Healthy	Healthy
69	HOMI	Healthy	Healthy	Healthy	Healthy
70	KBAG	Healthy	Healthy	Healthy	Healthy
71	PURI	Healthy	Healthy	Healthy	Healthy
72	ATAP	Healthy	Healthy	Healthy	Healthy
73	ROCK	Healthy	Healthy	Healthy	Healthy

Source: Processed data, 2025

Table 9 shows that in 2020 and 2021, Sixty-eight companies were classified as healthy, while five companies were classified as unhealthy. In 2022, 69 companies were classified as healthy, while 4 companies were classified as unhealthy. In 2023, 68 companies were classified as healthy, while 5 companies were classified as unhealthy.

Accuracy Level

After obtaining a number of companies with negative net income in the 2020-2023 period and the results of each model calculation, the next step is to measure the accuracy of bankruptcy predictions using the type I error and type II error methods. The following are the results of calculating the accuracy of bankruptcy predictions for each period and each prediction model:

Accuracy Level Calculation Results for the 2020 Period

The accuracy level calculation results for the 2020 period for property and real estate companies are as follows:

Table 10. Accuracy Level Calculation Results for the 2020 Period

INFORMATION	MODEL			
	ALTMAN Z-SCORE	SPRINGATE	TAFFLER	ZMIJEWSKI
Correct Prediction	40	44	49	39
Type Error I	25	2	17	33
Type II Error	8	27	7	1
Total	73	73	73	73
Accuracy Level	54,79%	60,27%	67,12%	53,42%
Type Error I	34,25%	2,74%	23,29%	45,21%
Type Error II	10,96%	36,99%	9,59%	1,37%

Source: Processed data, 2025

Table 10 reveals that in 2020, Taffler's model achieved the highest predictive accuracy (67.12%), correctly identifying 49 companies, while 24 companies were misclassified (Type I or II errors). Springate's model came in second with an accuracy rate of 60.27%, and Altman's Z-Score model reached 54.79%. Zmijewski's model recorded the lowest accuracy (53.42%).

Accuracy Level Calculation Results for the 2021 Period

The accuracy level calculation results for the 2021 period for property and real estate companies are as follows:

Tabel 11. Accuracy Level Calculation Results for the 2021 Period

INFORMATION	MODEL			
	ALTMAN Z-SCORE	SPRINGATE	TAFFLER	ZMIJEWSKI
Correct Prediction	48	42	53	45
Type Error I	17	3	15	26
Type II Error	8	28	5	2
Total	73	73	73	73

INFORMATION	MODEL			
	ALTMAN Z-SCORE	SPRINGATE	TAFFLER	ZMIJEWSKI
Accuracy Level	65,75%	57,53%	72,60%	61,64%
Type Error I	23,29%	4,11%	20,55%	35,62%
Type Error II	10,96%	38,36%	6,85%	2,74%

Source: Processed data, 2025

According to Table 11, the Taffler model exhibiting the best accuracy rate in 2021 achieved a score of 72.60%. The Taffler model accurately identified 53 companies, whereas the other 20 companies constituted Type I and Type II errors. The Altman Z-Score model achieved the second highest accuracy rate at 65.75%, while the Zmijewski model followed with a score of 61.64%. In 2021, the Springate model had the lowest accuracy rate, achieving a score of 57.53%.

Accuracy Level Calculation Results for the 2022 Period

The accuracy level calculation results for the 2022 period for property and real estate companies are as follows:

Table 12. Accuracy Level Calculation Results for the 2022 Period

INFORMATION	MODEL			
	ALTMAN Z-*SCORE*	SPRINGATE	TAFFLER	ZMIJEWSKI
Correct Prediction	50	45	54	46
Type Error I	15	2	13	26
Type II Error	8	26	6	1
Total	73	73	73	73
Accuracy Level	68,49%	61,64%	73,97%	63,01%
Type Error I	20,55%	2,74%	17,81%	35,62%
Type Error II	10,96%	35,62%	8,22%	1,37%

Source: Processed data, 2025

Table 12 shows that the Taffler model predicted 54 firms with 73.97% accuracy in 2022, whereas 19 companies were misclassified as Type I or Type II errors. The Altman Z-Score model then reached 68.49%, the Zmijewski model 63.01%, and the Springate model 61.64%, the least accurate.

Accuracy Level Calculation Results for the 2023 Period

The accuracy level calculation results for the 2022 period for property and real estate companies are as follows:

Tabel 13. Accuracy Level Calculation Results for the 2023 Period

INFORMATION	MODEL			
	ALTMAN Z-*SCORE*	SPRINGATE	TAFFLER	ZMIJEWSKI
Correct Prediction	58	44	59	52
Type Error I	10	1	9	21
Type II Error	5	28	5	0
Total	73	73	73	73

INFORMATION	MODEL			
	ALTMAN Z-*SCORE*	SPRINGATE	TAFFLER	ZMIJEWSKI
Accuracy Level	79,45%	60,27%	80,82%	71,23%
Type Error I	13,70%	1,37%	12,33%	28,77%
Type Error II	6,85%	38,36%	6,85%	0,00%

Source: Processed data, 2025

Table 13 indicates that in 2023, the Taffler model achieved the highest accuracy at 80.82%, correctly predicting 59 companies, while 14 companies were misclassified as Type I or Type II errors. Following this, the Altman Z-Score model reached 79.45% accuracy, and the Zmijewski model achieved 71.23%. Meanwhile, the Springate model had the lowest accuracy rate in 2023 with a value of 60.27%.

Discussion of Accuracy Level Calculation Results for the 2020-2023 Period

Based on the accuracy calculations for each model for the 2020-2023 period, the Taffler model achieved accuracy rates of 67.12%, 72.60%, 73.97%, and 80.82%. In 2020–2023, the Taffler model continuously had the highest accuracy for assessing and predicting property and real estate company bankruptcy. Over the same period, the Altman Z-Score model recorded accuracy rates of 54.79%, 65.75%, 68.49%, and 79.45%. In 2020, it ranked third in predictive accuracy, but between 2021 and 2023, it consistently held the second position, following the Taffler model.

The Zmijewski model recorded accuracy rates of 53.42%, 61.64%, 63.01%, and 71.23% from 2020 to 2023. In 2020, it showed the lowest accuracy among the three models. However, between 2021 and 2023, its performance improved, ranking third after the Taffler model and the Altman Z-Score model. During 2020–2023, the Springate model showed the lowest accuracy compared to other models, with scores of 60.27%, 57.53%, 61.64%, and 60.27%, respectively. While it ranked second in accuracy in 2020, its performance declined, resulting in the lowest accuracy from 2021 to 2023.

Conclusion

The Covid-19 pandemic has had a significant impact on Indonesia's economic growth. Based on statistical data compiled by Badan Pusat Statistik (BPS), Indonesia's economic growth contracted by -2.07% nationally across all sectors in 2020. All expenditure components experienced a significant decline, including the property and real estate sectors. Indonesia's economy rebounded in 2021, with the economy growing by 3.70% and continuing to increase until 2022 to 5.31% (bps.go.id, 2025). A similar situation was also seen in companies in the property and real estate sector, where in 2020, 40% of companies recorded negative net profits. In 2021 and 2022, only 31% of companies remained in the red. And in 2023, 28% of companies still recorded losses. Continuous losses can potentially lead to bankruptcy. Bankruptcy is a term used to describe companies experiencing financial difficulties. Bankruptcy can be predicted several years in advance. This prediction can be made using a discriminant analysis approach with an emphasis on its compatibility with financial analysis ratios, thereby producing a model that can predict a company's bankruptcy risk level (Shi & Li, 2019). Four models for bankruptcy prediction Altman Z-Score, Springate, Taffler, and Zmijewski forecasts yielded divergent outcomes for 73 real estate enterprises from 2020 to 2023. According to the Altman Z-Score, most companies remained in the safe category, while the number of firms classified as vulnerable or bankrupt fluctuated annually. The Springate model tends to classify most companies as unhealthy, while the Taffler model indicates that the majority of companies are healthy, with a small number in the vulnerable and unhealthy categories. The Zmijewski model consistently indicates that most companies are healthy. Furthermore, some companies show an improving trend in financial condition, while others show a decline in scores, indicating an increasing risk of bankruptcy. The accuracy assessment indicates that the Taffler model regularly surpassed its competitors from 2020 to 2023, attaining accuracy rates ranging from 67.12% to 80.82%. Altman Z-Score and Zmijewski models were moderately accurate, whereas Springate was the least effective. Thus, the Taffler model is considered the most dependable for forecasting future bankruptcy in property and real estate firms throughout this timeframe.

Limitation

As other studies, this study also has limitations. These limitations may influence the assessment of the tested samples to be excessive or insufficient. Firstly, the tests were conducted over a specific period, which means that the data used may not reflect the overall situation of the company based on previous historical data. Second, the testing only used some types of bankruptcy prediction models, where there is still the possibility of other models with more complex variables that produce more accurate calculations. Finally, future research is expected to benefit from this study and use different measurement dimensions to enrich and expand knowledge on this topic.

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