Evaluating the Predictive Accuracy of Z-Score and Springate Models in Assessing Bankruptcy Risk in the Tourism and Recreation Industry

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ABSTRACT

All companies are inherently exposed to the risk of bankruptcy. The ability to anticipate such financial distress is critical and can be enhanced through the application of robust bankruptcy prediction models. This study aims to compare the effectiveness of two widely used models—the Altman Z-Score and the Springate model—in predicting bankruptcy within the Tourism and Recreation Industry. The research employs secondary data derived from the financial statements of companies listed in the Tourism and Recreation sector on the Indonesia Stock Exchange for the period 2020–2022. A total of 41 companies were selected using purposive sampling to ensure relevance to the research objectives. The data were analysed using the Mann–Whitney U test to determine whether a statistically significant difference exists between the predictive accuracies of the two models. The results indicate that the Altman Z-Score model demonstrates higher predictive accuracy than the Springate model. The statistical analysis further confirms a significant difference between the two models, underscoring the superior performance of the Z-Score in identifying bankruptcy risk. These findings suggest that the Altman Z-Score model offers a more reliable tool for predicting financial distress in the Tourism and Recreation Industry, providing valuable insights for investors, regulators, and corporate stakeholders.

Keywords: Bankruptcy; Altman; Springate

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ABSTRAK

Setiap perusahaan berpotensi mengalami kebangkrutan. Kebangkrutan dapat diprediksi menggunakan model prediksi kebangkrutan yang akurat. Studi ini dilakukan dengan tujuan membandingkan model yang yang lebih baik di antara model Altman Z-Score dan model Springate dalam memprediksi kebangkrutan. Studi ini memanfaatkan data sekunder yakni laporan keuangan perusahaan industri pariwisata dan rekreasi yang tercatat di Bursa Efek Indonesia pada periode 2020-2022. Sampel berjumlah 41 perusahaan yang ditetapkan melalui teknik purposive sampling. Pengujian hipotesis menggunakan Mann-Whitney. Temuan studi mengindikasikan adanya tingkat akurasi model Z-Score yang lebih tinggi dibanding tingkat akurasi model Springate. Penelitian menunjukkan adanya perbedaan signifikan antara model Z-Score dan model Springate. Temuan ini mengimplikasikan bahwa model Z-Score lebih baik digunakan dalam memprediksi kebangkrutan pada industri pariwisata dan rekreasi dibandingkan model Springate.

Kata Kunci: Kebangkrutan; Altman; Springate

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INTRODUCTION

Bankruptcy represents one of the most critical consequences faced by companies, particularly during periods of financial distress such as the global economic downturn in 2020. During this period, many firms that relied heavily on external financing—whether through bank loans or investor funding—experienced increasing difficulty in accessing capital. This financial strain contributed to widespread insolvency (Papana & Spyridou, 2020). The approach to managing bankruptcy varies across jurisdictions (Alam *et al.*, 2021). In Indonesia, the enforcement of Pembatasan Sosial Berskala Besar (PSBB) in 2020 compelled many businesses to suspend operations, scale back activities, and ultimately declare bankruptcy (Fajarsari & Martini, 2022).

According to Indonesia's Badan Pusat Statistik, the country's economic growth contracted by 2.07% in 2020. This decline placed substantial financial pressure on both large corporations and small enterprises. Recovery efforts commenced in 2021, supported by government initiatives such as the Pemulihan Ekonomi Nasional (PEN) program, which served as a stimulus to revive key sectors, notably the tourism and recreation industry that had been among the most affected by the pandemic.

By 2022, Indonesia began transitioning into a new normal, allowing previously restricted economic activities to resume. The tourism and recreation sector, in particular, exhibited notable growth. Statistics from Badan Pusat Statistik indicate that international tourist arrivals doubled in 2022 compared to the previous year, while domestic tourist numbers increased by over 100%. This sector's contribution to Indonesia's Gross Domestic Product (GDP) rose to 3.83% by September 2023, up from 3.6% in 2022. The Ministry of Tourism and Creative Economy also reported 11.68 million foreign tourist arrivals in 2023, exceeding the initial target of 6 to 8.5 million.

Despite this positive trajectory, the tourism and recreation industry continues to encounter structural challenges. From 2020 to 2022, 80 companies were flagged with special notations by the Indonesia Stock Exchange (IDX), seven of which operated within the tourism and recreation sector. Two firms—Saraswati Griya Lestari and Mas Murni Indonesia—faced potential delisting and were assigned Code 8, indicating bankruptcy filings. This contrast between sector-wide growth and individual firm distress highlights the uneven distribution of recovery and profitability.

The persistence of bankruptcy risk within a recovering sector illustrates that not all firms are able to capitalise on emerging opportunities. As noted by Astawa and Utama (2025), bankruptcy rarely occurs without warning. Instead, early signals can often be detected through appropriate financial analysis. One widely accepted method involves the use of financial statements to predict bankruptcy risk (Intansari *et al.*, 2020), given that financial information serves as a reliable means of conveying a company's underlying economic health (Ayu *et al.*, 2020).

Bankruptcy prediction enables firms and stakeholders to assess financial risk proactively, allowing timely interventions before conditions deteriorate. The significance of this area of research is underscored by the high incidence of corporate failures, which has led to extensive academic interest over the past several decades (Abdullah, 2021). For creditors and investors, accurate bankruptcy forecasting is essential to assess firm viability, particularly in uncertain economic environments (Vochozka *et al.*, 2020). These predictions also serve as a foundation for evaluating investment risk and expected returns (Winata *et al.*, 2025).

Financial statements, which encapsulate a firm's performance through comparative analysis of financial ratios, form the basis for most bankruptcy prediction models (Sari & Yasa, 2021). These models assist investors and creditors in identifying firms at risk, thereby minimising exposure to financial loss (Ogachi *et al.*, 2020). Among the most prominent models used for such predictions are the Altman Z-Score and the Springate model (Matejić *et al.*, 2022). The Z-Score, developed by Edward Altman in 1968, combines several financial ratios to estimate bankruptcy probability. In contrast, the Springate model, developed by Gordon Springate in 1978, employs stepwise multiple discriminant analysis to identify four key ratios that effectively distinguish between solvent and insolvent firms.

Both models generate predictive scores and are often considered complementary, with their combined use offering a broader perspective on financial distress (Matejić *et al.*, 2022). The integration of financial indicators from both models can provide firms with early warning signals, supporting strategic interventions to mitigate bankruptcy risk (Kassidy & Handoko, 2022).

This study employs the modified versions of the Z-Score and Springate models. For a bankruptcy prediction model to be effective, it must meet two core criteria: high predictive accuracy and ease of interpretation (Park *et al.*, 2021). Accurate models support stakeholders in making informed decisions, while interpretability ensures that financial statement users—including investors and creditors—can act decisively to mitigate potential risks (Saladin *et al.*, 2022).

The rationale for comparing these models stems from prior inconsistent findings. For instance, Rj Nur et al. (2022) found that Springate had a 100% accuracy rate compared to 75% for Z-Score in companies listed for delisting on the IDX in 2018. Wulandari and Maslichah (2021) similarly reported higher accuracy for Springate (68.49%) than for Z-Score (61.64%). Conversely, Artini and Astika (2024) found no significant difference between the two models, while Ilmiyono et al. (2021) reported equal accuracy rates of 93.3%. Other studies, including Madanika (2021) and Lutfiyyah and Bhilawa (2021), found that Z-Score outperformed Springate in various contexts, including global retail and sports sectors.

This study is grounded in signalling theory (Spence, 1973), which posits that the quality of information signals—such as those derived from financial models—affects how they are interpreted by decision-makers. Accurate signals are essential for distinguishing between firms that are financially stable and those at risk of failure (Harmadji *et al.*, 2018). Inaccurate or inconsistent signals may lead to flawed decision-making, underlining the need for reliable predictive tools.

Recent studies further illustrate this variance. Deepika et al. (2024) found significant differences in the predictive accuracy of Z-Score and Springate models. Marsenne et al. (2024) reported that Z-Score had 100% accuracy, while Springate achieved only 67%. Ilias et al. (2024), examining Malaysian firms, similarly concluded that Z-Score yielded more accurate predictions. In the retail sector, Fahma and Setyaningsih (2021) recorded Z-Score accuracy at 80%, compared to 70% for Springate. Arini (2021), studying the top 30 global retail companies, also found higher accuracy for Z-Score (73.3%) than Springate (70%).

Based on the preceding discussion and evidence, this study hypothesises that the Z-Score model has higher predictive accuracy than the Springate model in assessing bankruptcy risk within the tourism and recreation industry.

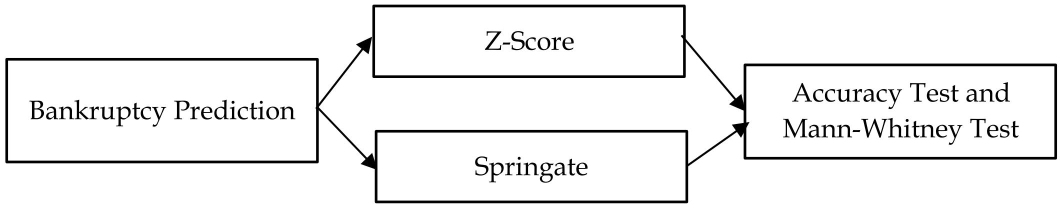

Image 1. Research Model

Source: Research Data, 2025

RESEARCH METHODS

The focus of this study is the prediction of bankruptcy among tourism and recreation industry companies listed on the Indonesia Stock Exchange (IDX) during the period 2020–2022. The initial population comprised 45 companies, with data drawn from published financial statements available on the official IDX website. The study employs a purposive sampling method, with the primary criterion being the availability of at least one financial statement for the period under review. Based on this criterion, a total of 41 companies were selected for analysis.

The study examines two bankruptcy prediction models: the modified Altman Z-Score and the Springate model. The Z-Score, originally developed by Edward Altman in 1968, was designed to assess bankruptcy risk in U.S. manufacturing firms. Altman employed Multiple Discriminant Analysis (MDA) to identify key financial ratios that could differentiate between solvent and insolvent firms (Brygała & Korol, 2024). Over time, the Z-Score model has served as a foundational tool for numerous subsequent models developed by economists seeking to refine bankruptcy prediction techniques (Jaki *et al.*, 2020).

To enhance its applicability across various sectors, Altman later introduced a modified version of the model, known as the Z"-Score. This third iteration reduced the number of financial ratios from five to four, eliminating the sales-to-total-assets ratio due to its sectoral sensitivity and reduced reliability in certain contexts, particularly where sales volumes are highly variable across industries or regions (E. I. Altman & Hotchkiss, 2006). As such, the Z"-Score was designed to be more universally applicable, including for service-oriented sectors like tourism and recreation, where the sales ratio may not consistently reflect financial health.

$Z'' = 6{,}56X_1 + 3{,}26X_2 + 6{,}72X_3 + 1{,}05X_4$ ……………………………………………………..(1)

Where:

Z'': Modified Altman Z-Score

X_1: Working Capital to Total Assets

X_2: Retained Earnings to Total Assets

X_3: Earnings before Interest and Taxes to Total Assets

X_4: Book Value of Equity to Total Liabilities

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Interpretation of Z”-Score:
Z”-Score > 2.60, healthy/non-bankrupt
1,10<Z”-Score<2.60, grey area
Z”Score<1.10, bankrupt

The Springate model was developed by Gordon Springate (1978) using stepwise multiple discriminant analysis to select four ratios considered most effective in categorizing healthy and failing companies (Bărbuță-Mișu & Madaleno, 2020).

S = 1,03A + 3,07B + 0,66C + 0,4D
Where:
S : Springate score
A: Working Capital to Total Assets
B: Earnings before Interest and Taxes to Total Assets
C: Earnings before Taxes to Current Liabilities
D: Sales to Total Assets
Interpretation of Springate Score:
S > 0,826, healthy/safe
S <= 0,826, bankrupt

Each model is analyzed for its level of accuracy using confusion matric. Accuracy test refers to the percentage that a model is able to correctly predict actual outcomes (Sammut & Webb, 2017:8). The percentage indicates how accurate the model is (Rahman, 2021). The accuracy rate is calculated using the following formula:

Accuracy Rate: $\frac{TP+TN}{TP+FP+FN+TN}\,x\ 100\%$..(2)

Table 1. Confusion Matrix for Accuracy Test

		Springate’s Prediction	
		Non-Bankrupt	Bankrupt
Actual	Non-Bankrupt	True Negative (TN) Correct Absence of Result	False Positive (FP) Unexpected Result
	Bankrupt	False Negative (FN) Missing Result	True Positive (TP) Correct Result

Source: Research Data, 2025

Where:
True Positive (TP) : Predicted bankrupt, actually bankrupt.
True Negative (TN) : Predicted non-bankrupt, actually non-bankrupt.
False Positive (FP) : Predicted bankrupt, actually non-bankrupt.
False Negative (FN) : Predicted non-bankrupt, actually bankrupt.

The classification in this study assigns a value of “0” to companies deemed non-bankrupt and “1” to those classified as bankrupt. A company is categorised as bankrupt if it meets two conditions: it has incurred losses for two consecutive years (Fathi & Jean-Pierre, 2001) and has experienced a temporary trading suspension on the Indonesia Stock Exchange (IDX). The analytical procedures employed include descriptive statistical analysis, normality testing, model accuracy testing, and the Mann–Whitney U test. The hypothesis is supported if the Z"-Score model exhibits higher predictive accuracy than the Springate model and if a statistically significant difference exists between the two.

RESULTS AND DISCUSSIONS

In the classification of prediction outcomes, the modified Z"-Score model uses the following thresholds: a score below 1.10 indicates a company is in the bankruptcy zone; a score between 1.10 and 2.60 represents the grey area; and a score above 2.60 suggests a healthy financial condition. In contrast, the Springate model classifies companies with a score below 0.862 as bankrupt and those above 0.862 as non-bankrupt. For consistency in analysis, companies in the healthy and grey zones are coded as "0" (non-bankrupt), while those in the bankruptcy zone are coded as "1" (bankrupt).

Table 2. Z-Score Prediction

Companies	Z"-Score	Code (Z")	Companies	Z"-Score	Code (Z")
AKKU	2,322	0	KOTA	4,335	0
ARTA	15,381	0	KPIG	4,965	0
BAYU	5,189	0	LUCY	4,061	0
BLTZ	-3,419	1	MAMI	2,776	0
BOLA	15,868	0	MAPB	0.052	1
BUVA	-9,013	1	MINA	18,244	0
CLAY	-3,868	1	NATO	477,461	0
CSMI	-5,418	1	PANR	0,015	1
DFAM	0,299	1	PDES	-2,597	1
EAST	15,069	0	PGLI	2,883	0
ENAK	-1,025	1	PJAA	0.610	1
ESTA	3,953	0	PLAN	0,208	1
FAST	0,459	1	PNSE	0,939	1
FITT	-0,508	1	PSKT	3,094	0
GWSA	15,409	0	PTSP	-0,294	1
HOTL	0,531	1	PZZA	1,113	0
HRME	1,707	0	RAFI	9,754	0
JGLE	2,232	0	SHID	1,929	0
JIHD	3,114	0	SNLK	3,867	0
JSPT	2,267	0	SOTS	0,509	1
KDTN	7,765	0			

Source: Resarch Data, 2025

Table 3. Springate Prediction

Companies	Springate	Code (S)	Companies	Springate	Code (S)
AKKU	-0,051	1	KOTA	-0,12	1
ARTA	-0,211	1	KPIG	0,142	1
BAYU	0,992	0	LUCY	0,848	1
BLTZ	-0,646	1	MAMI	-0,242	1
BOLA	2,012	0	MAPB	0,273	1
BUVA	-1,698	1	MINA	-1,156	1
CLAY	-0,879	1	NATO	-0,335	1
CSMI	-0,906	1	PANR	-0,149	1
DFAM	-0,157	1	PDES	-0,912	1
EAST	1,245	0	PGLI	1,466	0
ENAK	0,143	1	PJAA	-0,164	1
ESTA	0,519	1	PLAN	-0,268	1
FAST	0,158	1	PNSE	-0,252	1
FITT	-0,873	1	PSKT	-0,328	1
GWSA	0,198	1	PTSP	0,278	1
HOTL	-0,155	1	PZZA	0,536	1
HRME	-0,934	1	RAFI	2,095	0
JGLE	-0,888	1	SHID	-0,313	1
JIHD	0,023	1	SNLK	1,432	0
JSPT	-0,084	1	SOTS	-0,594	1
KDTN	2,392	0			

Source: Research Data, 2025

The bankruptcy predictions using the Z″-Score model for the 41 sampled companies indicate that 17 are classified as bankrupt, 6 fall within the grey area, and 18 are categorised as financially healthy or non-bankrupt. In contrast, the Springate model predicts a higher number of bankruptcies, identifying 34 companies as bankrupt and only 7 as non-bankrupt.

The descriptive statistical analysis provides an overview of the data distribution, including the minimum and maximum values, mean, and standard deviation. These metrics offer insights into the central tendency and variability of the financial ratios used in both models, serving as a preliminary step in evaluating the consistency and predictive capacity of the models under examination.

Table 4. Descriptive Statistics

	N	Minimum	Maximum	Mean	Standard Deviation
Z″-SCORE	41	-9.013	477.461	14.69868	74.309586
SPRINGATE	41	-1.698	2.392	0.06394	0.904891
Valid N	41				

Source: Research Data, 2025

The descriptive analysis results for the Z″-Score model, based on a sample of 41 companies, show a mean value of 14.69868 and a standard deviation of 79.309586. The standard deviation being significantly higher than the mean suggests considerable variability in the Z″-Score distribution, indicating that financial conditions among the sampled companies are highly dispersed.

Among the 41 companies, BUVA recorded the lowest Z″-Score at –9.013, placing it firmly within the bankruptcy zone. Conversely, NATO reported the highest Z''-Score at 477.461, categorising it as financially healthy and unlikely to face bankruptcy.

Similarly, the descriptive statistics for the Springate model reveal a mean score of 0.06392 and a standard deviation of 0.904891. Again, the standard deviation exceeding the mean indicates a wide spread in the financial health scores across the sample, highlighting the heterogeneity of the data.

BUVA also recorded the lowest Springate score at –1.698, consistent with the Z''-Score result, and was thus predicted bankrupt for the period 2020–2022. In contrast, KDTN achieved the highest Springate score at 2.392, indicating a strong financial position and a non-bankrupt classification. These results further illustrate the differing performance of firms within the tourism and recreation sector over the study period.

Table 5. Actual Data

AKKU	NB	ESTA	NB	KOTA	NB	PJAA	NB
ARTA	NB	FAST	NB	KPIG	NB	PLAN	NB
BAYU	NB	FITT	B	LUCY	NB	PNSE	B
BLTZ	B	GWSA	NB	MAMI	NB	PSKT	NB
BOLA	NB	HOTL	B	MAPB	NB	PTSP	B
BUVA	B	HRME	NB	MINA	NB	PZZA	NB
CLAY	B	JGLE	NB	NATO	B	RAFI	NB
CSMI	B	JIHD	NB	PANR	NB	SHID	B
DFAM	NB	JSPT	B	PDES	NB	SNLK	NB
EAST	NB	KDTN	NB	PGLI	NB	SOTS	B
ENAK	NB			PJAA	NB		

Sumber: Data Penelitian, 2025

Where:

B= Bankrupt

NB= Non-Bankrupt

A total of 12 companies were actually bankrupt, while 29 companies were non-bankrupt. The actual data was compared with the prediction results using confusion matrix to evaluate the accuracy level of each model.

Table 6. Confusion Matrix of Z″-Score

		Z″-Score Prediction		
		Non-Bankrupt	Bankrupt	Total
Actual	Non-Bankrupt	21	8	29
	Bankrupt	3	9	12
Total		24	17	41

Source: Research Data, 2025

Z″-Score predicted 24 companies as non-bankrupt, of which 21 were accurate and 3 were not. Z″-Score predicted 17 companies as bankrupt, of which 9 were accurate and 8 were not. Therefore, the Z″-Score model made accurate predictions for 30 out of 41 companies. Based on this data, the accuracy test was carried out using the following formula.

Accuracy Rate = $\frac{21+9}{9+8+3+21} x\ 100\% = 73{,}2\%$

Table 6. Confusion Matrix of Springate

		Springate Prediction		
		Non-Bankrupt	Bankrupt	Total
Actual	Non-Bankrupt	7	22	29
	Bankrupt	0	12	12
Total		7	34	41

Source: Research Data, 2025

Springate predicted 7 companies as non-bankrupt, all of which were accurate. Springate predicted 34 companies as bankrupt, of which 12 were accurate and 22 were not. Therefore, the Springate model made accurate predictions for 19 out of 41 companies. Based on this data, the accuracy rate is calculates using the following formula.

Accuracy Rate = $\frac{12+7}{12+22+7+0} x\ 100\%$ = 46,3%

The accuracy test results show that Z"-Score model is more accurate, with an accuracy rate of 73.2%, while Springate has an accuracy rate of 46.3%. Z"-Score successfully predicted 30 companies out of 41 companies and Springate successfully predicted 19 companies out of 41 companies.

Table 7. Mann-Whitney Test

Test Statistics[a]	
	SCORE
Mann-Whitney U	416,000
Wilcoxon W	1277,000
Z	-3,937
Asymp. Sig. (2-tailed)	0,000
a. Grouping Variable: MODEL	

Source: Research Data, 2025

Referring to the results of the Mann–Whitney test, the Asymp. Sig. (2-tailed) value is 0.000, which is below the 0.05 significance threshold. This indicates a statistically significant difference between the Z″-Score and Springate models in predicting bankruptcy among companies in the tourism and recreation industry. The finding suggests that the two models apply fundamentally different approaches in classifying firms as either financially sound or at risk of bankruptcy.

The accuracy test further supports this conclusion. The Z″-Score model achieved an accuracy rate of 73.2%, compared to 46.3% for the Springate model. Coupled with the Mann–Whitney results, these findings confirm that the Z″-Score model performs significantly better in predicting bankruptcy within the observed industry. Accordingly, the hypothesis that Z″-Score has greater predictive accuracy than Springate is accepted.

These findings are consistent with previous research. Deepika et al. (2024) reported a higher accuracy rate for Z-Score at 78%, compared to 70.7% for Springate. Similarly, Madanika (2021) found the Z-Score model more accurate (73.7%) than Springate (70%). Lutfiyyah & Bhilawa (2021) also noted Z-Score's higher predictive capability (71% vs. 66%). Pelitawati & Kusumawardana (2020) concluded that the Z-Score model offered superior accuracy, while Marsenne *et al.*. (2024) reported Z-Score accuracy at 100%, compared to 67% for Springate. Rachmandika *et al.*. (2024) further supported this with findings of 81% accuracy for Z-Score and only 24% for Springate.

These results align with signalling theory, which posits that financial information acts as a signal to investors and creditors. In this context, a reliable bankruptcy prediction model serves as a credible signal of a firm's financial condition. A score that places a company in the "safe zone" provides a positive signal, encouraging investment and lending. Conversely, a score indicating bankruptcy acts as a negative signal, cautioning stakeholders against potential financial risk. The superior performance of the Z″-Score model in this study implies that it offers a more accurate and thus more valuable signal to financial statement users in the tourism and recreation industry.

SUMMARY

Based on the findings and discussion of bankruptcy prediction accuracy among tourism and recreation industry companies listed on the Indonesia Stock Exchange during the 2020–2022 period, the results indicate that the Z″-Score model outperforms the Springate model in predicting bankruptcy. The Z″-Score demonstrates higher accuracy and stronger discriminatory power in identifying firms at risk of financial distress within this sector.

Future research may consider comparing the predictive performance of the Z″-Score model under varying economic conditions, particularly distinguishing between periods of economic stability and crisis. Additionally, extending the study period beyond 2022 could provide more up-to-date insights and capture post-pandemic economic dynamics, offering a broader understanding of the model’s applicability in different macroeconomic contexts.

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