# **CHAPTER FOUR**

# Accuracy of Bankruptcy Prediction Models in Forecasting Company Delisting During an Economic Crisis: Evidence from Sri Lanka

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#### Abstract

This study aims to investigate the validity of Altman's Z-score model and Zmijewski's X-score model as a tool for predicting the delisting risk of Sri Lankan companies. Although the two models have been frequently tested for assessing financial distress, their effectiveness in predicting delisting remains under-researched, particularly in terms of their predictive capability during economic crisis conditions. Sri Lanka has been experiencing a severe economic and political crisis since 2019, and listed companies have been constantly threatened with survival during this period. Considering the data availability, 18 delisted companies were selected as the sample of delisted companies, and data were collected two years prior to the company's delisting. For comparison purposes, 18 non-listed companies were also selected based on their highest market capitalisation, considering their unlikelihood of delisting in the near future. The results showed that the revised Altman's Z-score model has a higher accuracy rate of 69.45% compared to the Zmijewski X-score model, which has an accuracy rate of 63.89%. The Chi-square model's results indicate a relationship between Altman's Z-score model and the delisting status of the companies, but no relationship between the Zmijewski X-score model and delisting. Additionally, Altman's Z-score model is more accurate in predicting delisting than the Zmijewski X-model. The study contributes to validating the bankruptcy prediction models as a tool for delisting prediction and recommends the revised Altman's Z'score model as a predictor of delisting companies in the Sri Lankan context..

**Keywords:** Altman's Z-score model, Bankruptcy, Delisting, Financial distress, Zmijewski X-score model

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### 1. Introduction

The delisting of companies from stock exchanges is a pivotal event in financial markets, signifying the removal of a publicly traded entity and its subsequent exemption from the regulatory frameworks and reporting obligations that govern listed firms (Martinez & Serve, 2017) Several reasons may cause a company to become delisted: voluntary delisting, mergers or acquisitions, and failure to meet the listing requirements set by the stock exchange (Bortolon & Silva, 2015). These requirements typically include maintaining minimum levels of financial performance, adhering to reporting and disclosure obligations, and meeting corporate governance standards. Another reason is financial distress (Croci & Giudice, 2014). If a company experiences financial difficulties, such as bankruptcy or insolvency, it may be delisted from the exchange. In such cases, the company's shares may be removed from the exchange as part of a restructuring process or liquidation (Chan, 2016). Accordingly, the majority of reasons for a company's delisting indicate financial distress and failure to meet listing requirements (Martinez & Serve, 2017; Wang & Campbell, 2010). Understanding the factors that contribute to a company's delisting and accurately predicting its likelihood can provide valuable insights into market dynamics, economic conditions, and managerial effectiveness.

As of May 31, 2023, the Colombo Stock Exchange (CSE) comprises 289 firms across 20 GICS industry categories, with a total market capitalisation of Rs. 3,598.30 billion (CSE, 2023). According to the information published by CSE, 100 companies were delisted from the CSE as of June 30, 2021, and by May 31, 2022, this number had increased to 106. Moreover, the number of companies going delisted is increasing day by day. The accurate prediction of financial distress and potential delisting of companies holds significant importance for investors, creditors, regulators, and other stakeholders. The ability to identify and forecast companies at risk of delisting provides valuable insights for making informed investment decisions, managing credit risk, and implementing proactive measures to mitigate financial distress.

Altman's Z-score model and Zmijewski's X-score model are two prominent models developed primarily to predict financial distress, including bankruptcy. The Altman Z-score model and Zmijewski X-score model have historical significance in assessing financial health and have also been applied to predict delisting events. However, while both models have proven their worth in bankruptcy prediction, their application in predicting delisting events necessitates further investigation. Delisting does not necessarily equate to bankruptcy, and companies may exit public trading for reasons unrelated to financial distress (Celli, 2015; Grice Jr & Dugan, 2003; Gunathilaka, 2014; Kpodoh, 2010; Nanayakkara & Azeez, 2015; Pavlović et al., 2012;

Radivojac et al., 2021). However, Previous studies (Benny & Hutagaol, 2013; Bortolon & Silva, 2015) show that profitability and liquidity are determining factors for most delisting and are also commonly associated with bankruptcy. Thus, it is reasonable to assume that bankruptcy models can be used for predicting delisting; however, very few studies have tested the validity of these models for such predictions, particularly in a country facing an economic crisis, such as Sri Lanka.

This research aims to contribute to the existing body of knowledge by evaluating the accuracy of the Altman Z-score model and the Zmijewski model in predicting delisting. By examining the model's performance against real-world delisting outcomes, this study aims to illuminate the model's strengths, limitations, and potential areas for improvement. While numerous researchers have attempted to develop these models and validate their effectiveness (Hari et al., 2019; Nenengsih, 2018), findings have often varied across different countries and time periods. This inconsistency raises questions about the reliability and applicability of established models in diverse market environments. Thus, this study addresses a significant gap in the existing literature on delisting prediction models, particularly in emerging economies, where such research is rare. Notably, selecting Sri Lanka as the context for this study contributes to the literature by enabling the investigation of the delisting prediction capabilities of these models in an economic crisis setting. Given these perspectives, it is crucial to investigate delisting within the Sri Lankan context while understanding delisting dynamics and enhancing the predictive frameworks in a region where such insights are sorely needed.

The organisation of the study is as follows: Following the introduction, a review of the literature on bankruptcy theories and prediction models will be presented. The methodology section will succeed this. The subsequent section presents the results and their discussion. Finally, the concluding remarks will be provided, along with suggestions for future research.

# 2. Literature Review

Delisting a company from a stock exchange is a complex process influenced by various factors. Several financial and economic theories and concepts are relevant to understanding the reasons and implications of delisting. These theories affect the predictability of delisting possibilities.

### **Signalling Theory**

Signalling Theory, as articulated by Ross (1977), stated that "company management benefits from the information they possess and share with investors." The information is primarily

related to the company's financial and operational performance, which in turn influences expectations about prospects and, consequently, impacts the company's stock price. Information serves as a crucial asset for investors, encompassing insights into a company's current status, historical performance, and even its prospects. The information should be valuable if it meets criteria such as relevance, accuracy, timeliness, and completeness. Investors use this information as a tool for analysis when making financial market decisions. Through the publication of information announced in the media, investors may receive a positive or negative signal that affects their investment decision (Endri et al., 2020). The level of trading activity in stocks serves as a reflection of the market's response to economic conditions. When the information provided contains a positive signal, the company has more favourable expectations for the future. According to Endri et al. (2020), market efficiency will reveal the connection between publicly disclosed information, including financial, political, environmental, and social reports, and its impact on fluctuations in stock trading volume. According to signalling theory, companies exhibit early signs of financial distress.

# **Early Warning System Theory**

An early warning system (EWS) is another theory that detects and anticipates potential risks or threats, enabling timely intervention and mitigation. EWS is employed in various domains, including financial crises. Duwipa (2013) defined the EWS as a series of systems that function to notify the occurrence of an event, which can be natural or social in nature. Early warning activities provide information in a clear and easily understood language. Since signal models can also be viewed as a type of trend analysis, the Early Warning System (EWS) can be considered a 'development of the form of signal theory'. Mainly, the EWS model was developed to anticipate economic crises (Berg et al., 2005; Kaminsky & Reinhart, 1999)

Both of these theories are grounded in the fact that reliable, accurate information on company performance signals potential distress, such as the possibility of delisting. However, the usefulness of the data for its user depends on the predictive model used to analyse the relevant data. Bankruptcy prediction models, such as the revised Altman Z-score model and Zmijewski X-score model, which utilise a range of financial ratios to predict financial distress, have the potential to be used to predict delisting possibilities due to financial distress. However, their suitability for predicting delisted companies should be further ascertained.

### Altman's Model and Zmijewski Model for Delisting Prediction

The prediction of a firm's delisting, financial distress, or bankruptcy is significant for many parties, including investors, creditors, suppliers, and customers. Companies often end up in bankruptcy due to economic distress stemming from a decline in industry operating income

and poor management, resulting from consistently negative operating income over five years (Whitaker, 1999). Delisting and bankruptcy are two significant events that, although distinct in nature, share certain similarities in the corporate world. Both processes often signify a company's financial distress.

Many studies have examined the ability of Altman's Z-score model and the Zmijewski model to predict bankruptcy, while few researchers have investigated whether these models can also be used to predict delisting (Anugrah, 2019; Fatmawati, 2012; Husein & Pambekti, 2014; Nenengsih, 2018). Fatmawati (2012) investigated the empirical evidence that the Zmijewski model, the Altman model, and the Springate models could be used as predictors of a company's delisting. He collected samples randomly during the same timeframe when the company was delisted and used the logistic regression method for analysis. The results showed that among the three predictor models for delisting, only the Zmijewski model could effectively predict companies delisted during the observation period. Neither the Altman model nor the Springate models could be used effectively as predictive models for delisting (Fatmawati, 2012). Confirming the results of his study, Husein and Pambekti (2014) and Nenengsih (2018) pointed out that the Zmijewski model can be used to predict bankruptcy. Apart from Fatmawati (2012), they tested one additional bankruptcy model (the Grover model) in their study. According to their results, the Zmijewski model stands out as the most suitable model for predicting delisting due to its high level of significance compared to the other models (Husein & Pambekti, 2015). Additionally, the Zmijewski X-score model is used to emphasise the leverage ratio as an indicator of financial distress in companies. The greater the amount of debt, the more accurate the prediction of the company's delisting (Fatmawati, 2012). According to Fatmawati's (2012) opinion, the Altman Z-model and the Springate Xscore model are also less suitable for predicting delisting because these models emphasise profitability measures more than the Zmijewski model.

In contrast, some researchers pointed out that the Zmijewski X-score model is not suitable for predicting delisting, and Altman's Z-score model is more suitable (Anugrah, 2019; Hadi & Anggraeni, 2008; Rachmania, 2016). Rachmania (2016) demonstrated that, among the modified Altman Z-score model, the Springate model, and the Zmijewski model, only the modified Altman Z-score model (3rd version) and the Springate model could be used to predict delisting companies. As a reason for this, he mentioned that the modified Altman Z-score model and the Springate model showed a completeness ratio when compared to the Zmijewski model. Additionally, a similar study was conducted by Hadi & Anggraeni (2008), who concluded that, among bankruptcy prediction models, the Altman Z-score model is the most effective predictor, while the Zmijewski model does not predict delisting. Additionally, research conducted by Anugrah (2019) showed that both the Altman X-score and Taffler

models are significantly better compared to the Zmijewski X-score model. According to the literature reviews, various researchers offer differing opinions regarding the prediction model for delisting. Therefore, it is essential to assess the accuracy of Altman's Z-score model in identifying companies for delisting in the Sri Lankan context.

Several studies have attempted to develop an early warning system model to predict delisting (Endri et al., 2020; Hari et al., 2019; Hwang et al., 2014). Endri et al. (2020) developed an early warning system model for detecting the potential delisting of the Indonesian Sharia Stock Index. They utilised Support Vector Machines (SVM) to develop this model, incorporating several financial ratios, including debt-to-equity, return on invested capital, quick ratio, asset turnover ratio, current ratio, return on assets, return on equity, leverage, long-term debt, and interest coverage. Most of these ratios are also contained in Altman's Zscore model. Similarly, Hari et al. (2019) developed a delisting prediction model employing logistic regression. In this study, the same financial ratios and sample were used to develop the model, as done by Endri et al. (2020). However, they developed the prediction model with a higher level of accuracy, 93.85%. In 2014, Hwang et al. (2014) developed a delisting prediction model based on non-financial information. The use of non-financial information in the delisting model holds greater significance, as it can provide a broader range of stakeholders with advanced indicators for anticipating delisting events. Their results suggested that shareholders should closely consider many qualitative factors not reflected in financial statements to forecast delisting and thereby reduce the social drawbacks associated with delisting companies. Siripokakit (2005) attempted to develop an early warning sign to predict the probability of mandatory delisting from the stock exchange, examine the price and trading volume reactions to delisting, and investigate the macroeconomic conditions surrounding delisting.

Several previous studies conducted by different countries have tested the validity of bankruptcy models, including Altman's Z-score and Zmijewski's X-score model, in predicting the delisting status of companies. According to the literature reviews, different researchers offer various opinions regarding the prediction model for delisting. Existing research contradicts the idea that Altman's Z'-score model and Zmijewski's X-score model can be used to predict delisting companies. Notably, the accuracy of these models in predicting the delisting of companies operating during a national economic crisis has not been assessed yet, which is a significant research gap that this study aims to fill.

### 3. Methodology

This research is conducted using a predictive research design approach. The study aims to evaluate the effectiveness of Altman's Z-score model and Zmijewski X-score model in predicting outcomes related to delisting in a new context. A predictive research design is a type of research design that aims to predict future occurrences by identifying patterns and relationships in existing data. This type of research design is commonly employed in various fields, including economics, finance, healthcare, and social sciences. This research will use a quantitative research approach.

### 3.1. Model Explanation

### Altman's Z'-Score Model

Altman's Z-score model is predictive (a linear combination of several financial ratios) developed by Altman (1968) to predict the near-term likelihood of companies failing into bankruptcy or insolvency. He estimated the model using multiple discriminant analysis to derive a linear equation that combined multiple financial ratios, such as liquidity, leverage, and solvency. This Z-score value helps investors, creditors, and analysts make informed decisions about the company's financial health. The original model, developed in 1968, was for public manufacturing companies as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.99X_5$$
 (1)

Where:

 $X_1$  = Working Capital/ Total Assets

X<sub>2</sub> = Retained Earnings/ Total Assets

 $X_3$  = Earnings before Interest and Taxes/ Total Assets

X<sub>4</sub> = Market Capitalisation/ Total Liabilities

 $X_5$  = Total Sales/ Total Assets

Altman later revised the Z-score model for private firms (1982), non-manufacturing firms, and emerging markets in 2006.

For private manufacturing firms:

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.42X_4 + 0.998X_5$$
 (2)

For non-manufacturing firms:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$
 (3)

For emerging markets:

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$
 (4)

This study evaluates the revised Altman's Z-score model for non-manufacturing companies in Sri Lanka to predict the delisting of companies, as most delisted companies in the country are non-manufacturing companies.

Table 3.1: Revised Altman's Z-score cut-off points

Classification Zones	Z	Z-Score Models	
Classification Zolles	${f Z}$	<b>Z</b> '	Z''
Safe	> 2.99	> 2.90	> 2.60
Grey	1.81 - 2.99	1.23 - 2.9	1.1 - 2.6
Distress	< 1.8	< 1.23	< 1.10

Source: Altman (2006)

# Zmijewski X-Score Model

Zmijewski employs ratio analysis to measure a company's performance, leverage, and liquidity in predicting bankruptcy (Zmijewski, 1984). Using the financial ratios formulated by Zmijewski, the status of a company can be predicted using two classifications, namely, distress and non-distress. Zmijewski estimated the model using probit analysis, which weights the log-likelihood function by the ratio of the population frequency rate to the sample frequency rate of the individual groups, bankrupt and non-bankrupt (Belyaeva, 2014). The formula used is:

$$X-Score = -4.3 - 4.5X_1 + 5.7X_2 - 0.004X_3$$
 (5)

X1 = Net Income/ Total Assets

X2 = Total Liabilities / Total Assets

X3 = Current Assets/ Current Liabilities

Table 3.2: Zmijewski X-score Cut-off Points

Classification Zones	X-Score
Distress	X > 0
Non-Distress	X < 0

Source: Zmijewski (1984)

### 3.2. Variables Calculations

### Variables Calculation of revised Altman's Z"- score model

Revised Altman's Z''-score model (2006) is based on four variables, each one representing a financial ratio. The following table shows how each variable is measured and the sources that will collect data for the study.

Table 1.3: Variables Calculation- Altman's Z"-score model

Variables	Sign	Measurement/ Reference	Source
WCTA	$X_1$	Working capital  Total assets	Annual reports of delisted & listed companies
RETA	$X_2$	Retained earnings Total assets	Annual reports of delisted & listed companies
EBITA	$X_3$	Earnings before interest and tax Total assets	Annual reports of delisted & listed companies
MVETL	$X_4$	Market value of equity  Total liabilities	Annual reports of delisted & listed companies

Source: Altman (2006)

# Variables Calculation of the Zmijewski X-score Model

The Zmijewski X-Score model (1984) is based on three variables, each representing a financial ratio. The following table shows how each variable is measured and the sources that will collect data for the study.

Table 3.2: Variables Calculation- Zmijewski X-Score model

Variables	Sign	Measurement	Source
ROA	$X_1$	Net income Total assets	Annual reports of delisted & listed companies
TLTA	$X_2$	Total liabilities  Total assets	Annual reports of delisted & listed companies
WC	$X_3$	Current liabilities	Annual reports of delisted & listed companies

Source: Zmijewski (1984)

#### 3.3. Data Collection Method

Secondary data were mainly collected using the financial statements of delisted and listed companies in Sri Lanka. Secondary data sources (data from delisted companies) do not provide data to data collectors directly because, after companies are delisted, the Colombo Stock Exchange removes the financial statements of those delisted companies from its official website (the CSE library). Therefore, the data used in this study were collected from the websites of delisted companies, as well as some other websites, such as 'investing.com'. The data of the listed companies were collected from the CSE website.

### 3.4. Population and Sampling

The study population comprises all delisted and listed companies in Sri Lanka as of May 31, 2023. As of May 31, 2022, the number of delisted companies is 106. This study uses a purposive sampling technique as a sampling approach. Specific considerations or criteria guide the selection of the sample. The criteria used to select the delisted company sample in this study are as follows:

- a) Should be a company which have been delisted from the Colombo Stock Exchange as of 31<sup>st</sup> May 2023.
- b) Should be a company whose financial data for three consecutive years prior to the stated delisted date by the Colombo Stock Exchange (CSE) is publicly available.

Only 18 companies met the above criteria out of the delisted companies as of May 31, 2023. Data were collected from the annual report of the 3 years preceding the company's delisting. Therefore, the sample size of this study consists of 72 observations drawn from the company's financial statements. To further maintain the accuracy of the study and for comparison purposes, the study collected data from 18 listed companies (which have managed to maintain their listing continuously). These companies were selected based on the highest market capitalisation criteria. Eighteen non-manufacturing listed companies that recorded the highest market capitalisation as of October 5, 2023, were selected, considering their likelihood of not being subject to delisting in the near future due to their higher market capitalisation. Additionally, non-manufacturing companies were selected because this study evaluates the revised Altman's Z-score model, which is typically used for non-manufacturing companies.

### 3.5. Data Analysis Methods

Secondary data collected via the financial statements of both listed and delisted companies were analysed using Excel. Furthermore, test the accuracy of Altman's Z''-score model and Zmijewski's X-score model to answer the hypothesis that is proposed in this study. The

hypothesis was checked by using the Chi-square test. The prediction results' distress or not distress' were determined by looking at the cut-off point of both models. Then, the accuracy level of the model is calculated by comparing the number of correct predictions with the number of samples.

### **Accuracy Level Model**

The method used by Najib & Cahyaningdyah (2020) to calculate the accuracy level is employed in this study to assess the accuracy of Altman's Z-score model in predicting delisting.

$$Model's\ Accuracy = \frac{Prediction's\ Correct}{Number\ of\ Samples}*100\%$$

# 3.6. Hypothesis Development

This research aimed to check the accuracy level of Altman's Z''-score and Zmijewski's X-score model in predicting delisting companies in Sri Lanka. The model achieves the highest level of accuracy, enabling it to predict the delisting experienced by the company. Therefore, the proposed hypothesis is as follows:

H<sub>0</sub>: Altman's Z"-score model and Zmijewski's X-score model do not have predictive ability in accurately identifying the likelihood of company delisting in Sri Lanka..

H<sub>1</sub>: Altman's Z"-score model and Zmijewski's X-score model have predictive ability in accurately identifying the likelihood of company delisting in Sri Lanka.

The hypothesis is tested by comparing the calculated chi-square value to the critical value (tabular value). The critical value depends on the significance level and the degrees of freedom of the data set. If the calculated chi-square value is greater than the critical value, then the null hypothesis is rejected, and the alternative hypothesis is accepted.

### 4. Results and Discussion

The data were analysed using Altman's Z-score model and Zmijewski X-score model for 36 companies, including delisted and listed companies. This section of the study provides an overview of the study variables, Altman's Z-score model, and Zmijewski X-score model. Finally, a detailed examination of the analysis's outcomes is presented.

### 4.1. Altman's Z"-Score Values for Delisted Companies

Table 4.1 is the result of the calculation of Altman's Z"-score values for delisted companies from the Colombo Stock Exchange. According to the calculated Z-scores for the past 3 years, out of 54 results, 21 results fall within the safe zone, and 33 results fall within the moderate and distress zones. This means Altman's Z-score model gave 33 correct predictions and 21 incorrect predictions for delisted companies.

Table 4.1: Calculated Altman's Z"-score values for Delisted Companies

No.	Company	Company Code	Altman Z-Score		
NO.	Company	Company Code	t-1	t-2	t-3
DL1	AIA Insurance Lanka PLC	CTCE	1.01	1.80	0.65
DL2	Arpico Finance Company PLC	ARPI	4.90	4.74	2.79
DL3	Commercial Leasing Company PLC	COML	0.44	-0.52	0.09
DL4	Hotel Developers (Lanka) PLC	HDEV	13.49	15.16	15.47
DL5	Huejay International Investments PLC	HUEJ	-10.84	-9.50	-8.18
DL6	Morison PLC	MORI-N	1.04	3.34	4.80
DL7	MTD Walkers PLC	KAPI	-43.66	-1.60	-1.68
DL8	Orient Finance PLC	ORIN	0.67	4.81	4.59
DL9	Prime Finance PLC	GSF	2.46	1.59	-1.07
DL10	Property Development PLC	PDL	6.90	6.26	6.88
DL11	Trade Finance and Investments PLC	TFIL	0.18	-0.06	0.07
DL12	Beruwala Walk Inn PLC	BINN	-5.22	-5.14	0.43
DL13	Ceylon Leather Product PLC	CLPL	6.64	4.86	2.46
DL14	Entrust Securities PLC	ESL	-15.69	-15.51	-29.87
DL15	Finlays Colombo PLC	JFIN	16.62	10.30	8.95
DL16	Kalpitiya Beach Resort PLC	CITK	-1.21	-0.72	-1.38
DL17	Kuruwita Textile Mills PLC	KURU	-0.53	-0.82	-0.51
DL18	Metropolitan Resource Holding PLC	MPRH	20.59	29.54	13.70

**Source:** Author Calculations

# 4.2. Test Altman's Z''-score Values for Listed Companies

Table 4.2 is the result of the calculation of Altman's Z"-score values for listed companies from the Colombo stock exchange. Here, listed companies were selected based on the highest market capitalisation criteria, as those companies are unlikely to delist in the near future due to their higher market capitalisation. According to the calculated Z-scores for the past 3 years, out of 54 results, 41 results fall within the safe zone, and 13 results fall within the moderate and distress zones. This means that Altman's Z-score model made 41 correct predictions and 13 incorrect predictions for the listed companies.

Table 4.2: Calculated Altman's Z''-score values for listed companies

No	Company	Crombal	Alt	Altman Z-Score		
No.	Company	Symbol	t-1	t-2	t-3	
L1	John Keells Holdings PLC	JKH.N0000	7.48	7.64	56.45	
L2	Expolanka Holdings PLC	EXPO.N0000	3.63	3.02	1.34	
L3	LOLC Holdings PLC	LOLC.N0000	4.05	3.34	1.24	
L4	Sri Lanka Telecom PLC	SLTL.N0000	53.70	39.08	37.44	
L5	LOLC Finance PLC	LOFC.N0000	0.85	0.98	0.60	
L6	Commercial Bank of Ceylon PLC	COMB.N0000	3.06	4.18	2.64	
L7	Melstacorp PLC	MELS.N0000	1.98	3.03	7.54	
L8	Browns investments PLC	BIL.N0000	-0.68	4.08	0.78	
L9	Sampath Bank PLC	SAMP.N0000	3.77	5.53	3.32	
L10	Hatton National Bank PLC	HNB.N0000	1.52	1.49	1.39	
L11	Lanka IOC PLC	LIOC.N0000	2.97	1.14	2.82	
L12	Aitken Spence PLC	SPEN.N0000	7.81	7.59	5.63	
L13	Carson Cumberbatch PLC	CARS.N0000	22.66	20.99	14.51	
L14	Valibel One PLC	VONE.N0000	20.70	34.88	8.42	
L15	Ceylinco Insurance PLC	CINS.N0000	9.81	3.29	3.09	
L16	C T Holdings PLC	CTHR.N0000	11.61	58.72	56.41	
L17	Hemas Holdings PLC	HHL.N0000	14.31	61.02	25.37	
L18	Richard Pieris and Company PLC	RICH.N0000	2.28	3.91	1.30	

**Source:** Author Calculations

In Table 3.1, based on Altman's Z''-score model cut-off points, a Z" greater than 2.6 is a safe zone (companies that are not bankrupt), and less than 1.1 is a distressed zone (companies that go bankrupt). The value between 2.6 and 1.1 is a grey zone (cannot determine whether the company will go bankrupt or not). When applying this model to predict delisted companies, if the value of Z"> 2.6 means 'listed', Z''< 1.1 'delist' and 1.1 < Z''< 2.6 means 'can't be determined whether the company will go delisted or not'. Here, Altman's z-score value is calculated for three years because Altman's model has the ability to predict bankruptcy three years prior to the company's bankruptcy.

# 4.3. Zmijewski X-Score values for Delisted Companies

Table 4.3 is the result of the calculation of Zmijewski X-score values for delisted companies from the Colombo Stock Exchange. According to the calculated X-scores for 2 years, out of 36 results, 18 results were distress and 18 results were non-distress. This means the Zmijewski X-score model gave 18 correct predictions and 18 incorrect predictions for delisted companies.

Table 4.3: Calculated Zmijewski X-score values for delisted companies

No.	Company	Company	Zmijewski x	-score results
NO.	Company	Code	t-1	t-2
DL1	AIA Insurance Lanka PLC	CTCE	Non-Distress	Non-Distress
DL2	Arpico Finance Company PLC	ARPI	Non-Distress	Non-Distress
DL3	Commercial Leasing Company PLC	COML	Distress	Distress
DL4	Hotel Developers (Lanka) PLC	HDEV	Distress	Distress
DL5	Huejay International Investments PLC	HUEJ	Distress	Distress
DL6	Morison PLC	MORI-N	Non-Distress	Non-Distress
DL7	MTD Walkers PLC	KAPI	Distress	Distress
DL8	Orient Finance PLC	ORIN	Non-Distress	Non-Distress
DL9	Prime Finance PLC	GSF	Non-Distress	Non-Distress
DL10	Property Development PLC	PDL	Non-Distress	Non-Distress
DL11	Trade Finance and Investments PLC	TFIL	Distress	Distress
DL12	Beruwala Walk Inn PLC	BINN	Distress	Distress
DL13	Ceylon Leather Product PLC	CLPL	Non-Distress	Non-Distress
DL14	Entrust Securities PLC	ESL	Distress	Distress
DL15	Finlays Colombo PLC	JFIN	Non-Distress	Non-Distress
DL16	Kalpitiya Beach Resort PLC	CITK	Distress	Distress
DL17	Kuruwita Textile Mills PLC	KURU	Distress	Distress
DL18	Metropolitan Resource Holding PLC	MPRH	Non-Distress	Non-Distress

**Source:** Author Calculations

# 4.4. Test Zmijewski X-Score Values for Listed Companies

Table 4.4 shows the calculation of Zmijewski X-score values for listed companies on the Colombo Stock Exchange. For two years, 36 X-scores were calculated: 11 were distressing, and 25 were non-distressing. This means the Zmijewski X-score model gave 5 correct predictions and 11 incorrect predictions for delisted companies.

Table 4.4: Calculated Zmijewski X-score values for listed companies

No.	Company	Cymbol	Zmijewski X-score results		
110.	Company	Symbol	t-1	t-2	
L1	John Keells Holdings PLC	JKH.N0000	Non-Distress	Non-Distress	
L2	Expolanka Holdings PLC	EXPO.N0000	Non-Distress	Non-Distress	
L3	LOLC Holdings PLC	LOLC.N0000	Non-Distress	Non-Distress	
L4	Sri Lanka Telecom PLC	SLTL.N0000	Distress	Distress	
L5	LOLC Finance PLC	LOFC.N0000	Non-Distress	Non-Distress	
L6	Commercial Bank of Ceylon PLC	COMB.N0000	Non-Distress	Non-Distress	
L7	Melstacorp PLC	MELS.N0000	Distress	Non-Distress	
L8	Browns Investments PLC	BIL.N0000	Distress	Non-Distress	
L9	Sampath Bank PLC	SAMP.N0000	Non-Distress	Non-Distress	
L10	Hatton National Bank PLC	HNB.N0000	Non-Distress	Non-Distress	
L11	Lanka IOC PLC	LIOC.N0000	Non-Distress	Non-Distress	

Aitken Spence PLC	SPEN.N0000	Non-Distress	Distress
Carson Cumberbatch PLC	CARS.N0000	Distress	Distress
Valibel One PLC	VONE.N0000	Non-Distress	Non-Distress
Ceylinco Insurance PLC	CINS.N0000	Non-Distress	Non-Distress
C T Holdings PLC	CTHR.N0000	Distress	Non-Distress
Hemas Holdings PLC	HHL.N0000	Distress	Non-Distress
Richard Pieris and Company PLC	RICH.N0000	Distress	Distress
	Carson Cumberbatch PLC Valibel One PLC Ceylinco Insurance PLC C T Holdings PLC Hemas Holdings PLC	Carson Cumberbatch PLC  Valibel One PLC  Ceylinco Insurance PLC  CT Holdings PLC  Hemas Holdings PLC  CARS.N0000  CTHR.N0000  CTHR.N0000	Carson Cumberbatch PLC Valibel One PLC Vone.N0000 Ceylinco Insurance PLC CTHoldings PLC CTHR.N0000 CTHR.N0000 Distress Hemas Holdings PLC HHL.N0000 Distress

**Source:** Author Calculations

The primary function of bankruptcy prediction models is to predict future business failures. This study tries to evaluate the effectiveness of bankruptcy prediction models to predict delisting status. According to the results, there are two types of errors that are,

Type 1 error: if the model predicts the samples did not experience delist when, in fact, experiencing distress.

Type 2 error: if the model predicts a sample experiencing delist when it is not experiencing delist.

According to that, error rates are calculated as follows:

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

Type 2 Error =  $\frac{\text{Number of Type 2 Errors}}{\text{Number of Sample}} * 100\%$ 

# 4.5. Model Comparison

Table 4.5: Model Comparison: Prediction Power One Year Prior to Delisting

	Result: Listed predict: Listed	Result: Delisted predicted: Delisted	Result: Delisted predicted: Listed	Result: Listed predicted: Delisted	Overall accuracy	Type 1 error	Type 2 error
Alman's Z''-score model	13	12	6	5	69.44%	16.67%	.3.89%
Zmijewski X-score model	11	9	9	7	55.56%	25.00%	9.44%

**Source:** Author Calculations

The results are based on the 18 listed companies and 18 delisted companies one year prior to delisting. The revised Altman's Z-score model has the highest accuracy rate of 69.44%, while the Zmijewski X-score model has a lower accuracy than the listed category with a type 1 error

rate of 25%. One year prior to the rate of 55.56%. Zmijewski X-score model has a tendency to misclassify delisted firms into delisting- Revised Altman's Z''-score model.

Table 4.6: Chi-square test: One year prior to delisting - Altman's Z''-score Model

	Altman's (2006) Z''-score Model		
	<b>Delisted</b>	Listed	Total
Z < 2.6	12	5	17
Z > 2.6	6	13	19
Total	18	18	36
$X^2 = 5.46$			

Source: Output Results

According to the significance level (0.05) and degree of freedom, the critical value (tabular value) is 3.841, and the calculated chi-square is 5.46. Therefore, the chi-square test rejects the null hypothesis and accepts the alternative hypothesis; there is an association between delisting and Altman's Z''-score model. Table 4.6 above shows the chi-square statistics.

Table 4.7: Chi-square test: One year prior to delisting- Zmijewski X-score Model

	Zmijewski (19		
	Delisted	Listed	Total
Z < 0	9	11	20
Z > 0	9	7	16
Total	18	18	36
$X^2=0.45$			

Source: Output Results

According to the significance level (0.05) and degree of freedom, the critical value (tabular value) is 3.841, and the calculated chi-square is 0.45. Therefore, the chi-square test accepts the null hypothesis that there is no association between delisting and the Zmijewski X-score model. Table 4.7 above, shows the chi-square statistics.

Table 4.8: Model Comparison: Prediction Power Two Years Prior to Delisting

	Result: Listed predict: Listed	Result: Delisted predicted: Delisted	Result: Delisted predicted: Listed	Result: Listed predicted: Delisted	Overall accuracy	Type 1 error	Type 2 error
Alman's Z''-score model	15	10	8	3	69.45%	22.22%	8.33%
Zmijewski X-score model	14	9	9	4	63.89%	25.00%	11.11%

Source: Output Results

The results show that the revised Altman's Z''-score model has the highest accuracy rate of 69.45%, while the Zmijewski X-score model has a lower accuracy rate of 63.89%. The Zmijewski X-score model tends to misclassify delisted firms as listed, with a Type 1 error rate of 25%.

Table 4.9: Chi-square test: Two years prior to delisting- Revised Altman's Z''-score model

	Altman's (20		
	Delisted	Listed	Total
Z < 2.6	10	3	13
Z > 2.6	8	15	23
Total	18	18	36
$X^2 = 5.90$			

Source: Output Results

According to the significance level (0.05) and degree of freedom, the critical value (tabular value) is 3.841, and the calculated chi-square is 5.90. Therefore, the chi-square test rejects the null hypothesis and accepts the alternative hypothesis that there is an association between delisting and Altman's Z"-score model.

Table 4.10: Chi-square test: Two years prior to delisting- Zmijewski X-score Model

	Zmijewski (1983) X-score Model			
	Delisted	Listed	Total	
Z < 0	9	14	23	
Z > 0	9	4	13	
Total	18	18	36	
$X^2 = 3.01$				

Source: Output Results

According to the significance level (0.05) and degree of freedom, the critical value (tabular value) is 3.841, and the calculated chi-square is 3.01. Therefore, the chi-square test accepts the null hypothesis that there is no association between delisting and the Zmijewski X-score model.

The findings are further discussed in light of the conclusions drawn from the present study. The results of the study are consistent with those of previous studies by Hadi & Anggraeni (2008), Rachmania (2016), Anugrah (2019), and Supitriyani et al. (2022). Rachmania (2016) shows that among the modified Altman Z'-score model, Springate model, and Zmijewski model, only the modified Altman Z-score model (3<sup>rd</sup> version) and the Springate model can be used to predict delisting companies. The results of this study confirmed his findings again. Additionally, Hadi & Anggraeni (2008) concluded that, among bankruptcy prediction models, the Altman Z-score model is the most effective predictor, while the Zmijewski model does

not predict delisting. Additionally, research conducted by Anugrah (2019) showed that both the Altman X-score and Taffler models are significantly better compared to the Zmijewski X-score model. Additionally, Supitriyani et al. (2022) noted that the Altman model is the most accurate prediction model for predicting bankruptcy, achieving the highest degree of accuracy compared to other bankruptcy prediction models.

However, the results of the study are inconsistent with several previous studies (Fatmawati, 2012; Nenengsih, 2018; Winaya et al., 2020). Fatmawati (2012) demonstrated that only the Zmijewski model could effectively predict companies delisted during the observation period; neither the Altman model nor the Springate model could be used as predictive models for delisting. Confirming the results of his study, Husein & Pambekti (2014) and Nenengsih (2018) pointed out that the Zmijewski model can be used to predict bankruptcy. In the study by Husein & Pambekti (2014), the Zmijewski X-model stands out as the most appropriate model for predicting delisting due to its high level of significance compared to other models, such as the Altman Z-score model and the Grover model. Overall, they demonstrated that the Altman Z-score model is less suitable for predicting delisting, especially in the context of companies operating during an economic crisis.

### 5. Conclusion

The primary objective of the researcher was to assess the predictive capabilities of Altman's Z''-score model and Zmijewski's X-score model as tools for predicting companies with delisting potential. The research was conducted based on a sample of 18 delisted companies and 18 listed companies. To generate results relevant to the research problem, the model's accuracy rate, error rate, and Chi-square test were conducted.

Based on the results obtained by data analysis for one and two years, the revised Altman's Z''-score model has a higher accuracy rate in predicting delisting companies than the Zmijewski X-score model in the Sri Lankan context. Zmijewski's X-score model tends to misclassify delisted firms as listed, resulting in a type 1 error rate of 25%. Therefore, compared to the accuracy level of Altman's Z''-score model, the Zmijewski X-model is not suitable for predicting the delisting of companies. According to the overall results obtained from the analysis, it can be concluded that the revised Altman's Z''-score model can be used as a predictor of delisting companies and has a higher predictive ability than the Zmijewski X-score model, especially when assessing the delisting possibility during a period of national economic crisis.

This study offers several implications for various stakeholders, including investors and corporate decision-makers. Stakeholders can enhance their decision-making by analysing the

company's financial status using Altman's Z-score model. Companies can utilise Altman's Z-score model as a predictive measure in anticipation of delisting, as it provides early warning signals about potential future financial distress and delisting, particularly during uncertain environmental conditions resulting from economic crises. Investors and creditors can perform predictive analysis on companies using Altman's Z-score model, and therefore, they can make informed decisions that will help them minimise credit losses. For corporate decision-makers, identifying companies at risk of delisting well in advance is essential to take preventive measures and mitigate potential financial losses. Therefore, they can use Altman's Z-score model as a predictor of delisting.

Although the study makes significant contributions, a few limitations should be noted, which pave the way for future studies. The study is limited by restricted access to previous years' financial data of delisted companies, as their annual reports were removed from the Colombo Stock Exchange library after delisting. This poses a challenge in collecting a substantial sample, which may affect the generalizability and statistical power of the findings. Another limitation is that this study only examined the validity of Altman's Z''-score model and Zmijewski's X-score model. Future studies can test the validity of other bankruptcy prediction models, such as the Springate model, the Ohlson model, the Groever Model, and the CA-Score model, in special environmental conditions similar to those of this study. The results can be extended to similar countries in the South Asian region, but may not be generalizable to developed countries or nations with larger stock markets. Therefore, future follow-up studies comparing Altman's Z-score model with the Zmijewski X-model, using data from countries other than Sri Lanka, especially developed and larger countries, will provide further insights.

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